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Capturing and analyzing verbal and physical collaborative learning interactions at an enriched interactive tabletop

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Abstract Interactive tabletops can be used to provide new ways to support face-to-face collaborative learning. A little explored and somewhat hidden potential of these devices is that they can be used to enhance teachers' awareness of students' progress by exploiting captured traces of interaction. These data can make key aspects of collaboration visible and can highlight possible problems. In this paper, we explored the potential of an enriched tabletop to automatically and unobtrusively capture data from collaborative interactions. By analyzing that data, there was the potential to discover trends in students' activity. These can help researchers, and eventually teachers, to become aware of the strategies followed by groups. We explored whether it was possible to differentiate groups, in terms of the *extent* of collaboration, by identifying the interwoven *patterns of* students' *speech* and their *physical actions* on the interactive surface. The analysis was validated on a sample of 60 students, working in triads in a concept mapping learning activity. The contribution of this paper is an approach for analyzing students' interactions around an enriched interactive tabletop that is validated through an empirical study that shows its operationalization to extract frequent patterns of collaborative activity.

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Introduction

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Research on learning and instruction has shown that *collaboration* can lead to improved critical thinking, reduced task workload, increased retention, and a more positive attitudes towards the subject matter (Felder and Brent 1994; Johnson and Johnson 1986). Particular cognitive mechanisms that may result into learning have an increased probability to be triggered when students argue to convince others to change their views on problems, reach shared understanding, or integrate individual with group knowledge (Scardamalia and

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Bereiter 1991; Stahl 2006). This makes collaboration skills key conditions for value 37
generation, not only for learning but also in the workplace (Scheuer et al. 2010). 38

However, students working together to achieve a shared goal do not spontaneously 39
collaborate (Dillenbourg 1998), even if they are supported by a computer system (Kreijns 40
et al. 2003). Collaborative learning is not a single mechanism; it often requires all group 41
members to engage on a coordinated effort to provide a joint solution to a problem 42
(Roschelle and Teasley 1995). It also demands the development of a number of skills, and 43
thus teachers have a central role in providing feedback and helping students to be more 44
aware of their group dynamics (Dillenbourg et al. 2011; Kirschner 2001; Slavin 1983; Webb 45
2009). 46

Face-to-face collaboration offers *particular* benefits that are not easy to achieve in other 47
forms of group work (Johnson et al. 2000). These include a natural channel for continuous 48
interaction, exchange of non verbal cues, and increased productivity in completing tasks 49
(Olson et al. 2002). The classroom is an environment where teachers commonly conduct 50
small group activities to promote students' learning and collaboration (Leonard et al. 1997). 51
However, teachers have to manage their limited resources, particularly in terms of the 52
attention they can give to each student, each with different learning styles, strengths and 53
needs (Zhang et al. 2004). They may try to identify the groups that are collaborating more 54
effectively and leave them to work more independently so that they can focus on groups that 55
need more attention. As a teacher cannot attend to all groups at once, they generally cannot 56
be aware of the process that some groups followed (Race 2001). 57

The development of emerging pervasive shared devices, such as *interactive tabletops*, is 58
very promising for providing a new form of support for students to collaborate and for 59
teachers to monitor group work (Kharrufa 2010). The affordances of interactive tabletops 60
include the provision of a work space that offers equal opportunities for each learner, 61
repeatability when working with virtual content, and digital tools that give students access 62
to different resources for building a solution (Piper and Hollan 2009). Tabletops provide an 63
environment in which students can decide whether they work in parallel, or together as a 64
group (Martinez-Maldonado et al. 2012b). They also open up new opportunities for captur- 65
ing learners' *digital footprints,* creating the possibility that teachers and researchers can gain 66
new understanding of the collaborative processes. In particular, there is the promise that 67
analysis of the digital footprints can be used to recognize patterns that can distinguish *higher* 68
from *lower achieving* groups (Martinez-Maldonado et al. 2011c). 69

There is a large body of research on the analysis of computer-supported collaboration 70
(Soller et al. 2005), and on the emerging fields of Educational Data Mining (Baker and Yacef 71
2009) and Learning Analytics (Siemens and Baker, 2012). However, most of the proposals 72 **Q4**
for automatic analysis have considered networked settings, where, in principle, all the 73
interactions between students can be recorded by the system (Soller et al. 2005). When 74
applied to face-to-face settings, computer supported collaboration analysis is mostly based 75
on video and audio recordings (Jeong and Hmelo-Silver 2010), and oriented to researchers, 76
whose focus is on the deep and detailed insights enabled by streams of data. 77

Teachers need tools that can provide them with coarse-grained feedback that allows them 78
to monitor what is happening in their classes (Dillenbourg et al. 2011). One challenge in the 79
field is to create reliable indicators of collaborative work that can be used by teachers to 80
monitor the activity, and by students to self-regulate their collaboration. Additionally, co- 81
located collaboration is strongly based on verbal, as well as subtle non-verbal, interaction 82
and therefore important aspects of the communication are not mediated by the technology. 83
The integration of evidence of verbal activity with the data stored by the learning systems is 84
not straightforward. For this reason, most of the tools that provide support to teachers, even 85

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if applied in face-to-face settings, do not include these verbal utterances as part of the   86
automatic input, yet it is very important. There is a need to provide technological infrastruc-   87
tures that are able to integrate these verbal interactions. This leads to a more important need,   88
which is the definition of analysis methods that exploit this integration.   89

We present an approach to exploit the affordances of an interactive tabletop to automat-   90
ically and unobtrusively capture students' *verbal interactions* (speech), their *physical* activ-   91
ity (touches on the tabletop) and their *knowledge representations* to produce indicators of   92
collaborative work. These indicators can make visible the strategies followed by students   93
and highlight possible problems in small group work. The contribution of this paper is an   94
approach for capturing and analyzing students' interactions around an enriched interactive   95
tabletop, which is validated with an empirical study showcasing its operationalization for   96
extracting frequent patterns of collaborative activity.   97

The specific face-to-face collaborative context of our work is *a small group learning*   98
activity in an enriched interactive tabletop. We identified the *sources* from which informa-   99
tion can be captured in this kind of learning environment: the group as a hole, individual   100
contributions, and the digital artifacts they create during the learning activity. We also   101
identified the *target users* of the data analysis. These typically are: (i) the learners, (ii) their   102
teacher, (iii) researchers, or (iv) the learning environment itself. There are three main   103
components of our approach: data capture, data analytics, and data presentation. The *Data*   104
Capture component gathers rich contextual information from the tabletop environment (in   105
this study: identified actions, detected speech and aspects of the collaborative concept maps).   106
The *Data Analytics* component can transform the captured data to produce key indicators of   107
interaction or possible strategies followed by students. The third component, *Data*   108
Presentation, which is beyond the scope of this paper, has the potential to provide the target   109
users with results of the data analysis in the form of a teacher's dashboard or knowledge.   110
This paper is limited to present key information to be directly used by researchers or that can   111
be used to implement a recommended system for further stages. The design of such a system   112
is important and independent from the focus of this paper, although some promising work   113
towards it has been reported (Martinez-Maldonado et al. 2013) and this points to the   114
potential of our approach for broader uses.   115

The paper is organized as follows. The next three sections present the state of research on   116
interactive tabletops in education, collaboration analysis and concept mapping. Then, we   117
describe our technological infrastructure. After this, we present our research questions, the   118
design of the study, and an exploratory analysis of the captured data. Then, we describe our   119
approach to extract patterns of activity by applying a sequence mining technique. We discuss   120
the results in the final section.   121

Collaborative learning around interactive tabletops   122

The proliferation of surface devices, such as tablets, smart phones, and more expensive   123
tabletops, is causing a shift in the possible ways that people can interact with computers   124
(Hilliges et al. 2010). This is creating opportunities to make computers more ubiquitous   125
rather than the center of the activity as is often the case with most of desktop/laptop   126
computers. In particular, interactive tabletops can enrich a typical face-to-face setting by   127
providing unconstrained orientation of a shared space, allowing the placement of physical   128
items, and offering each group member equal opportunity to participate (Müller-Tomfelde   129
and Fjeld 2012). However, like other technologies, tabletops themselves do not provide a   130
direct improvement in learning or collaboration. Instead, they open the possibility of new   131

ways to design activities that teachers and researchers can take advantage of, to enhance   132
instruction (Dillenbourg and Jermann 2010).   133

The common denominator of most of the research on tabletops for education is the study   134
of some interaction data, mainly obtained from observations and activity logs that the   135
hardware can capture, to support qualitative analysis of collaboration. A few examples   136
include the use of group observations to reveal social relationships (Falcao and Price   137
2009; Fleck et al. 2009; Rogers and Lindley 2004), the analysis of symmetry of interaction   138
based on the number of learner's touches (Harris et al. 2009; Rick et al. 2009), quantitative   139
measures of verbal turn taking and communication (Jermann et al. 2009; Marshall et al.   140
2008; Martinez-Maldonado et al. 2012c; Rick et al. 2011), the exploration of the impact of   141
users' positions around the tabletop (Tang et al. 2010), the assessment of group products   142
(Do-Lenh et al. 2009; Kharrufa 2010; Oppl and Stary 2011) and the analysis of the process   143
of scripted collaboration (Kharrufa 2010).   144

One of the most promising examples of work where the use of tabletops can directly help   145
teachers is deploying multiple tabletops in the classroom. One approach was presented by   146
AlAgha et al. (2010), who designed a multi-tabletop classroom, orchestrated by a teacher's   147
monitoring tool. This setting offers students the opportunity to work face-to-face, and they   148
have access to multimedia content. It also allows the teacher to monitor, orchestrate and   149
improve the class management by controlling students' tabletops remotely (Mercier et al.   150
2012). A second approach by Martinez-Maldonado et al. (2012a) explored the use of   151
multiple tabletops in an authentic classroom. Notably, that work provided explicit support   152
for the teacher to design, enact and assess small group activities linked to the curriculum.   153

However, most of these studies were done not for the purpose of exploiting data   154
automatically. Some exceptions include the visualization of tabletop data to increase   155
teacher's awareness (Al-Qaraghuli et al. 2011; Martinez-Maldonado et al. 2012b), the use   156
of data mining to discover differences between groups (Martinez-Maldonado et al. 2011c)   157
and an approach to analyze logs to assess teachers' activity design (Martinez-Maldonado   158
et al. 2012a).   159

