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HAUPTBEITRÄGE - THEMENTEIL

Do you see us?—Applied visual analytics for the investigation of group coordination

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Abstract
Group coordination is a relevant prerequisite for understanding the effectiveness of groups. But, contrary to the large number of empirical studies, only a few studies concentrate on the development of analysis methods of coordination in groups. Hence, the purpose of this paper is to give a summary of the opportunities and limitations of common methods for capturing group coordination in applied field settings and to outline how visual analytics approaches might add to the common methods. Based on two illustrated visual analytics implementation examples—1) coordination and movements of soccer players, and 2) spatio-temporal event data—the potential of visual analytics approaches is identified for studying a greater variety of types of group coordination, and to consider the multifaceted nature of group processes in order to go beyond traditional coding processes.

Keywords Group processes · Group coordination · Measurement · Visual analytics

Siehst Du uns? – Applied visual analytics zur Analyse von Koordinationsprozessen in Gruppen

Zusammenfassung
Koordinationsprozesse in Gruppen sind eine zentrale Voraussetzung für den Erfolg von Gruppenarbeit. Doch im Gegensatz zur hohen praktischen Relevanz existieren bisher nur wenige Studien, die sich mit der Analyse von Koordinationsprozessen in Gruppen befassen. Ziel dieses Beitrags ist es, die Möglichkeiten und Grenzen der üblichen Analysemethoden von Koordinationsprozessen in Gruppen in der angewandten Forschung aufzuzeigen. Basierend auf zwei empirischen Beispielen – 1) zur Koordinations- und Bewegungsanalyse im Fussball und 2) für die Analyse raum-zeitlicher Ereignisse – werden die Potenziale des Visual Analytic Ansatzes identifiziert, um eine grössere Vielfalt an Gruppenprozessen über traditionelle Kodierverfahren hinausgehend zu untersuchen.

Schlüsselwörter Gruppenprozesse · Gruppenkoordination · Analysemethoden · Visual Analytics

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1 Group coordination and its current measurement—Relevance for identifying new methods

Group coordination is described as a fundamental and complex phenomenon that largely impacts the functioning of small groups (Boos et al. 2011). It is an important prerequisite for group effectiveness, especially in complex tasks like decision making (Kolbe and Boos 2009). In this regard, group coordination is defined as the group task-dependent management of inter-dependencies of individual goals, meanings, and behaviours (e. g., Arrow et al. 2000) by a hierarchically and sequentially regulated action and information flow in order to achieve a common goal (Boos et al. 2011, p. 12).

On the empirical level, psychological work has shown that group processes and the outcomes of group work (e. g., performance) are connected (e. g., input-process-outcome models, Boos et al. 2011). To be more specific, research has revealed that group coordination and its explicit (e. g., information sharing) and implicit processes (often labelled as "team knowledge", Ellwart et al. 2011; Cannon-Bowers et al. 1993) are related positively to group performance and group effectiveness depending on the performed task (for a review, see DeChurch and Mesmer-Magnus 2010; Riethmüller et al. 2012).

Due to the empirical importance, some researchers have concentrated on deep analysis or the development of observation and analysis methods for group interaction analysis (Brauner et al. 2018) and specifically for collaboration and coordination in groups (e. g., Goldman et al. 2014; Kolbe et al. 2009, 2011, 2013). Yet, the analysis of group processes like coordination also has its limitations for at least three different reasons: First, it is mostly limited to controlled laboratory conditions, as well as small and distinct groups with specific tasks (Lewis 2003). Hence, group coordination is defined in a very task-specific way, and it is difficult to compare these operationalizations across different settings. Second, and based on the task-specific characteristics, various competing methods and tools have been developed to capture group coordination (e. g., see a review of the coordination measurement landscape, Schultz et al. 2013). Third, the empirical data basis for analyzing group coordination especially in field settings is very complex and rich in nature: it is based on manifold behavior indicators (e. g., oral communication and nonverbal behaviors in relation to the physical space) which can be analyzed on different levels (individual vs. group level, micro vs. macro processes) or from different perspectives (hierarchically vs. sequentially), which also can be combined. This complexity makes it difficult for applied psychological research to analyze group coordination as a whole and to capture its natural complexity to enlarge the empirical foundation, especially in advanced field settings (see also the "double-edged sword" of big data, Wenzel and Van Quaquebeke 2018).

