

Group-based flow: The influence of cardiovascular synchronization and identifiability

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Abstract

Previous work has demonstrated the role of group-based flow in group performance and experience, but the physiological correlates of these relations are largely unknown. We examined the relation between cardiovascular synchronization, self-reported flow, and performance in a three-person online gaming task. We included measures of Heart Rate (HR), Pre-Ejection Period (PEP), and Cardiac Output (CO) as indices of task engagement and challenge (vs. threat) motivation. Group members were identifiable (i.e., visible) or anonymous during the game. Results indicated that PEP (as a marker of task engagement) and within-group synchronization in PEP, predicted flow, and that synchronization in PEP mediated the relation between group performance and experienced flow. The anonymity vs. identifiability of group members did not play a role in these effects. Results are discussed in terms of implications for flow theory, group dynamics, and physiological synchrony.

KEYWORDS

cardiovascular synchronization, challenge and threat, group flow, group performance, social identity

1 | INTRODUCTION

Being in a group is part of everyday life and people belong to a wide variety of groups, like a team at work, a sports team, or an activist group. In these situations, optimal group outcomes, in terms of productivity, winning games, or obtaining social change, are often directly related to optimal group performance. Therefore, it is pivotal to understand the dynamics of optimally functioning groups.

One of the correlates of optimal (group) performance is the psychological state of *flow* (Nakamura & Csikszentmihalyi, 2009). Flow is the peak moment when sense of time is lost, one is completely

absorbed in an activity and acts at the top of one's abilities (Csikszentmihalyi, 1990). Although previous work has shown how flow can arise in group contexts (Armstrong, 2008; De Moura & Bellini, 2019; Heyne et al., 2011; Olsson & Harmat, 2018; Salanova et al., 2014; Van den Hout & Davis, 2019; Walker, 2010) the physiological correlates and contextual determinants of group-based flow are largely unknown. In the current work we address these two issues. More in particular we address the role of cardiovascular synchronization between group members as a physiological correlate, and the role of anonymity (vs. identifiability) as a contextual determinant of the emergence of flow in groups.

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1.1 | Flow

Flow theory describes both the phenomenology and determinants of flow (Engeser et al., 2021; Nakamura & Csikszentmihalyi, 2009). The state of flow has several core characteristics. One characteristic is distortion of time: Time seems to move in slow motion, or rather seems to pass quickly despite the size and complexity of the work. Other characteristics of flow include an extreme focus, strong feelings of control, a loss of self-consciousness, and a merging of action and awareness i.e., in flow a person becomes completely focused on the task and forgets that they are the one doing it. Another element of flow is autotelicity, which means that people are internally driven to proceed on flow-eliciting activities, as the action in itself is the main goal and rewarding on its own.

Apart from the phenomenological state of flow, flow theory has also described the necessary conditions for flow to emerge, including a clear proximal goal and immediate feedback on one's actions regarding the progression towards the goal. Moreover, flow arises when there is a balance between the demands of a task and the person's skills to deal with these demands (Csikszentmihalyi, 1975; Shernoff et al., 2003).

Individual flow is related to a number of positive effects, including increased feelings of happiness (Fullagar & Kelloway, 2009), satisfaction, achievement, and sense of self (Baker & MacDonald, 2013). Moreover, high (vs. low) flow during an activity typically relates to higher quality- and more creative output (Nakamura & Csikszentmihalyi, 2009) and higher performance outcomes in for example sports (e.g., Bakker et al., 2011) and at work (e.g., Demerouti, 2006). The performance-enhancing character of flow has been attributed to its functional properties, like increased concentration, but also to that flow makes an activity rewarding, which in turn stimulates task persistence and setting challenging goals (Engeser & Rheinberg, 2008).

1.2 | Group-based flow

Although flow has mainly been studied during individual tasks, it can also arise in groups (Admiraal et al., 2011; Aubé et al., 2014; Bakker, 2005; Bakker et al., 2011; Walker, 2010; Zumeta et al., 2016). In this context, a distinction can be made between two types of flow in group contexts: "Group flow", referring to a dynamic process at the group level, like the coordinated or synchronized actions by dancers or athletes during group performance (Sawyer, 2017; Jackson et al., 2018), and "Group-based flow", referring to a state of subjectively experienced flow in a group context. The latter concept is similar to the idea

of "group-based emotions", i.e., the experience of certain emotions (guilt, anger) on the basis of one's group identification (Mackie & Smith, 2018). Obviously, group flow and group-based flow can, and often will, occur in combination. However, individually experienced group-based flow can also occur relatively independently of group flow, for example because of individual differences in how group members appraise a certain situation. Nevertheless, since group-based flow is based on a group situation one would expect that, like group-based emotions, it correlates with other aspects of group experience, like group identification (Mackie & Smith, 2018).

There is evidence that social situations elicit higher levels of flow compared to solitary situations (Magyaródi & Oláh, 2017) and that flow in social contexts is more enjoyable (Walker, 2010). Indeed, flow relates positively to relationship quality (Graham, 2008), well-being, collective efficacy, and—particularly for the present aims—group performance (Admiraal et al., 2011; Pels et al., 2018; Salanova et al., 2014; Zumeta et al., 2016). However, the physiological correlates of group-based flow have not yet been examined.

1.3 | Physiological correlates of flow

There is a growing interest in the biological underpinnings of flow (De Manzano et al., 2010; Keller et al., 2011; Khoshnoud et al., 2020; Knierim et al., 2017; Peifer, 2012; Tozman et al., 2015). For example, previous research have examined autonomic activation, and heart rate variability (HRV) more in particular, during flow-eliciting situations. This research has typically found reduced HRV during activities eliciting flow, which may be due to decreased parasympathetic activation and/or increased sympathetic activation (Harmat et al., 2015; Keller et al., 2011; Khoshnoud et al., 2020; Tozman et al., 2015).

Particularly relevant for the current work are two recent overviews of the literature on peripheral nervous system measures and flow (Knierim et al., 2017), one of which specifically focused on gaming contexts (Khoshnoud et al., 2020). This latter overview illustrates how different peripheral measures (e.g., heart rate variability, electromyography, and electrodermal activity) may index different flow related states (e.g., attention, positive affect, arousal). Moreover, both overviews signal challenges for the study of the physiology of flow, including the difficulty in differentiating flow from other psychological states (e.g., stress) by psychophysiological measures, as well as the complex, and sometimes even contradictory, role of sympathetic versus parasympathetic arousal in flow (Khoshnoud et al., 2020; Knierim

et al., 2017). In partly addressing these challenges, the current work includes a more unambiguously cardiovascular (CV) index of sympathetic activation (i.e., pre-ejection period; PEP), as well as a broader conceptual framework for differentiating specific motivational states (i.e., engagement, challenge and threat).

