Pers Ubiquit Comput (2016) 20:821–832
DOI 10.1007/s00779-016-0953-5

ORIGINAL ARTICLE

A framework for physiological indicators of flow in VR games: construction and preliminary evaluation

Yulong Bian[1,3] · Chenglei Yang[2,3] · Fengqiang Gao[1] · Huiyu Li[2] · Shisheng Zhou[2] · Hanchao Li[2] · Xiaowen Sun[2] · Xiangxu Meng[2,3]

Received: 30 January 2016 / Accepted: 12 June 2016 / Published online: 1 September 2016
© Springer-Verlag London 2016

Abstract Flow experience is often considered as an important standard of ideal user experience (UX). Till now, flow is mainly measured via self-report questionnaires, which cannot evaluate flow immediately and objectively. In this paper, we constructed a physiological evaluation model to evaluate flow in virtual reality (VR) game. The evaluation model consists of five first-level indicators and their respective second-level indicators. Then, we conducted an empirical experiment to test the effectiveness of partial indicators to predict flow experience. Most results supported the model and revealed that heart rate, interbeat interval, heart rate variability (HRV), low-frequency HRV (LF-HRV), high-frequency HRV (HF-HRV), and respiratory rate are all effective indicators in predicting flow experience. Further research should be conducted to improve the evaluation model and conclude practical implications in UX and VR game design.

Keywords Flow experience · Physiological evaluation model · User experience · Virtual reality game

✉ Chenglei Yang
chl_yang@sdu.edu.cn

✉ Fengqiang Gao
gaofq_11@163.com

1 School of Psychology, Shandong Normal University, Jinan, China

2 School of Computer Science and Technology, Shandong University, Jinan, China

3 Engineering Research Center of Digital Media Technology, MOE, Shandong University, Jinan, China

1 Introduction

User experience (UX) delineates a multifaceted and complicated process. According to ISO9241-210, UX is defined as focusing on a person–user's perceptions and responses that result from the use and/or anticipated use of a product, system, or service. Because of the complexity of UX, many different components and measure approaches have been evolved to evaluate the process [1]. Traditionally, UX is usually assumed to be synonymous with usability. Yet, it involves much more than that. Nowadays, researchers pay increasing attention to the affective experience in UX. It could be summarized that UX is a process involves two important aspects: traditional human–computer interaction usability and accessibility balanced with hedonic and affective design [2].

Flow experience is a key component of UX in virtual reality (VR) [3]. Flow is a state in which an individual is completely immersed in an activity without reflective self-consciousness but with a deep sense of control [4]. It represents a highly enjoyable mental state where the individual is fully immersed and engaged in the process of activity [3–5]. In flow state, the emotions are positive and aligned with the task at hand. For this reason, keeping the user in a flow state contributes to optimizing UX and improving VR games design [6, 7]. Therefore, flow experience, an important standard of ideal experience, is used to evaluate the UX in VR game designs [8–10]. Consequently, how to accurately and comprehensively measure flow becomes a key issue.

The most common methods to measure flow experience are questionnaires and interviews which are retrospective by nature. But flow appears during an activity, in which a person is fully immersed in the task and self-referential thoughts are completely inhibited. Thus, the conflict here is that when participants are asked for experience, they have left the flow state and entered into self-reflection. Namely, the self-report method is subjective and performed after the activity. An available solution is to provide physiological flow indicators that are objective and can be measured during the activity without interrupting the participant [11].

Existing theoretical and empirical researches discuss possible physiological mechanisms of flow and associate the flow state with cortex activity, cortisol activity, autonomic nervous system (ANS) activity, dopamine, and facial muscle activity [12–16]. These physiological indicators cover several characteristics of flow, such as arousal, positive valence, mental effort, and attention. Although some valuable evidences were found, there are also some inconsistent results [17], and a comprehensive frame of physiological indicators is absence. Besides, flow experience is considered as one important goal in VR system design [7]. Researchers in the field of HCI show increasing interest in physiological investigation of flow [18–20]. By measuring physiological parameters of the user, they aim to distinguish ideal flow experience from boredom or frustration. Their common purpose is using physiological indicators to develop real-time adaptive systems that optimize gaming experience and/or efficiency of interaction. However, few empirical researches on physiological flow were conducted in VR games, so the possibility to evaluate flow in VR games based on previous results should be further tested. For above reasons, a reliable physiological flow evaluation model for VR games is necessary to be put forward.