Based on these limitations, many researchers state that there is a need to identify new methods for collecting and analyzing small group data to understand behavioral dynamics to gain a better understanding on how behavior in groups unfolds over space and time (e. g., Keyton 2016). For example, there is a need for options to capture and to analyze group coordination like the overlap of macro processes (e. g., interactions between multiple levels) and micro processes (e. g., nonverbal behavior, Burgoon and Dunbar 2018). The question is, why is it so difficult to extend existing methods for analyzing group coordination?

Lehmann-Willenbrock et al. (2017b) argue that research on the analysis of processes like group coordination has made some important contributions toward understanding micro-processes that constitute group interactions, but dynamics in groups are still difficult to capture and analyze (for a detailed critique, see Leenders et al. 2016). One reason for this continuing challenge might be that group processes are fluid and can change from second to second, which makes them notoriously difficult to be identified reliably. Commenting on this fluidity, Lehmann-Willenbrock et al. (2017b, p. 521) postulate that "researchers need to account for the temporal sequencing of the behaviors of all group members and for multiple predictors that can explain why a certain behavior occurs, including previous behaviors, individual characteristics, group characteristics, or other context factors". Hence, group processes should be investigated dynamically, spatially and temporally.

For example, in situations of complex problem solving at work (e. g., coordination in teams of physicians in an emergency situation or teams of workers at a construction site), or in analyzing personal experiences of place (e. g., relating personal experiences and memories to local infrastructure, cf. Bleisch and Hollenstein 2018), or in observations of parent-child interactions (e. g., coordination of mother and child in language learning), or coordination in real-world learning situations (e. g., in class, in museum exhibitions, on field trips), the spatio-temporal positioning of group members in relation to one another or to places and locations can be an important indicator and thus needs to be videotaped for analysis (e. g., Goldman et al. 2014). But in doing so, researchers struggle with the sheer volume of data, leading to substantial manual labor (for detailed information about coding efforts, see Lehmann-Willenbrock et al. 2017a). If analytical visualization techniques for such complex data existed, psychologists who study group processes could benefit from applying automated and visual behavioral data analysis and its technologies (Lehmann-Willenbrock et al. 2017b). They could better cope with complex data and maybe even detect new patterns that would become obvious *due* to the new methods. Hence, what could a solution be?

To measure the natural complexity, visual analytics (VA) provides a set of options and workflows for analyzing multidimensional data, including hierarchical or sequential data dimensions, for example, resulting from capturing group behaviors and their multifaceted nature. VA is the concept of augmenting human cognitive and reasoning abilities through specifically designed representations, coupling them with underlying algorithmic analytical processes and enhancing the resulting displays by effective interaction metaphors (Kerren and Schreiber 2012) thus supporting the

