Mouse Movement Coupling in a Computer-Based Collaborative Problem Solving Task

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Abstract

The purpose of this paper is to investigate whether mouse movement coupling facilitates enhanced performance in a computer-based collaborative problem solving (CPS) task. Although multi-scale coordination in CPS is observed consistently, no consent has been established on when and how interpersonal coordination relates to performance outcomes. The presented research contributes to existing literature by reporting the first empirical evidence for mouse movement coupling in complex CPS. I drew on dynamical systems theory and have applied cross-wavelet transformation to analyze behavioral coupling of 30 dyadic teams at multiple frequency scales. Participants collaborated on the Moonbase Alpha simulation, which is a genuine, computer-based CPS task. Mouse movement coordination was significantly greater than expected due to chance at the scales 18s, 36s, 60s, and 180s. However, coordination did not significantly predict dyadic CPS performance. I further discuss these findings and propose theoretical and practical implications on their basis.

Keywords: collaboration, dynamical systems, interpersonal coordination, mouse movement coupling, problem solving, team dynamics, team performance

Mouse Movement Coupling in a Computer-Based Collaborative Problem Solving Task

Collaboration is a key driver for business performance and success (Kristensen & Kijl, 2010), and collaborative problem solving (CPS) is widely recognized as one of the most important skills of the 21st century (Fiore, Graesser, & Greiff, 2018; Graesser, Kuo, & Liao, 2017; OECD, 2017). As the world is becoming increasingly complex, the major problems of our time require coordinated efforts of multidisciplinary teams beyond individual problem solving (Fiore et al., 2018). Consequently, “collaboration is likely to become an even more prevalent aspect in people’s daily use of computing technologies and interactions” (Papangelis, Potena, Smari, Storti, & Wu, 2019). Recent technological developments furthermore enhance the capabilities and design of computer-supported collaboration, both local as well as remote (Chanel, Bétrancourt, Pun, Cereghetti, & Molinari, 2013; Papangelis et al., 2019). However, the opportunities technology offers do not suffice for successful collaboration as such. In order to fully exploit the potential of technological advances, we need to better understand the dynamics of CPS and define characteristics of an efficient and successful collaboration (Papangelis et al., 2019).

By applying propositions from dynamical systems theory, I aim to contribute to a better comprehension of the observable interaction dynamics, which facilitate effective CPS. More precisely, in this paper, I want to examine whether computer mouse movement coordination helps to achieve performance goals in CPS.

Societal and Scientific Relevance of CPS

Despite the fact that collaboration has become increasingly important (OECD, 2017; Papangelis et al., 2019), students and professionals around the globe currently seem to lack collaboration competencies which are highly demanded concerning the workforce (Fiore et al., 2018; OECD, 2017). Collaborative Problem Solving (CPS) is defined as “a process whereby two or more individuals attempt to solve a problem by sharing the understanding and effort required to come to a solution and pooling their knowledge, skills and efforts to reach that solution” (OECD, 2017, p. 134). Hence, as the efforts of a team working towards a common goal are distributed, by definition, explanations focusing on isolated individuals are deficient (Gorman, Dunbar, Grimm, & Gipson, 2017). Instead, *teams* should be the unit of observation, as they constitute the decisive factor in accomplishing organizational outcomes (Johnson et al., 2007).

Collaborative problem solving is viewed as a process rather than an outcome of a team (Cooke, Gorman, Myers, & Duran, 2013). Interactive relationships among team members unfold over time and provoke complex, non-linear shifts in behavior. Consequently, individuals become *coupled* through communication and perception when engaging in collaborative tasks. This means that behavioral and physiological features are coordinated, may it be intentional or unintentional (Gorman et al., 2017).

Regardless of the context (from sports teams to work and family relationships), collaborators consistently appear to coordinate their actions when interacting with each other. This phenomenon occurs across various modalities (e.g., aligned speech, bodily movements, and cardiovascular measures; Abney, Dale, Louwerse, & Kello, 2018; Louwerse, Dale, Bard, & Jeuniaux, 2012; Palumbo et al., 2016; Silva, Vilar, Davids, Araújo, & Garganta, 2016) and is associated with intra- (e.g., positive affect) as well as interpersonal benefits (e.g., affiliative outcomes, prosocial behavior; Mogan, Fischer, & Bulbulia, 2017; Vicaria & Dickens, 2016). However, it is not yet clear how coordination facilitates these positive outcomes (Abney, Paxton, Dale, & Kello, 2015), particularly not so in collaborative team contexts (Wiltshire, Steffensen, & Fiore, 2019).

Technological advances enable us to explore the cognitive and social constructs associated with effective collaboration, which were inaccessible before (Graesser et al., 2018; Stoeffler, Rosen, Bolsinova, & von Davier, 2020). Stoeffler et al. (2020) urge that the cultivation of CPS skills substantially depends on our ability to identify, measure and track CPS performance. Thus far, much of the research on complex CPS is theoretical and we lack a thorough understanding of CPS processes (Wiltshire, Butner, & Fiore, 2018). Empirical insights are necessary to structure successful interaction among individuals and provide optimal instructional support and feedback (Fiore et al., 2018; Kobbe et al., 2007).

Only an informed understanding of CPS processes allows to incorporate strategies to develop and foster collaboration skills in curricula and the workforce (Fiore et al., 2018; OECD, 2017). Hence, uncovering the dynamics of collaborating individuals is of utmost relevance for both theory and practice, as it can ultimately facilitate enhanced team performance (Graesser et al., 2018; Kobbe et al., 2007).

Dynamical Systems Theory

To study CPS, I will draw on dynamical systems theory. Team dynamics, in essence, are the interactions between individuals of a team (Cooke et al., 2013). As team processes are widely acknowledged as being dynamic, i.e. non-linear, they should be studied utilizing non-linear models correspondingly (Eloy et al., 2019; Ramos-Villagrasa, Marques-Quinteiro, Navarro, & Rico, 2018). As opposed to linear models (where the output is the weighted sum of the inputs), dynamical systems theory aims to understand, model, and predict a teams' behavior and how it changes *over time*. This is applicable to any kind of system (Richardson, Dale, & Marsh, 2014), may it be cells collectively prompting a muscle contraction, fish of a swarm navigating the course and pacing their movements, or humans in a work force coordinating their efforts to solve a difficult problem.

Interpersonal Coordination in Collaboration

How team processes emerge and evolve is described by *interpersonal coordination*. Vicaria and Dickens (2016) characterize interpersonal coordination as “an umbrella term that describes nonrandom patterned behaviors during a social interaction” (p. 336) and the literature further describes examples by terms such as alignment, compliance, convergence, coupling, linkage or synchronization (Abney et al., 2015; Chanel et al., 2013; Fujiwara, Kimura, & Daibo, 2019; Gorman et al., 2017; Miles, Lumsden, Flannigan, Allsop, & Marie, 2017; Vicaria & Dickens, 2016). These nonrandom patterns, i.e. coordinated actions of two or more collaborating individuals, are observed not only at a single scale. Team coordination is rather supported by many different spatial and temporal scales (e.g., from adjusting minor postural movements to the position of a football player in the field, and coordination at milliseconds to hours or even years; Davis, Brooks, & Dixon, 2016; Gorman et al., 2017; Vicaria & Dickens, 2016).

Davis et al. (2016), for example, found highly multi-scale properties in hand movements of individuals who collaborated on a physical manipulation task. Interpersonal movement coordination was widely distributed across a range of spatiotemporal scales, rather than being locally isolated. Hence, coordination in collaboration tasks is not separable into narrow sub-processes as it emerges on a global scale (Davis et al., 2016; Gorman et al., 2017; Richardson et al., 2014). These findings were confirmed by subsequent studies, where coordination of bodily movements and speech occurred on several different scales (Fujiwara et al., 2019; Louwerse et al., 2012; Miles et al., 2017; Wiltshire et al., 2019).

The Functional Role of Coordination in Effective Collaboration

Whereas the occurrence of multi-scale coordination in CPS is well documented, the question of its functionality remains (Abney et al., 2015; Amon, Vrzakova, & D’Mello, 2019; Miles et al., 2017). Although interpersonal coordination in CPS is generally associated with benefits (Mogan et al., 2017; Vicaria & Dickens, 2016), there is no consistent support for the positive effects of coordination and thus indices of effective CPS need to undergo further investigation (Chanel et al., 2013; Palumbo et al., 2016).

In order to achieve a common goal, individuals may implicitly alternate synchronous and complementary coordination strategies (Richardson et al., 2014; Skewes, Skewes, Michael, & Konvalinka, 2015). Thereby, simultaneous movement is called “in-phase”, whereas alternating movement is called “anti-phase” (Miles et al., 2017). The temporal lag in coordination can take on any value in between, and describes the behavioral latency between coordinated movements (Skewes et al., 2015). However, when individuals become coupled they tend towards either in-phase or anti-phase coordination (Miles et al., 2017).

Interpersonal coordination seems to increase with advanced task difficulty (Louwerse et al., 2012; Ramenzoni, Davis, Riley, Shockley, & Baker, 2011), and Miles et al. (2017) propose that coordinating actions serves a reduction of complexity in goal-oriented social interaction, which ultimately improves collaborative performance outcomes (Miles et al., 2017). Davis et al. (2016) for example found the level of hand movement coordination predictive of dyadic performance in a physical coordination task.

In the same vein, Chanel et al. (2013) could predict self-reported performance measures from eye-movement and physiological coupling in a computer collaboration task. Eye-movement coupling could predict the factors convergence (of emotions and ideas) and co-constructing (i.e., building new ideas, deepening as well as broadening them), which are measures of effective collaboration. When participants looked at the same regions on their computer screens at approximately the same time (i.e., in-phase coordination), they reported higher synchronized action and co-elaboration on ideas. Moreover, higher levels of coordination in electrical brain activity (EEG) measures predicted higher ratings in the factor grounding, which refers to maintaining a shared understanding, managing task progress and relationship quality. These results suggest that interpersonal coordination plays an active role in facilitating effective collaboration.

However, forms of coordination such as synchronization can also act counterproductive in achieving performance goals (Abney et al., 2015; Gorman & Crites, 2015; Wiltshire et al., 2019). When trying to collaboratively tie a knot for example, the tendency to show in-phase movements is obstructive as solving this task requires simultaneous, although independent action of individuals. Therefore, synchrony can also be associated with poorer team performance (Gorman & Crites, 2015). Abney et al. (2015), for example, found higher coordination associated with poorer performance in a physical collaboration task. Instead, moderate levels of bodily movement coupling yielded the best performance outcomes.

In some contexts, interpersonal coordination seems to lower the ability to react to changes in task demands and environment due to less degrees of freedom for behavioral adaption. Hence, at certain frequencies or when coordination becomes too strong, coupling appears to impair rather than enhance performance (Amon et al., 2019; Ramos-Villagrasa et al., 2018). Team performance may not be linearly related to any team process but follow an inverted U-shape, where extremely high or low levels of one variable negatively affect the outcome variable (Ramos-Villagrasa et al., 2018).