In this paper, one main purpose was to summarize a physiological flow evaluation model based on previous studies. The other purpose was to test the effectiveness of partial indicators in predicting flow in a VR game. Our work can be used to guide future studies to develop more comprehensive and credible psychological flow indicators.

This paper makes the following contributions:

1. We design a physiological flow evaluation model. The model includes five first-level indicators and their respective second-level indicators, which may significantly predict flow experience.
2. We carry out an examination on the effects of partial indicators on flow experiences in a VR game. The outcome shows they are all effective indicators in predicting game flow in VR environment.

Moreover, our work contributes to optimizing the VR game design. For example, if rich physiological data can be captured and accurately computed to reflect flow experience, the parameters of dynamic motion seat can be controlled more appropriately for different players (see Fig. 1).

2 Related work

2.1 Flow in VR system

Flow is an autotelic nature experience, which suggests that flow is generally related with positive consequences for the individual engaging in an activity [21]. Flow is also an optimal experience. People simultaneously feel cognitively efficient, motivated, and happy in the state [22, 23]. Thus, flow is a positive experience and is associated with feelings of enjoyment [11].

For above reasons, keeping users in the flow state is considered as one important goal in VR system design [7]. For instance, Sweetser and Wyeth developed a GameFlow model to evaluate UX and improve game design [5]. The model consists of eight elements, and each element includes a set of criteria. The evaluations show that the GameFlow model is useful for reviewing VR games and identifying issues, as well as developing a concrete

(a) (b)

Fig. 1 Screenshot of the VR game "Air Bombardment" and the experimental scene. **a** A snapshot of a VR game, **b** a snapshot of experimental scene understanding of what constitutes good design and player enjoyment. In addition to guiding the VR design, the flow is also used as an important criterion to evaluate the UX in different VR environments. The components of UX are usually integrated with flow theory, which has been studied in various human activities. Takatalo [24] provided a psychological Presence-Flow-Framework (PFF) to study the components of UX in virtual environments Later, they developed it to Presence-Involvement-Flow Framework2 (PIFF2) to evaluate the UX in 3D Stereoscopic Games [25]. Hwang et al. developed embodiment interactive video games and measured flow as the evaluation indicator [26]. In another research, Cheng et al. [27] evaluated virtual experience in a three-dimensional VR interactive simulator environment by examining the flow state.

However, flow was mainly measured with method of questionnaire and interview in above researches. As previously noted, these methods have limitations. In order to make better use of flow in UX, a small portion of researchers tried to evaluate flow experience in VR [10, 28] with physiological indicators. The physiological mechanism of flow and related indicators needs to be introduced first.

2.2 Physiological definition of flow experience

Flow is one kind of subjective experience. However, the psychological phenomena can be expressed in bodily and biological process, which can be used as objective indicators of flow. De Manzano et al. [17] provided a physiological definition of flow experience, "flow is experienced during task performance as a result of an interaction between emotional and attentional systems," in which both cognitive and physiological processes can be evoked. They held that flow is "a state of effortless attention, which arises through an interaction between positive affect and high attention." However, this definition is not clear enough on the physiological processes of flow.

Later, summing up the existing theoretical approaches and the reported empirical findings, Engeser [11] integrated affective, cognitive, physiological, and behavioral component and arrived at a working definition, which means that flow is a positively valenced state (affective component), resulting from an activity that has been appraised as an optimal challenge (cognitive component) and characterized by optimized physiological activation (physiological component) for full concentration on coping with environmental/task demands (behavioral component). Optimized physiological activation during flow refers to:

1. A decreased activation in default networks of the brain.
2. Moderate peripheral arousal following a u-shaped function of activation.

2.3 Theoretical perspectives related to physiological mechanisms of flow

Some theoretical works discuss the physiological process of flow experience. These theories are mainly produced from the view of brain activity, ANS activity, and endocrine system activity.

2.3.1 Flow in the brain

Hamilton et al. [29] investigated physiological aspects of flow experience and concluded that individuals are different in ability and effort needed to control attention. Referring to their findings, Csikszentmihalyi [3] firstly concluded that individuals with autotelic personality have the ability to shut down mental activity in all information channels that are irrelevant for task fulfillment. Later, Goleman [12] described the neurophysiology of flow experience as a subjective state of effortlessness. He suggested that flow is connected to a decrease in cortical activation, which means a minimum of mental energy leads to maximum efficiency in highly practiced activities. And he showed that activation and inhibition of neural circuitry are fully adapted to momentary activity demands during flow experience.