The analysis of verbal participation in non-interactive tabletops has shown that even   160
modest indicators of speech, that can be automatically captured, are effective in supporting   161
inferences about important aspects of collaboration. These include: interaction patterns, the   162
evolution of the discourse flow, leadership, and behavioral changes (Roman et al. 2012). The   163
automated analysis of verbal participation in interactive tabletops is an important aspect   164
where there has been little research (Martinez-Maldonado et al. 2012b). Previous research   165
has also investigated the impact of multi-user interactions afforded by tabletops on certain   166
aspects of collaboration such as equity of participation and self-regulation (Marshall et al.   167
2008). A deep understanding of the connection between the speech and physical dimensions   168
of the interactions in the tabletop is still lacking. The next section describes how research on   169
online collaborative systems can serve as a basis for analyzing collaboration in the tabletop.   170

Collaborative learning analysis and mining   171

Over the last two decades, there has been substantial progress in the development of   172
technologies that enable learners to collaborate, mainly through networked systems (Soller   173
et al. 2005). Large amounts of data can be captured as a result of the interaction of students   174
with these systems and, indirectly, with their peers. Students' activity can be recorded at   175
different levels, from video capture, that has mostly been manually analyzed, to logging the   176
system events that can be automatically analyzed by software tools. Students' data can be   177

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used for self-regulation (by students); for scaffolding, coaching and evaluation (by teachers); or for post-hoc analysis, design-based interventions, etc. (by researchers). This information can be presented to the actors through visualizations so that they can quickly interpret the information and take appropriate actions. Software agents can also trigger automatic regulating actions.

The use of Data Mining or Artificial Intelligence techniques in collaborative learning environments has proven successful in gaining insights on the interactions within groups in terms of collaboration. Some research has studied collaborative learning by applying data mining techniques. Notable is the work done by Soller et al. (2002), who used Hidden-Markov Model to identify the episodes when students were sharing knowledge at a constrained and scaffolded object modeling networked system. Other key initial work was conducted by Talavera and Gaudioso (2004) who presented a case in which they applied a **Q5** clustering technique to e-learning data; they were able to build student profiles based on a set of features related to the user interaction with the system. Building on this previous work, Anaya and Boticario proposed both a supervised classification (2011) and unsupervised clustering (2009) techniques for grouping students according to their level of collaboration. Additionally, some researchers have addressed the analysis of collaboration using sequential pattern extraction. One important study on online learning data was performed by Perera et al. (2009) who explored the use of sequence mining alphabets and clustering to find trends of interaction associated with effective group work based on data from long term use of a collaborative software development tool.

Most of these examples are based on learning settings where most of the recorded communication is mediated by the system, making it easier to automatically log students actions compared with face-to-face environments. Alternatively, in these examples it is commonly ignored that students can interact face-to-face or via other media (e.g., emails, chats or IM). There is less research in developing systems that can support collocated collaboration and automatically analyze students' data compared with networked systems (Jeong and Hmelo-Silver 2010). Yet, research on *collaboration* through these systems, can provide the foundation for automated capture and analysis of face-to-face interaction through tabletops.

Work on the *analysis of indicators of collaborative learning* can be found as subsets of research in learning analytics (Siemens and Baker 2012), educational data mining (Baker and Yacef 2009) or analysis of collaborative interactions (Harrer et al. 2009). These fields have created techniques to produce models and indicators of learners in a wide range of technology-based learning situations. The analysis can be targeted to develop meta-cognitive support, enhance regulation, facilitate assessment, or improve awareness. Dimitracopoulou et al. (2006) presented a taxonomy of indicators that can be used to represent aspects of *group interaction*, for example, *collaboration intensity, participation rate,* or *division of labour.* Some of these indicators, such as *quality of collaboration* or *common understanding* are difficult to detect even through human judgment. Therefore, they impose limitations to what can be measured automatically.

The *Data Capture* and *Analytics* components of our approach are highly influenced by the taxonomy of group indicators proposed by Dimitracopoulou et al. (2004). This defines the indicators of collaborative work that can automatically be captured and processed from non face-to-face learning systems. This taxonomy sets an initial standard, which can be extended to face-to-face settings. It informs the definition of what data should be captured by a collaborative learning environment that is intended to produce indicators of group activity. It distinguishes five sources of information for analyzing the collaborative process: (i) individuals (the actions and products of specific learners), (ii) undifferentiated group

(information that concerns the whole group, without identifying individual contributions or 227
roles), (iii) differentiated group (information in which the contribution of each learner is 228
identified), (iv) the community (considering multiple groups), and (v) the society or com- 229
munity). Our approach concerns only the first four aspects. 230

In face-to-face settings there is substantially more information being externalized by 231
learners in comparison with networked applications, for example, hand gestures, body 232
language and gestures of assent, among others (Olson et al. 2002). The collaborative 233
situation and channels of communication are significantly different in collocated settings. 234
Therefore, the technology can capture some aspects of students' interactions in a face-to-face 235
setting (Yu and Nakamura 2010). 236

Collaborative concept mapping 237

We combined face-to-face collaborative learning mediated through an interactive tabletop 238
with an educational tool that has the potential to foster students' meaningful learning: 239
concept mapping. This is a well established learning strategy that can be applied in a number 240
of domains and is backed up by a strong community of research and practice (Cañas and 241
Novak 2008). Concept mapping enables students to externalize their understanding through 242
a visual representation of knowledge (Novak 1995). A concept map consists of a directed 243
graph in which nodes represent *concepts*. These are defined as perceived regularities in 244
events or objects of a domain (Novak and Cañas 2008). For example: *balanced diet*, *proteins* 245
or *meat*. Concepts can be connected with a labeled link to create a meaningful statement 246
called a *proposition*. For example, the concepts *meat* and *proteins* might be linked in the 247
proposition: *meat contains proteins* using the link *contains*. Similarly, the earlier concepts 248
can form the proposition: *balanced diet includes proteins*. Concept maps can serve as 249
vehicles of discussion and negotiation of meaning between students (Novak 1995). They 250
can be used for facilitating collaborative learning, offering students the opportunity to 251
discuss ideas, present knowledge from multiple angles, identify misunderstandings, reach 252
agreement, or agree to disagree (Gao et al. 2007; Novak 1995; Stahl 2006). 253

Some studies have specifically explored concept mapping at the tabletop. An early example 254
was a single user system that used concept maps for wiki navigation (Baraldi et al. 2006). 255
Tanenbaum and Antle (2009) built a system that permitted a student to create a concept map 256 **Q6**
using tangible tokens. Do-Lenh et al. (2009) compared the use of a tabletop with a shared 257
desktop computer to build collaborative concept maps. Results were negative for the tabletop; 258
because sharing a personal computer *forced* negotiation. By contrast, a tabletop does not force 259
collaboration. Later, Oppl et al. (2011) found that tabletop concept mapping offers students 260
equal opportunities for participation when compared with other media. Martinez-Maldonado 261
et al. (2012c) also demonstrated that tabletop concept mapping can provide students the 262
opportunity to decide how to coordinate their strategies. Overall, this body of work points to 263
a complex picture of the potential benefits of collaborative concept mapping at tabletops. 264

System setup 265

In this study, the data capture, if not comprehensive, is low cost, unobtrusive and very large 266
volume; and it has the promise of generating imperfect, but useful indicators of collaboration 267
similar to those described by Dimitracopoulou et al. (2004) and, more specifically, to address 268
a set of research questions that are described in the next section. We used a number of tools 269

to permit students to create concept maps (individually and collectively) and, we simulta- 270
neously capture information of the process followed. These tools are a desktop-based 271
(CmapTools) and a tabletop-based (Cmate) concept mapping tools; and a system to unob- 272
trusively capture differentiated users' actions (Collaid). 273

CmapTools (Novak and Cañas 2008) is a concept mapping editor for personal com- 274
puters. In this study, students use it to build their concept maps individually. CmapTools 275
offers an *Extensible Language* based on XML to share and export the concept maps to 276
other environments. We exploit this functionality to connect the artifacts that students 277
first build in private with the tabletop environment that they use to build a new artifact, 278
the concept map created collaboratively in the tabletop. 279

Cmate (Martinez-Maldonado et al. 2010) is a tabletop application that enables learners 280
to draw a concept map that represents their collective understanding about a topic 281
(Fig. 1, bottom left). Cmate provides each student with a personal menu to add the 282
concepts they used in the concept map that they individually created using CmapTools. 283
Students can also add any new concepts they wish. When students create propositions, a 284
menu appears around the new link so they can select any of the top six linking words 285
they used before or they can type a new linking word. Students also have access to a 286
screenshot of the map that they created in private; this enables them to recall or to share 287
their perspectives with others. Students can decide to build upon their previous concept 288
maps or create a totally new group artifact. 289

Collaid (Martinez-Maldonado et al. 2011a). The tabletop used in this study had a 46-in. 290
LCD touch screen, offering comfortable space for up to four participants. The tabletop 291
hardware can detect multiple touches at a time, but—like most current touch 292
hardware—it cannot recognize which user provides an input. In order to log each 293
student's individual actions, we used Collaid. 294

Collaid extends an ordinary interactive tabletop, so that it can unobtrusively determine 295
which learner is touching what. It relies on an overhead depth sensor (http://www.xbox.com/ 296
kinect) that associates each touch performed on the interactive surface with the student who 297
did the action. The system captures the overhead depth video stream and then, making use of 298
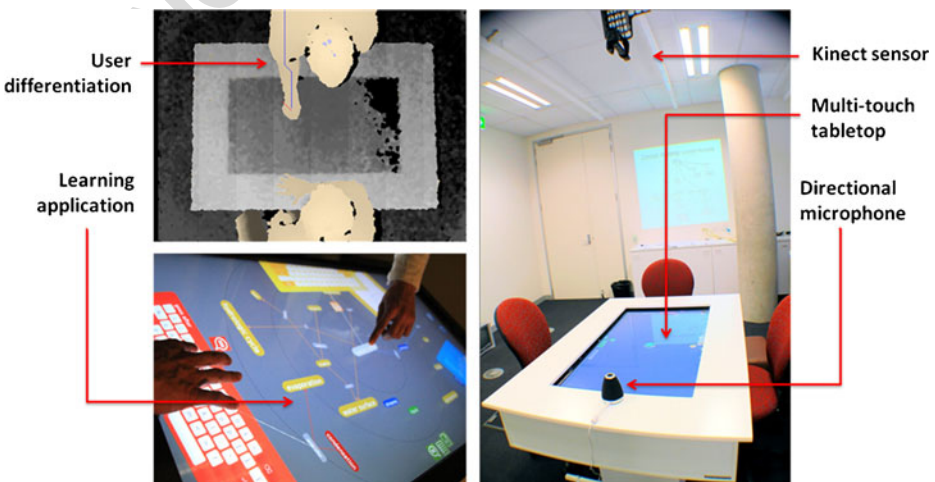
Fig. 1 Digital learning environment and capturing system

a greedy search algorithm, matches the touch with the position of each learner (Fig. 1, top 299
left). We capture verbal participations and turn taking through a microphone array situated 300
on one of the edges of the tabletop (Fig. 1, right). We used a 7-channel microphone (http:// 301
www.dev-audio.com) that distinguishes sounds based on the location of the source. In our 302
case, the learners sit around the tabletop. The audio information is recorded into audio files 303
and the shared database. 304