In the current research, we build on the previous work on the psychophysiology of flow, but zoom in on more specific patterns of sympathetic activation on the basis of the biopsychosocial model of challenge and threat (BPS-CT; Blascovich, 2008). The BPS-CT describes the CV markers of two motivational states: *challenge* and *threat*. Challenge and threat operate under conditions of task engagement, which is indicated by increased sympathetic activation, as indexed by increased heart rate (HR) and decreased PEP. The sympathetic nervous system influence on the heart is most directly measured by PEP, however, while HR is under both sympathetic and parasympathetic influences (Brownley et al., 2000). As a result, PEP has been described as the most direct CV measure of task engagement (Kelsey, 2012; Richter et al., 2016), while HR is a more secondary index. In turn, under challenge, increased cardiac activity (i.e., increased HR, decreased PEP) is coupled with decreased vascular resistance, leading in turn to increased levels of cardiac output (CO) compared to baseline. Under threat, by contrast, vascular resistance increases, leading to low or even decreased levels of CO compared to baseline, despite increased cardiac activation.¹

Challenge and threat are—just like flow—hypothesized to result from a balance between the demands of a task, and the resources that the person has to deal with these demands. When there is a balance between the demands of the task and the skills of the person, a challenge motivational state arises, whereas when the demands of the task outweigh the person's resources a threat motivational state arises (Blascovich, 2008; Blascovich & Mendes, 2010; Blascovich & Tomaka, 1996; Manigault et al., 2020; Mendes & Park, 2014; Seery, 2011; Wormwood et al., 2019). Thus, the shared appraisal profile of flow as described by flow theory on the one hand and challenge as described by the BPS-CT on the other, makes the challenge pattern a likely

candidate to represent a relevant physiological dimension of flow (see also Scheepers & Keller, 2022).

Although there is other work on the psychophysiology associated with flow (Khoshnoud et al., 2020; Knierim et al., 2017), the relation between physiological responses and flow has not yet been examined in a group context. This will be a first core contribution of the current work. Interestingly, however, examining physiological responses in a group context also enables us to move beyond looking just at individual physiological responses, but opens up the possibility to also examine physiological synchronization between group members as a correlate of group-based flow. Examining this is another main contribution of the current work.

1.4 | Synchronization in groups

During social interactions, people tend to mimic each other's social signals (e.g., facial mimicry; Chartrand & Bargh, 1999; Lakin et al., 2003). However, emerging evidence suggests that people also synchronize their physiological responses (e.g., heart rate, skin conductance, or pupil dilation) during interactions with others (Behrens et al., 2020; Kaplan et al., 1963; Kret et al., 2015; Levenson & Gottman, 1983; Thorson, Dumitru, & West, 2021; Timmons et al., 2015). Such physiological synchronization may in turn relate to diverse psychological processes and outcomes, ranging from emotional cohesion, connectedness, rapport, social bonding and prosocial behavior (Behrens et al., 2020; Bernieri, 1988; Hess & Fischer, 2013; McAssey et al., 2013) to competition and conflict escalation (Danyluck & Page-Gould, 2018; Timmons et al., 2015).

Different (psychological) mechanisms have been suggested to underlie physiological synchrony. For example, an obvious candidate for a mechanism is shared metabolic demands, although this cannot fully explain physiological synchrony under all circumstances (Palumbo et al., 2017). Moreover, in clinical settings like therapist-client interactions (one of the main areas where physiological synchrony has been studied) empathy has been proposed to underlie physiological synchrony (see also Karine Jospe et al., 2020; Kleinbub et al., 2020; Palumbo et al., 2017). Finally, and particularly relevant for the current research, in research on small interactive groups, the process of shared attention has been proposed to drive physiological synchrony in for example heart rate (Kazi et al., 2021; Thorson, Dumitru, Mendes, & West, 2021; Thorson, Dumitru, & West, 2021; West et al., 2017).

Although several of these mechanisms may be relevant in the current setting where three-person groups are engaged in a cooperative online game (see Method), especially the latter mechanism, shared attention, seems

¹In addition to HR, PEP, and CO, the BPS-CT also describes Total Peripheral Resistance (TPR) as a marker to differentiate challenge and threat. TPR is described as the mechanism through which increased cardiac activation (increased HR, decreased PEP) leads to either increased CO (through decreased TPR, indicative of challenge) or stable/decreased CO (through increased TPR, indicative of threat). We were not able to measure TPR in the current study. However, we think that looking at HR, PEP, and CO provides a tentative basis for a BPS-CT interpretation of cardiovascular reactivity, because in the context of the BPS-CT, increases and decreases in CO are assumed to be due to changes in TPR.

relevant. First, the empathy explanation seems more relevant in dyadic settings than in the context of groups, and seems particularly relevant when sharing personal experiences, rather than when gaming together. Moreover, although shared metabolic demands are always at least to some extent a likely process, in the current situation the task is more cognitive in nature than more metabolically demanding physical tasks (e.g., playing basketball). However, because shared attention lays at the heart of the current task, where communication is only possible by viewing, anticipating on, and responding to each other's actions, this is a likely underlying mechanism of physiological synchronization in the current situation. Indeed, the game that we used in the current study is quite dynamic, with some events likely being more exciting and goal relevant than other events, and some situations eliciting a stronger interdependence between group members than other situations. As a consequence, we expect that moments of high excitement, goal-relevance, and interdependence are the moments that (CV indices of) attention will likely synchronize. This may especially be the case for physiological measures that have been related to (cognitive) effort, like pre-ejection period (Kelsey, 2012; Richter et al., 2016; West et al., 2017).

Although physiological synchrony has not yet been examined as a correlate of flow arrived in groups, there is previous evidence that (emotional) contagion is an underlying dynamic of the experience of flow (Bakker, 2005; Walker, 2010). Moreover, Bakker (2005) directly investigated the contagiousness of flow and showed a positive correlation between the flow experienced by music teachers and their students. Further suggestive evidence for the role of synchronization in flow in a social context comes from a qualitative study, where flow experienced during collaboration was described as “becoming one with the group” (Łuczniak et al., 2020, p. 10). Finally, flow in groups has also been related to synchronization of thoughts, for example when group members finish-off each other's sentences during a collaborative task (Armstrong, 2008). Together, these previous findings have thus pointed to the key role of synchronization in the development of flow in groups.

In the current research, we extend this line of reasoning and investigate the relation between physiological synchronization and the experience of flow in groups. More specifically, we examined whether synchronization between CV indices of challenge (vs. threat) predicts group-based flow. Apart from shedding more light on the physiological markers of group-based flow, a further aim is to examine its contextual determinants; in the current work, we examine the role of anonymity in this respect.

1.5 | The role of anonymity and identifiability

We propose, for two reasons, that groups might be the ideal habitat for flow to arise. First, groups are defined by goals. Second, engaging in groups may lower self-awareness, which is a core aspect of flow. Work on deindividuation effects has illustrated that anonymity in groups lowers self-awareness. More specifically, work on the Social Identity Model of Deindividuation Effects (SIDE; Postmes & Spears, 1998; Postmes et al., 2001) describes deindividuation as a shift in self-definition from a personal level to the group level (i.e., “social identity”). Thus, the SIDE model describes deindividuation not as a “loss of self” but as a shift towards a higher-level self-definition, in terms of the characteristics, norms, and goals of the group. In combination, by lowering self-awareness and directing attention to salient group goals, anonymity in groups might stimulate flow.