In line with above-mentioned approaches [3, 12, 13], Dietrich proposed a neurophysiological theory [30] addressing the brain processes during flow. His hypofrontality hypothesis suggests that flow results from a down-regulation of prefrontal activity in the brain [14]: During flow, well-trained activities are performed without interference of a conscious control system, which makes the process very fast and efficient. Given that the conscious control system is subserved by prefrontal regions, a flow experience must occur during a state of transient hypofrontality that can bring about the inhibition of the explicit system."

Moreover, Austin [31] suggested the thalamic gateway hypothesis, which argued that the thalamus plays a key role in effortless attention as experienced during flow. The thalamus serves as a filter selecting events becoming aware and events shielded from awareness. Further, a deactivation of thalamic nuclei inhibits self-referential pathways in order to enter a state characterized by selflessness and effortlessness as typical for flow.

Aggregating the existing theories on the physiology of flow in the brain, it seems that flow results from a down-regulation of task-irrelevant processes, which leads to decreased activity in default networks due to focused attention [11].

2.3.2 Endocrine system activity, ANS activity, and flow

Another theory focusing on the physiology of flow is synthetic theory suggested by Marr [13]. He confirmed that flow is a highly intrinsically rewarding state. This process could be seen as an upward spiral of positive reinforcement that increases people's motivation toward the rewarding activity. The mesolimbic dopamine system is regulating reward-related motivational, emotional, and cognitive processes [32]. Therefore, he discussed the neurotransmitter dopamine as a possible neurophysiological correlation of flow experience.

Moreover, the flow channel model adapted from Csikszentmihalyi [4] and Rheinberg [15] was often referred to in later empirical studies: physiological arousal increases continuously from a low arousal state (boredom/relaxation) to a high arousal state (anxiety/stress). It suggests that flow experience comes along with moderate physiological arousal. From a physiological point of view, Peifer et al. [16] further detailed the model. Physiological arousal state can be indicated by increased hypothalamic–pituitary–adrenal (HPA) axis activation (an end product of the HPA is cortisol). Flow experience occurs between high arousal (characteristic for anxiety) and low arousal (characteristic for boredom). Thus, flow experience is at a state of moderate activation of the HPA axis. Similarly, physiological arousal state can also be indicated by increased sympathetic nervous system; thus, flow state is at moderate activation of sympathetic nervous system.

It can be summarized that previous flow theory on the physiological mechanism mainly associated the flow state with cortex activity, dopamine, ANS activity, etc.

2.4 Empirical researches on physiological mechanisms of flow

Theoretical views of the physiological flow processes are needed to be comprehensively tested. Some empirical papers examined these views to some extent.

2.4.1 Brain activity and flow

In order to test the theoretical view, researchers investigated default networks in the brain to study the physiological process related to flow experience. It is consistently found that blood flow in regional brain activity, like in the medial prefrontal cortex (mPFC), decreases in a passive, relaxing state compared to a task-focused state [33–35]. However, few researchers directly studied flow in the brain.

Berta et al. conducted a different study. In order to distinguish flow state from non-flow state (boredom and frustration) during playing video games, they investigated the relations between electroencephalogram (EEG) and flow experience [7]. The results revealed that the difference in shape for alpha (8–12 Hz), low beta (12–15 Hz), and mid-beta (15–20 Hz) bands could distinguish the flow condition from non-flow conditions (both boredom and frustration). The results were in line with conclusion of Sheikholeslami et al. [36].

2.4.2 ANS activity and flow

Recently, researchers have paid more and more attention to the relationship between ANS and flow.

Peifer et al. investigated flow experience with psychophysiological arousal indicators in a computer program [16]. They suggested that the relation of flow with sympathetic arousal and HPA axis activation follows an inverted-u-curve function: Moderate physiological arousal should facilitate flow experience, whereas excessive physiological arousal should hinder flow [16].

Harmat et al. analyzed cardiovascular and respiratory responses during computer game playing and showed that flow experience was associated with respiratory depth and low-frequency band of heart rate variability (LF-HRV) [9]. Here, larger respiratory depth and lower LF-HRV are indicative of a more relaxed state with an increased parasympathetic activity.