Through this set of software and hardware, we can capture a multi-dimensional dataset: 305
verbal interactions between learners, without attaching microphones to people; and tabletop 306
data logs with the authorship of each touch at the tabletop, without attaching any gadget to 307
learners' hands or imposing additional hardware restrictions. Figure 1 shows the generic 308
hardware we used, including the sensors. 309

Study design and exploratory analysis 310

This section describes how we designed a study to assess whether the data captured in a tabletop 311
learning environment can provide useful information about learner collaboration. We began by 312
formulating research questions; these come from considering open issues in previous studies on 313
collaboration in tabletops and the potential power of our four data sources (audio, touch, touch 314
on other learner's artifacts and access to individual perspectives). Next, we describe the design 315
of the study to identify interaction patterns around tabletops. 316

Research questions 317

We identified four research questions that link the observable patterns or strategies that are 318
promising for differentiating groups according to the *extent* of their collaboration. First, 319
previous research on collaboration around interactive and non interactive tabletops sug- 320
gested that groups that produce *better* solutions have more equality in discussion (Martinez- 321
Maldonado et al. 2012c; Roman et al. 2012). This finding motivated our first two questions; 322
these primarily focus on the exploration of *verbal activity*, and its timing in relation to the 323
physical tabletop *activity*. 324

1) Can we distinguish more collaborative from less collaborative groups by the interwoven 325
    stream of students' *verbal and physical participation*? 326
2) Can we distinguish more collaborative from less collaborative groups by extracting 327
    patterns of interaction based on just students' *verbal participation?* 328

Other studies inspired our third question; these suggested that when a learner interacts 329
with digital artifacts created by other students, this may trigger further discussion that is 330
beneficial for collaboration (Fleck et al. 2009; Martinez-Maldonado et al. 2012b). In the 331
context of collaborative concept mapping, this may be associated with the concept of 332
transactivity, which is the extent to which one group member refers to, or builds their 333
own ideas upon, their peer's contribution (Molinari et al. 2008; Stahl 2013). Strictly, this 334
would be measured in terms of the number of links that each learner creates using concepts 335
that other learners added to the group map (Martinez-Maldonado et al. 2012c). Our approach 336
goes a step further by including all the interactions a student performs on others' objects, 337
including moving them. The third question is: 338

3) Can we distinguish more collaborative from less collaborative groups based on patterns 339
    involving *traces of interaction of students with others' objects*? 340

We also explored the strategies followed by different groups to access individual   341
learners' representations of knowledge inspired by the studies on mutual awareness by   342
having access to individual concept maps (Engelmann and Hesse 2010). The fourth   343
question is: 344

4) Can we distinguish more collaborative from less collaborative groups in terms of the   345
     actions that follow up the access to others' knowledge structures?   346

Participants and approach   347

One approach that has proved successful to foster meaningful learning is to follow the   348
construction of individual concept maps with a collaborative phase (Engelmann and Hesse   349
2010; Novak 1995). This provides students with the opportunity to first think about their   350
personal understanding and then focus on establishing common ground with others, nego-   351
tiating meanings, and generating group knowledge. This strategy is supported by the theory   352
of *Group Cognition* in which the process of knowledge building is modeled as a continuous   353
loop of individual and collaborative periods of learning (Stahl 2006). Our approach builds   354
on these approaches by providing both an individual and a shared space for group members   355
to build concept maps.   356

A total of 60 students enrolled in science courses participated in the study. An initial   357
focus question was posed to the students: What types of food should we eat to have a   358
balanced diet? Their goal was to create concept maps after studying the Australian Dietary   359
Guidelines 2011 published by the National Health and Medical Research Council of   360
Australia. Participants were organized in triads mainly grouped so they knew each other.   361
Before the activity, students received instruction on concept mapping and were requested to   362
draw a training concept map not related to the nutrition domain. Then, they were asked to   363
read a one-page article based on the dietary guidelines and draw a concept map individually   364
at a personal computer using CmapTools (Fig. 2, 1). After this, each triad was asked to build   365
a concept map in the tabletop (Fig. 2, 2). This application was loaded with the individual   366
maps previously built, allowing learners to have access to the concepts, linking words and   367
an image of their maps. The group activity was structured in two phases: i) *brainstorming,*   368
where students were only asked to add the most general concepts for their joint map   369
without creating propositions (they were advised to dedicate the first 5 to 10 min for this);   370
and ii) *linking*, where students could create propositions and add more concepts if needed   371
(20–25 min.). They had 30 min for building individual maps and 30 min or more for the   372
collaborative step. Finally, each learner was asked to draw an individual map again   373
(Figs. 2 and 3).   374

In this study we made a clear distinction between the brainstorming and linking phases   375
since the learning goals, the duration and the range of students' actions are different for both   376
activities. Therefore, we describe the exploration and analysis of students' data for each of   377
them separately. Our research questions are aligned with this exploratory approach. Through   378
these, we show that the same approach is applicable, and the results can be informative, for   379
both classes of learning activity.   380

Meaningful physical actions   381

The tabletop application initially provides each learner with three tools: a list of   382
concepts, an onscreen keyboard for editing phrases, and a resizable representation of   383
their individual concept map. Learners can add concepts by simply selecting them from   384
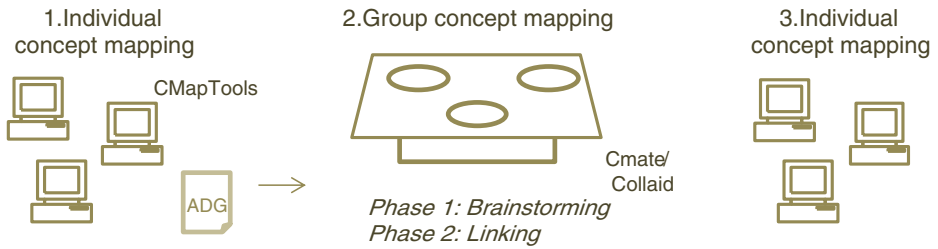
Fig. 2 Learning setting: *1*) concept mapping based on the Australian Dietary Guidelines (ADG); *2*) group concept mapping; and *3*) individual concept mapping

a list that contains those they each used when building their individual map externally. 385
They can add links by dragging a concept and dropping it on another concept; and 386
delete elements by dropping them on one of the two black holes at the corners of the 387
tabletop. 388

All elements of the tabletop are colored according to the user who created the object. 389
In this paper, we distinguished between the touch events captured by the tabletop 390
hardware and what we call *meaningful physical actions,* which produce a change in 391
the collaborative artifact. For example, to add a concept, a learner can search for the 392
desired word from their list or decide to create a new concept. For simplification we 393
associated all the touch events with only one higher-level action: *adding a concept*. The 394
meaningful physical actions are illustrated in Fig. 3. These include adding, deleting, 395
editing and moving concepts or linking words, and accessing individual maps on the 396
tabletop. For the brainstorming phase the interface only allowed students to add concepts 397
from their lists, create new concepts and open their individual concept maps. This 398
includes the core task for this stage, creating propositions. 399

Fig. 3 Meaningful physical actions. Two individual maps are open on the tabletop (*left*). Editing a linking word, adding a concept from a personal list and creating a link from the eight most used in learner's map (*right, top to bottom*)

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Quantitative assessment of quality of collaboration

All 20 sessions in the tabletop were assessed quantitatively. The goal of this analysis was to *differentiate* the groups in terms of whether the quality of their collaboration was assessed as high or low. We applied the analysis method designed by Meier et al. (2007) which defines nine qualitative dimensions of collaboration that are rated quantitatively. These dimensions are: mutual understanding, dialogue management, information pooling, consensus reaching, task division, time management, technical coordination, reciprocal interaction, and individual task orientation. The first 8 dimensions are group assessments and the last one includes individual assessments per student. Each dimension is quantified with a whole number ranging from −2 (very bad) to 2 (very good). We aggregated the numerical results of all dimensions to obtain a single score to categories the groups.

An aggregated score below zero was treated as *less collaborative* (or low collaboration) and positive scores as *more collaborative* (or high collaboration). This gave 10 groups with negative scores (−10 to 0). The other 10 groups had scores from 5 to 19. The averages were −4 (±3) (low collaboration) and 13 (±5), (more collaborative), where these differ by at least twice the standard deviation in each case. Two different raters tagged the sessions following the same rubrics as (Meier et al. 2007). Inter-rater reliability was high (Cohen's k = 0.80). This qualitative rating scheme was useful to generate a quantitative measure to distinguish the groups. However, it still has the limitation of requiring human judgment. There is ongoing research that aims to automate part of this assessment to offer a rating using a machine learning model, so making it possible to provide direct insights to teachers or perform analysis on the fly (Martinez-Maldonado et al. 2013).

Preliminary analysis

Before any pattern mining was undertaken, we explored the data to analyze if, by using simple statistics, it is possible to distinguish groups in terms of their extent of collaboration. First, we looked at the time that each group spent in each phase.

Table 1 shows the time spent by both more collaborative and less collaborative groups to complete the activity. We can observe that the majority of more collaborative groups kept to the suggested time for each phase (5–10 and 20–25 min respectively). While the less collaborative groups had similar averages, they had higher deviations. Even though the differences are not statistically significant, this suggests that some groups spent either less or more time of the allocated time for both phases. The issue to address is whether quantitative data can provide insights of the strategies that lead these groups to be less collaborative.