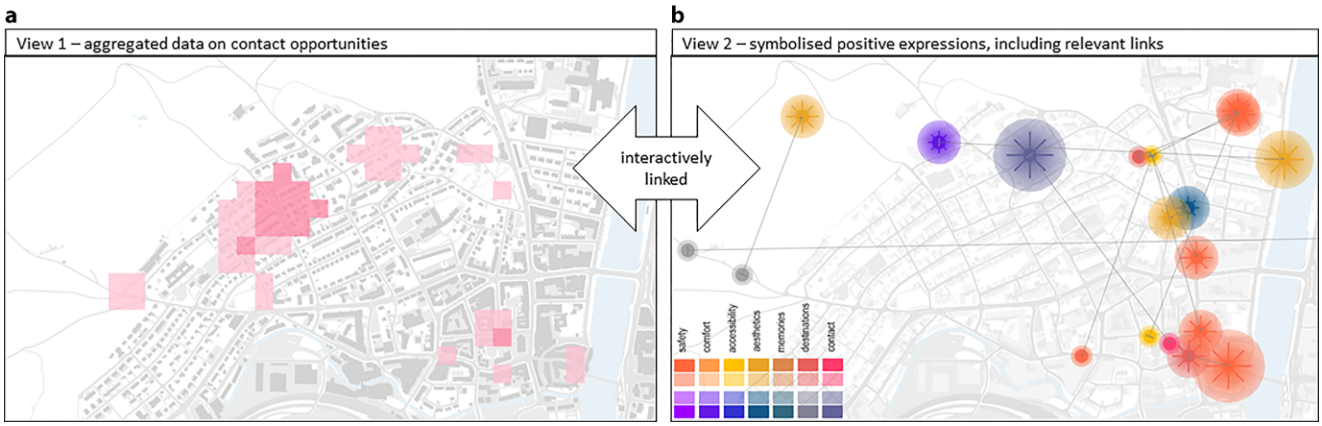

Fig. 1 Two example views from a simple interactive VA display (Bleisch and Hollenstein 2018). *Left*: Data about expressions on contact opportunities are aggregated across an area and displayed as a density map. This view is interactively linked with—*Right*:—a symbolized representation of positive expressions with regard to different topics. In an explorative VA setting, the interdisciplinary research team interactively works with the two views to refine data categorization as well as linking the areal coverages of the different topical data dimensions

researchers in their explorative or confirmative visual analysis processes.

To do so, VA builds on established methods in a range of disciplines (e. g., qualitative and quantitative methods in computer vision or the social sciences) and combines them with representations of data dimensions in interactive displays (see Fig. 1). Selected existing algorithmic (e. g., deep learning for the analysis of movement in videos) or manual (e. g., qualitative coding of behaviors) methods are combined within specifically designed representations to integrate the different perspectives of the described phenomenon. The selection of methods and visualizations is ideally defined in interdisciplinary teams of visual analytics specialists and research domain experts. VA thus enables the comprehensive investigation and interpretation of large and complex data sets as well as integrative and *concurrent* analysis of the different aspects under scrutiny (cf. Fig. 1).

To conclude, the potential of applying VA methods and workflows to group interaction analyses lies in the tight coupling of algorithmic analysis and visualizations through interaction by the analyst. For example, changes to the analysis parameters from visualizations could be supported so that researchers can compare the results of two analyses with differing parameters or the analysis results to representations of selected data dimensions.

Consequently, the purpose of this paper is to suggest how VA approaches may extend traditional analysis of group processes. Fig. 2 illustrates how the traditional process of group research (on the left side) can be augmented by visual analytics aspects (example on the right, with blue background) that could be integrated iteratively and interactively (left with blue background).

In the following sections, two VA examples, one analyzing soccer player movements (Stein et al. 2018), the other analyzing spatio-temporal event data (Robinson et al. 2016), are used for illustration purposes. Then two empirical examples from psychological research help to describe chances for studying a greater variety of group processes by using VA.

2 Visual analytics approaches—Two examples of mapping and analyzing multidimensional patterns

VA is employed in a wide range of application areas. It builds on a range of existing methods for data collection and algorithmic analysis, for example, tracking players in sports (e. g., Stein et al. 2018) or including real movements in animation movies, and for capturing the spatio-temporal interaction aspects of individual and group coordination (for an overview of object tracking in computer vision, see Wu et al. 2013) and extends them with interactive visualizations. We introduce these examples here, albeit in a limited and incomplete way with regard to the abundance of VA opportunities, because they exemplify contrasting approaches for applying VA to different data and settings.

In approach 1, Stein et al. (2018) present VA for the analysis of soccer teams and player movements in sports. Traditionally, a range of video-based analyses have existed to gain insights into the tactics of the player's movements in the game. With VA, the player movements are automatically extracted from a video stream, mapped onto a rectified playground, and analytics algorithms are run to detect, for example, specific game sequences over time. The results—here, for instance, relevant player movements—are then projected back into the video. In this way, the analysis results (such as the player trajectories that led to a certain moment in the game or alternative options for a pass played) can be viewed in combination with the video stream of the