Recently, Tozman et al. investigated the relationship between heart rate variability (HRV) and flow in a VR game [8]. They found that in a balanced skill-demand task, experiencing flow was associated with a decreased LF-HRV activity compared to anxiety condition, in which higher levels of flow were related to moderate parasympathetic activity (HF-HRV) as well as to moderate baroreflex function (LF-HRV).

Aggregating the existing empirical results on the ANS activity of flow, both linearly and nonlinearly relationships can be found.

2.4.3 Endocrine system activity and flow

The empirical studies on endocrine secretion and flow mainly focus on two kinds of secretions: dopamine and cortisol.

As far as we know, the first and only demonstration of an association between flow proneness and dopaminergic function was given by de Manzano et al. [37]. They tested the hypothesis that the availability of dopamine D2 receptors in the striatum is positively associated with flow proneness. They suggested that the proneness to experience flow is related to personality dimensions that are under dopaminergic control.

In addition, Peifer et al. [38] and Keller et al. [39] found empirical evidences of the association between flow and the hormonal stress mediator cortisol. A positive relation of the stress hormone cortisol and flow experience was found. Additionally, Peifer et al. [40] found an inverted-u function of flow and cortisol, which was further tested and verified [41].

2.4.4 Facial muscle activity and flow

The muscles that are close to the eyelid (involved in genuine smiling) are often used as physiological indicators of emotional valence [42]. Since flow experience is considered to be a positive state, researchers have started to use facial electromyography (EMG) measures to investigate flow.

In a representative study, Kivikangas [43] concentrated on facial electromyographic (EMG) activity indicating emotional valence. He found the corrugator supercilii (CS, "frowning muscle") activity can negatively predict flow in a HCI game. However, neither effect of zygomaticus major (ZM, "smiling muscle") nor that of OO (orbicularis oculi, indicating positive valence) was found. In contrast to Kivikangas, Nacke and Lindley found flow associated with increased activity of ZM and OO, but not with CS [44].

De Manzano et al. [17] investigated physiological aspects of flow experience. They found high flow values associated with activation of ZM. However, no relation between CS activity and flow was found.

So far, empirical researches have associated flow with the facial EMG [17, 43, 44], release of dopamine and cortisol [16, 41, 45], EEG [7, 36], and an activation of the ANS [16, 17, 40]. These physiological indicators cover several characteristics of flow, such as arousal, positive valence, mental effort, and attention. Thus, Peifer et al. described flow as a state of effortless attention that arises through an interaction between positive affect and high attention, in which both sympathetic and parasympathetic systems are activated [46, 47]. In sum, we can conclude that flow is a state of moderate arousal accompanied by a state of joy [8]. Any physiological parameters related to these psychological processes are likely to predict flow state.

Nevertheless, a comprehensive evaluation model is lacked. Therefore, a physiological flow evaluation model is necessary to be put forward.

3 Design of physiological flow evaluation model

After integrating existing studies, we summarize an evaluation model to provide a reference frame to investigate the physiological flow experience in VR game (see Table 1). Although the relationship of dopamine and cortisol activity to flow is discussed, they are excluded from the model, because the two indicators cannot be captured immediately. They are not suitable to optimize UX in VR game in real time. The model hence contains five first-level evaluation indicators, with their own second-level indicators.

Table 1 Physiological evaluation model for flow experience

First-level physiological indicators	Second-level physiological indicators	Functions
Electromyography (EMG)	Corrugator supercilii (CS)	Increased by negative affect and inhibited by positive affect; indicator for mental effort
	Zygomaticus major (ZM)	Increased by positive affect and inhibited by negative affect
	Orbicularis oculi (OO)	Increased by positive affect and inhibited by negative affect
Cardiovascular activity	Heart rate (HR)	Increased by sympathetic nervous system activity and decreased by parasympathetic nervous system activity
	Heart period (HP)	Inverse of HR
	Interbeat interval (IBI)	Decreased by sympathetic nervous system activity
	Heart rate variability (HRV)	An indicator for mental effort
	Low-frequency band (LF)	Indicator for sympathetic activity; a marker for physiological arousal
	High-frequency band (HF)	Indicator for parasympathetic activity
	LF/HF ratio (LF/HF)	Reflecting sympathetic modulation; a marker for physiological arousal
Electrodermal activity (EDA)	Skin conductance (SC)	Increased by sympathetic activation; increased by stressful situation
	Skin resistance (SR)	Inverse of skin conductance
	Tonic EDA	Indicator for vigilance, sustained attention, and heightened arousal over time
	Phasic EDA	Event-related skin conductance response
Respiratory activity	Respiratory rate (RR)	A marker for physiological arousal
	Respiratory depth (RD)	Indicator for parasympathetic activity
Electroencephalogram (EEG)	Alpha	Indicator of relaxed, but not drowsy, tranquil, conscious mental state
	Low beta	Indicator of relaxed yet focused, integrated mental state
	Mid-beta	Indicator of thinking, aware of self and surroundings