To further explore the dataset, we draw on previous work by Martinez-Maldonado et al. (2011b, 2012b), who modeled quantitative information of students working at a shared device, for three aspects of tabletop collaboration: *physical interaction*, *verbal interactions,* and the synergy between these two. We analyzed the *brainstorming* and *linking* phases separately as the range of actions and learning objectives were different. First, regarding the *physical activity*, we explored the cumulative interaction by each learner with other students' objects through the visualizations designed by Martinez-Maldonado et al. (2012b).

Table 1 Average time taken by groups to complete each collaborative phase

	More collaborative	Less collaborative
Phase 1 (brainstorming)	10′ (±3)	10′ (±7)
Phase 2 (linking)	21′ (±2)	24′ (±9)

*Time in minutes

Q10

t1.1
t1.2
t1.3
t1.4

Figure 4 shows three examples of the visualizations, where the size of the circles indicates the number of touches by learner. The thickness of the lines linking the circles represents the amount of interaction between pairs of learners, in terms of actions on objects created by the other. The visualization in Figure 4-*a* corresponds to a group that behaved quite collaboratively on this aspect. It shows three similar sized size circles, each linked to the other, with two lines, albeit each of various widths. Groups that are less collaborative groups on this dimension are illustrated in *b* and *c*, with different sized circles and, notably in *c* just one connection of the green using acting on objects of the yellow user.

Additionally, it has been found that for tasks like ours that called for equal participation, groups in which learners participate asymmetrically sometimes indicate cases of social loafing or disengagement (Dillenbourg 1998). For this, we explored one indicator of symmetry that has been used to study collaboration in tabletops: the G*ini coefficient* (Harris et al. 2009). This is a measure that represents *inequality* with a single number between 0 and 1, where 0 is perfect symmetry and 1 total inequality. Previous work with tabletops has found that coefficients close to 0.5 can be associated with non equal activity (Martinez-Maldonado et al. 2012c). Table 2 summarizes the amount of physical activity in our triads, the interaction of learners' with others' objects and the symmetry.

According to Table 2, for the *brainstorming* phase, all groups (both more and less collaborative) had similar levels of physical activity and high symmetry (>300 raw touches, gini coeff. 0.18). The main difference between Phase 1 and 2 was that in the *linking* phase, learners interacted more (and more unequally) with objects created by their peers. Overall, the level of action on others' objects was 29 % high groups and 25 % for low groups.

For the symmetry of physical activity, the high groups, shifted to less symmetric (rising gini coeff. from 0.18 to 0.35) while the low groups were rather consistent, 0.18 to 0.20). In fact, learners in low groups appeared to show more equality in their physical activity, consistent with the trend reported in (Martinez-Maldonado et al. 2011b). Contrary to what the visualizations of Figure 4 suggest, we found that low groups had more signs of symmetry in the physical interaction with other's objects (gini coeff. 0.2 for low and 0.36 for high groups). However, there were no significant differences that could distinguish groups as either more or less collaborative. Overall, these simple analyses provide a rather complex picture that makes it unclear how a group of learners, or their facilitator or teacher, might make use of these measures.

Secondly, we explored simple indicators of speech that might provide hints of possible issues in group work. Table 3 shows that the more collaborative groups had higher levels of verbal activity. In Column 1, we see time spent speaking of 457 against 270 in Phase 1 and 773 against 531 for Phase 2. For the number of utterances, in Column 3, there is a similar situation, with 138 against 91 in the brainstorming phase, 229 against 109 in the *linking*
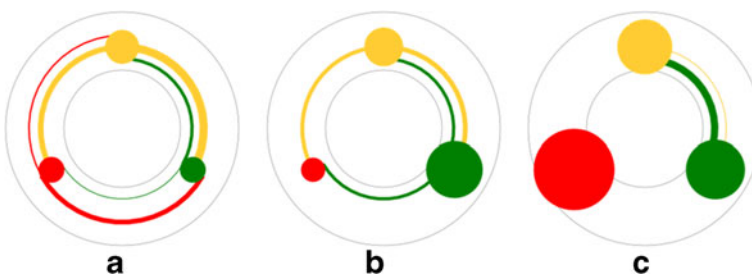
Fig. 4 Graphs of interactions with others' objects for (**a**) a collaborative group, **b** a group with a passive student, and (**c**) a non-collaborative group

t2.1 **Table 2** Average values of physical activity, interaction with others' objects, and symmetry

t2.2		Collaboration	Physical activity (touches)	Physical activity (symmetry)	Touches on others' objects	Touches on others' objects (symmetry)	Touches on others' objects (% all actions)
t2.3	Phase 1 (brainstorming)	Low	344 (±184)	0.18 (±0.1)	39 (±54)	0.63 (±0.3)	10 % (±10)
t2.4		High	320 (±120)	0.18 (±0.1)	32 (±25)	0.63 (±0.2)	9 % (±7)
t2.5	Phase 2 (linking)	Low	897 (±475)	0.20 (±0.1)	211 (±80)	0.20 (±0.1)	25 % (±6)
t2.6		High	740 (±120)	0.35(±0.1)	205 (±78)	0.36 (±0.2)	29 % (±11)

phase. Both phases had greater symmetry for the high collaboration groups (Column 2, gini 477
coeff. 0.19 against 0.34, then 0.19 and 0.30 for the linking phase). Even though the large 478
standard deviations affect the analysis of significance, these indicators suggest trends that 479
point to the potential value of deeper exploration at a lower level of granularity. 480

Table 3 also shows the average values of what we call *meaningful physical actions*, which 481
affect the size, shape or content of the group artifact. We observed no difference between low 482
and high collaborators in the number of these actions for the *brainstorming* phase (114 and 483
105 actions respectively) but some difference in the *linking* phase, where the less collabo- 484
rative groups had more of these actions. Lastly, we also accounted for the number of times 485
group members accessed their *individual maps*. The main difference was that the more 486
collaborative groups *always* accessed their maps, while *some* of the low groups never 487
opened a concept map (deviations equal to the average). 488

We additionally explored the *relationship between verbal and physical actions*. Previous 489
work by Martinez-Maldonado et al. (2011b, 2012b) suggested that the more collaborative 490
groups had higher levels of symmetric speech and lower levels of physical actions when 491
using a tabletop. They proposed a way to visualize this with a radar that showed the amount 492
and symmetry of physical and verbal activity. The triangles in Fig. 5 depict the number of 493
touches and amount of speech by each learner (red and blue respectively). Each small circle 494
represents a student. The closer the corner of the triangle is to a circle, the more that a student 495
was participating. An equilateral triangle means that learners participated equally. Figure 5 496
shows the representations of three groups. Visualization *a* shows a collaborative group in 497
which the 3 learners participated quite equally on both dimensions. Visualization *b* shows a 498
disengaged learner from the activity (left lower red circle); and visualization c shows a 499
learner who had a high level of physical activity but little verbal participation (also left lower 500
red circle). 501

t3.1 **Table 3** Average values of verbal activity, meaningful physical actions and number of accesses to individual concept maps at the tabletop

t3.2		Collaboration	Audio time (seconds)	Audio time (symmetry)	Utterances	Meaningful physical actions	Access to individual map
t3.3	Phase 1 (brainstorming)	Low	270 (±297)	0.34 (±0.19)	91 (±84)	105 (±65)	4 (±4)
t3.4		High	457 (±286)	0.19 (±0.20)	138 (±86)	114 (±53)	7 (±5)
t3.5	Phase 2 (linking)	Low	531 (±519)	0.30 (±0.13)	109 (±176)	407 (±227)	7 (±7)
t3.6		High	773 (±366)	0.19 (±0.07)	229 (±106)	286 (±50)	8 (±3)

Meaningful physical actions = Actions that made an impact on the collaborative artefact only
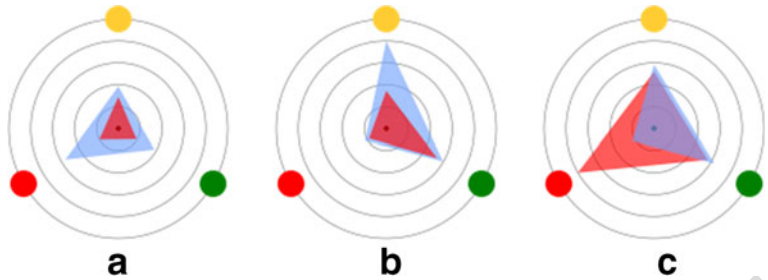
Fig. 5 Mixed radars of verbal (*blue/light triangle*) and physical (*red/dark triangle*) participation for (**a**) a collaborative group, **b** a group with a passive student, and (**c**) a non-collaborative group

Table 4 presents the analysis of the *physical actions* and how these were associated with verbal activity. First, we observed a weak trend in the less collaborative groups performing more physical actions without speech (Column 2, 20 % and 75 % of all actions for low compared with 13 % and 64 % for the high groups). By contrast, for actions accompanied by speech, we found that in all groups, individual learners tended to not to talk while performing physical actions (Columns 3 and 4).

For the *brainstorming* phase just the 16 % of such actions were performed in high groups and 14 % in low groups. For the *linking* phase this proportion was even lower (below 10 %). For the case of physical actions where the speech was from another learner, we found a different situation. An average of 44 % of the actions by the more collaborative groups were performed while other students were speaking (29 % of actions for low groups). For the *linking* phase this difference was smaller though but still with some difference (25 % and 17 % respectively).

Overall, the measures of activity presented above, each aggregated in isolation at the end of the activity, were not indicators of significant difference between groups that were either more or less collaborative. These averaged values do not take account of additional fine grain information that can be exploited, like the order, authorship or the balance between verbal and physical actions. This suggests the need to integrate contextual information and multiple sources of information simultaneously. Next, we present our approach that includes such contextual information with the sequence of learners' actions in order to explore patterns that can help to differentiate groups.