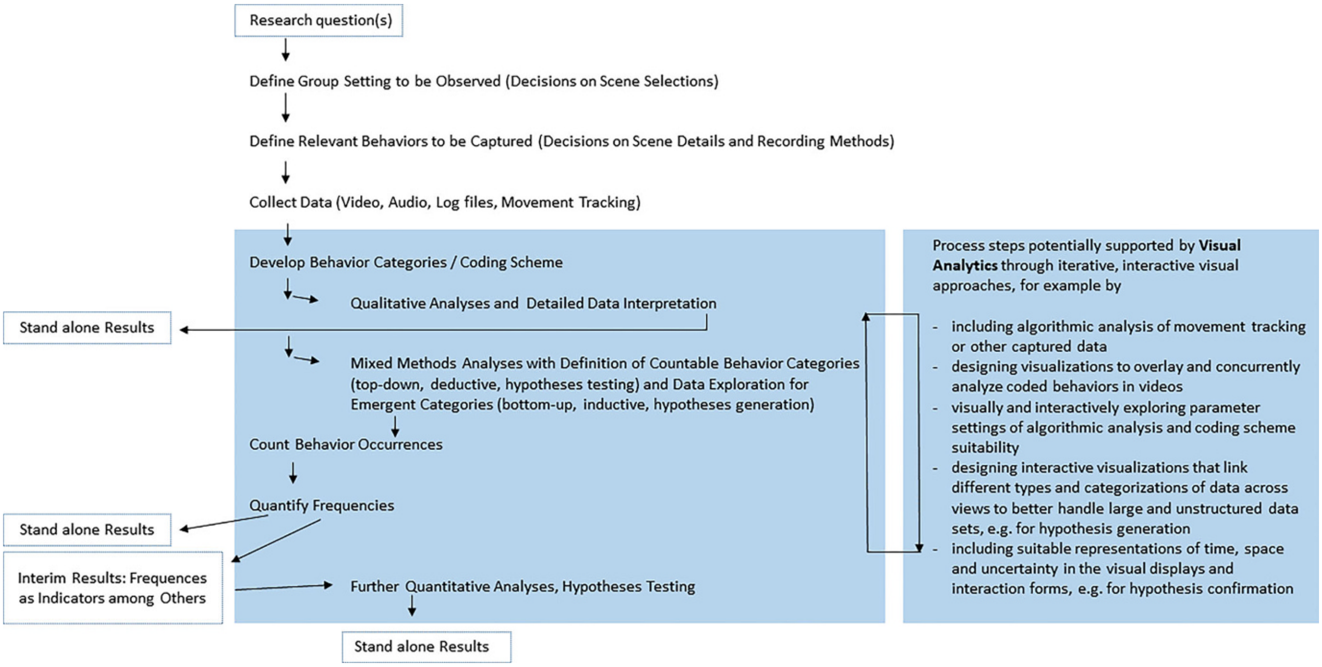

Fig. 2 A group research process (*left*) in the blue area can be supported by VA approaches (*right*). Where the iterative VA approaches are integrated with the traditional methods is defined in an interdisciplinary research team depending on the research questions to be answered

original game. The authors conclude from their work that VA in this approach of viewing the analytic results together with the video stream is more effective than traditional game analysis where knowledgeable analysts watched and commented on video streams or abstract sketches of selected game situations were commented on (for further information, see Stein et al. 2018). Viewing the same or different data dimensions concurrently in interactive displays for visual exploration is a key concept of VA (cf. Fig. 1).

In approach 2, Robinson et al. (2016) implemented an interactive display with different data views that allowed the exploration of spatio-temporal event data of political, social and economic events in Syria from unstructured textual sources, such as news feeds. They implemented a VA tool called STempo that employs T-pattern analysis (identifies sequences of significantly co-occuring events, Magnusson 2000) to extract and visualize space-time events and sequences thereof. Different types of visualizations highlight selected dimensions of the data, to show or overlay results from T-pattern analysis with the original data. The different views of the data, for example, representations on a map, on a timeline as well as text snippets of the original news, are interactively linked within a single display to support comparison or differentiation. For example, interactively highlighting an often occurring sequence of events in the spatial map display could show that this sequence of events occurs in specific locations only. The potential of the implemented VA system to support visual exploration and analysis of patterns, events and sequences in space and time was evaluated for usability. They conclude that their implementation supports the understanding of political, social and economic and potentially other event data but also stress the potential for including additional options, e.g. different pattern analysis algorithms or visualization types, into their approach (Robinson et al. 2016).