3.1 Facial electromyography (EMG)

Electromyography measures action potentials discharged during facial muscle activity [48]. Some facial EMG indicators are associated with affective valence. Flow experience is considered to be a positive state. Thus, facial EMG might be used as effective measures to measure flow [17, 43, 44].

The CS, ZM, and OO are usually selected as potential physiological indicators of flow. Compared to baseline activity, CS activity is increased by negative affect and inhibited by positive affect, so it will be inhibited in flow; ZM and OO activities are stimulated by positive affect, so they increase in flow [49]. Moreover, CS activity can be served as an indicator for mental effort [50]. When objective effort decreases during subjective effortlessness in flow, the activity in CS will increase [11].

3.2 Cardiovascular activity

The cardiovascular activity is further influenced by the ANS: The sympathetic part is related to physiological arouse, and on the contrary, the parasympathetic part is related to the relax state [51, 52].

Cardiovascular activity is a common indicator for measuring flow in games. The main parameters are show in Table 1. Specifically, heart rate (HR) is stimulated by the sympathetic nervous system activity and inhibited by parasympathetic nervous system activity. Heart period does the opposite way. The interbeat intervals (IBI), also known as R–R intervals (R waves to R waves intervals), are inhibited by sympathetic nervous system activity.

HRV represents the variability in the length of the IBI, and it represents a high ability to adapt to environmental demands [51, 53]. HRV is a sensitive cardiovascular measure that allows a differentiation of central sympathetic and parasympathetic influence. HRV includes time-domain features and frequency-domain features. Time-domain features are computed from the mean and standard deviation of the detected R peaks. Frequency-domain features are computed with power spectral analysis. The differentiation can be realized by decomposing different frequencies within a series of IBIs. Low-frequency band (LF 0.14–0.15 Hz), high-frequency band (HF 0.15–0.4 Hz), and quotient LF/HF are seen as common indicators of HRV [9]. LF-HRV is an indicator for sympathetic activity; HF-HRV is a reliable indicator for parasympathetic efferent activity. Besides, LF/HF ratio is also a parameter for physiological arousal, and the ratio reflects sympathetic modulation [51, 53].

Flow experience is related to cardiovascular activity [16, 17, 40]. An activation of the sympathetic branch of the ANS might be associated with flow [17]. Accordingly, increased HR and increased LF/HF ratio may be found. An interesting aspect of HRV is that flow is an indicator for mental effort: Higher mental effort is associated with lower HRV (mainly in HF band) [54, 55]. Therefore, if objective effort is increased during flow, one may find a decrease in HRV.

LF-HRV and HF-HRV were also associated with flow [9]. It is remarkable that the relations of LF-HRV and HF-HRV to flow may be inverted-u-curve nonlinear relations instead of simple linear relations [8, 16].

3.3 Electrodermal activity

EDA, defined by the skin's power to conduct (or resist) electricity, is an indicator for general arousal or attention. It is a reliable measure for sympathetic activation [56]. EDA contains four main second-level indicators (see Table 1): SC and SR are two sides of the same coin. Tonic refers to a long-term skin conductance level (SCL), indicating vigilance, sustained attention, and heightened arousal over time [56]. Phasic EDA reflects an event-related skin conductance response.

EDA is a promising measure to investigate flow [43]. It is generally elevated during task performance, information processing, and cognition [57]. In flow state, a down-regulation of irrelevant brain processes may come along with sympathetic activation as reflected by an increase in EDA. Furthermore, flow experience is associated with physiological arousal, and EDA is a reliable indicator to reflect arousal [11, 16]. However, the relation of EDA and flow might be inverted-u-curve nonlinear relations instead of simple linear relations. The increase in EDA depends on the demands of the task in relation to the skills of the person to a great extent. Higher levels of flow are related to moderate EDA levels, which can be visualized in an inverted-u function.

3.4 Respiratory activity

Respiratory activity mainly contains respiratory rate (RR) and respiratory depth (RD). RR is related to arousal [58], while RD is an indicator of relaxed state.