In a computer-based CPS task, Wiltshire et al. (2019) found substantial coordination of bodily movements in collaborating individuals. Moreover, the observed movement coordination was significantly greater than what can be expected due to chance or task demands alone. Particularly at smaller time scales, individuals showed meaningful bodily movement coordination. Smaller time scales correspond to highly frequent movements, and these explained a considerable amount of variance (30.2%) in team level performance. However, the relationship strength differed across frequency scales and was not always positive. The best predictor of dyadic CPS performance was coordination including its form, namely in-phase, at the 1 second scale. These findings support the assumption that particularly in-phase coordination, i.e. movement synchronization, is associated with beneficial outcomes.

The positive effects of in-phase movements are explained by the close connection of body and mind (Cooke et al., 2013; Richardson et al., 2014). In complex environments, in-phase coordination is believed to function as “social glue” due to a reduction of complexity (Fujiwara et al., 2019; Miles et al., 2017). In a manipulation experiment, Miles et al. (2017) provoked dyads with in- and anti-phase movement exercises, respectively, before they collaborated on a cognitive CPS task. Performance was assessed both on team and individual level. Compared to participants in the anti-phase and control group, individual performance of in-phase induced participants was superior. However, the overall measured dyadic team performance has not been affected by the experimental group. These findings suggest that synchronous coordination may yield individual, but not necessarily collective benefits on team level.

Moreover, the benefits of interpersonal coordination might be limited by context-specific qualities such as dyad composition and history, personal characteristics, role assignment, or task constraints (Abney et al., 2015; Fujiwara et al., 2019; Miles et al., 2017; Vicaria & Dickens, 2016; Wiltshire et al., 2018). In a study conducted by Fujiwara et al. (2019), for instance, the form of coordination was significantly moderated by context factors. They did find positive effects of coordination at smaller time scales (below 2 and 40 seconds, respectively) on perceived rapport. However, this applied only to dyads of strangers, not friends. Thus, when and why in-phase coordination yields positive performance outcomes in CPS remains subject to further investigation.

Summarized, although recent methods and research did yield important insights, a comprehensive understanding of the dynamic interactions between collaborating individuals is yet to be established (Zapata-Fonseca, Dotov, Fossion, & Froese, 2016). Findings show that the effects of interpersonal coordination differ across varying frequency scales and modalities (Chanel et al., 2013; Fujiwara et al., 2019; Wiltshire et al., 2019), and to this date, we know little about how and when coordination indeed facilitates enhanced CPS performance (Abney et al., 2015; Miles et al., 2017; Palumbo et al., 2016; Wiltshire et al., 2019).

Present Research

What distinguishes this work from previous research is that I examine a thus far unobserved modality, namely mouse movements, and how it relates to CPS performance in a naturalistic, computer-based task setting. To account for the multi-scale nature of collaborative processes I distill meaningful features of low-level motor movements across varying time scales, i.e. frequencies, and try to relate them to an objective CPS outcome on a team level.

Insights from authentic CPS assessment are pivotal to identify, measure and track effective collaboration and ultimately develop strategies to cultivate CPS skills (Stoeffler et al., 2020). Automated, computer-based assessment of CPS processes can help to gain insights which are inaccessible with traditional methods such as questionnaires on subjective impressions, and therefore present an important advancement (Graesser et al., 2018; Stoeffler et al., 2020). The Moonbase Alpha task is such a genuine, computer-based CPS task which requires high levels of collaboration to solve it (NASA, 2011). Unlike previous research (Chanel et al., 2013; Fujiwara et al., 2019), this task allows one to examine the effect of team dynamics on an objective performance measure.

Finally, performance is measured on the level of the dyad. Whether collaboration is effective or not should be measured on team level performance, as it is the overall team output which is crucial to solve complex problems rather than individual performance (Fiore et al., 2018; Graesser et al., 2018; Papangelis et al., 2019). This is an important aspect, as effects on team level have been shown to deviate from those on individual level (Miles et al., 2017).

As introduced above, empirical findings support the general idea that multiple spatiotemporal scales determine collaborative outcomes (Davis et al., 2016; Fujiwara et al., 2019; Wiltshire et al., 2019). To capture these complex CPS interaction patterns, complex computational processes from the *dynamical systems perspective* are suitable as they observe teams as non-linear systems and depict how team processes evolve over time (Amon et al., 2019; Gorman et al., 2017; Richardson et al., 2014).

Drawing on dynamical systems theory, I utilize cross-wavelet transformation (CWT) in this study. This time-series analysis method allows to quantify patterns which emerge during collaboration. CWT can precisely detect the multi-scale properties of complex signals derived from CPS and thus uncover behavior of collaborating individuals (Issartel, Bardainne, Gaillot, & Marin, 2015; Richardson et al., 2014). This method is reliable and viable to gain a deeper understanding of complex team interactions, and hence to exceed the knowledge derived from traditional, linear approaches (Cooke et al., 2013; Gorman et al., 2017; Issartel et al., 2015; Ramos-Villagrasa et al., 2018; Richardson et al., 2014). These insights into team-level dynamics may facilitate the prediction of effective collaborative processes (Amon et al., 2019; Ramos-Villagrasa et al., 2018) and further enable enhancement in team development and training (Gorman et al., 2017; Graesser et al., 2018).

Furthermore, a comprehensive understanding of team dynamics in CPS can only be established by aggregating insights derived across multiple modalities. Different individual measures might act complementary in explaining effective collaboration, thus different modalities allow distinct inferences on collaborative processes (Amon et al., 2019; Chanel et al., 2013). In the data set I utilize, Wiltshire (2015) and Wiltshire et al. (2018, 2019) explored coordination of bodily movements as well as teams' communication already. In this paper I examine a novel modality and thereby aim to complement the valuable findings from these studies to advance the knowledge of how interpersonal coordination in computer-based CPS functions in real-time.

To my best knowledge, one motor component that has not been studied in CPS yet, is the coupling of computer mouse movements; neither in this present data set, nor in the prevailing literature. Freeman et al. (2011) promote the employment of mouse movement data, as it can reveal unknown linkages between individuals' action, perception, basic and team cognition (Cooke et al., 2013; Freeman et al., 2011; Richardson et al., 2014; Schoemann, O'Hora, Dale, & Scherbaum, 2019). This is in line with *embodied cognition* theory, which states that cognitive processes are realized in the body outside of the brain. Embodied movements allow teams to perform sophisticated behavior and be adaptive to different contexts and changes in the environment. This key idea is often applied in team research and views the body, i.e. motor movements, as central in understanding the nature of mind and team cognition (Farina, 2020).

Following this line of thought, mouse movement trajectories constitute a continuous source of manual action which exposes the underlying cognitive processes in real-time (Calcagnì, Lombardi, & Sulpizio, 2017; Freeman et al., 2011; Schoemann et al., 2019). As observable behavior such as mouse movements are effectuated by complex team interactions, they allow to draw conclusions on team dynamics (Richardson et al., 2014). In essence, team dynamics *are* the interactions between individuals of a team (Cooke et al., 2013). Hence, measuring how the relationship of individual mouse movements of collaborators change together over time can model team interactions, i.e. team dynamics. Team dynamics ultimately produce team outcomes, for which reason they can provide valuable insights into the characteristics of effective CPS processes (Gorman et al., 2017).

From a scientific point of view, examining mouse movement trajectories is a powerful method to observe behavior in naturalistic, computer-based CPS. It is a promising method to study interpersonal coordination as mouse movements are highly spatially sensitive, gained unobtrusively and at low cost (Calcagnì et al., 2017; Freeman et al., 2011; Hehman, Stolier, & Freeman, 2015; Schoemann et al., 2019; Spivey, Grosjean, & Knoblich, 2005). This efficiency makes them advantageous as opposed to labor-intensive alternatives such as video or audio analysis of bodily movements or speech, where one needs to hand-code movements frame by frame or transcribe whole conversations (Graesser et al., 2018; Paxton & Dale, 2013). In summary, mouse movements present a rich data source offering great potential for both theory and practice (Calcagnì et al., 2017; Cooke et al., 2013; Freeman et al., 2011; Hehman et al., 2015; Paxton & Dale, 2013).

Integrating relevant findings from related research, I expect individuals to exhibit significant mouse movement coordination while collaborating on the computer-based CPS task. Furthermore, the coordination strength will most likely vary across different frequency scales. Given previous findings (Fujiwara et al., 2019; Wiltshire et al., 2019), the nature of the task (Wiltshire et al., 2019) and the fact that mouse movements are composed of fast movement executions and motor pauses (Calcagnì et al., 2017), I expect coordination particularly on smaller time scales to be more important as compared to coordination at larger time scales. Here it is crucial to demonstrate that coordination occurs beyond pure chance (Moulder, Boker, Ramseyer, & Tschacher, 2018; Palumbo et al., 2016). This is done by creating a surrogate data set, described in the method section. Accordingly, I advance the following hypothesis (*H*):

H1: Mouse movement coordination is greater than chance.

Furthermore, I am interested in whether mouse movement coordination plays a functional role in shaping effective CPS. And if so, whether the phase of coordination is essential in predicting successful CPS. Consequently, I pose the following research questions (*RQ*):

RQ1: Can mouse movement coordination predict team level performance?

RQ2: Is the phase of coordination associated with team level performance?

The hypothesis will be confirmed for those frequency scales where mean values of observed mouse movement coordination are significantly greater than surrogate coordination values (with 95% confidence).

The research questions will be answered based on the results of multiple linear regression analyses. *RQ1* will be answered in the affirmative if mean coordination strength values of significant scales explain a significant amount of variance in dyadic CPS performance. *RQ2* will be answered in the affirmative if mean coordination strength and phase values of significant scales explain a significant amount of variance in dyadic CPS performance (both with 95% confidence).

Methods

Experimental Setup

The data set I use originates from a larger study on team dynamics during a computer-based CPS assignment (Wiltshire, 2015; Wiltshire et al., 2018, 2019). Data was collected in 2014 and consists of mouse movement data files in text format. The files were extracted using RUI (Recording User Input), a keystroke and mouse move logger (see http://acs.ist.psu.edu/projects/RUI/ for details). RUI is an unobtrusive application that records user actions and assigns timestamps to it. Thus, it is apt to provide valuable insights into human behavior (Hehman et al., 2015; Kukreja, Stevenson, & Ritter, 2006).

Participants

In exchange for credits towards course requirements at a southeastern United States university, 84 undergraduate students voluntarily participated in the experiment. The prerequisites for participation were general video game experience using mouse and keyboard, no prior history of seizures, no prior experience with the CPS assessment (Moonbase Alpha simulation, NASA, 2011) and no prior acquaintance. Twelve teams were excluded from the analysis because at least one of the participants barely used the computer mouse, but instead, predominantly used the keyboard to accomplish the task. This resulted in a total of 60 participants (22 female, M_{age} = 19.5 years, range 18-28 years; ≈ 68% White, 13% Asian, 8% Hispanic, 7% Black and 3% Other) comprising 30 dyadic teams of which 47% were mixed gender, 40% male and 13% female.