To conclude, interactive visual representations that support all dimensions of a given data set and integrate several data dimensions and levels of data abstraction concurrently (e.g., Lehmann-Willenbrock et al. 2017b) can support visual analytical reasoning and interpretation. Together, with human coding of selected dimensions as well as integration with videos, rich datasets result that—when interactively visualized from different perspectives and supported by automatic analysis algorithms—have the potential to improve the researchers' understanding of group coordination in the future. Traditionally, data capture is followed by coding and analysis which finally results in selected representations of the results (e.g., density plots, Rack et al. 2018). As explained above, VA is an iterative analysis approach that employs visualizations and human-computer interaction in an iterative loop to achieve hypotheses generation and understanding (e.g., Robinson et al. 2016 and illustrated in Fig. 2). VA does not replace traditional analysis processes but builds on those methods and extends them with iterative and interactive visual approaches. For example, the algorithmic analysis of spatio-temporal movements, such as changing the position of or waving an arm, of observed group members may provide pointers for further analysis

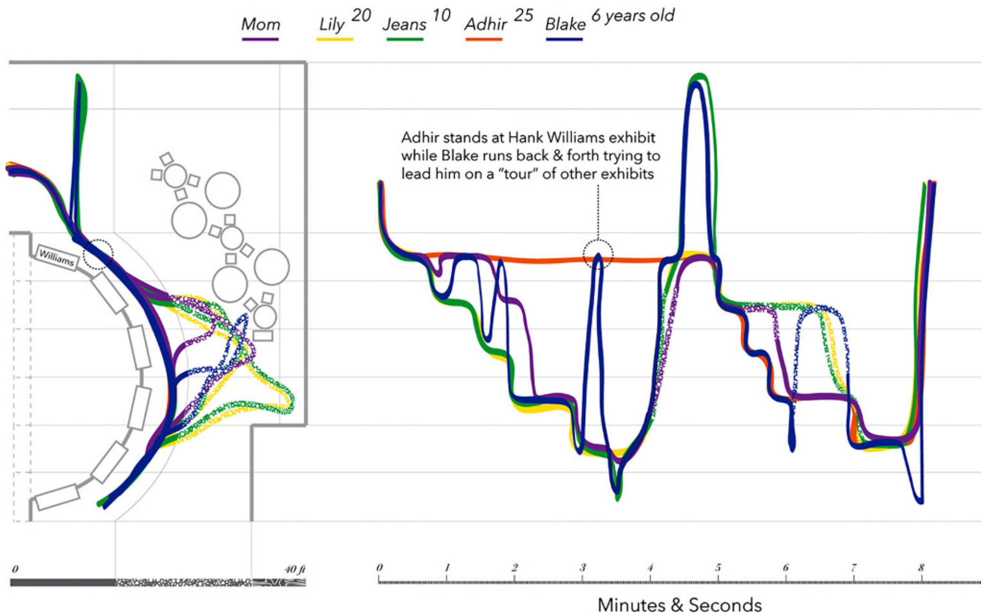

Fig. 3 The Bluegrass Family's movement in a museum gallery space is shown over space and space-time (Shapiro 2018, p. 10). Copyright © by Ben Rydal Shapiro. Reprinted by friendly permission of Ben Shapiro

of selected video sequences. Additionally, initial codings of group coordination aspects may be revised when reviewed through VA methods (Bleisch & Hollenstein, accepted). The interactive analysis, demand-driven combination and visual exploration of several data dimensions concurrently has the potential to lead to the understanding of more complex interactions and processes in small group research. Once hypotheses regarding group coordination and collaboration are developed by visual data exploration, visualization designs can be optimized to support confirmation of findings.

2.1 Potential of VA to measure and analyze group coordination—Two empirical examples from psychological group research

In the following section, two different psychological examples are described to explain the potential of VA to lead to the understanding of complex group coordination. The common advantage is that through the support of algorithms and the scalable design of interactive visualizations for large multivariate data sets, including dimensions of uncertainty, the iterative exploration and subsequent understanding of complex settings and processes becomes feasible.