As noted above, the physiological process of flow experience is associated with physiological arousal. So RR can be expected to increase with flow. Additionally, the higher RD is indicative of a more relaxed state with an increased parasympathetic activity. Thus, when flow enters an effortless stage, higher level of flow should be associated with larger RD [10].

3.5 Electroencephalogram (EEG)

Electroencephalogram detects electrical activity of the brain. This procedure tracks and records brain wave patterns. Alpha (8–12 Hz), low beta (12–15 Hz), and mid-beta (15–20 Hz) bands are main second-level indicators selected to evaluate flow.

The most effective indicators in investigating flow are in the alpha and beta bands when user playing video games [7, 36]. The difference in shape for alpha, low beta, and mid-beta bands can distinguish the flow condition from non-flow state (both boredom and frustration).

4 Validity test of physiological indicators in predicting flow experience

4.1 Purpose and hypotheses

The test aims to check the effectiveness of the model in predicting flow in a VR game. We select three physiological measures from the model: cardiovascular function, respiration, and ZM electromyography. The reason why select these measures is because they can reflect physiological arouse, affective valence, and mental effort, which are key characteristics of flow experience.

Referring to above analyses and reviews, we formulate hypotheses about the relations of these physiological indicators and flow.

Hypothesis 1 An increase in flow could be associated with (i) increased HR and decreased IBI; (ii) increased LF/HF; we postulated an inverted-u-shaped relationship between (iii) HRV and flow, (iv) LF-HRV and flow, as well as that between (v) HF-HRV and flow.

Hypothesis 2 An increase in flow could be associated with (vi) increased RR and (vii) increased RD.

Hypothesis 3 An increase in flow could be associated with (viii) increased activity in ZM.

4.2 Participant

Thirty-six undergraduates (20 males and 16 females) were recruited to participate the experiment with total voluntary. The ages of the sample range from 20 to 27 years ($M = 23.06$ years, $SD = 2.14$ years). All of them are healthy adults without any physical damage.

4.3 Experimental task

The VR game "Air Bombardment" is used as the experimental task. It is a shooting game based on interactive VR environment, where the player shall drive a fighter plane and battle with the enemy (see Fig. 1a). Shooting the target correctly scores, which is recorded by the game system. The higher the score, the better the performance of the player. An Oculus device is equipped to the game system to display an immersive virtual three-dimensional scene with a full range of views. A dynamic seat and a game gun are installed to the system to provide rich interaction experience (see Fig. 1b).

4.4 Measures and apparatus

In this work, a wireless Biopac MP150 physiological data acquisition system with the AcqKnowledge 4.3 software was used for physiological signals acquisition. A sampling rate of 1000 Hz was used for all channels. For all measurements, we used the recommended standard filter settings for the BioNomadix systems.

Cardiac activity. Cardiac activity was recorded with bipolar EL 504 Cloth Base Electrodes from the left and right chest, using an Electro Lead 3 × 30 cm (BN-EL30-LEAD3) connected to the BIOPAC Bio Nomadix RSP& ECG amplifier. The participant's skin was cleaned with a low-alcohol detergent to minimize impedance. Generally, the quality of the recorded data is high, with little interference caused by movement. Then, the recorded electrocardiographic (ECG) data were imported to AcqKnowledge 4.3 software to calculate HR, HP, and associated variability (HRV) [58]. HRV includes time-domain features and frequency-domain features. Using the time-domain analysis method, the overall HRV was calculated from the mean and standard deviation of IBIs. Using the frequency-domain method, power spectral analysis is performed to localize the sympathetic and parasympathetic nervous system activities associated with different frequency bands [59]. The power of the LF-HRV (0.04–0.15 Hz), the HF-HRV (0.15–0.40 Hz), and the LF/HF of the HRV was calculated in this study. Spectrum analysis was performed using FFT routine provided by the software.

Thoracic respiration was measured using a piezo-electric respiratory belt transducer with an output range of 20–400 mV and a sensitivity of 4.5 ± 1 mV/mm. The belt was attached around the chest below the nipple line for men (or below the breast for women) [9].

Muscle tone of the ZM was recorded using an Ag/AgCl Electro Lead 3 × 30 cm (BN-EL30-LEAD3) attached to muscle sites on the right side of the face. The participant's skin is also cleaned with a low-alcohol detergent to minimize impedance. The raw EMG signal was amplified and filtered for frequencies between 20 and 400 Hz by a notchfilter of 50 Hz and bandpass filter [9].