Materials and Task

The two collaborating individuals sat on their desks facing each other with two desktop computers placed slightly aside. The keyboard and mouse were placed on a tray attached to the desk. This setup enabled the dyad to perform the mission while being able to communicate with each other naturally. Cursor speed was captured using default settings of the Moonbase Alpha simulation.

The Moonbase Alpha game is a complex collaborative problem-solving task. It places individuals in a scenario where a meteorite strike damages critical parts of the life support system of the lunar base they are settled. The goal is to fully restore oxygen on the moon base by collaboratively fixing and/or replacing the damaged elements (such as solar panels, power cables, the life support system itself) within 25 minutes or less. To do so, they can use a variety of equipment and tools, but individuals are also bound to constraints. For example, they can hold and handle only one object at a time. Hence, collaboration and coordinated endeavors significantly enhance task progress. Although there are no precise guidelines for how to successfully complete the assignment within the given timeframe, some strategies are superior to others (NASA, 2011).

Procedure

After arriving at the laboratory, participants were informed about the nature of the experiment and invited to introduce themselves to each other. They gave informed consent and filled in a biographic survey.

A short tutorial covering the basics of the simulation was given to all participants and their understanding was tested with a quick 10-item multiple-choice knowledge assessment. The content for the tutorial was derived from the Moonbase Alpha instruction manual (NASA, 2011).

Before starting the game, participants were reminded of the essential role of collaboration for successful completion of the task. A short video introduced the problem and assignment (i.e., the lunar base was destroyed by a meteorite and oxygen must be restored in less than 25 minutes) before participants started. The game was finished either when the time has expired or when oxygen was fully restored (100%), whichever came first.

To conclude the experiment, participants were debriefed and filled in a research evaluation form.

CPS Performance

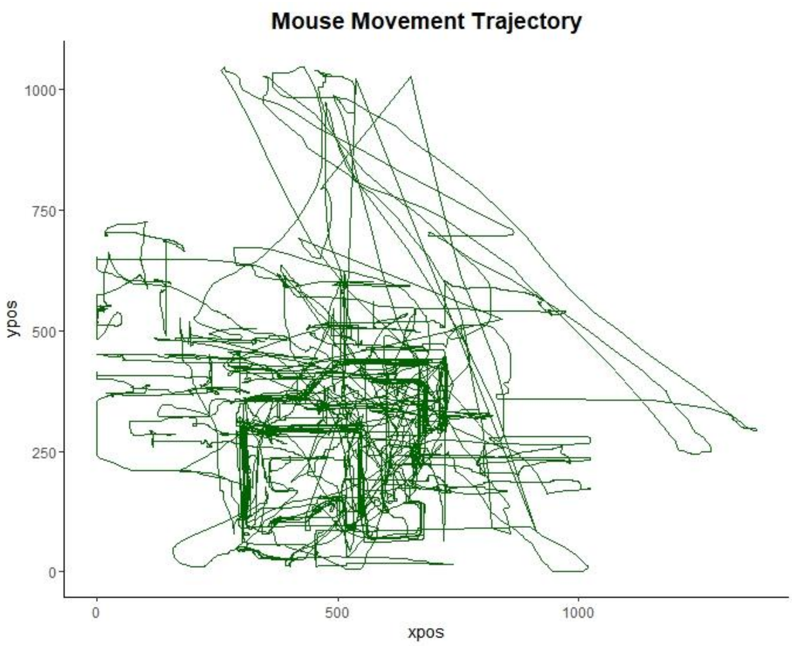
CPS performance was assessed by a rescaled combination of total time spent to complete the task (0-25 minutes) and the percentage of oxygen restored (0-100%). The total time spent to complete the task (in seconds) was rescaled into a range of 0-100 with the following formula: 100*(MaxObservedTime/ObservedTime)/Range, where 1500 seconds was the max observed time and the range was 488. Thus, shorter times result in higher values. These values were added to the total amount of oxygen restored (in percentage) and divided by two to obtain values back on a 0-100 scale.

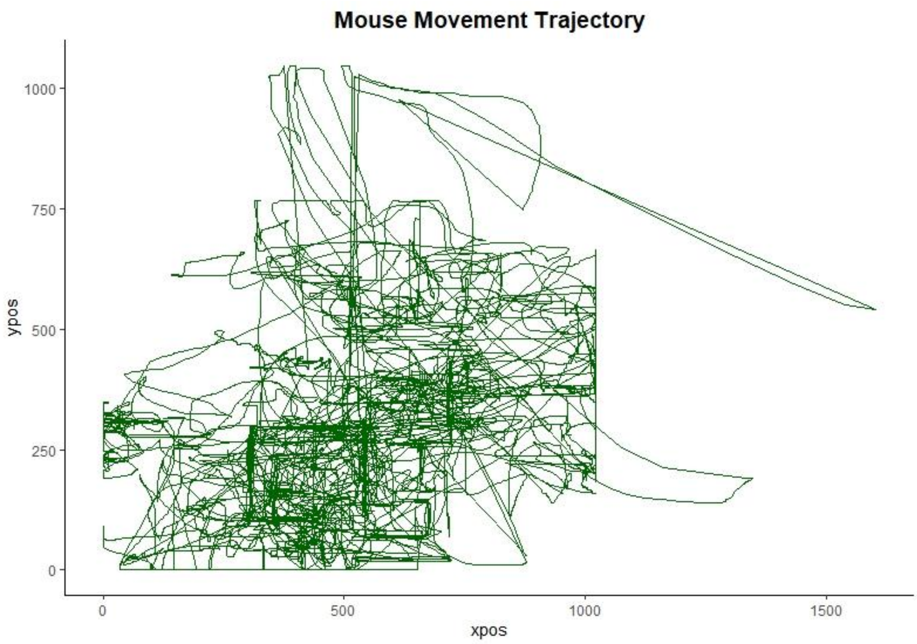
The fastest team to complete the task finished after 16.25 minutes, the mean time to complete the task was 23.94 minutes (*SD* = 2.11 minutes, range = 8.75 minutes).

Analytic Strategy

Preprocessing

Data was processed using R Studio (R Core Team, 2017) and as a first step, I subset the raw log data into mouse movements only by removing all keyboard entries from the logs. I plotted the time series for visualization and to detect possible oddities. Figure 1 shows three different mouse movement trajectories over the course of the task.





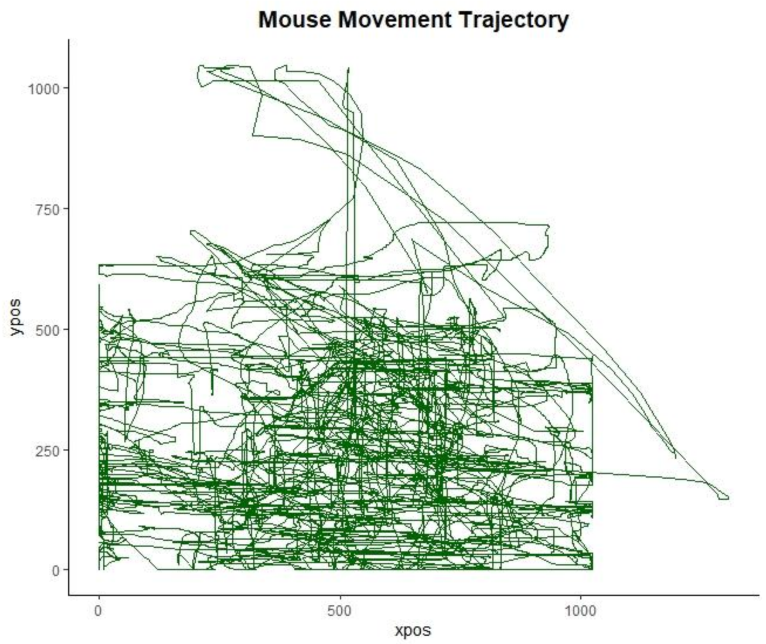


Figure 1: *Individual Mouse Movement Trajectories with Mouse Cursor X- and Y- Positions in Pixels on the x- and y-axes, Respectively.*

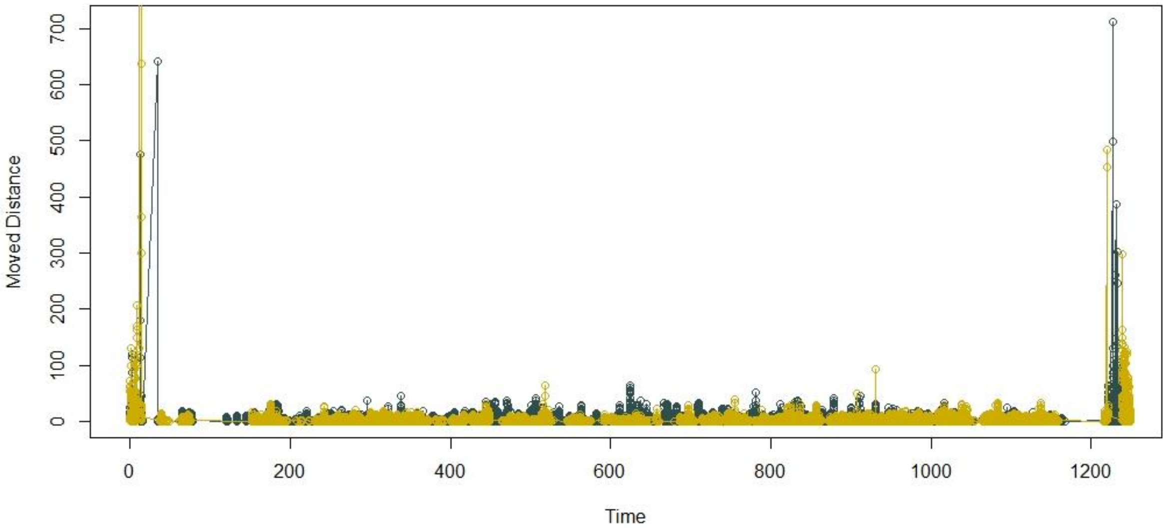
Second, I transformed the time series of the x, y mouse movement screen coordinates into time series of inter-point distances for each participant by using the following formula: $distance((x_t, y_t), (x_{t-1}, y_{t-1})) = \sqrt{(x_t - x_{t-1})^2 + (y_t - y_{t-1})^2}$.

The resulting interpoint distance values correspond to the general, time-localized mouse movement magnitude, i.e. the horizontal and vertical deviations in trajectories over time (Hehman et al., 2015). This is a common method to reduce dimensionality and distill a meaningful feature from multi-dimensional data (Davis et al., 2016; Paxton & Dale, 2013).