Initial evidence for the key role of social identity in the development of flow in groups comes from work showing a positive correlation between social identification and flow during group activities that foster personal development (Mao et al., 2016), as well as from work showing a significant association between a loss of self-consciousness and an amplified engagement and concentration during group flow (Olsson & Harmat, 2018). Another study found that flow mediated the relation between in-group identification and group performance outcomes (Zumeta et al., 2016). While these previous studies measured individual differences in the strength of social identification, in the current research we extend this by also examining a contextual factor known to increase the salience of social identity, namely anonymity vs. identifiability in the group.

1.6 | The current research

To recap, the current study examines the physiological correlates of flow and, more in particular, physiological synchrony between group members as a correlate of flow in groups. In addition, we examine whether group-based flow increases under conditions of anonymity. Finally, we examine the downstream consequences of this for group performance.

We conducted an experiment where three-person groups worked under anonymous and identifiable conditions on a cooperative video game. During the game the (synchrony in) CV responses (HR, PEP as indices of task engagement and CO as index of challenge) of the group members was measured. Group performance was measured during the game and the state of flow was measured afterwards using a self-report measure.

Physiological synchronization was quantified using dynamic time warping (DTW), an algorithm that calculates the local stretch vs. compression of two time series to compare and match them. This results in the cumulative distance between the two time series or, in other words, the difference between the two (Berndt & Clifford, 1994; Giorgino, 2009). This difference forms an indication of how similar the two time series are, and thus how much they are aligned or synchronized. Although DTW has only recently been introduced in research on physiological synchronization (Chikersal et al., 2017; Kleinbub et al., 2020), we selected this technique because of three requirements dictated by the current research design and data. First, we needed a technique that is easily applicable to more than two timelines (i.e., the data of more than two people), which excluded certain techniques that are specifically designed for dyads (e.g., SHME model; McAssey et al., 2013). Second, we needed a technique that can deal with ‘indistinguishable data’, where all time series have an equal role or status in the analysis. This excluded techniques that require one person’s physiological responses to function as a reference point for the other person’s responses (e.g., a mother’s heart rate as a reference for her infant’s heart rate; Thorson, Dumitru, Mendes, & West, 2021; Waters et al., 2014). Third, because interpersonal processes are dynamic we needed a technique that takes possible variations in time and speed into account by considering a varying rate of change, and not requiring a fixed delay or “lag” (Palumbo et al., 2017).

When considering these requirements as well as the diverse analytic techniques that are available, we concluded that DTW would be the most appropriate approach. First, DTW is easy to apply to multiple persons in a group by averaging all respective pairs in a group. That is, even though initially DTW also integrates just two time lines, the single and well-interpretable values that this yields makes it easier to integrate the data of multiple dyads in a single group, at least compared to other analytic techniques. For example, a popular alternative technique, windowed cross-correlation, yields two values per pair (e.g., a cross-correlation and a lag) while a “mean lag” is also hard to interpret psychologically. Moreover, DTW can deal with indistinguishable data and varying rates of change, and does not require a fixed delay. That is, DTW can match events even if (for example) a group member shows a peak in their physiological signal as much as 4 s before another group member, and can even match these events when they slightly differ in duration (e.g., 1 vs. 2 s).

Both task engagement (as indexed by HR and PEP) and being able to meet task demands (i.e., challenge, as indexed by CO) should contribute to optimal task experience (flow) and performance. Moreover, within-group synchronization in engagement and challenge should

relate to flow and performance because it should reflect a functional group process in, for example, being attentive in coordinating action (Kazi et al., 2021; Thorson, Dumitru, Mendes, & West, 2021; Thorson, Dumitru, & West, 2021; West et al., 2017). Finally, in line with previous findings, flow is expected to positively predict performance (Bakker et al., 2011; Demerouti, 2006; Engeser & Rheinberg, 2008; Nakamura & Csikszentmihalyi, 2009).

Thus, we predicted flow to be associated with HR, PEP and CO reactivity (Hypothesis 1a) and within-group synchronization in HR, PEP and CO (Hypothesis 1b). Moreover we predicted performance to be associated with HR, PEP and CO reactivity (Hypothesis 2a), within-group synchronization in HR, PEP and CO (Hypothesis 1b), and flow (Hypothesis 2c). Finally, we predicted higher levels of flow, performance, and CV reactivity and -synchronization in the anonymous condition than in the identifiable condition (Hypothesis 3).

We also included subjective measures of group-experience (perceived cohesion/group identification) which we analyzed in a more exploratory manner. Although one can generally expect positive relations between cohesion, identification, performance and flow in groups, the role of anonymity (vs. identifiability) is harder to predict. On the one hand, anonymity may shift attention to social identity and increase group experience (Postmes et al., 2001; Postmes & Spears, 1998); on the other hand, being able to see each other during team performance may also increase group cohesion. Therefore, group experience will be examined in a more exploratory fashion.

2 | METHOD

The study was approved by the research ethics committee of the Department of Psychology at Leiden University. Materials and data are available via osf.io/94wpy.

2.1 | Participants

Hundred-seventeen participants (51% female; age: $M = 22$; range: 17–34) participated in 39 three-person groups, for either € 7.50 or course credits. We performed a sensitivity analysis using G*Power v3.1.9.7 (Faul et al., 2009) for the test with the smallest number of units, i.e., the regression analysis predicting performance, for which the relevant sample size is $n = 39$ as there is just one performance outcome per group (see Section D of the supplementary materials for the G*Power syntax for these analyses). We reasoned that if this would indicate sufficient power to detect relevant effects, we could deduce from this that we would also have sufficient power for the analyses with a larger number of units (e.g., the regression predicting flow, which was measured



at the individual level and for which $n = 117$). Following hypothesis 2 we based the sensitivity analysis on a linear regression model with three predictors (CV reactivity, CV synchronization, flow), which yielded sensitivity to detect an effect of $f^2 > .31$ ($R^2 > .23$) and a critical $F > 2.87$ (power 80%, $\alpha = .05$) for the total model (note that the sensitivity of a test with single predictors would have been even higher). The obtained sensitivity seems sufficient when considering similar effects reported in the literature, like the relationship between flow and group performance ($R^2 = .32$; Gaggioli et al., 2017), the relation between CV synchrony and group performance ($F = 4.24$; Thorson, Dumitru, & West, 2021), and the relation between CV responses and self-reported flow ($R^2 = .32$; Tozman et al., 2015).

In addition, we also performed sensitivity analyses for the t -tests involving condition (for details see Section D of the supplementary materials). This indicated that the t -tests on the individual data ($n = 117$) seemed able to detect effects of a small/medium size (more precisely, Cohen's $d > 0.46$) while the t -tests on the group data (e.g., performance; $n = 39$), seemed somewhat underpowered, as they could only detect large effects (Cohen's $d > 0.81$).