Table 4 Average values of physical actions *with no speech* in parallel; and physical actions *with speech* in parallel from the *same* student and *other* students

Collaboration			Actions with *no speech*	Actions with *no speech* (% all actions)	Actions with speech by *the same author*	Actions with speech by *the same author* (% all actions)	Actions with speech by *other author*	Actions with speech by *the same author* (% all actions)
Phase 1 (brainstorming)	Low		76 (±61)	20 % (±8)	14 % (±13)	14 % (±9)	29 % (±22)	29 % (±16)
	High		52 (±44)	13 % (±12)	16 % (±12)	16 % (±9)	45 % (±35)	44 % (±20)
Phase 2 (linking)	Low		307 (±234)	75 % (±23)	29 % (±28)	8 % (±7)	70 % (±64)	17 % (±20)
	High		185 (±73)	64 % (±61)	29 % (±28)	10 % (±6)	77 % (±39)	25 % (±15)

Physical actions= Actions that made an impact on the collaborative artefact only

Method: Data mining approach

One of the data mining techniques that have been used to identify patterns that differentiate
high from low achieving students is sequence pattern mining. We used this technique
because it takes account of the order of the events in, rather than simply the accumulated
statistical analysis in the previous section. For example, Perera et al. (2009) modeled key
aspects of teamwork for groups working with an online project management system; the
researchers defined *alphabets* to represent sequential events that had promise for
distinguishing strong from weak groups. Martinez-Maldonado et al. (2011c) proposed a
semi-supervised approach to extract sequential patterns of students' activity at a pen-based
tabletop and cluster similar patterns to link them with group strategies. Kinnebrew et al.
(2012) presented a *differential sequence mining* method which automatically compares
patterns that characterize high and low-achieving learners including contextual information
of students' actions. In this paper, we implemented a mixed technique that combined these
three previous approaches as described in the next subsections.

The *raw data* for each group initially consists of two long sequences of actions: evidence
of *verbal* speech by each learner and identified *touch* actions. These are transformed into a
list of *meaningful actions* and *verbal utterances*, which are defined as: *item action* =
{ActionType, Resource, Author, Owner, Time, Duration}, where ActionType can be: *Add*
(create a concept or link), *Rem* (delete), *Mov* (move), *Chg* (editing a concept or linking
word), *Open* or *Close* (individual maps). Resources can be: *Conc* (concept), *Link*
(proposition), *Indmap* (individual map) or *Speech* (utterance). Author is the learner who
performed the action, Owner is the learner who created or owned the Resource, Time is the
timestamp when the action occurred, and Duration is the time taken to complete the action.
Multiple touches to perform a single action and interaction with menus were not included.
The original filtered sequence obtained for each group had from 434 to 1467 *physical
actions* and from 83 to 627 *utterances*.

Data preparation and formatting

Even though the content of each *item action* in its raw format may appear simple, the level of
complexity of these data is actually high. Each student's action is associated with rich
contextual information obtained by interlacing the three sources of information: student'
physical actions on the tabletop application, the identified speech participation and the status
of the artifact.

The enriched tabletop can capture not just the students' actions, but it can also link these
to whether students were talking whilst interacting with the interface or just talking without
touching the table. Furthermore, in terms of the group artifact, student actions can have an
impact on the knowledge represented in the concept map or their actions may just modify
surface aspects of it. However, not all of this contextual data is relevant to the research
questions. In fact, if all this rich contextual information were taken into account when
extracting patterns, the information would be too detailed to find *meaningful trends* in the
interaction.

For example, whilst the authorship of learners' actions seems likely to be important, the
exact detail of who is doing what is not necessarily relevant: if the intention is to detect how
often students take turns versus a single student performing a sequence of actions, we only
need to know whether actions were performed by the same student or by different students.
Suppose that in one group, there is a sequence of actions (A, A, B) performed by two
students in the following order: student1-A, student2-A, student1-B. In a second group, a

similar sequence occurs but the authorship is different: student 3-A, student1-A, student3-B. Our encoding system must recognize this pattern to be found, regardless of which pairs of the students among 1, 2 and 3 are involved. Consider a second example, for the verbal participation: In one group, two students may perform the following sequence: student1-A and then student2–B. In parallel, a third student may be speaking: student3-utterance for 5 s. In this case, it is important to encode the sequence of events in a way that captures parallelism (e.g., speech and touch at the same time).

We therefore designed several alphabets, to encode the raw item actions at the level of abstraction needed for each research question, so that relevant patterns could be discovered. Next, we describe the design of a number of alphabets to encode student actions into item actions that capture required contextual information.

Alphabets to encode actions and contextual information

Inspired by previous work on design of alphabets to mine group behaviors (Martinez-Maldonado et al. 2011c; Perera et al. 2009) and the suffix nomenclature proposed in (Kinnebrew et al. 2012), we designed four alphabets. Each is associated with one research question, to enable discovery of the relationship between physical actions, presence of speech, verbal responses, parallelism, ownership, concurrency and access to individual maps.

We encode each action using the alphabets in Table 5. The coding for an action has *one keyword from each level*. The first two levels correspond to *Resource* and *ActionType*. Levels 3 and 4 add contextual information. We perform three steps to apply the four alphabets:

i) All *actions* that can be performed on the *resources* are coded with two *keywords,* from Levels 1 and 2;
ii) All the utterances that did not happen in parallel with any touch actions are coded in the same sequence, with 2 keywords: *Speech* and *Shrt* or *Full* for utterances shorter or longer than *u* seconds respectively (*u*=2).
iii) The keywords from Levels 3 and 4 are added to each action or utterance. These are different for each alphabet.

Next, we present a detailed description of each alphabet focusing on the specific keywords that are added in the third encoding step.

Alphabet 1 seeks to address the first question by exploring the interweaving of *verbal and physical participation traces.* First*,* it focuses on adding the contextual information about the s*peech that occurs in parallel with physical actions* (Alphabet 1, Level 3). This includes the keywords: *Sauthor*, which represents that the learner was talking while performing an action; *Sother*, which means that another learner was speaking while the author was performing the action; and *NoSpeech*, which means that when the action was performed no learner spoke.

Alphabet 1 also considers the time, order and author of each action to explore if only one student was building the solution or if their work was more reciprocal (by working either concurrently or completely in parallel). This is represented by the keywords in Level 4, which include: *Tsame*, which means that the previous action was performed by the same author; *Tother*, when the previous action was performed by a different learner (consecutive actions with the keyword *Tother* may indicate *concurrent* work); and *Tparallel*, when the previous action was performed by a different learner less than one second earlier, which is

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| t5.1 | **Table 5** Four alphabets. 1) Physical/verbal participation; 2) verbal participation; 3) physical action on others' objects; and 4) access to individual maps. The keywords that characterize each alphabet are highlighted in bold letters |

	Alphabet 1: Physical-Verbal participation				Alphabet 1: Verbal participation			
t5.3	Level 1	Level 2	Level 3	Level 4	Level 1	Level 2	Level 3	
t5.4	Link	[L,C]Add/Rem/Chg	NoSpeech	**Tsame**	Link	[L,C]Add/Rem/Chg	**NoSpeech**	
t5.5	Cone	Mov/Mult	Sauthor	**Tother**	Conc	Mov/Mult	**Sauthor**	
t5.6	Indmap	[I]Open/Close	Sother	**Tparallel**	Indmap	[I]Open/Close	**Sother**	
t5.7	Speech	Shrt/Full			Speech	Shrt/Full	**Start**	
t5.8							**Resp**	
t5.9							**Assen**	
t5.10	Alphabet 3: Touches on other objects				Alphabet 4: Access to individual maps			
t5.11	Level 1	Level 2	Level 3	Level 4	Level 1	Level 2	Level 3	Level 4
t5.12	Obj	[L,C]Add/Rem/Chg	NoSpeech	**Owner**	Link	[L,C]Add/Rem/Chg	NoSpeech	[I]**Pers/NoPers**
t5.13		Mov/Mult	Sauthor	**Difowner**	Conc	Mov/Mult	Sauthor	
t5.14		[I]Open/Close	Sother		**Indmap**	[I]**Open/Close**	Sother	
t5.15					Speech	Shrt/Full	**Start**	
t5.16							**Resp**	
t5.17							**Assen**	

[I] Only applicable for Individual map objects (Indmap)

[L,C] Only applicable for Concepts and Links (Conc, Link)

about the time for users to perceive immediateness (Nielsen 1993). Multiple and consecutive 614
Move actions by the same learner were compressed aggregating the keyword *Mult*. 615

Figure 6 shows an example of a set of eleven encoded *item actions* of one group. The 616
graph shows three timelines for the physical actions and other three for the utterances 617
performed by each learner. The sequence starts with an *add concept* action performed by 618
U1 accompanied by an utterance of the same learner, encoded as follows: *Conc-Add-* 619
Sauthor. Then, learner U3 adds another concept while the first learner is still talking: 620
Conc-Add-Tother-Sother. U3 then adds a link while speaking: *Link-Add-Tsame-Sauthor*. 621
Actions with no utterances in parallel have the keyword *NoSpeech* (e.g. item action 6). 622
Utterances with no physical actions in parallel are encoded like item actions 4, 9, 10 and 11 623
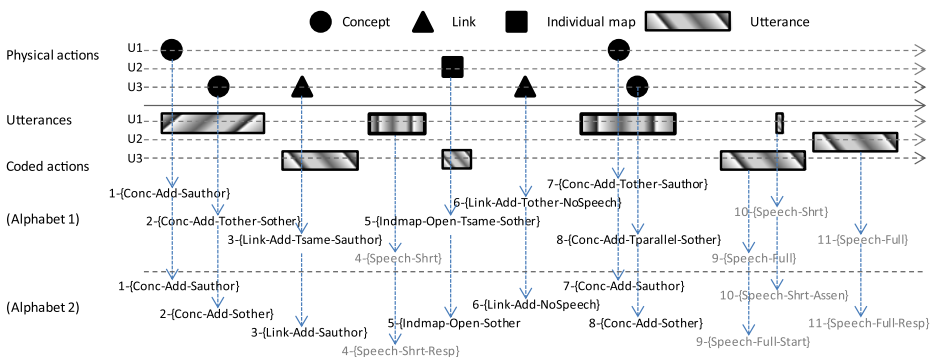
Fig. 6 Example of an excerpt of a group's events using alphabets 1 and 2. Vertical arrows associate each event with the resulting encoded item actions

(*Speech-Shrt/Full*). Item action 8 illustrates a case where two physical actions were performed in parallel (*Tparallel*).