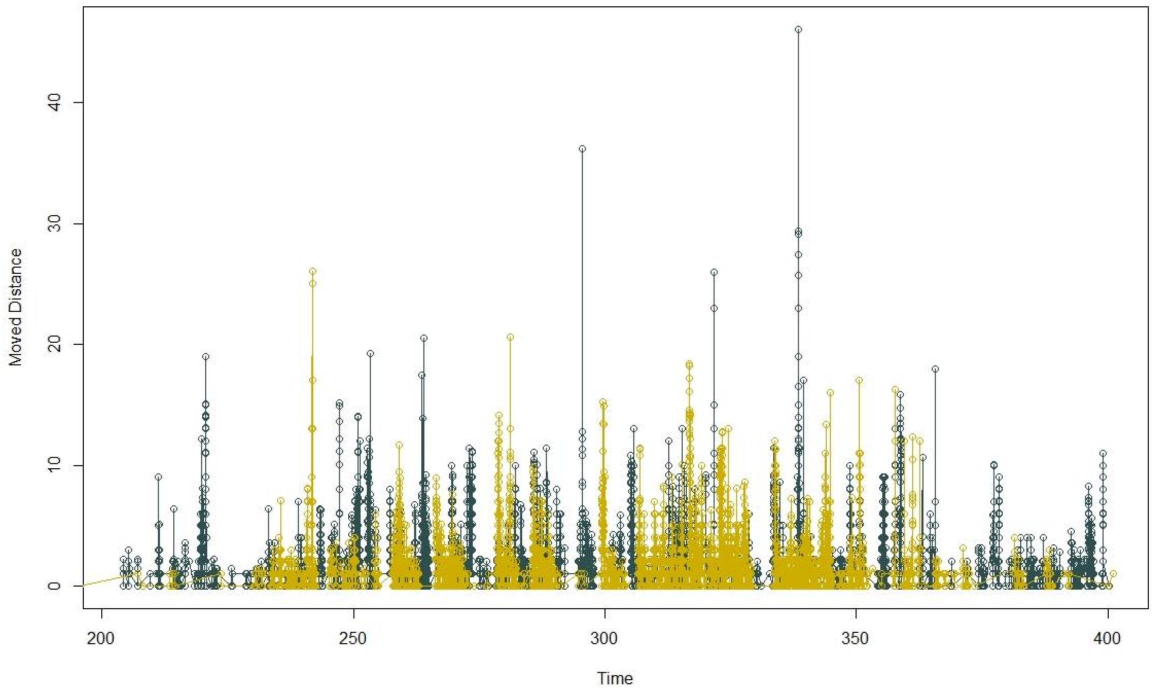
The lag variables (x_{t-1} and y_{t-1} in the formula above) between consecutive observations was calculated by applying the Lag function of the Hmisc package (Harrell, 2020), and I removed the first entries of each time series as they do not have valid lag values (see Appendix A for an example excerpt of a data frame).

Figure 2 shows an example of the movement magnitude of collaborating individuals throughout the task. On the x-axes is the time on task in seconds, on the y-axes the moved distance, i.e. movement magnitude, in pixels. The first example (A) shows the covarying signals over the whole course of completion time, the second (B) and third (C) examples show more zoomed in visualizations to demonstrate the covariation of mouse movement magnitudes in more detail.

(A) Entire Time Series



(B) Zoomed In Time Series From 200 to 400 Seconds



(C) Zoomed In Time Series From 1000 To 1150 Seconds

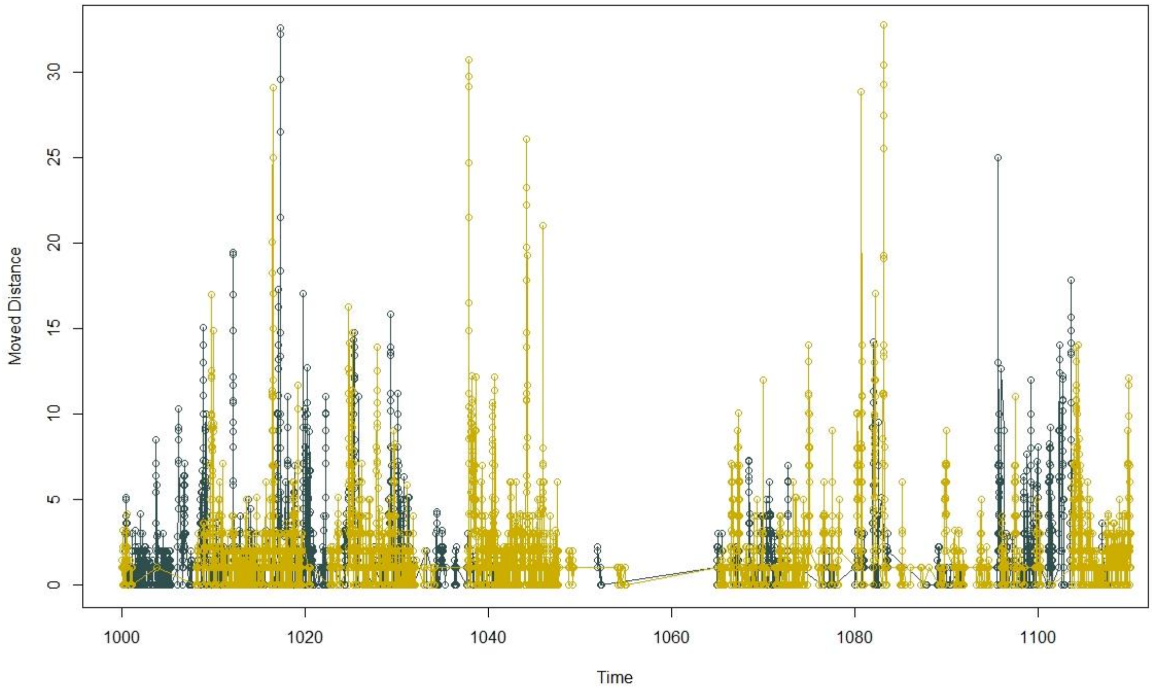


Figure 2: *Individual Mouse Movement Magnitudes of Collaborating Individuals in Dark Green and Yellow, Respectively, With Time on Task on the x-axes and Moved Distance on the y-axes. Entire (A) and Detailed Display (B and C) of One Team.*

Previous research on mouse movement data facilitated a sampling rate of 36 Hz, which is a suitable frequency to examine quick changes of this rich source of data (Spivey et al., 2005). The method I employed (cross-wavelet transformation) requires two time series of the same length and a constant sampling rate (Issartel et al., 2015). Therefore, I created a new time series of conjoint action for each team, i.e. I removed the first few log entries where only one individual was active because the other team member did not yet start the task and the last few log entries where one individual stopped performing the task already. Using the interp1 function of the pracma package (Borchers, 2019), I up-sampled the time series of the newly obtained length by 36 observations per second, i.e. 36 Hz. This method returns linearly interpolated values of the movement magnitude data at the evenly spaced time steps of the new time series I created previously. Thus, two mouse movement magnitude time series with identical time steps for each team (one for each individual) are obtained. Linear interpolation has been applied in numerous human movement studies and is straightforward to calculate and interpret (Long, 2016). Chanel et al. (2013), for example, linearly interpolated gaze position data to further examine eye movement coupling. The gaze trajectories share similar characteristics to the mouse movement trajectories in this paper.

To compare the interpolated time series to the original ones, I plotted both signals to validate whether they looked good or if deviations occurred (see Appendix B for an example). Linearly interpolated values are estimates along the linear path between known values. As illustrated in the example visualization (Appendix B) towards the end of the task (at around 1700 seconds), the interpolated values suggest mean movement magnitude values in between no and very high movement magnitudes of the original time series. Thus, the interpolated values may indicate mouse movement before it actually occurred in the unevenly spaced data. Given that, other interpolation methods such as inverse-distance weighting (IDW) might appear more suitable for this kind of data. However, IDW like any other interpolation method does not come without limitations. In calculating interpolated values, IDW draws more weight from closer locations. However, the weight needs to be determined a priori and remains constant, disregarding the spatial pattern of the original time series. As movement magnitude time series do not show a constant distance decay but rather large local variability (as can be seen in Appendix B), IDW might even produce less accurate interpolated values than the linear method (Lu & Wong, 2008). Furthermore, the values of my time series are closely spaced so the number of consecutive values to be estimated by interpolation is typically small. For this case, Long (2016) showed that linear interpolation performs identical or even better than more sophisticated interpolation methods. Hence, I chose linear interpolation.

Surrogate Data Set

I generated a surrogate data set by random permutation of each of the original time series using the permute function of the gtools package (Warnes, Bolker, & Lumley, 2020). This method eliminates any temporal connection between observations while preserving the characteristics of the distribution. Hence, this data set of shuffled time series represents uncorrelated noise and serves as null hypothesis of no time dependency when testing for *Hypothesis 1* (Lancaster, Iatsenko, Pidde, Ticcinelli, & Stefanovska, 2018; Moulder et al., 2018). Various different surrogate methods associated with different null hypotheses exist (Cazelles, Cazelles, & Chavez, 2013; Lancaster et al., 2018). When beginning to assess interpersonal coupling, however, random permutation is very useful and suggested to start with to see whether the data set is suitable for further analysis (Lancaster et al., 2018; Moulder et al., 2018). Superior to testing coordination above and beyond no coordination, the associated null hypothesis allows to test for significant coordination above and beyond random chance (Moulder et al., 2018). Furthermore, this method has been employed in recent studies on synchrony (Louwerse et al., 2012; Wiltshire et al., 2019).

Cross-Wavelet Coherence

To analyze the time series data, I applied the cross-wavelet transformation method by utilizing the wtc function of the biwavelet package (Gouhier, Grinsted, & Simko, 2019). This method is suitable for largely unstructured data (Issartel et al., 2015) and has successfully been used in recent research to study CPS processes (Miles et al., 2017; Wiltshire et al., 2019). Wavelet transformation does not require any hypothesis about the nature of the time series and decomposes them into different time-frequency scales, which allows one to analyze different levels, i.e. frequencies, of time series independently (Issartel et al., 2015). Although traditional methods such as Fourier transformation, including adapted versions, can model relations in time, they fail to capture the dynamic, i.e. time-varying, nature of collaborative interaction. The biggest advantage of wavelet transformation as opposed to traditional methods is that it provides high precision in both the frequency as well as the time domain (Issartel et al., 2015; Skoura, 2019).

The application of the wtc function allows one to measure the similarity and convergence of timing between time series, i.e. coherence and relative phase (RP) at different frequencies. Frequency refers to the rate of oscillations per second and - when using the Morlet wavelet - is inversely related to the scale. In this case, scale and period are identical and refer to the duration of time of one cycle or oscillation (Cazelles et al., 2008). The smaller the scale (or period), the higher the frequency and the larger the scale, the lower the frequency. Mouse movements on smaller scales, hence, are fast movements with a high frequency.

Coherence indicates the relationship strength between two time series. Values lie between zero and one and can be interpreted similar to a cross-correlation ranging from no (= 0) to perfect (= 1) congruence. However, using simple cross-correlation to indicate the relationship strength between mouse movement time series could lead to false conclusions. In general, time series data derived from studies on human perception and performance is non-stationary. It tends to be highly autocorrelated with varying mean and variance values, thus violating the assumption of independent and identically distributed values which parametric tests require (Dean & Dunsmuir, 2016). As opposed to cross-correlation, coherence values are robust to this kind of data and thus superior (Dean & Dunsmuir, 2016; Issartel et al., 2015).