Participants were allocated to three-person groups that were randomly assigned to either the anonymous (20 groups) or the identifiable condition (19 groups). When inviting them to the lab we checked that group members did not know each other, at least not on the basis of their names. Because it would still be possible that they would know each other by face, for example from seeing each other during educational activities, we again checked for acquaintance during the lab session, and indeed found that some participants (21 out of 117) indicated that they knew one or two other members of their group. As a consequence, we decided to control for this in the analysis. The majority of the participants ($113 = 96\%$) indicated that they had never played the “Monaco” game before. There were 29 mixed-gender groups (14 with one male and two females; 15 with one female and two males), four all-male groups, and six all-female groups. Due to technical issues (i.e., low signal quality, movement artifacts), we lost all physiological data of two groups. For four additional groups we excluded the CO and/or PEP data for all group members, and for 11 groups either the HR, PEP, or CO data was excluded for one group member. For these latter groups the remaining data of the other two members were still included in the analyses. This resulted in 37 group with HR data, 34 groups with PEP data, and 33 groups with CO data.

2.2 | Procedure

Upon arrival at the lab all participants were initially seated in distinct cubicles in front of a computer. First,

participants received written information about the study, and signed an informed consent form when they wanted to participate. Next, the experimenter attached the electrodes to measure CV responses. The instructions for the game were provided via the computer. After this, but before starting the actual game, participants filled out some questionnaires² after which 5 min of baseline recordings of the CV measures were taken while participants watched a soothing movie.

In the second part of the study the participants played the game “Monaco” (see *Materials and Measures*). The participants in the identifiable condition were moved—together with the laptop they worked on—to another (larger) room where they met their teammates and were seated at a large table, facing each other. Participants in the anonymous condition stayed in their cubicle to play the game. During the game, participants wore headphones to prevent verbal communication with their teammates. The game was played for 15 min.

After finishing the game, participants in the identifiable condition were brought to their separate cubicles again. All participants then filled out questionnaires measuring flow (the flow state scale) and group experience (identification and cohesion; see *Materials and Measures*). At the end of the experiment the participants were debriefed, thanked, and compensated for their contribution.

2.3 | Materials and measures

2.3.1 | Task

Monaco: What's Yours Is Mine (Pocketwatch Games, 2013) is a cooperative multiplayer action video game about a group of burglars who have to work together in heists or robberies. The main goal of the game is to reach certain objectives, such as releasing a co-player out of prison, to move to the next level. Participants were instructed to try to get through as many levels as possible. Each player was assigned to a specific role: The *Locksmith* (who could quickly open and lock doors), the *Lookout* (who had a superior vision on the map), and the *Cleaner* (who could easily knock-out enemies). If a group “died” in the game, they started again at their last level. The first level was a practice level; from the second level on the game became more challenging. Theoretically, the most successful

²We included measures of personality, creativity, experience with gaming, and trait flow. These data were not the focus of the current article and are therefore not further discussed. The supplementary materials contain all materials and the descriptive statistics of the questionnaires. All materials and data are available at OSF: osf.io/94wpv.

scenario for the group is when each participant follows their role and helps each other out. The Monaco game was chosen because of its potentially high group-based flow producing features: it requires cooperative actions, provides immediate feedback about the players' success, and gets increasingly harder as players proceed to higher levels. The performance of a group was determined by the final level that was reached, ranging from 1 to 7.

2.3.2 | Flow

For all questionnaire items, 7-point Likert scales were used with (1) "totally disagree" and (7) "totally agree" as end-points. The flow state scale (FSS; Jackson & Marsh, 1996) was used to measure flow. For the purpose of this study, the questionnaire was shortened to 27 questions, divided across nine sub-scales comprising three items each. The subscales cover the nine core dimensions of flow: "challenge-skill balance" (e.g., "My abilities matched the demands of the task"), "action-awareness merging" (e.g., "I made the correct movements without thinking about trying to do so"), "clear goals" (e.g., "I knew clearly what I wanted to do"), "feedback" (e.g., "I was aware of how well I was performing during the game"), "concentration" (e.g., "My attention was focused entirely on the game"), "control" (e.g., "I felt in total control of what I was doing"), "loss of self-consciousness" (e.g., "I was not concerned with what others may have been thinking of me"), "distortion of time" (e.g., "It felt like time stopped while I was performing"), and "autotelic experience" (e.g., "I really enjoyed the experience"). In the current study the total flow state scale was used in the analyses (Cronbach's $\alpha = .91$).

2.3.3 | Group experience

To capture the participants' group experiences we measured perceived group cohesion and identification. Group cohesion was measured using five items (e.g., "It felt like this group formed a unity" and "Even though the group consists of different individuals, I think that we were able to collectively work towards our goals"; $\alpha = .77$). Group identification was measured using seven items (e.g., "I identify myself with this group"; $\alpha = .83$).

2.3.4 | Control variables

The following control variables were collected: gender, gender composition of the group, and acquaintance of group members.

2.4 | Physiological data acquisition and preparation

CV responses were measured at baseline (5 min) and during the game (15 min). Impedance-cardiographic (ICG) and electrocardiographic (ECG) signals were measured using a Biopac MP150 system, comprising BioNomadix BN-NICO and BN-RSPEC modules, and using standard electrode configurations (e.g., see <https://www.biopac.com/product/bionomadix-cardiac-output-amplifier/>). Signals were recorded at a sampling rate of 1 kHz using AcqKnowledge software (AcqKnowledge v. 4.3.1; BIOPAC Systems Inc.).

The following CV measures were calculated using the automatic scoring module of the AcqKnowledge software: heart rate (HR), pre-ejection period (PEP), and cardiac output (CO). The B-point was scored automatically using the ICG-scoring module which used as a criterion the maximum of the third derivative of the Zt signal before the C (i.e., dZdt max) point (Debski et al., 1993; Seery et al., 2016; see Árbol et al., 2017 for an examination of the reliability of this procedure using this software). After the automatic scoring, the scores were visually inspected, and erroneous scores (e.g., due to movement artifact) were excluded from further analysis. The data were then extracted from AcqKnowledge with one sample per second.

CV reactivity scores were calculated by subtracting the mean from the first minute of the baseline from all data points (between-condition differences on the baseline scores on the three CV measures turned out to be not significant, $F_s < 1$). Outliers in the resulting reactivity scores, defined as 3.3SD above/below the mean were handled through winsorizing (Seery et al., 2013); i.e., outliers were assigned a value 1% lower/higher than the next (non-outlying) value. Missing values in the physiological data where interpolated by using na.approx in R (Zeileis & Grothendieck, 2005). There was, on average, per person 1% of the HR data, 5% of the PEP data, and 13% of the CO data missing.

2.5 | Statistical analysis

2.5.1 | Cardiovascular synchronization

To quantify CV synchronization between the players in a group, dynamic time warping (DTW) analysis was performed. DTW is used to align time series to find an "optimal match" between the two. Specifically, an optimum path (i.e., warping path) is sought in a distance matrix containing the distances (i.e., the dissimilarities) between all the elements of two time series. Based on this warping path, a final distance is computed and normalized by

dividing it by the sum of the length of the two sequences (Giorgino, 2009; see Section B of the supplementary materials for a more detailed description of our DWT analysis). The result is a measure of the dissimilarity of two time series. The higher the number, the more dissimilar the time series are. Thus, lower numbers indicate more synchronization.