2.1.1 Empirical example 1: VA for investigating non-verbal and implicit group coordination during informal learning in a museum setting

Applied empirical examples, where employing VA approaches could be helpful, derived from research on informal learning. Informal learning is in most cases social by nature and includes collaborative efforts (e. g., of peers or families) in understanding a topic as well as negotiations of meaning. Moreover, implicit group coordination in relation to the physical environment where the learning takes place is necessary (e. g., in museums or outdoor). For instance, Shapiro et al. (2017) report a case study on learning in a museum gallery where they focused on a family visit in the gallery and applied what they call an "interaction geography" approach: They mapped the interactions of the family members with one another and their movements throughout the physical space of the gallery and created integrated visual representations of these data.

Based on the visualizations (including overlays of movement maps of different persons, see Fig. 3), the researchers interpreted and discussed their findings with museum curators afterwards during a focus group. As a consequence, the authors found developments in professional vision on the side of the curators as well as in their knowledge about museum visitors. Specifically, the curators changed their perspectives on playful and interested visitor learning (the initially seeming unproductive actions and movements of one young person were later considered learning-relevant after deeper reflection based on the visualizations). This result is important because such playful learning in groups is the first step in a long chain of the development of young people leading to academic careers in the natural sciences. Limiting this behavior thus could ultimately influence whether or not our society will have enough young academics interested in the natural sciences (and thus: job candidates in the future) to remain successful in global markets.

Overall, this study can help illustrate how VA could enhance scientific research into informal learning. Here is why and how: VA enables the processing of larger amounts of data, and that the complexity of such interaction and move-

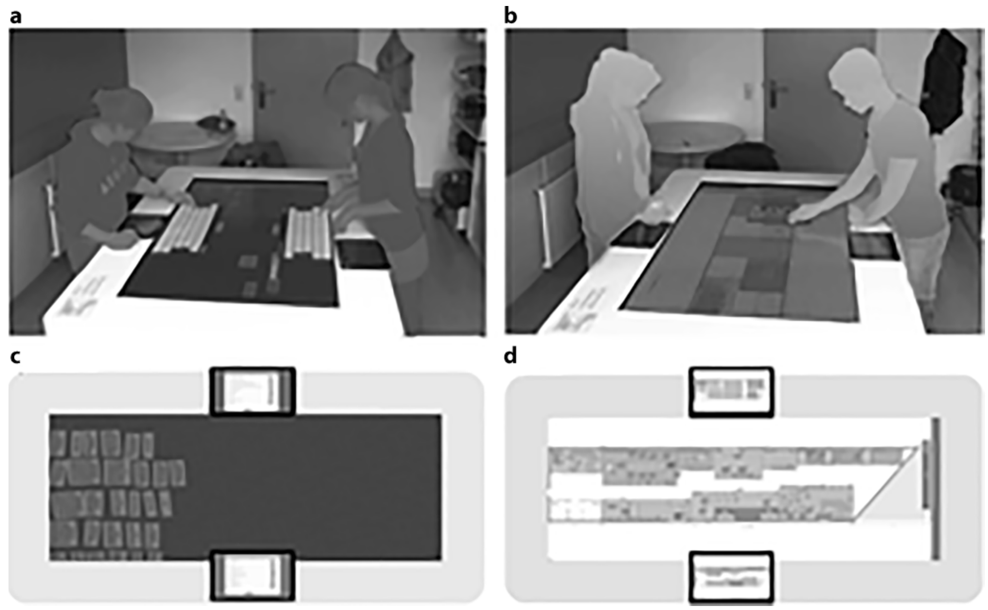

Fig. 4 Tabletops for task types "team brainstorming" (**a, c**) or "team design" (**b, d**)

ment data not only from one case, but from many cases, could still be handled in order to substantiate the obtained results.