The *relative phase* is a relational variable that determines transitions and quantifies potential time lags between two series. RP values lie between 0° (“in-phase”) and 180° (“anti-phase”) and summarize the relations between spatial and temporal information. Therefore, they express critical facets of team behavior (Issartel et al., 2015; Skoura, 2019).

I applied the wtc function utilizing the Morlet mother wavelet with 100 Monte Carlo randomizations, all other arguments were on default options (see Gouhier et al., 2019). For behavioral data, Issartel et al. (2015) suggest the Morlet as a mother wavelet. This practice finds continued support and is frequently applied in human movement studies (Fujiwara et al., 2019; Issartel et al., 2015; Issartel, Marin, Gaillot, Bardainne, & Cadopi, 2006; Schmidt, Nie, Franco, & Richardson, 2014; Wiltshire et al., 2019). As opposed to other mother functions, the Morlet function allows to extract relative phase values in addition to coherence values, which is essential in quantifying signal interaction (Issartel et al., 2015, 2006) and furthermore is required to answer *RQ2*. To my best knowledge, this is the only mother function applied to movement magnitude data (i.e. interpoint distance time series). As in the present research, in all these data, values range from zero (no movement) to the maximum movement magnitude (Fujiwara et al., 2019; Schmidt et al., 2014; Wiltshire et al., 2019).

The wavelet and cross-wavelet power spectra are automatically computed bias-corrected (Gouhier et al., 2019) as described in Veleda, Montagne, and Araujo (2012). As I compare the power of time series to noise from 100 Monte Carlo simulations (used to calculate surrogate coherence values), instantaneous power is reliable. The calculated coherence values are robust as well, as 100 Monte Carlo simulations and bias-corrected power spectra were used for the analysis. The step size of the wavelet was 0.0278, and zero padding was applied to reduce edge effects.

Based on previous findings on the occurrence of coordination in CPS (Fujiwara et al., 2019; Khoramshahi, Shukla, Raffard, Bardy, & Billard, 2016; Wiltshire et al., 2019), I extracted the average coherence and RP values from the frequencies at .25 seconds (s), .5s, 1s, 3s, 9s, 18s, 36s, 60s, and 180s, respectively. However, as mentioned above and in accordance with Wiltshire et al. (2019), I expect coordination on smaller scales to be most meaningful in predicting CPS performance. The frequency scales were converted into the time domain by multiplying them by the sampling rate of 36 Hz and dividing them by 60 (for seconds in a minute).

Coordination Beyond Chance

To examine *H1* (if coordination is greater than chance), I compared the average coherence values of dyadic real and surrogate data with a paired sample *t*-test at each of the nine frequencies mentioned above. Coherence values of the surrogate data series are generally considered to denote coordination expected due to pure chance (Moulder et al., 2018; Wiltshire et al., 2019). Therefore, the surrogate data set serves as H0 when testing for *Hypothesis 1* (Moulder et al., 2018; Palumbo et al., 2016).

The Association between Coordination and Performance

To answer the two research questions, I was planning to perform two multiple linear regression analyses with dyadic performance as the dependent variable.

For *RQ1* (whether team coordination can predict performance), coherence values of the significant frequency scales (where coordination is found higher than chance with 95% confidence) were entered in the model as independent variables.

To answer *RQ2* (whether the form of coordination is associated with performance), the RP values of frequencies found predictive of performance in the former analysis were planned on being entered as independent variables in addition to coherence values. However, as none of the four coherence values were found significantly associated with CPS performance, this last step of analysis was omitted.

Commonality Analysis

Previous research indicates that cross-wavelet coherence values of different frequencies in dyadic interactions are highly correlated (Fujiwara et al., 2019). Standardized (beta) coefficients indicate the relative importance of individual predictors when they are uncorrelated. However, when predictor variables are correlated, beta weights cannot disentangle the effects of the predictors on the outcome from the deviations of predictor variables, but cofound them (Nimon & Oswald, 2013). Hence, to avoid biased results and address the issue of multicollinearity, Fujiwara et al. (2019) conducted a commonality analysis with the coherence values obtained from cross-wavelet transformation. This method decomposes the effects of coherence on dyadic performance into the unique contributions of coordination at each frequency. It can identify the presence, location and extent of multicollinearity and also suppression (Nimon, Lewis, Kane, & Haynes, 2008) and thus is useful to enhance the interpretation potential of regression results (Kraha, Turner, Nimon, Zientek, & Henson, 2012). I adopted this approach by implementing the commonalityCoefficients function of the yhat package (Nimon, Oswald, & Roberts, 2020) in order to isolate the distinct frequencies which may ultimately relate to performance. This function partitions the total variance explained (R^2) into variance unique to each predictor and variance shared between each combination of predictors. The unique coefficients or effects are the squared semi-partial correlations between predictor and outcome and hence indicate how much variance is uniquely accounted for by this predictor. The common variance describes the variance common to a predictor set (Nimon & Oswald, 2013). For a detailed description of the computation see (Nimon & Oswald, 2013).

Post hoc Power Spectrum Analysis

Using the wt function of the biwavelet package (Gouhier et al., 2019), I computed the primary power spectra of individual mouse movement time series. The corresponding plots (see Appendix C) allow to analyze where there is power in a given frequency band for individual signals by plotting the power in both time (x-axes) and frequency (y-axes) domain. The figures in Appendix C show higher concentration of power (warmer colors) at larger scales, but also significant power concentrations at small and very small scales (at the top of the plots) – these are surrounded by black lines. The semi-transparent area underneath the white line marks the cone of influence (COI) area. This region may be affected by edge effects (Gouhier et al., 2019).

Results

Hypothesis Testing

Coordination of mouse movements among collaborating individuals in the CPS task was hypothesized to be greater than chance (*Hypothesis 1*). To test for this hypothesis, I compared the observed coherence values from the real data set to the coherence values of the surrogate data set. Interestingly, considerable mouse movement coordination occurred at larger rather than smaller scales, contrary to my expectations. Results suggest that observed coherence was significantly greater than chance at the frequency scales of 18s ($t(29) = 3.35$, $p = .002$, 95% CI[0.02, 0.1]), 36s ($t(29) = 5.88$, $p < .001$, 95% CI[0.14, 0.29]), 60s ($t(29) = 7.4$, $p < .001$, 95% CI[0.24, 0.42]) and 180s ($t(29) = 3.16$, $p = .004$, 95% CI[0.09, 0.42]). The mean differences are also significant after Bonferroni correction for multiple comparisons. Means and standard deviations for all frequency scales can be found in Table 1.

Table 1
Paired Sample t-tests Comparing Observed to Surrogate Coherence Values, Including Means and Standard Deviations

Frequency Scale	Observed Coherence	Surrogate Coherence
.25s	0.20 (.04)	0.25 (.02)
.5s	0.22 (.04)	0.28 (.02)
1s	0.24 (.04)	0.29 (.02)
3s	0.29 (.04)	0.31 (.03)
9s	0.33 (.06)	0.31 (.04)
18s	0.4 (.09)**	0.34 (.06)
36s	0.52 (.16)**	0.30 (.06)
60s	0.63 (.21)**	0.30 (.11)
180s	0.75 (.28)**	0.49 (.25)

Note. * indicates $p < .05$. ** indicates $p < .01$.

The four coherence values which were significantly higher than expected due to chance (18s, 36s, 60s, 180s) were entered in a multiple linear regression model to predict CPS performance (*RQ1*). Figure 3 contrasts observed mouse movement coordination of a low and a high performing team and thereby aims to illustrate the relationship between coherence and performance.

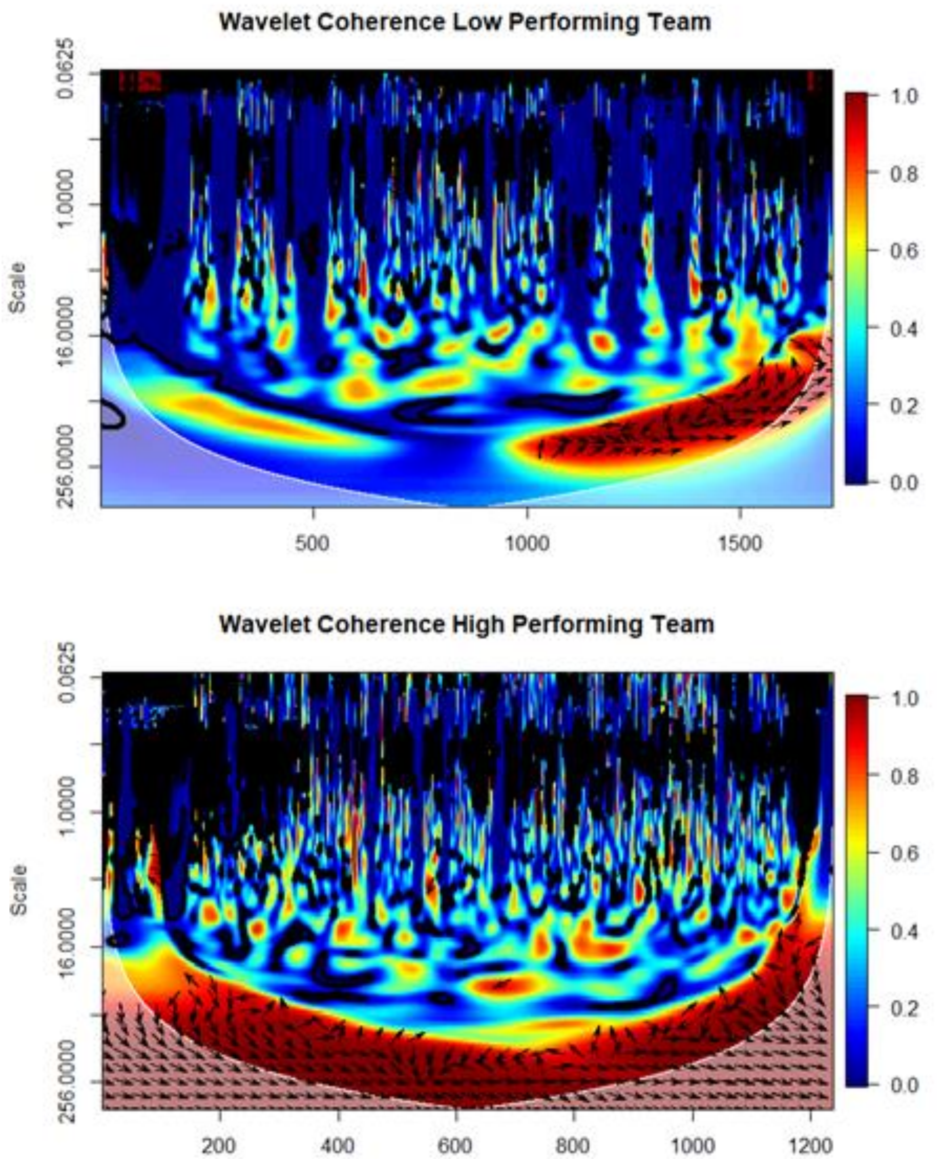


Figure 3: *Wavelet Coherence of One Low and One High Performing Team with Time in Seconds on the x-axes and the Scale on the y-axes*

The x-axes show the time on task, and each unit represents 1/36 of a second. The scale on the y-axes shows the period, i.e. scale, which can be converted into time domain in seconds by multiplying it with 36 and dividing it by 60. The regions with warmer colors (red) are those where individuals exhibit high coordination, whereas regions with colder colors (blue) are those where time series indicate less or no coordination. The black arrows represent relative phase values. When pointing to the right, they indicate in-phase mouse movement, whereas arrows pointing to the left indicate anti-phase mouse movement. One can see that the high performing team (in the bottom plot) exhibits visibly higher coordination as opposed to the low performing team (in the top plot). Hence, these visuals suggest that the high performing team coordinated their mouse movements more than the low performing team did.