For the DTW algorithm, we used the *dtw* function of the *DTW* R package with default values (Giorgino, 2009). We wrote a function in R to apply the DWT analysis to the current physiological data. To capture an overall trend of synchronization in the time series, the data was split into segments of a specific width. These segments sliced the whole time series, partly overlapping the previous segment (Boker et al., 2002). Segmentation has been shown to improve the DTW's prediction performance (Yamauchi et al., 2015). For the current dataset, a segment size of 15 (i.e., 15 s) was used, with moving time windows in steps of three. Per "window" the DTW analysis was applied and per "step" it jumped to the next window (see also supplementary materials).

The DTW analysis was performed on each pair of participants in a given group. For the results the normalized distances (nd) were taken. Subsequently, the mean of the pairs of one group was calculated for further analyses. The correlations between the mean and SD within the groups were rather large (CO: $r = .75$; HR: $r = .99$; PEP: $r = .94$; all $ps < .001$), indicating that the overall synchronization of the group was virtually the same as the synchronization between the three separate pairs in the group. Therefore, we aggregated across the three time series within a group, and did not include the SD in the further analyses. The analyses were done separately for the three physiological measures, resulting in the measures synchronization in HR, synchronization in PRP, and synchronization in CO.

2.5.2 | Hypothesis testing

Performance and CV synchrony were aggregated at the group level while for all other variables (flow, CV reactivity, cohesion and identification) individual-level scores were calculated. However, for the analyses on the group-level dependent variables (performance and CV synchronization) the scores for the predictor variables were also aggregated at the group level.

The data was analyzed using multiple regression (examining the relations among physiological reactivity, physiological synchrony, flow, and performance) and *t*-tests (examining differences between the conditions). We considered multi-level modeling, but given that we only had within-person variance for the physiological measures and not for flow, there was no within-person variance to

be explained in the dependent variable. Therefore, we eventually opted to conduct multiple regression, using the individual level data, which seemed justified after examining the intra-class correlations. That is, an initial multi-level intercept-only model (i.e., without predictors) for flow yielded an intra-class correlation of .01, meaning that the variance between the groups was relatively low compared to the variance within the groups (i.e., the groups cannot be clearly distinguished from the entire sample). For identification and cohesion we found similarly low ICCs (i.e., rounded .01), and therefore the analyses on these variables were also conducted on the individual scores, rather than aggregated at the group level or using multi-level modeling.

The analysis path consisted of 4 parts. First, we present a preliminary correlation analysis and tests of overall CV reactivity based on the individual level data. Second, to test Hypothesis 1 and 2 on predicting flow and performance on the basis of (synchronization in) HR, PEP, and CO we performed three linear regression analyses per hypothesis, i.e., one for each CV measure separately. Third, we then tested Hypothesis 3 by testing between-condition differences in CV reactivity and -synchronization, flow, and performance by means of *t*-tests. More exploratory, we also tested the interaction between condition and the physiological response in predicting flow and performance by adding condition and its interaction with the respective physiological responses to the models described in Step 2. Finally, and also in a more exploratory way, we added the group cohesion and identification measures to the flow and performance models described in Step 2, to examine whether these had an additional predictive value. For all models condition was dummy coded as 0 (anonymous groups) and 1 (identifiable groups) and all other variables were centered using the grand mean (Paccagnella, 2006).

3 | RESULTS

Controlling for gender, gender composition of the group, and acquaintance of group members in the analyses yielded results that were virtually identical to those that are currently reported below.

The correlations among the different variables in this study are displayed in Table 1; Table 2 provides the descriptive statistics (means and standard deviations) of these variables. Lower numbers of CV synchronization indicated less dissimilarity and therefore more synchronization. As can be seen in Table 2, there is substantial variation in CV synchronization, which was intended and of course a prerequisite to be able to use it in the analyses. However, when considering the mean, SD, and range of the synchronization measures, it seems that for all three

TABLE 1 Pearson correlations between main variables

Correlations	<i>n</i>	1	2	3	4	5	6	7	8	9
1. Performance	117									
2. Flow	117	.22*								
3. HR	107	.02	-.15							
4. PEP	102	-.01	.18 [†]	-.13						
5. CO	91	-.00	-.06	.09	-.12					
6. HR sync ^a	111	-.27**	.07	-.17 [†]	.16***	.09				
7. PEP sync ^a	105	-.47***	-.32***	.12	-.36	.08	.15			
8. CO sync ^a	99	-.35***	-.17 [†]	-.02	-.08	.09	.12	.39***		
9. Cohesion	117	.05	.25**	-.15	.04	.02	-.00	-.22*	-.04	
10. Identification	117	.08	.44***	-.11	-.04	-.10	-.13	-.07	.03	.47***

Abbreviations: CO, cardiac output; HR, heart rate; PEP, pre-ejection period; sync, synchronization.

^aLower numbers indicate more synchronization.

[†] $p < .10$;

* $p < .05$; ** $p < .01$; *** $p < .001$.

measures the mean falls at the lower end of the scale, indicating more synchronization and suggesting a general tendency towards relatively more synchronization in most groups.

As can be seen in Table 1, and in line with Hypothesis 1b, synchronization in PEP, and to a lesser extent CO, during the task related to higher reports of experienced flow after the task. Moreover, in line with Hypothesis 2b, synchronization in HR, PEP and CO correlated significantly with group performance, indicating that a higher CV synchronization was associated with higher group performance. In line with Hypothesis 3c, flow also correlated with performance. By contrast, CV reactivity was not related to flow or performance, which was not in line with the hypotheses. It is also worth noting that group identification and perceived group cohesion related positively to flow, and that perceived cohesion related positively to synchrony in PEP; thus, group members who perceived their group to be more cohesive were also more in sync with regard to the contractibility of their hearts. Finally, in line with previous theory and empirical findings, flow related positively to performance.

We then examined overall CV reactivity throughout the task by testing the HR, PEP, and CO reactivity scores against 0 (i.e., baseline). Overall, PEP decreased significantly from baseline ($M = -11.27$; $SD = 27.47$), $t(101) = -4.14$, $p < .001$, indicating sympathetic activation, although HR remained stable ($M = -.40$; $SD = 9.39$), $t(106) = -0.44$, $p = .660$. The absence of HR reactivity as index of task engagement is not uncommon in more subtle motivated performance situations (e.g., a computer task; Scheepers, 2017), compared to more metabolically demanding situations, like public speaking tasks which

typically also result in strong increases in HR (Blascovich et al., 2004). However, as indicated in the introduction, PEP is the more primary index of task engagement and therefore we concluded that sufficient signs of task engagement were present to warrant an interpretation of CO in terms of relative challenge (vs. threat). Cardiac output increased marginally significantly from baseline ($M = .16$; $SD = 0.82$), $t(90) = 1.83$, $p = .071$. In combination, this indicates overall task engagement as well as a (small) tendency towards challenge during the game.