2.1.2 Empirical example 2: VA in applied work settings—Coordination in computer-supported groups

Spatio-temporal aspects are not only important in learning situations, but also in small group research on group coordination in groups at work. For instance, in Mateescu et al. (2017), it was investigated how technology affordances of interactive tabletops can have subtle influences on group coordination and outcomes when groups solve creative problems together. Such research is important because, in the future, groups will increasingly have to focus on such problems at their work. To this end, an experiment with 160 participants investigated, among other issues, the following research question: What are the effects of personalized workspace structures and task type on group coordination? Precisely, they focused on two creative task types of design professionals: active design and brainstorming studying the different interface solutions of the tabletops. They compared four workspace structures of the tabletop including the availability of a personal territory, a mobile personal territory (tablet), and no personal territory for the group members. Fig. 4 shows how groups worked at the tabletops.

The overall measurement approach included self-assessment and expert ratings of group coordination. Therefore, the groups were videotaped during their task work. As indicative for the quality group coordination, a measure of *group process effectiveness,* rated by a trained observer for each group upon video observation and based on an adapted rating scheme by Meier et al. (2007) was defined. Apart from this, they were also interested in the territorial behaviors of the study participants.

The analyses revealed interesting task-specific and time-dependent event and interaction sequences: brainstorming group members often created their own personal territories at the interactive tabletop at the *beginning of the collaborative phase* (e.g., in brainstorming, by moving their notes closer together and delimiting them by means of white spaces on the tabletop). It was observed that these territories disappeared as the groups moved forward with their task and started clustering and prioritizing ideas together. By contrast, in the design task (with the tabletop displaying a floor plan as the main group artefact) personal territories were not created.

As becomes obvious, the data are very rich and contain very different spatio-temporal and social behavior dimensions, similar to the soccer example by Stein et al. (2018). However, limitations include that all video data could not be analyzed due to restrictions in time and resources, and even the ones where regression analysis was used showed various dual or triple interactions which were difficult to interpret. Generally, the results from regression analysis in the form of numbers, means and statistical significance were limited in application concerning the complex team behavior patterns observed. While the regression analysis offers a method to look at multidimensional data, it also creates a high level of abstraction of the original very rich data set making it sometimes difficult to relate the results to the original data. Thus, a part of the data and results remained somewhat vague. Interactive VA approaches would provide means to re-explore the original data dimensions as well as the analysis results in more detail to better understand the interactions between the data dimensions as suggested by the analysis results (Liu et al. 2017). Additionally, algorithmic data analysis results might be combined with the original video stream of the group settings, comparable to the soccer game analysis (Stein et al. 2018). Implementing video analytics methods in VA for visual analysis of event sequences and text outputs at different granularities (Robinson et al. 2016) might offer different explanations or hypotheses than those found by traditional, somewhat limited, analysis methods.

3 Conclusion

VA can enhance methods for studying group interaction in small group research, as already many—often interactive—methods for the analysis of such data sets exist but need to be adapted to the specific application area of group coordination research and integrated with suitable visual representations supporting interactive changing of visualization and analysis parameters. Including automated methods for spatio-temporal data capture, algorithmic analysis methods and specifically designed interactive visual displays would support the iterative exploration of selected or combined dimensions of data sets, as exemplified above.

Yet, an important aspect for the development of measurement methods for group coordination is the interdisciplinary workflow between VA and group science to adapt the methods for this specific application area and its research questions. Additionally, this would allow for better understanding of the combined potential of both domains as well as the design of adapted methods for specific methods and questions. A number of phenomena in small group interactions like group coordination cannot be seen or measured with the current state-of-the-art methodologies in the social sciences, but would be able to be measured and/or analyzed with new methods either manually or automatically (for details about this discussion, see Lehmann-Willenbrock 2017b, p. 518). As new and more sophisticated methods for the capture and interpretation of human social behavior are developed, they reach an impasse where the interpretation becomes too complex to be learned automatically without help from group science. VA has become possible through the development of high-performance computing approaches as well as new or improved interface and interaction designs, both of which enable the efficient analysis and handling of very large data sets. However, VA is still developing, for example, regarding the task-specific, optimized combination of interactive visualizations, but promising research and developments in various application areas is being conducted to improve the approaches and to optimize them for specific problems like group research.

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