Although the observed coherence of all four scales accounted for 27% of variability on CPS performance (R^2 = 27.28%, adj. R^2 = 15.65%), this effect was not significant ($F(4, 25)$ = 2.35, p = .08). Whereas coherence at 18s and 60s showed a positive trend towards CPS performance (b = 177.87, p = .10, 95% CI[-38.99, 394.72], and b = 106.72 , p = .07, 95% CI[-10.00, 223.45], respectively), coherence at 36s and 180s indicated tendencies towards poorer performance (b = -134.76, p = .14, 95% CI[-315.29, 45.76], and b = -15.92, p = .53, 95% CI[-67.99, 36.15], respectively). The regression results can be found in Table 2.

Table 2

Regression Results Using Dyadic CPS Performance as the Outcome

	Unstandardized Coefficients		Standardized Coefficients			95% CI for *b*	
	b	*SE*	β	*t*	*p*	LL	UL
(Constant)	-29.59	25.65		-1.15	.26	-82.43	23.25
18s	177.87	105.29	.55	1.69	.10	-38.99	394.72
36s	-134.76	87.65	- .72	-1.54	.14	-315.29	45.76
60s	106.72	56.68	.76	1.88	.07	-10.00	223.45
180s	-15.92	25.28	- .15	-0.63	.53	-67.99	36.15

In addition to the multiple linear regression analysis, a commonality analysis was conducted. Commonality coefficients are more specific than regression weights and are uniquely able to detect suppressing predictor variables (Nimon et al., 2008; Nimon & Oswald, 2013). The results of the commonality analysis revealed that coherence at 60s had the highest unique contribution to the regression effect (10.3%), followed by 18s (8.3%) and 36s (6.9%). Coordination at 180s had the smallest unique contribution (1.2%) and was involved with only 3.4% of the explained variance in total. The unique, common and total contribution of each frequency to the regression effect are displayed in Table 3.

Table 3
Unique, Common and Total Effects of the IVs

	Unique	Common	Total
18s	0.083	0.071	0.154
36s	0.069	0.036	0.104
60s	0.103	0.072	0.175
180s	0.012	0.022	0.034

Note. The total is the sum of unique and common contribution.

The commonality coefficients and total variance explained by all possible sets of predictors can be found in Table 4. Although there was little common variance in the dependent variable shared across all four predictor variables (8.9%), multicollinearity between the three frequencies at 18s, 36s, and 60s accounted for half of the regression effect (50.11%).

Table 4
Commonality Coefficients

	Coefficient	% Total
Unique to 18s	0.0830	30.43
Unique to 36s	0.0688	25.20
Unique to 60s	0.1031	37.81
Unique to 180s	0.0115	4.23
Common to 18s, and 36s	-0.0616	-22.58
Common to 18s, and 60s	-0.0249	-9.12
Common to 36s, and 60s	-0.0661	-24.23
Common to 18s, and 180s	0.0018	0.67
Common to 36s, and 180s	-0.0101	-3.72
Common to 60s, and 180s	0.0037	1.36
Common to 18s, 36s, and 60s	0.1367	50.11
Common to 18s, 60s, and 180s	0.0046	1.70
Common to 18s, 60s, and 180s	-0.0099	-3.62
Common to 36s, 60s, and 180s	0.0077	2.81
Common to 18s, 36s, 60s, and 180s	0.0244	8.94
Total	0.2728	100.00

Beyond that, commonality analysis allows one to examine the amount of variance explained by suppression (Kraha et al., 2012). Suppressors are independent variables which increase predictive power, i.e. heighten the estimated regression coefficients, of one or more other predictors by suppressing their irrelevant variance when added into a regression model (Hsu & Chiang, 2020). These effects are indicated by negative commonality coefficients and should augment the interpretation of regression coefficients (Kraha et al., 2012).

Here, coherence at 36s might act as a suppressor and impact the regression effects of the frequency scales at 18s and 60s. If the 36s scale was excluded as a predictor, coherence at 18s would predict only 2.1% of performance and coherence at 60s only 3.7%.

Discussion

By observing mouse movement coupling in a computer-based CPS task, the central aim of this research was to explore whether mouse movement coordination plays a functional role in effective CPS. By examining interpersonal coordination of a yet unobserved modality in computer-based CPS, I sought to extend and thereby complement knowledge gained from previous research (Amon et al., 2019; Chanel et al., 2013; Malmberg, Haataja, Seppänen, & Järvelä, 2019; Wiltshire, 2015; Wiltshire et al., 2018, 2019). Studying mouse movement trajectories builds upon to the recommendation to employ automated measures in order to advance the studies of CPS (Graesser et al., 2018; Papangelis et al., 2019), as this rich source of data poses significant theoretical and practical potential (Calcagnì et al., 2017; Farina, 2020; Freeman et al., 2011).

In support with *Hypothesis 1,* I found coordination at 18s, 36s, 60s, and 180s significantly greater than coordination expected due to pure chance. This is in line with previous findings (Amon et al., 2019; Davis et al., 2016; Fujiwara et al., 2019; Wiltshire et al., 2019) and provides further empirical evidence for the multi-scale nature of interpersonal coordination in complex CPS. Regarding *RQ1,* coordination did not significantly predict dyadic CPS performance, although the results suggest trends. Subsequently, I did not continue the analysis to answer *RQ2* (whether the form of coordination related to CPS performance).

Contributions

This study contributes to existing literature in several ways. First, beyond theoretical conceptualization of team dynamics, empirical studies investigating team dynamics in ecologically valid tasks are necessary to advance our understanding of complex CPS (Graesser et al., 2018; Stoeffler et al., 2020). The present research does not only address this demand by attempting to demonstrate the interactional dynamics in complex CPS. Drawing on dynamical systems theory, this study also helps to overcome the limitations of linear approaches which are still frequently employed despite the fact that team processes are widely acknowledged as being complex and non-linear (Ramos-Villagrasa et al., 2018).

By observing mouse movements, I approached a thus far unobserved modality in CPS. This is the first empirical evidence reported for mouse movements coordination to occur beyond chance and at multiple frequency scales in computer-based CPS. However, the methodology I used can be applied to any modality (Issartel et al., 2015). Future research should continue to utilize cross-wavelet transformation to measure interindividual coupling, as it has proven to be a valuable method to examine collaboration dynamics. Comparing the resulting cross-wavelet plots from this study to those of other authors examining human movement magnitude coordination (Schmidt et al., 2014; Wiltshire et al., 2019), the time series show commensurable patterns. This confirms the choice of parameters selected for the present analysis.

Previous empirical research often relied on basic collaboration tasks such as physical object manipulation (Davis et al., 2016; Paxton & Dale, 2013) and/or subjective outcome measures (Chanel et al., 2013; Fujiwara et al., 2019) and hence does not adequately reflect the complex task environment organizational teams face. Certainly, valuable insights are gained from these studies, though it remains questionable whether these findings can be generalized concerning real-world settings. The authentic design of this study allowed me to examine unobtrusively gained behavioral data and its relation to an objective measure of CPS performance. In team research, ecological validity is important to advance our understanding of genuine team dynamics (Cooke et al., 2013; Graesser et al., 2018; Palumbo et al., 2016; Stoeffler et al., 2020).

Furthermore, this study aims to reveal cognitive team processes by observing behavioral patterns. Even though evidence indicates a relationship between low-level, embodied movement and high-level team cognition in collaborative tasks (Farina, 2020), behavioral coordination has not yet been employed to assess CPS skills and performance (Graesser et al., 2017; Stoeffler et al., 2020; Wiltshire et al., 2019). Explicitly studying embodied team cognition is a promising paradigm to deliver informed insights about CPS processes (Cooke et al., 2013; Graesser et al., 2017). This study may stimulate subsequent research to better understand how cognition flows into observable action such as mouse movements (Freeman et al., 2011) and how and why these in turn may facilitate effective CPS.

General Discussion

Although the findings support mouse movement coordination in CPS to occur beyond chance, those frequencies found significant were rather the larger time scales than the smaller ones. This diverges from previous research, which found decreased bodily movement coordination with increasing sizes of time scales (Fujiwara et al., 2019; Wiltshire et al., 2019). Given the characteristics of mouse movement trajectories (Calcagnì et al., 2017) as well as the task environment, I presumed mouse movement coupling to be significant particularly at smaller time scales, too.

One reason for this divergent finding could be that coordination at smaller scales was omitted due to an insufficient amount of frequencies extracted at these smaller scales. Indeed, post hoc visual inspection of the individual wavelet transform as well as coherence plots indicates significant power (see Appendix C) and quite some coordination to occur at smaller scales (see Figure 1). As mentioned before, this study is the first to examine mouse movement coupling in a CPS setting and I based the extracted frequency scales on previous findings (Fujiwara et al., 2019; Paxton & Dale, 2013; Wiltshire et al., 2019). However, suitable for the observed modality in these studies, viz. bodily movement, the authors facilitated a considerably lower sampling rate of 8 Hz. As mouse movements exhibit relatively rapid changes and a high spatial sensitivity, I applied a sampling rate of 36 Hz to fit this type of data (Spivey et al., 2005). Compared to the high sampling rate, however, the amount of frequency bands I extracted is small and it would be interesting to obtain more values, particularly at smaller time scales. This might reveal a more complete picture of coordination at these frequency bands.

Furthermore, random shuffling destroys low-frequency characteristics more than high-frequency characteristics, so it eliminates potential coherence more for larger scales, i.e. lower frequencies (Bandrivskyy, Bernjak, Mcclintock, & Stefanovska, 2004; Lancaster et al., 2018). This may be an explanation for the unexpected pattern of significant observed coherence scales, namely lower observed coherence values compared to the surrogate values at the smaller scales and significant larger scales.