3.1 | Predicting flow

To examine Hypotheses 1 we fitted three linear regression models, for each CV measure (HR, PEP, and CO) separately. For all models, flow was the outcome variable and CV synchronization (synchronization in HR, synchronization in CO, or synchronization in PEP) and CV reactivity (i.e., HR, PEP, or CO) were added as fixed effects.

As can be seen in the Table 3, in line with Hypothesis 1b, PEP synchronization predicted flow: More synchronization in PEP was related to higher flow. The PEP Model explained 7% of the variance ($R^2 = .07$), $F(2,95) = 4.59$, $p = .012$. The HR model explained 1% of the variance ($R^2 = .01$), $F(2,104) = 1.72$, $p = .138$, and the CO model explained 1% of the variance ($R^2 = .01$), $F(2,85) = 1.48$, $p = .234$.

In sum, Hypothesis 1b was only partly conformed: We found a relationship between synchronization in PEP and self-reported flow; however Hypothesis 1a was not confirmed as we did not find relationships between CV reactivity and flow.

TABLE 2 Means and standard deviations (SD) of Main variables

	Overall			Anonymous			Identifiable						
	<i>n</i>	<i>M</i>	(<i>SD</i>)	Range	<i>k</i>	<i>M</i>	(<i>SD</i>)	<i>k</i>	<i>M</i>	(<i>SD</i>)	<i>t</i>	<i>df</i>	<i>p</i>
Performance	117	6.49	(1.78)	3 to 10	20	6.30	(2.03)	19	6.68	(1.49)	−1.18	115	.239
Flow	117	4.56	(0.74)	3.7 to 5.4	20	4.58	(0.42)	19	4.53	(0.38)	0.34	115	.733
HR	115	−.040	(9.39)	−68.8 to 68.3	20	−1.46	(12.94)	17	0.80	(9.79)	−1.25	105	.2155
PEP	113	−11.27	(27.47)	−309 to 298	18	−6.50	(47.62)	17	−16.63	(50.25)	1.88	100	.063 [†]
CO	111	0.16	(0.82)	−5.89 to 16.4	18	0.13	(1.58)	15	0.19	(1.43)	−0.38	89	.708
HR sync ^a	115	26.95	(18.61)	10.65 to 109	20	29.80	(24.33)	17	23.60	(13.27)	1.00	35	.325
PEP sync ^a	113	0.11	(0.05)	0.04 to 0.27	18	0.11	(0.05)	17	0.11	(0.06)	0.03	33	.975
CO sync ^a	111	3.39	(1.54)	1.15 to 6.88	18	3.71	(2.38)	15	3.02	(2.05)	1.28	31	.209
Cohesion	117	4.43	(1.05)	2.7 to 5.5	20	4.28	(0.57)	19	4.58	(0.60)	−1.51	115	.133
Identification	117	4.23	(0.95)	3.1 to 5.33	20	4.03	(0.51)	19	4.44	(0.39)	−2.37	115	.019 [*]

Abbreviations: CO, cardiac output; HR, heart rate; PEP, pre-ejection period; sync, synchronization.

[†]Lower numbers indicate more synchronization.

^a*p* < .10;

^{*}*p* < .05.

TABLE 3 Regression models predicting flow

	HR model				PEP model				CO model			
	<i>b</i>	SE	<i>t</i>	<i>p</i>	<i>b</i>	SE	<i>t</i>	<i>p</i>	<i>b</i>	SE	<i>t</i>	<i>p</i>
(Intercept)	4.54	(0.07)	64.20	<.001***	4.57	0.07	62.00	<.001***	4.52	0.08	55.58	<.001***
CV Synchronization	0.00	(0.00)	0.99	.327	−3.92	1.75	−2.25	.027*	−0.09	0.05	−1.70	.092 [†]
CV Reactivity	−0.01	(0.01)	−1.39	.168	3.45	3.17	1.09	.279	−0.01	0.10	−0.08	.935

Abbreviations: CO, cardiac output; HR, heart rate; PEP, pre-ejection period.

[†]*p* < .10;

p* < .05; *p* < .01; ****p* < .001.

3.2 | Predicting performance

For Hypothesis 2, we examined the relations between CV reactivity, CV synchronization and performance. Again, three linear models were run (one for each CV measure) to test the predictive value of CV reactivity, CV synchronization, and flow on performance (Table 4); flow was added to the model to test Hypothesis 2c, as well as to be able to determine whether physiological or psychological variables were a better predictor of performance.

As can be seen in the table, in line with Hypothesis 2a and 2b, PEP reactivity and synchronization both predicted performance: A shorter PEP (indicative of task engagement) and more synchronization in PEP were related to better performance outcomes. The PEP Model explained 28% of the variance ($R^2 = .28$), $F(3,31) = 5.47$, $p = .004$. Moreover, synchronization in HR also predicted performance; the HR model explained 22% of the variance ($R^2 = .22$), $F(3,33) = 4.43$, $p = .010$. Thus, synchronization in group members' physiological markers of task engagement (HR and PEP) related to a better group performance.

In sum, Hypothesis 2 was partly conformed: We found a relationship between self-reported flow and performance, and between PEP reactivity and -synchronization and performance, but not between CO reactivity or synchronization and performance.

Interestingly, although we observed a reliable overall relation between flow and performance (see Table 2), flow was not significant in the PEP model regarding performance. This may suggest that the relation between performance and flow could be mediated by PEP synchronization. To examine this possibility more systematically we conducted—in a more exploratory manner—mediation analysis, for which three regression equations were calculated. In the mediation analysis we treated flow as the dependent variable as this also reflects the chronological order in which the variables were measured (a prerequisite for mediational analysis).

The first regression equation confirmed that performance (*X*) predicted flow (*Y*), ($\beta_{YX} = 0.09$, $p = .008$) and the second regression equation confirmed that performance (*X*) predicted synchronization in PEP (*Z*) ($\beta_{ZX} = -0.01$, $p = .005$). Moreover, when regressing flow on synchronization in PEP and performance simultaneously in a third regression equation, the former relation was significant, ($\beta_{YZ.X} = -4.51$, $p = .002$) while, performance no longer predicted flow ($\beta_{YX.Z} = 0.04$, $p = .319$). This show that the effect of performance on flow was fully mediated via synchronization in PEP (see Figure S1 in the supplementary materials for the full mediation model).

TABLE 4 Regression models predicting group performance

	HR model				PEP model				CO model			
	<i>b</i>	SE	<i>t</i>	<i>p</i>	<i>b</i>	SE	<i>t</i>	<i>p</i>	<i>b</i>	SE	<i>t</i>	<i>p</i>
(Intercept)	6.51	.26	24.90	<.001***	6.38	.27	23.17	<.001***	6.47	.30	21.48	<.001***
Flow	2.06	.66	3.14	.004**	1.16	.83	1.39	.175	1.50	.78	1.91	.066 [†]
CV Reactivity	−0.01	.05	−0.21	.836	−47.22	21.49	−2.197	.036*	0.14	.59	0.25	.807
CV Synchronization	−0.03	.01	−2.20	.035*	−20.98	7.81	−2.684	.012*	−0.30	.21	−1.44	.160

Abbreviations: CO, cardiac output; HR, heart rate; PEP, pre-ejection period.