Because one electrode loosens during the experimental task, one participant is excluded from ECG analysis and another participant is excluded from EMG analysis. Their recording data are no longer analyzable.

Flow experience is measured with the Flow Short Scale to provide a criterion for evaluating these physiological measures. The scale has been proved to be a reliable measuring instrument [11, 21]. The scale includes two subscales: absorption by activity and fluency of performance. The items are assessed on a seven-point Likert scale from 1 (I don't agree) to 7 (I agree). Absorption by activity consists of four items (e.g., "I am totally absorbed in what I am doing") and fluency is measured by six items (e.g., "My thoughts/activities run fluidly and smoothly"). The reliabilities of absorption (Cronbach's $\alpha = 0.815$) and fluency (Cronbach's $\alpha = 0.890$) are good in this study. Participants answered the scale immediately after they finish the experimental task.

4.5 Procedure

First, each participant is put on a chest belt and surface electrodes before the experiment. Second, they are clearly shown experimental instructions. Prior to the experimental task, each participant takes a 5-min baseline measure. In this time, they are instructed to sit back and relax. Fourth, they are trained with the handling of the game in an exercise program. In the last, participants are exposed to the formal experimental task lasting for about 6 min. When the mission is over, the participants are asked to complete a flow questionnaire.

4.6 Result

To investigate the relations between these physiological indicators and flow, we conduct a series of descriptive statistics and Pearson's bivariate correlation analyses. Results are shown in Table 2. In order to further explore the prediction effect from these indicators on flow, a series of linear regression and quadratic regression models from flow value to these physiological parameters are tested. Table 3 shows the detailed results of the linear and quadratic regression models.

4.6.1 Cardiovascular measures and flow experience

To investigate Hypothesis 1, we test the relations between cardiovascular measures and flow experience. Correlation analysis results reveal a marginally significant positive correlation between HR and flow experience, as well as a marginally significant negative correlation between IBI and flow experience. Moreover, significant positive correlations of HRV and LF-HRV to flow experience are found.

Next, regression analysis results reveal that the linear regression model of flow regressed on HR and IBI is marginally significant while the quadratic model of flow experience regressed on the two indicators is not. The result means the relations from HR and IBI to flow are linear. The linear and quadratic regression model of flow experience regressed on HRV and LF-HRV is all very significant. Moreover, the linear model of flow experience regressed on HF is not significant while the quadratic regression model is very significant.

Taken together, above results support (i) of Hypothesis 1, suggesting that increased HR, decreased IBI, and increased HRV could significantly predict an increase in flow. That is, if user's HR is increasing, or IBI is decreasing when playing a VR game, it is likely that his/her flow level is improving.

Moreover, the results also support (iii), (iv), and (v) of Hypothesis 1. Significant quadratic regression model reveals an inverted-u-shaped relationship between HRV, LF-HRV, HF-HRV, and flow experience. These inverted-

Table 2 Descriptive statistics and intercorrelations of physiological indicators and flow experience

Physiological indicators	*M*	SD	*R*	*p*
Flow	48.88	10.90	1	
HR	80.29	9.53	0.329^{+}	0.058
IBI	0.75	0.89	-0.312^{+}	0.073
HRV	0.05	0.18	0.521**	0.002
LF-HRV	80.47	97.72	0.356*	0.039
HF-HRV	55.74	123.19	0.213	0.227
LF/HF	2.51	3.82	−0.003	0.988
RR	8.28	1.84	-0.338^{+}	0.051
RD	4.46	2.58	0.171	0.333
ZM EMG	0.04	0.04	0.221	0.259

$^{+}$ $p < 0.08$ (two-tailed); * $p < 0.05$ (two-tailed); ** $p < 0.01$ (two-tailed)

Table 3 Linear and quadratic regression models for flow experience regressed on physiological parameters

Physiological indicators	Linear model		Quadratic model	
	R^2	*p*	R^2	*p*
HR	0.108	0.058^{+}	0.141	0.094
IBI	0.097	0.073^{+}	0.146	0.086
HRV	0.272	0.002**	0.543	0.000**
LF	0.127	0.039*	0.416	0.000**
HF	0.045	0.227	0.286	0.005*
LF/HF	0.000	0.988	0.032	0.601
RR	0.114	0.051^{+}	0.115	0.151
RD	0.029	0.333	0.056	0.407
EMG	0.049	0.259	0.111	0.231

R^2 indicates the explanation of variance of the regression model

$^{+}$ $p < 0.08$ (two-tailed); * $p < 0.05$ (two-tailed); ** $p < 0.01$ (two-tailed) u-shaped relationships mean that flow experience does not simply linearly increase/decrease with the increasing in HRV, LF-HRV, and HRV. There are moderate levels for these parameters, lower and higher levels of them are associated with lower levels of flow, whereas moderate levels of them are associated with higher levels of flow.