    Alphabet 2 focuses on the detailed description of the verbal participation in context with the physical actions. Following the same rationale described above, this alphabet introduces information about the length, order and authorship of verbal utterances where there are no physical actions in parallel. Figure 6 shows an example of the encoding of the same actions for Alphabet 2. It introduces three keywords (Table 5, Alphabet 2, Level 3). These are: *Start* (e.g. Fig. 6, item action 9), when a utterance has no other utterance immediately before it; *Resp* (response), when a utterance immediately follows a previous utterance by another learner (e.g. item actions 4 and 11); and *Assen* (assenting), for short utterances (1 to 2 s long) that occur while another learner speaks (e.g., item action 10). We used these rules to automatically code all the utterances. We compared this rule-based tagging with a human tagging in a 10 % of the dataset and we found 76 % of agreement in identifying learners' verbal responses. The alphabet also keeps the keywords associated with speech to encode physical actions (NoSpeech, Sauthor and Sother).

Alphabet 3 captures the *interaction of students with others' objects*. This alphabet considers contextual information about the actions that are performed by learners, either on the objects they initially created, or the ones created by others. This is achieved by the keywords *Owner* and *Difowner* respectively (Table 5, Alphabet 3, Level 4). The alphabet also keeps the keywords associated with speech to encode physical actions (NoSpeech, Sauthor and Sother), but it does not include independent utterances. To keep the alphabets as simple as possible but, at the same time, to capture the essential aspects of interactivity on others students' objects, this alphabet does not differentiate among types of objects (only 1 keyword *Obj* for Level 1).

Alphabet 4 targets the research question that explores the *influence of the access to knowledge structures*. This alphabet keeps the keywords associated with speech in Level 3 as in Alphabet 2, and adds information provided by the keywords *Pers* and *NoPers* in Level 4. *Pers* is associated to actions performed on concepts or links that were contained in a *personal/*individual map while this is being displayed on the tabletop (as in Fig. 3, left) or immediately before. *Nopers* corresponds to the rest of the actions on concepts and links, those that are not in any individual map displayed on the tabletop. The objective of this alphabet is to find possible differences in the actions performed *after* learners *open* their individual maps (*Indmap*).

The algorithm: Differential sequence mining

As a result of encoding the groups' actions, according to the four alphabets described above, we obtained four datasets of encoded item actions with two sub-sets of data each. Each sub-set contains 10 long sequences of item actions for either a high or low collaboration groups. In order to extract patterns of activity we applied the *differential sequence mining* technique (DSM) developed by Kinnebrew et al. (2012), which looks for sequential patterns that differentiate two datasets.

    A sequential pattern is a consecutive or non consecutive ordered sub-set of a sequence of events that is considered frequent when it meets a minimum *support* criteria (Jiang and Hamilton 2003). For the DSM technique this is called sequence-support (*s-support*) that corresponds to the number of sequences in which the pattern occurs, regardless of how frequently it repeats within each sequence. We set the minimum threshold to consider a

Q1

pattern as frequent if this was present in at least half of the sequences (*s-support* = 0.5)   670
following previous work by Kinnebrew et al. (2012). The algorithm also calculates consec-   671
utive and repeated patterns within the dataset of sequences. This is called instance support (*i-   672
support*). We set the maximum error threshold to 1 to allow the matching of patterns with   673
sub-sequences if there was an edit distance of 0 (perfect match) or 1 (one different action in   674
the sub-sequence) between them. This has the impact of allowing a larger number of   675
sequences to be considered as *differential* even if the matching is not perfect. This has   676
proved effective in matching similar sequences of actions in learning environments   677
(Kinnebrew et al. 2012; Martinez-Maldonado et al. 2011c). The output of this algorithm is   678
a list of frequent patterns that meet the minimum support in each dataset and that distinguish   679
more collaborative from less collaborative groups (*p*<0.1) also following previous work by   680
Kinnebrew et al. (2012). Next, we present the results of running the algorithm for each   681
research question.   682

Results   683

Question 1: Can we distinguish more collaborative from less collaborative groups by the   684
interwoven stream of students' verbal and physical participation? After applying the DSM   685
algorithm on Alphabet 1, we selected the patterns whose i-support distinguished high from   686
low groups with a confidence of at least 90 % (*p*<=0.10) and that were composed of at least   687
two item actions (e.g. {Conc-Add-Tother-Sother} > {Speech-Shrt}).   688

We obtained 261 differential patterns. Table 6 shows the top-4 most differential patterns that   689
were found in each sub-set for each phase. For the brainstorming phase, the patterns A, B, C,   690
and D are very similar. All are patterns where students added (Add) and arranged (Mov)   691
concepts without speaking (NoSpeech) and with some degree of parallelism and concurren-   692
cy (Tparallel and Tother keywords respectively; found in A, B and C). By contrast, the more   693
collaborative groups displayed a different strategy by interleaving periods of just verbal   694
activity (Speech) with physical actions that were accompanied by other students' talk   695
(Sother in patterns E, F, G and H).   696

To summarize the rest of the patterns that were found, Table 7 shows the frequency of   697
appearance of keywords in patterns that met the differential criteria (*p*<=0.1). Confirming   698
the trends suggested by the examples (Table 6), for *brainstorming,* the main difference was   699
that high collaboration groups had more patterns in two main classes: ones with speech and   700
no actions in parallel; ones with speech while other students performed actions (*Speech* and   701
Sother appeared in 93 % and 43 % of the frequent sequences for the high collaboration   702
groups against 50 % and 18 % of the less collaborative groups).   703

For the *linking* phase, a similar trend remained. The low collaboration groups had an   704
increased presence of parallelism in their actions (*Tparallel* = 36 % for low against 3 % for   705
high groups) as in the patterns I, K and L. Additionally, more than 65 % of the low   706
collaboration groups' actions were not accompanied by speech (*NoSpeech* >60 % for low   707
and <10 % for high groups). High collaboration groups showed patterns of sequenced   708
speech in the linking phase (patterns O and P).   709

This alphabet enabled us to discover that learners tend to not talk while touching the   710
tabletop (*Sauthor* keyword is not present in the top patterns of Table 6, and in Table 7, the   711
second last column (*Sauthor*) shows very low occurrence). There is evidence that a strategy   712
followed by the more collaborative groups involved maintaining high levels of both speech   713
levels and turn taking, accompanied by some physical actions, (Table 6, pattern P) and   714

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Table 6 Top sequential patterns found using Alphabet 1. Repetitive keywords and descriptions in bold letters

		Top-4 most differential patterns	Description
t6.3	Brainstorming	Low collab.	A=Con-Mov-Tsame-Mult-**NoSpeech** > Con-Add-**Tparallel-NoSpeech**	Actions in parallel **with no speech**
t6.4			B=Con-Add-Tother-NoSpeech > Con-Add-Tother-**Sother**	Actions on others' objects with others' speech
t6.5			C=Con-Add-Tother-**NoSpeech** > Con-Add-**Tparallel-NoSpeech**	Actions in parallel **with no speech**
t6.6			D=Con-Mov-Tsame-Mult-**NoSpeech** > Con-Mov-Tsame-**NoSpeech** > Con-Mov-Tsame-**NoSpeech**	Actions on own objects **with no speech**
t6.7		High collab.	E=Speech-Shrt > Con-Add-Tsame-**Sother** > Con-Mov-Tsame-**Sother**	Speech and actions on own objects with **other's speech**
t6.8			F=Speech-Shrt > Con-Mov-Tsame-Mult-**Sother** > Con-Mov-**Tparallel-Sother**	Speech and actions in parallel with **other's speech**
t6.9			G=Speech-Full > Speech-Shrt > Con-Mov-Tsame-**Sother**	Speech and actions on own objects with **others' speech**
t6.10			H=Con-Mov-Tsame-Mult-**Sother** > Con-Mov-**Tparallel-Sother**	Actions in parallel with **other's speech**
t6.11	Linking	Low collab.	I=Con-Mov-Tsame-Mult-NoSpeech > Con-Mov-**Tparallel-NoSpeech** > Link-Mov-Tother-**NoSpeech**	Actions in parallel **with no speech**
t6.12			J=Speech-Shrt > Con-Mov-Tsame-Mult-**NoSpeech** > Con-Mov-**Tparallel-NoSpeech**	Speech and actions in parallel **with no speech**
t6.13			K=Link-Add-Tsame-**NoSpeech**>Link-Mov-Tsame-**NoSpeech**> Link-Mov-Tother-**NoSpeech**	Actions on own objects **with no speech**
t6.14			L=Con-Mov-**Tparallel**-NoSpeech > Link-Add-Tsame-**NoSpeech** > Speech-Shrt	Speech and actions in parallel **with no speech**
t6.15		High collab.	M=Con-Mov-Tother-**Sother** > Link-Mov-Tsame-**Sother** > Speech-Shrt	Speech and actions on own objects with **other's speech**
t6.16			N=Speech-Full > Con-Mov-Tsame-Mult-**Sother** > Con-Mov-**Tparallel-Sother**	Speech and actions in parallel with **other's speech**
t6.17			O=Speech-Full > Speech-Full > Speech-Full > Con-Mov-Tsame-Mult-NoSpeech	**Sequenced** utterances and multiple actions
t6.18			P=Speech-Shrt > Con-Mov-Tsame-Mult-**Sother** > Speech-Shrt > Speech-Shrt>Speech-Full>Speech-Shrt>Speech-Shrt	**Sequenced** utterances and multiple actions

$p <= 0.05$

Q1

t7.1 **Table 7** Proportions of keywords in frequent patterns by using Alphabet 1

t7.2		Collaboration	Speech	Tother	Tsame	Tparallel	Nospeech	Sauthor	Sother
t7.3	Phase 1 (brainstorming)	Low	50 %	**50 %**	25 %	18 %	**62 %**	0 %	18 %
t7.4		High	**93 %**	**10 %**	39 %	16 %	**7 %**	5 %	**43 %**
t7.5	Phase 2 (linking)	Low	45 %	**32 %**	53 %	**36 %**	**65 %**	2 %	11 %
t7.6		High	**92 %**	**4 %**	31 %	3 %	**10 %**	0 %	24 %

p-value<=0.1

keeping parallelism low. By contrast, the less collaborative groups had higher levels of   715
physical activity with just a few unchained verbal interventions (see patterns J and L).   716