[†]*p* < .10;**p* < .05; ***p* < .01; ****p* < .001.

The significance of the indirect effect ($[-.01]*[-4.51] = .054$) was tested using a bootstrap procedure using the R package, *mediation* (Tingley et al., 2014). The bootstrap analysis revealed a significant indirect effect of .05 ($p = .002$), with a 95% confidence interval ranging from .02 to .11., showing that the effect of performance on flow was fully mediated via synchronization in PEP (see Table S6 in the supplementary materials for further details of the mediation analysis).

3.3 | Anonymity vs. identifiability

To test the difference between the identifiable and anonymous condition on CV reactivity and -synchronization, *t*-test analyses were conducted (see Table 2). There was a marginally significant effect of condition on PEP, indicating somewhat lower PEP (indicative of task engagement) in the identifiable condition compared to the anonymous condition. There were no reliable effects on the other CV reactivity scores as well as on the CV synchronization indices.

Subsequently, to test for the interaction between CV reactivity and condition in predicting flow and performance, condition and the interaction between condition and CV reactivity were added in a second step as fixed effect in the models predicting flow and performance described above. However, adding condition and the interaction did not improve the fit for the three models predicting flow: $LRT_{\text{ModelHR1 vs.2}} = 1.97$, $\chi^2_{df=3}$, $p = .123$; $LRT_{\text{ModelPEP1 vs.2}} = 0.56$, $\chi^2_{df=3}$, $p = .644$; $LRT_{\text{ModelCO1 vs.2}} = 1.04$, $\chi^2_{df=3}$, $p = .379$. Moreover, adding condition and the interaction did not improve the fit of the three models predicting performance. $LRT_{\text{ModelpHR1 vs.2}} = 1.13$, $\chi^2_{df=3}$, $p = .352$; $LRT_{\text{ModelpPEP1 vs.2}} = 0.06$, $\chi^2_{df=3}$, $p = .981$; $LRT_{\text{ModelpCO1 vs.2}} = 0.23$, $\chi^2_{df=3}$, $p = .869$ (see Tables S4 and S5 in the supplementary materials for the full model summaries).

Therefore, Hypothesis 3 was not confirmed as we found no evidence for the role of being anonymous (vs. identifiable) in the emergence of flow, CV indices of challenge, CV synchrony, or group performance.

3.4 | Group experience

We analyzed the measures of group experience (perceived cohesion and group identification) in a more exploratory way. First we examined between-condition differences in cohesion and identification. This indicated that identification was higher in the identifiable condition ($M = 4.44$) than in the anonymous condition ($M = 4.03$), $t(115) = -2.37$, $p = .019$. There was no significant difference

between conditions in perceived cohesion, $t(115) = -1.51$, $p = .133$ (see Table 2).

We then examined the relation between group experience and flow further by adding cohesion and identification to the final models reported above (also including condition). Adding the group experience variables indeed improved the fit of the three models: $LRT_{\text{ModelHR2b vs.3}} = 14.03$, $\chi^2_{df=2}$, $p < .001$; $LRT_{\text{ModelPEP2b vs.3}} = 13.36$, $\chi^2_{df=2}$, $p < .001$; $LRT_{\text{ModelCO2b vs.3}} = 13.07$, $\chi^2_{df=2}$, $p < .001$, and indicated that a stronger group identification predicted higher flow, $t(92) = 4.66$, $p < .001$. There were no significant effects of group experience on performance (Table S5 in the supplementary materials).

Finally, as can be seen in Table 1, a higher perceived cohesion related to stronger synchronization in PEP. In sum, group identification was higher in the identifiable condition compared to the anonymous condition, group identification related positively to flow, and there was a positive relation between PEP synchronization and perceived cohesion.

4 | DISCUSSION

The current study is—to the best of our knowledge—the first to address the physiology of flow in a group context. We examined the physiological mechanisms related to the emergence of flow in three-person groups that worked under anonymous or identifiable conditions on a cooperative game. We examined whether CV reactivity and synchrony among group members predicted group-based flow and performance.

In line with Hypothesis 1 we found a relationship between synchronization in PEP and self-reported flow. Moreover, in line with Hypothesis 2, both PEP reactivity and within-group synchronization in PEP were related to group performance. These effects were not found for other CV measures (CO most notably), and not further moderated by the extent to which group members were anonymous (vs. identifiable) during the task. In line with previous research we also found reliable relations between group identification, cohesion and flow in a group context (Mao et al., 2016; Zumeta et al., 2016). Finally—but importantly—synchronization in PEP mediated the relation between performance and flow.

The current findings contribute to the literature by showing—for the first time—the role of flow in the relation between CV synchronization and performance in groups. This finding relates to recent work on synchrony in autonomic nervous system activation and the performance of groups and dyads. More specifically, the current results are in keeping with the work by Gordon et al. (2020) who showed how synchrony in heart rate enhanced group

performance, as well as the work by Behrens et al. (2020) who showed how synchrony in skin conductance predicted the cooperative success of dyads. The current work extends this work not just by showing the role of subjectively experienced flow but also by isolating the role of a particular component of the autonomic nervous system, i.e., the sympathetic branch, which is at the CV level most directly indexed by PEP.

Beyond performance outcomes, the current results may also have implications for the development of well-being in groups. As indicated in the introduction, at the individual level flow relates to happiness, satisfaction with the activity at hand, and an increased sense of self (Baker & MacDonald, 2013; Fullagar & Kelloway, 2009). Moreover, work in the social identity tradition has shown how groups provide a source of self-esteem, certainty and meaning, and how identification with groups can have diverse positive health benefits (Jetten et al., 2012; Scheepers & Ellemers, 2019). The current work can be seen as a first attempt to connect these different literatures by showing positive relations between group-identification, cohesion, flow and CV synchronization (see Table 1). Thus, the current work provides a first indication of how CV synchronization may stimulate not just performance, but also well-being in groups. This in turn may relate to work showing how collectively performing a ritual at work, like starting the day with ritualistic chants and stretches, relates to meaning, well-being and productivity in organizations (Kim et al., 2021). An exciting possibility for future research would be further tying together these perspectives and phenomena by directly testing the mediating role of CV synchrony in the relation between collective rituals and well-being in teams.

Although the current data cannot shed light on the definitive psychological process related to CV synchrony in the current study, the current findings fit well with previous work on shared attention, as marked by CV synchrony, during group tasks (Kazi et al., 2021; Thorson, Dumitru, Mendes, & West, 2021; Thorson, Dumitru, & West, 2021; West et al., 2017). As explained in the introduction, shared attention is crucial in the current online gaming setting. Moreover, the specific CV measure (i.e., PEP) that was most predictive of flow and performance has in other work been related to cognitive effort (Kelsey, 2012; Richter et al., 2016). Together this suggests that shared attention is a likely psychological process that was marked by synchronized PEP during the game.