The lack of frequency bands at smaller time scales may also be an explanation for the non-significant findings of the relationship between mouse movement coordination and CPS performance (*RQ1*). Furthermore, previous research which guided the formulation of *RQ1* mostly related aggregated or overall levels of coordination to an outcome measure (Abney et al., 2015; Chanel et al., 2013; Davis et al., 2016; Miles et al., 2017), whereas this study aimed to relate coordination at specific frequencies to dyadic task performance. Maybe the overall level of mouse movement coordination does relate to performance and would show similar findings to those of prior studies (Chanel et al., 2013; Davis et al., 2016; Miles et al., 2017).

Another reason for the non-significant effects of coordination on performance might be that factors of heterogeneity (e.g., personality traits, or race; Vicaria & Dickens, 2016) over-rule or moderate the statistical effects of mouse movement coupling on effective collaboration. Wiltshire et al. (2018), for example, observed task knowledge as well as the gender composition of teams to impact CPS performance in the data set I utilize in this present study. The benefits of coordination for team level outcomes were found to be constrained by interindividual and contextual factors in previous research (Abney et al., 2015; Louwerse et al., 2012; Miles et al., 2017; Vicaria & Dickens, 2016) and perhaps, this applies to the context of mouse movements in computer-based CPS as well.

However, results do suggest trends regarding *RQ1*. Coordination at two frequencies inclines positively (18s and 60s), and at two frequencies negatively (36s and 180s) towards CPS performance. This conforms with earlier findings indicating that coordination at particular time scales seems to inhibit CPS performance rather than enhancing it (Abney et al., 2015; Wiltshire et al., 2019). Nevertheless, commonality analysis revealed that the frequencies which showed positive trends towards performance had the highest contributions to the regression effect, albeit it was non-significant. The most relevant frequency was the scale at 60s, analogous to the results of Wiltshire et al. (2019). Furthermore, commonality analysis suggests that the frequencies which exhibit negative trends towards CPS performance may act as suppressor variables.

As I could not predict CPS performance from frequency-specific coherence values, the question whether mouse movement coordination at these larger scales is relevant for effective collaboration in the Moonbase Alpha task remains. However, considering the maximum duration of 25 minutes in the present collaboration task, coordination on the largest scale (180s) might not unfold within this stretch of time. The small beta ($\beta = -.15$) and unique contribution (1.2%) of mouse movement coordination at the 180s scale also indicate that this scale might be less relevant for the given task. Nonetheless, this study found evidence for the occurrence of coupling on those scales and perhaps future research can relate it to processes yet unknown.

In accordance with Fujiwara et al. (2019), multicollinearity accounted for a considerable amount of variance in the regression effect, indicating that coordination measures at different frequencies are highly correlated (Kraha et al., 2012).

Limitations and Future Directions

This study's findings need to be considered in the light of their limitations, which future research might resolve. Although cross-wavelet transformation is a suitable method to study interpersonal coordination in CPS, it is not without limitations. That is, the frequency scales one extracts are chosen semi-arbitrarily. This is the suggested practice (Issartel et al., 2015) and I did choose the scales to my best knowledge as explained above. Notwithstanding, visual inspection of the wtc plots indicates that the examination of more high frequency scales may reveal further important insights. This was supported by a post hoc visual inspection of primary wavelet power spectra (see Appendix C), which suggests power at smaller scales of the original wavelet transforms as well. Unlike in this study, future research should analyze power spectra beforehand to make more informed choices about the frequency scales to be extracted. This can prevent overseeing relevant frequencies, which probably happened in the present work.

Therefore, an essential next step will be to extract coherence and RP values at smaller scales and examine their relationship to team outcomes. As the evident dynamics of behavioral data depend on the frequency scale that is being observed (Zapata-Fonseca et al., 2016), examining more time scales will contribute to characterize the mouse movement dynamics of teams in CPS better. However, the post hoc inspection of individual wavelet transform spectra (see Appendix C) confirms that the overall observed pattern of results of this study are plausible.

Should coordination of mouse movements at different frequency scales be found to relate to CPS performance, the predictive role of the form of coordination should be investigated as well. Concerning *RQ2*, as none of the coherence values could significantly predict CPS performance, this was not further investigated in this paper. Nonetheless, it is to mention that previous findings suggest that temporal proximity, i.e. in-phase movement, can trivialize the predictive power of coordination strength in primitive physical collaboration tasks (Abney et al., 2015) and hence, might be more important than the magnitude of coordination itself. Whether this is applicable to complex CPS settings too, should be subject to further investigation. Unlike in this paper, relative phase values (which indicate temporal latency in coordination) could be examined independent of the predictive ability of the coherence values in future research.

As argued in the methods, a randomly shuffled surrogate data set is appropriate to test whether the observed data is time dependent and hence suitable for further analysis (Lancaster et al., 2018; Moulder et al., 2018). However, a large variety of different surrogate methods exist, and each of them is associated with different null hypotheses. Therefore, the choice of surrogate method strongly affects the statistical evaluation of periodic patterns and, hence, the conclusions made about a certain time series (Cazelles et al., 2013; Lancaster et al., 2018). Surrogate methods other than random shuffling, such as inter-subject (i.e., participant shuffling/random pairs) or time-shifted surrogates, are more robust and might be even better suited to test for the occurrence of meaningful interpersonal coupling. Future research, hence, should apply different and more complex null-hypotheses to compare their results to each other (Lancaster et al., 2018; Moulder et al., 2018).

Another limitation of this study might be that the keyboard entries were simply removed from the logs if they were not predominantly used by participants. Maybe future research can either prevent usage of the keyboard entirely when examining mouse movement coordination or find a way to incorporate the keyboard entries into the analysis.

Mouse movement trajectories do have a high spatial sensitivity, but they can capture movements only in two dimensions, not three. The range of movements measured is comparatively small and restricted through the table surface (Freeman et al., 2011; Spivey et al., 2005) which is disadvantageous as compared to other modalities such as speech, which is less constrained. Another point to mention is that yet, no agreed standards on facilitating mouse movement trajectories exist, even though Schoemann et al. (2019) demonstrated that even minor experimental design features of mouse movement observations can affect the outcomes in significant ways. The flexible application is among the advantages of the employment of mouse movement trajectories, but future research should precisely choose and report subtle design features such as cursor speed and response requirements. This may help systematic knowledge accumulation and hence to fully exploit the potential of this method in studying team cognition (Schoemann et al., 2019).

Besides that, mouse movement trajectories proved to be an effective alternative to labor-intensive manual coding of interactions in studying interpersonal coordination, as data logging is automated. Likewise, their application poses interesting opportunities for real-time behavioral tracking and intervention to optimize team processes (Graesser et al., 2018; Stoeffler et al., 2020).

However, each measure reflects a unique process and collecting several modalities leads to greater specificity of the processes related to each of them. Previous research which included multiple modality measures in one study (Amon et al., 2019; Chanel et al., 2013) showed that this promotes more comprehensive insights into the functional role of interpersonal coordination in CPS.

As this study confirmed interpersonal coordination across different frequency bands to be highly correlated (Fujiwara et al., 2019), commonality analysis may prove valuable in future research as well, to avoid biased regression results and interpretation (Kraha et al., 2012). Moreover, future research may consider to report on and control for interindividual and contextual sources of heterogeneity when examining coupling in CPS as they were found to contribute to collaborative outcomes (Abney et al., 2015; Miles et al., 2017; Wiltshire et al., 2018). Unfortunately, despite these discoveries, most studies fail to provide information on potentially interesting and important moderating factors (Vicaria & Dickens, 2016).

Although the ecological validity of this study is high, future research can observe teams consisting of triads or more individuals and include collaborating with a computer to approximate real-world work settings even closer (Amon et al., 2019; Papangelis et al., 2019).

We are only beginning to understand the role of motor coupling in CPS. Yet, the role of mouse movement coordination and whether it has a primary influence on shaping functional CPS outcomes, remains subject to further investigation. Future research should continue to investigate how mouse movement coupling emerges, and at which time scales coordination is critical for effective CPS.

Conclusion

To conclude, my study suggests that mouse movements of individuals in a computer-based CPS task are coordinated beyond chance. Results could not support a relationship between mouse movement coordination and dyadic CPS performance. Nonetheless, examining mouse movement coupling in complex CPS remains a promising subject to further investigation. To gain a comprehensive understanding on the functionality mouse movement coordination may have in CPS, more emphasis should be placed on particularly smaller time scales, i.e. high frequencies.

Dynamical systems theory proved to fit well in collaboration research and provided valuable insights as it is apt to depict the multi-fractal nature of team processes in CPS. Hence, the paradigm should be further adopted and applied also to other contexts to better understand team dynamics in complex environments.

CPS certainly is a challenging construct to measure, but it poses great potential for learning, training and performance of teams likewise (Graesser et al., 2018; Stoeffler et al., 2020). Collaboration is of pivotal strategic importance for business and society and recent developments in technology significantly changed and enabled computer-supported collaboration (Fiore et al., 2018; Kristensen & Kijl, 2010; Papangelis et al., 2019).

Consequently, organizations will benefit from systematic, structured investment in tools and methods which help to understand and assess computer-based CPS. Only if we begin to comprehend collaborative processes better, technology can be designed to improve connectivity and efficiency. Training and support for shaping efficient collaboration can be provided so teams ultimately are enabled to exceed their current level of competence and hence fully exploit their potential (Graesser et al., 2018; Kobbe et al., 2007; Kristensen & Kijl, 2010; Papangelis et al., 2019).