Question 2: Can we distinguish more collaborative from less collaborative groups by   717
extracting patterns of interaction based on just students' verbal participation? Pattern P   718
in Table 6 exemplifies the patterns that need deeper exploration analysis (sequenced   719
utterances). Alphabet 2 was designed to provide more information for these verbal patterns.   720
We obtained 225 differential patterns using Alphabet 2.   721

Table 8 shows that most of the less collaborative groups' sequences include actions   722
performed on concepts and links with no speech in parallel both in brainstorming (patterns A   723
to D) and even more frequently in the linking phase (patterns J, K and L). Additionally,   724
patterns show that some utterances were not followed by any response (patterns A, C, D and   725
I with keyword Speech-Start).   726
By contrast, high collaboration groups tended to combine physical actions performed   727
with speech from the same author or other learners (*Sauthor-Sother*); and sequences of   728
utterances that can be associated with conversation patterns (patterns G and M). Another   729
trend found is the keyword *Start* followed by a *Resp*onse, or at least some verbal reaction in   730
both phases of the activity (patterns E, F, N and O). Pattern H shows that in the brainstorm-   731
ing phase, these students tend to open their individual maps and follow this action with long   732
speech activity. A similar pattern in these high collaboration groups was found for the   733
linking phase, with the difference that, the speech was accompanied by physical actions (see   734
pattern P). It is not clear how they interacted with these individual maps hence the need of   735
further exploration that is formulated in our Research Question 4.   736
Table 9 shows the proportion of keywords in the rest of the patterns that met the   737
differential criteria. The presence of verbal utterances, and especially, responses to other   738
students, distinguished high from less collaborative groups in both phases (60 % and 45 % of   739
the patterns in high groups had at least one responding utterance (*Resp*) respectively, in   740
contrast to just 12 % and 8 % of patterns for the corresponding phases in the low groups).   741
Short assenting verbal utterances by learners, while another learner was speaking, were more   742
common in more collaborative groups (*Assen*=25 % for high and 13 % for low collabora-   743
tion). This confirms the differences suggested in the examples described above.   744

Question 3: Can we distinguish more collaborative from less collaborative groups based on   745
patterns involving traces of interaction of students with others' objects? After running the   746
DSM algorithm using Alphabet 3 we obtained a total of 174 patterns. Table 10 presents the   747
top differential patterns. It shows that the main distinction, for ownership and interaction,   748
was not between high and low collaborative groups but between phases.   749

Table 8 Top sequential patterns found using Alphabet 2

			Top-4 most differential patterns	Description
t8.3	Brainstorming	Low collab.	A= Con-Add-**NoSpeech** > Con-Add-**NoSpeech** > **Speech**-Shrt- **Start** > Con-Add-**NoSpeech**	Start utterance, no response, actions **with no speech**
t8.4			B= Con-Mov-**NoSpeech** > Con-Add-**NoSpeech** > Con-Add-**NoSpeech** >Con-Add-**NoSpeech**	Actions **with no speech**
t8.5			C= Con-Add-**NoSpeech** > Con-Add-**NoSpeech** > Con-Add-**NoSpeech** > **Speech**-Shrt-**Start** > Con-Add-**NoSpeech**	Start utterance, no response, actions **with no speech**
t8.6			D= Con-Add-**NoSpeech** > **Speech**-Shrt-**Start** > Con-Add-**NoSpeech**	Start utterance, no response, actions **with no speech**
t8.7		High collab.	E=Con-Mov-Sother > Con-Mov-Sauthor > **Speech**-Shrt-**Resp**	Actions with speech and speech by others with **response**
t8.8			F= Con-Mov-Sother > **Speech**-Shrt-**Resp** > **Speech**-Shrt-Assen	Action with speech by others with **response**
t8.9			G= **Speech-Full-Resp** > **Speech**-Shrt-**Resp** > **Speech**-Shrt-**Resp** > **Speech-Full-Resp**	Conversation
t8.10			H= Indmap-Open-Sother > **Speech-Full-Start**	Open map and speech
t8.11	Linking	Low collab.	I= **Speech-Shrt-Start** > **Speech**-Shrt-**Resp**> Con-Mov-Mult-**NoSpeech**> **Speech-Shrt-Start**	Start utterance, with short response
t8.12			J= Link-Add-**NoSpeech** > Con-Mov-**NoSpeech** > Link-Mov-Mult-**NoSpeech** > Con-Mov-**NoSpeech**	Actions **with no speech**
t8.13			K= Link-Add-**NoSpeech** > Con-Mov-**NoSpeech** > Link-Rem-**NoSpeech** > Con-Mov-Mult-**NoSpeech**	Actions **with no speech**
t8.14			L= Link-Mov-**NoSpeech** > Link-Rem-**NoSpeech** > Con-Mov-**NoSpeech** > Link-Add-**NoSpeech**	Actions **with no speech**
t8.15		High collab.	M= **Speech**-Shrt-**Resp** > **Speech**-Shrt-**Resp** > **Speech-Shrt-Start** > **Speech-Full-Resp** > **Speech**-Shrt-Assen	Conversation
t8.16			N= Con-Mov-Sother > **Speech-Shrt-Start** > **Speech-Full-Resp**	Action with speech by others with **response**
t8.17			O= Con-Mov-Sother > **Speech**-Shrt-Assen > Con-Mov-Sauthor	Actions with speech and speech by others with **response**
t8.18			P = **Speech**-Shrt-Assen > Indmap-Mov-Sother > Con-Mov-Sother	Speech, Open map and actions with speech

$p <= 0.05$

Q1

Table 9 Proportions of keywords in frequent patterns by using Alphabet 2

	Collaboration	*Speech*	*Start*	*Resp*	*Assen*	*Nospeech*	*Sauthor*	*Sother*
Phase 1 (brainstorming)	Low	27 %	14 %	12 %	10 %	**77 %**	2 %	**14 %**
	High	**83 %**	**43 %**	**60 %**	25 %	10 %	6 %	43 %
Phase 2 (linking)	Low	12 %	**7 %**	8 %	1 %	**94 %**	2 %	8 %
	High	**59 %**	45 %	**45 %**	13 %	39 %	2 %	19 %

$p <= 0.1$

These patterns suggest that most of the groups performed actions on their own objects during the brainstorming, without interacting with others' objects (no *Difowner* keyword in patterns from A to G). Only one of the top patterns shows that members of high collaboration groups also interacted with others' objects to some extent (pattern H).

In line with previous findings, the speech also marked a difference between high and low collaboration groups (patterns F, G and H). For the *linking* phase we can see a prevalence presence of actions performed on objects created by others (*Difowner* keyword in most of the patterns in the linking phase). The more collaborative groups presented strategies of interaction with others' objects to a lesser degree, combining interaction of students on their own objects with speech by the same learner or others'.

Table 11 shows the proportion of keywords for the rest of the patterns. Both high and low groups had fewer physical interaction with others' elements during the brainstorming, similarly to the example patterns (14 % and 3 % for *Difowner* respectively). Indeed, the low collaborative groups always performed actions on their own objects (100 % for the keyword *Owner*).

The above suggests that the strategy of splitting the work, without verbally communicating with other members, is what most distinguished the low collaborative groups in the brainstorming phase. For the linking phase the patterns of the low groups had a higher level of interaction with others' objects (*Difowner* =83 %). However, patterns for the high collaboration group also had high rates of interaction with others' objects (*Difowner* =62 %) in additional to patterns of speech.

Question 4: Can we distinguish more collaborative from less collaborative groups in terms of the actions that follow the access to others' knowledge structures? To investigate the actions learners performed in association with accessing learners' maps, the analysis to address question 4 was different from the previous questions. Here, we only considered the actions that occurred while each individual concept map remained open. The statistics show a difference in the number of times groups' accessed individual maps (145 for high and 102 for low groups); therefore, we expect to find more patterns in the high collaboration groups.

Table 12 shows the differential sequences for both groups. For the *brainstorming* phase, the less collaborative groups did not have any differential patterns meeting the *support* condition. By contrast, patterns for the more collaborative groups had increased levels of conversation after students accessed their individual maps (see patterns B, C and E). Patterns also show evidence that students took turns to open and explore individual maps one after the other (*Open* and *Close* events in patterns A, D and E). For the *linking* phase, the less collaborative groups had some patterns; however, unlike the dominant strategy followed by the more collaborative groups, these were mostly physical actions (*Move* actions) without verbal interaction after accessing individual maps (*NoSpeech* keyword in the patterns F to I).

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Table 10 Top sequential patterns found using Alphabet 3