Although generally CO increased somewhat during the task compared to baseline levels (in line with a challenge motivational state), it did not predict flow or performance. This is noteworthy because much of our a priori reasoning was based on a possible connection between the state of challenge and flow. That is, we reasoned that as both

challenge and flow are the result of a balance between task demands and personal or social resources, it is likely that these two states itself are also related. The absence of a relation in the current study may be due to methodological reasons, however. One reason may be that aggregating CO over the total task may have been a rather conservative test, obscuring subtle changes in CO throughout the task. This explanation is somewhat weakened, however, by additional analyses in which we split-up the task in three 5-min parts, and generally found the same results (see also Table S3). Still, also in these additional analyses the time frames were relatively long (5 min), again not fully excluding the possibility that certain parts of the game may have led to important changes in CO and the other CV measures, or that these measures were predictive of performance and flow during specific moments.

A second reason for the absence of strong challenge effects may be that the current task is one that called for a somewhat vigilant state, which is related to a threat CV profile (increased Total Peripheral Resistance [TPR] more in particular, lowering CO) rather than a challenge CV profile. Indeed, there is some evidence that on tasks calling for vigilance, threatened people outperform challenged people (Hunter, 2001). Thus, the mix of eagerness and vigilance that the current game likely elicited may have ultimately resulted in relatively stable CO, again at least when looking at the total task.

In relation to this it should of course be noted that we did not measure total peripheral resistance (TPR) in this study, despite that, according to the BPS-CT, TPR most clearly differentiates between the states of challenge and threat. That is, under threat TPR increases compared to baseline, while under challenge TPR decreases. Thus, future research, making use of other tasks, examining shorter timespans, and including measures of TPR, should shed more light on the role of (synchrony in) challenge and threat in explaining flow and performance in groups.

It is also noteworthy that we only obtained evidence for PEP reactivity as the primary index of task engagement throughout the task, and not HR reactivity, being a more secondary index of task engagement (Kelsey, 2012; Richter et al., 2016). Again, testing overall reactivity over the (15-min) task may have represented a rather conservative test because it is possible that engagement was more or less present during specific phases of the task. Moreover, as indicated, the absence of HR reactivity as index of task engagement is not uncommon in more subtle motivated performance situations. It is possible that examining more intensely engaging (and potentially stressful) tasks will also lead to stronger effects on challenge and threat related CV reactivity (e.g., CO), compared to the more basic effects on PEP, an index of (cognitive) effort, that was particularly relevant in the current interactive gaming situation.

Another aspect of the current work that deserves further attention concerns the absence of effects of condition on CV responses and/or flow. There may be both methodological and theoretical reasons for these null-effects. First, as noted, the *t*-tests testing for the influence of condition on the group level variables (performance, CV synchronization) were somewhat underpowered. A second more methodological reason may be that even in the identifiable condition participants did not know each other well, while there was also no means to get to know each other better, as all communication took place through the game itself. Thus, the specific task that we used may have also undermined identifiability as participants were mainly focused on their computer screens, no verbal communication was allowed, and there was only limited further non-verbal communication possible.

Another, more theoretical reason for the absence of an effect of condition may be that the relation between identifiability, flow and CV responses may be more complex than we initially proposed. That is, the visual information about group members in the identifiable condition may actually may also have actually operated as a facilitator of physiological synchrony (Behrens et al., 2020; Karine Jospe et al., 2020; Thorson et al., 2018). The positive effect of identifiability on group identification and task engagement that we found may also point in that direction. As a result, in the identifiable condition the positive effect of visual information and the negative effect on (lowered) self-awareness may have canceled each other out, leading to 0-effects of condition on some of these variables. Thus, future research, making use of a different task and research design, is necessary to provide more clarity about the role of anonymity in (the physiology of) group-based flow.

A limitation of the current study that should be discussed is that flow was measured only once, at the end of the experiment. However, repeated (self-report) measures of flow during task performance are not ideal as—apart from more general learning effects—filling out a questionnaire is likely to disrupt the flow. However, as noted above, it is well-possible that flow is dependent on the specific task stage: In an early stage one might not be in flow yet because the task is too demanding but in later stages flow may drop again as a result of that the task is no longer challenging. One way to address this issue in future work would be to pilot the task more extensively, for example by varying time on task, to create a task situation with an optimal flow intensity.

The noted limitations of self-report measures to examine flow in dynamically interactive group situations also point to the actual potential of physiological measures for examining optimal motivation and performance in

groups. Indeed, the measures of CV synchrony were the most consistent predictor of group performance in the current study. Future work might further explore possible practical applications of this, for example by continuously monitoring synchronization in work or sports teams, or in orchestras. Such applications could also form the basis of designing interventions for optimizing group performance and flow.

Two final limitations that should be noted concern the size of the effects as well as the role of causality. First, it should be noted that although reliable, the effect of (synchronization in) PEP on flow was relatively small in size. That is, the PEP model explains just 7% of the variance in flow ($R^2 = .07$). Even though the size of this effect is comparable to similar effects reported in the literature (Jaque et al., 2020), future work, in more applied contexts, should provide more clarity about the practical relevance of the relations between physiological synchrony, flow, and performance.

Finally, the current study was mainly correlational, and as such we cannot draw definitive conclusion about causality. For example, did flow lead to better performance, or better performance to flow? Did flow predict synchrony in PEP, or was this the other way around? These different possibilities all make sense to some extent, and it seems also likely that flow, CV responses and performance all influence each other during the task in an iterative fashion. The reason for the order of the variables in the mediation model was based on the order in which we measured the variables (i.e., flow after the task). However, we stress that we have to be cautious at this point about making strong causal claims.

To conclude, when the force with which hearts pumps becomes more similar across group members, this predicts better group performance, higher flow and stronger group cohesion. Follow-up research should be focused on how the dynamic interplay between (shared) sympathetic and parasympathetic arousal shapes group performance and -experience in a variety of other group tasks and contexts. Ultimately, we hope that research on the physiological synchrony underlying flow in groups helps to develop and test interventions to optimize the performance of groups as well as the well-being of its members.

AUTHOR CONTRIBUTIONS

Joyce Snijdwint: Formal analysis; writing – original draft. **Daan Scheepers:** Conceptualization; investigation; methodology; writing – original draft.

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CONFLICT OF INTEREST

We have no known conflict of interest to disclose.

DATA AVAILABILITY STATEMENT

All materials and data are available via osf.io/94wpv.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Appendix S1

Table S1 Descriptive statistics on personality and creativity measures

Table S2 Descriptive statistics on flow trait scale

Table S3 Means and standard deviations (SD) of the synchronization over time in the groups

Table S4 Full regression models summary for “flow”

Table S5 Full regression models summary for “performance”

Table S6 Mediation analysis. Nonparametric bootstrap confidence intervals with the percentile method

Figure S1 Mediation model. The effect of performance on flow mediated by PEP synchronization among group-members

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