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Appendices

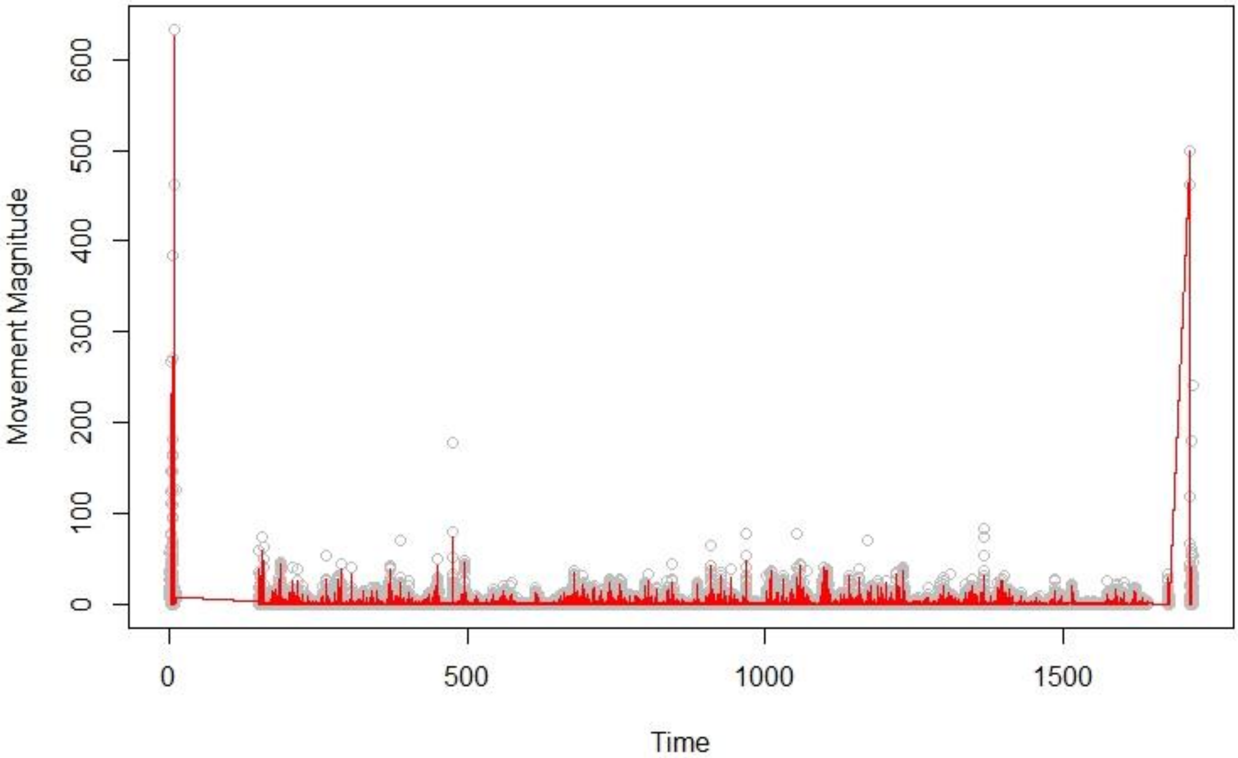
Appendix A

Excerpt of a Data Frame After Calculating All Relevant Variables

Elapsed Time	X	Y	X lag	Y lag	xdiff-sqrt	ydiff-sqrt	Moved Distance
0.449	153	487	169	484	256	9	16.278821
0.450	142	487	153	487	121	0	11.000000
0.451	131	492	142	487	121	25	12.083046
0.452	115	525	131	492	256	1089	36.674242
0.453	115	533	115	525	0	64	8.000000
0.455	115	568	115	533	0	1225	35.000000
0.456	115	595	115	568	0	729	27.000000
0.501	115	613	115	595	0	324	18.000000
0.505	134	667	115	613	361	2916	57.245087
0.552	161	724	134	667	729	3249	63.071388
0.553	210	823	161	724	2401	9801	110.462663
0.555	215	831	210	823	25	64	9.433981
0.641	234	861	215	831	361	900	35.510562
0.642	277	926	234	861	1849	4225	77.935871
0.644	301	950	277	926	576	576	33.941125
0.645	317	969	301	950	256	361	24.839485
0.677	325	971	317	969	64	4	8.246211
0.721	344	974	325	971	361	9	19.235384
0.722	368	974	344	974	576	0	24.000000
0.723	382	974	368	974	196	0	14.000000
0.724	398	974	382	974	256	0	16.000000
0.781	406	974	398	974	64	0	8.000000
0.783	409	974	406	974	9	0	3.000000
0.846	414	980	409	974	25	36	7.810250
0.847	441	1012	414	980	729	1024	41.868843
0.848	446	1017	441	1012	25	25	7.071068
0.910	446	1020	446	1017	0	9	3.000000
0.913	446	1023	446	1020	0	9	3.000000
0.915	449	1023	446	1023	9	0	3.000000
0.944	452	1023	449	1023	9	0	3.000000
0.955	465	1023	452	1023	169	0	13.000000
1.011	476	1023	465	1023	121	0	11.000000
1.013	484	1017	476	1023	64	36	10.000000
1.014	487	1015	484	1017	9	4	3.605551
1.047	490	1015	487	1015	9	0	3.000000
1.058	495	1009	490	1015	25	36	7.810250
1.126	498	1009	495	1009	9	0	3.000000

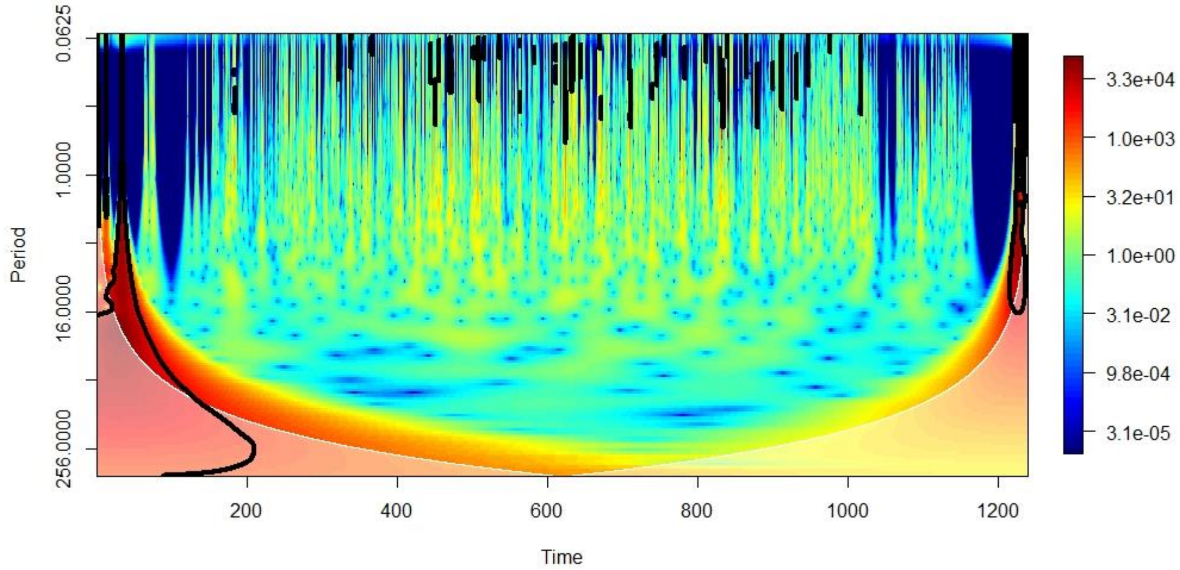
Appendix B

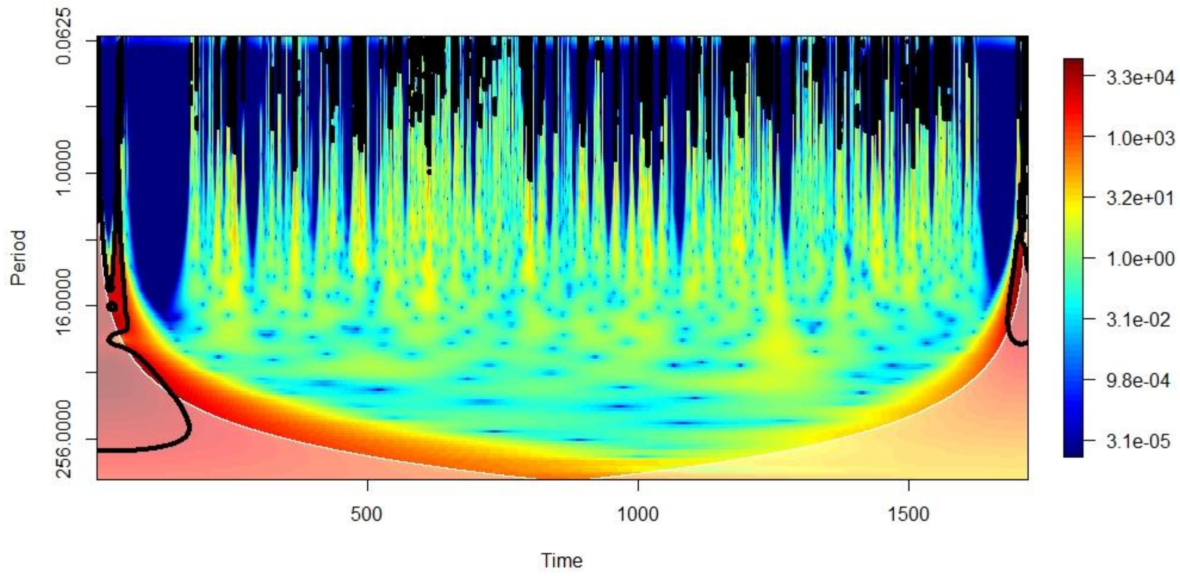
Visualization of the Original (Unevenly Spaced) Data in Grey and the Interpolated Time-Series in Red, with Time on Task in Seconds on the x-axis and Movement Magnitude in Pixels on the y-axis

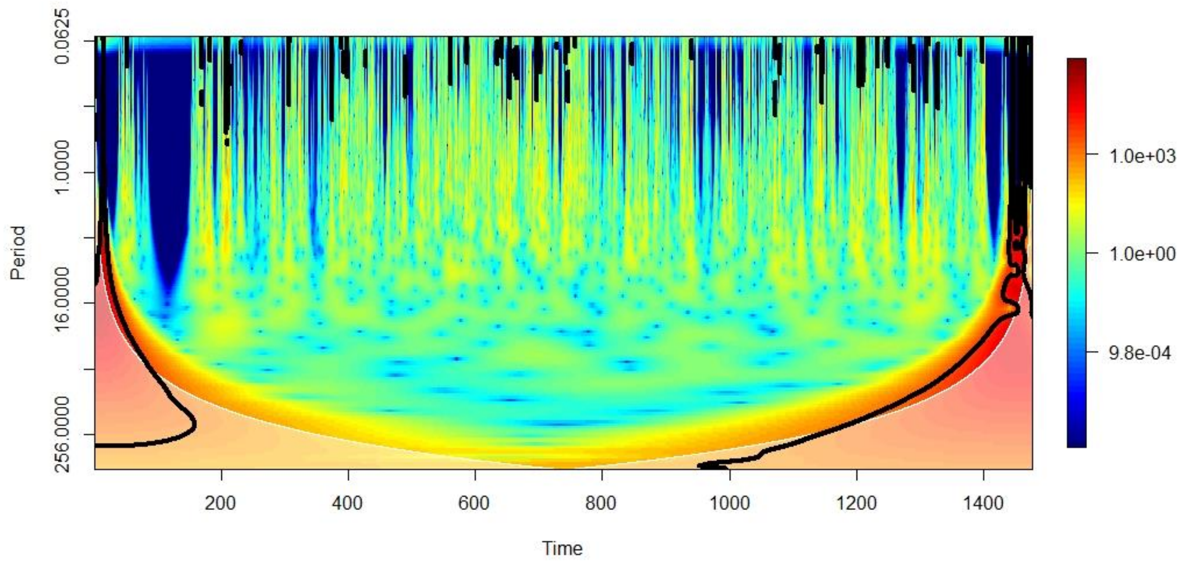


Appendix C

Primary Wavelet Power Spectra of Three Individual Mouse Movement Signal Time Series with Time on Task on the x-axes and Period/Scale on the y-axes







Period
0.0625
1.0000
16.0000
256.0000
200
400
600
800
1000
1200
1400
Time
1.0e+03
1.0e+00
9.8e-04