			Top-4 most differential patterns	Description
t10.3	Brainstorming	Low collab.	A= Obj-Mov-Owner-NoSpeech>Obj-Mov-Owner-NoSpeech>Obj-Mov-Owner-Mult-NoSpeech>Obj-Mov-Owner-Mult-NoSpeech	Actions on **own** objects, **no speech**
t10.4			B= Obj-Add-Owner-Sother > Obj-Add-Owner-NoSpeech > Obj-Add-Owner-NoSpeech > Obj-Add-Owner-NoSpeech	Actions on **own** objects, **some speech**
t10.5			C= Obj-Add-Owner-NoSpeech > Obj-Add-Owner-NoSpeech > Obj-Mov-Owner-NoSpeech> Obj-Add-Owner-NoSpeech >	Actions on **own** objects, **no speech**
t10.6			D= Obj-Mov-Owner-Mult-NoSpeech > Obj-Mov-Owner-NoSpeech > Obj-Mov-Owner-Mult-NoSpeech > Obj-Add-Owner-NoSpeech	Actions on **own** objects, **no speech**
t10.7		High collab.	E= Obj-Mov-Owner-Sother > Obj-Mov-Owner-NoSpeech > Obj-Mov-Owner-Mult-NoSpeech	Actions on **own** objects, **no speech**
t10.8			F= Obj-Add-Owner-Sother > Obj-Mov-Owner-Mult-Sother > Obj-Add-Owner-Sother	Actions on **own** objects, **others' speech**
t10.9			G= Obj-Add-Owner-Sother > Obj-Rem-Owner-Sother > Obj-Add-Owner-Sother > Obj-Add-Owner-Sother	Actions on **own** objects, **others' speech**
t10.10			H= Obj-Mov-Owner-Mult-Sauthor > Obj-Mov-**Difowner**-Sother > Obj-Mov-Owner-Sother	Actions on others' objects, **others' speech**
t10.11	Linking	Low collab.	I= Obj-Add-Owner-NoSpeech > Obj-Mov-**Difowner**-NoSpeech > Obj-Mov-**Difowner**-NoSpeech > Obj-Add-Owner-NoSpeech >	Actions on others' objects, **no speech**
t10.12			J= Obj-Mov-**Difowner**-NoSpeech > Obj-Mov-**Difowner**-NoSpeech > Obj-Mov-**Difowner**-NoSpeech > Obj-Add-Owner-NoSpeech	Actions on others' objects, **no speech**
t10.13			K= Obj-Mov-**Difowner**-Mult-NoSpeech > Obj-Mov-**Difowner**-NoSpeech > Obj-Mov-**Difowner**-NoSpeech > Obj-Add-Owner-NoSpeech	Actions on others' objects, **no speech**
t10.14			L= Obj-Mov-**Difowner**-NoSpeech > Obj-Mov-**Difowner**-NoSpeech > Obj-Mov-**Difowner**-NoSpeech > Obj-Add-Owner-NoSpeech	Actions on others' objects, **no speech**
t10.15		High collab.	M= Obj-Mov-Owner-Sauthor > Obj-Mov-Owner-Sother > Obj-Mov-**Difowner**-Sother > Obj-Mov-**Difowner**-Sother > Obj-Add-Owner-Sother	Actions on others' objects, **own and others' speech**
t10.16			N= Obj-Mov-**Difowner**-Sother > Obj-Mov-**Difowner**-Sother > Obj-Add-Owner-Sother	Actions on others' objects, **others' speech**
t10.17			O= Obj-Add-Owner-Sother > Obj-Mov-Owner-Sother > Obj-Mov-Owner-Mult-NoSpeech	Actions on own objects, **others' speech**
t10.18			P= Obj-Mov-**Difowner**-Mult-NoSpeech > Obj-Mov-**Difowner**-Mult-NoSpeech > Obj-Chg-**Difowner**-NoSpeech	Actions on others' objects, **no speech**

$p <= 0.05$

t11.1 **Table 11** Proportions of keywords in frequent patterns by using Alphabet 3

	Collaboration	*Owner*	*Difowner*	*NoSpeech*	*Sauthor*	*Sother*
Phase 1 (brainstorming)	Low	100 %	**3 %**	94 %	1 %	1 %
	High	56 %	**14 %**	25 %	22 %	97 %
Phase 2 nnlinking)	Low	95 %	62 %	66 %	27 %	40 %
	High	97 %	**83 %**	99 %	0 %	4 %

t11.2, t11.3, t11.4, t11.5, t11.6

$p <= 0.1$

In the *linking* phase, the higher collaboration groups continued using the individual maps as a tool to drive verbal communication (pattern K) and they opened more than one individual map at the same time, possibly for comparison (pattern M).

Against our expectations, the length of the patterns we found was not enough to detect *add* events for concepts and links contained in those accessed individual maps. The keyword *Pers* was found in some patterns (H and L but this corresponded to *move* actions.

Discussion and conclusions

In this paper, we presented an approach to explore whether we could automatically distinguish how and low collaboration groups, by exploiting the affordances of an enriched tabletop, with its learning environment that can keep track of students' physical and verbal activity. Our empirical study showed considerable promise for obtaining indicators of collaborative work.

We envisage that our work provides a foundation for creating a system with three components:

- the *data capture* system to track and gather data of group activity;
- the *data analytics* component, which is based on careful design of the alphabets that are a basis for producing group indicators via statistical and data mining techniques;
- and the *data presentation* component that aims to present to teachers, researchers or students with visual information or knowledge about the collaborative process but which implementation goes beyond the scope of this paper.

We have implemented the technological infrastructure to automatically and unobtrusively capture and integrate both verbal and physical students' interactions in the tabletop (Martinez-Maldonado et al. 2011a). The analysis technique, based on the design of alphabets, combines the integration of verbal and physical interactions, with the use of sequence mining in order to find patterns that can distinguish groups that worked either more collaboratively or less collaboratively. This analysis proved effective in addressing our four research questions regarding patterns that differentiate groups in interactive tabletops.

The *statistical exploration* of several indicators of interaction suggested that there were differences in groups' interactions based on their level of collaboration. However, such aggregating information at the end of the group activity has proven to have serious limitations. First, the statistical differences between the measures for the high or low collaboration groups were not significant. So they were not powerful enough to capture the differences. In addition, since they were only available at the end of the session, they would not be a useful basis for informing a teacher of potential problem groups during a class.

Table 12 Top sequential patterns found using Alphabet 4

		Top 4 most differential patterns	Description
Brainstorming	High collab.	A=Indmap-Close>Indmap-Open>**Speech**-Shrt	Speech after opening map, taking turns
		B=Indmap-Open>**Speech**-Full>**Speech**-Shrt>**Speech**-Shrt	Speech after opening map
		C=Indmap-Open>**Speech**-Full	Speech after opening full
		D=**Speech**-Shrt>Indmap-Mov.-Sother>Indmap-Close>Indmap-Open	Speech and open map, taking turns
		E=Indmap-Mov-Mult-Sother>Indmap-Close>Indmap-Open>**Speech**-Shrt	Speech after open map, taking turns
Linking	Low collab.	F=Indmap-Close > Indmap-Open > Indmap-Mov-Mult-NoSpeech > Indmap-Mov-NoSpeech	Opening map, **no speech**
		G=Indmap-Mov-Mult-NoSpeech > Indmap-Mov-NoSpeech > Indmap-Mov-Mult-NoSpeech	Move maps, **no speech**
		H=Indmap-Mov-NoSpeech > Con-Mov-NoSpeech-Pers > Con-Mov-NoSpeech-Pers	Move maps, **no speech**
		I=Indmap-Open>Indmap-Mov-Mult-NoSpeech> Indmap-Mov-NoSpeech> Indmap-Mov-NoSpeech	Opening map, **no speech**
	High collab.	J=Indmap-Open > Indmap-Close > Indmap-Open > Indmap-Mov-NoSpeech	Opening maps one by one
		K=Indmap-Open > **Speech**-Shrt > **Speech**-Shrt	Speech after opening map
		L=Indmap-Open > Con-Mov-NoSpeech-Pers	Open map and action
		M=Indmap-Open > Indmap-Mov-NoSpeech > **Indmap-Open**	Open more than one map in parallel

$P <= 0.05$

Q1

We then reported our approach to analyze students' actions at a fine-grained level taking account of the order of actions and the interplay between the differentiated actions of each group member. The DSM technique, along with the four alphabets, adds contextual information to the sequence of actions and this enabled us to find patterns of verbal participation, parallelism, concurrency, linkage between verbal and physical actions, access to individual knowledge representations and students' actions on others' digital objects.

First, by applying Alphabet 1, we discovered that the less collaborative groups had a predomination of patterns with physical interactions, high levels of physical concurrency and greater parallelism than the more collaborative groups. By contrast, the more collaborative groups had more verbal discussions in conjunction with physical actions, especially in the *brainstorming* phase. They also showed less concurrency in the physical dimension and less parallelism. This seems consistent with these students being more aware of their peers' actions and also making use of group discussions about the actions performed on the group map.

Second, we explored in more detail the patterns of *verbal participation* through the Alphabet 2. One of the most interesting findings for the less collaborative groups was the detection of patterns where a learner spoke briefly without getting response from other students. This aspect of communication was also considered by Meier et al. (2007), under the dimension of mutual understanding. For groups to maintain mutual understanding, they needed to provide verbal feedback on their understanding in the form of an appropriate response, or by asking for clarification. In line with this, the more collaborative groups had higher rates of responses after other learners had spoken. These groups also had patterns of physical actions accompanied by speech by other learners. This is also consistent with these students being more aware of others' actions and discussing each others' actions.

Third, the findings from applying Alphabet 3 to inspect interactions of students with others' objects partly contradicted the analysis carried out by Martinez-Maldonado et al. (2012b). We found that the more collaborative groups had some interaction with others' objects in the *brainstorming* phase but in the *linking* phase, the less collaborative groups interacted more with others' objects.

Fourth, we explored the patterns of actions that occurred after students opened their individual concept maps to share them with others or to recall what they had done in the initial private mapping activity (Alphabet 4). We found evidence that suggests that the more collaborative groups accessed their individual maps to trigger discussion. Their actions showed that they either opened one map after another, or opened at least two concept maps simultaneously for possible comparison. For the less collaborative groups, our data does not really show how they used their individual maps. Contrary to what we had expected, the patterns found did not show the addition of concepts or propositions from those maps. This may be explored further by refining the alphabet.

The patterns we discovered are important at multiple levels. First, they demonstrate that we have achieved our overall goal to exploit the digital footprints of learners in the tabletop. Importantly, this work provides a foundation for creating interfaces for bringing the collaboration quality to the attention of the stakeholders. This includes learners in the groups. It has the potential to be particularly valuable for teachers who need to manage several groups in a classroom. It also provides researcher insights more broadly. Overall, the indicators of physical activity and verbal participation, produced by the implementation of our approach, are modest, if not limited, when compared with a full qualitative analysis of the utterances that can be carried out by an expert human observer. However, we argue that our study provides evidence that our approach can serve as a basis for a further development of automatic supporting systems for students or monitoring tools for their teachers. We

designed each alphabet to correspond to the elements of a specific research question and therefore, each provides different information. This range of insights about collaboration cannot be obtained through a single alphabet that simply aggregates all the keywords. This would only lead to very long item actions. It would be harder to interpret, and more difficult for the algorithm to discover patterns, given the higher variability of contextual information that would have to be analyzed at once. The formulation of other questions requires different, new alphabets. The current work provides as basis for creating these.

Finally, the approach itself can serve as a basis for the design of interactive tabletop systems for collaborative learning, enabling a new level of support. We envisage systems that can capture, analyze and present students' information in order to enhance awareness for teachers, researchers or back to the students themselves. Real time visualizations of the group process can be designed for the teacher, either exclusively or shared with the students. For example patterns found can be used as a benchmark to compare against new groups' patterns. If we detect patterns associated with non collaborative strategies, the system can trigger an alarm in real time to help teachers to enhance their awareness and possibly help them make more informed decisions about when to intervene with particular groups.

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