4.6.2 Respiratory measures and flow experience

To investigate Hypothesis 2, we test the relationship between respiratory measures and flow. Correlation analysis results reveal a marginally significant positive correlation between RR and flow experience ($r = -0.329$, $p < 0.08$). The correlation between RD and flow was not significant.

Further regression analysis reveals a significant linear regression model of flow experience regressed on RR. Other regression models are not significant.

These results supported (vi) of Hypothesis 2, suggesting that an increased RR could linearly predict an increase in flow. That is, if user's RR is increasing when playing the VR game, it is likely that his/her flow level is improving. However, any relation between RD and flow is not found which does not support (vii).

4.6.3 ZM Electromyography and flow experience

To investigate Hypothesis 3, we test the relationship between ZM electromyography and flow experience. Yet, any significant effect in correlation analysis and regression analysis is not found. The result does not support Hypothesis 3.

Based on above results, it can be summarized that HR, HRV, RR can positively predict flow experience, while IBI can negatively predict flow. The results also reveal an inverted-u-shaped function between HF-HRV and flow as well as function between LF-HRV and flow. In the present study, however, LF/HF and RD do not predict the flow experience.

5 Discussion

Flow experience is often considered as an important standard of ideal UX in VR games. An accurate and comprehensive evaluation of physiological flow experience is helpful to accomplish better UX. In this paper, we propose a physiological evaluation model, which provides a reference frame to identify the physiological parameters of flow state in VR games.

Based on existing studies, physiological process of flow experience is characterized by positive affections, arousal, mental effort, and automaticity in action.. The physiological processes related to these characteristics include the activity of ANS, HPA axis, facial muscles, and brain [8, 9, 16, 17, 41, 43]. Existing physiological studies of flow mainly focus on these aspects. Thus, the evaluation model proposed in this study covers these available aspects in VR game with five first-level indicators and their own respective second-level indicators. The potential roles of these indicators in predicting flow are concisely introduced in the model. As far as we know, our model is the first comprehensive physiological flow evaluation model for UX and VR game design. It needs to be further improved and tested in future studies.

We select partial indicators (cardiovascular activity, respiration, and ZM electromyography) and investigate the relations of these parameters to flow experience in a VR game. The results partially support our hypotheses. When looking at cardiovascular activity, increased HR and decreased IBI could significantly predict an increase in flow, which are in line with previous studies [9, 40].

The heart is further influenced by the ANS. LF-HRV and HF-HRV are spectral components of the HRV, they are indicators for ANS activity. Researchers conclude an inverted-u-shaped relationship between HRV and flow, as well as that between LF, HF-HRV, and flow [8, 40], which is further supported by our study. Taken theoretical and empirical evidences together, it can be concluded that the relation of flow and ANS activation follows an inverted-u function rather than a linear one. Very low and very high cardiovascular activation indicates a state of relaxation and a state of stress, respectively. The optimal activation to experience flow should be located in between and might differ individually.

When considering respiratory activity measured by RR and RD, both consistent and inconsistent results with previous study are found. Our results show that increased RR can be used to predict an increase in flow, which further supports the hypothesis. However, any relation between RD and flow is not found, which is inconsistent with previous studies [9, 17], where an association between flow values and deep breathing was found. The reason may lie in the VR game, where the player is hanging in the sky, and the flying height and angle are always changing. In addition, the player needs to attack the enemy constantly. The features of this VR environment make it difficult to relax the breath.

Similarly, any relation between ZM EMG and flow is not found, either. The muscle activity representing the affective valence does not predict flow in this study. It is consistent with the conclusion of Kivikangas [43], but inconsistent with Nacke and Lindley [44]. This may also be caused by the situation, where the simulation of high-altitude flight is hard to excite a pleasant facial muscle response. The other possible reason may be the VR game used in our study contains violence. Thus, this result should be treated cautiously. Since only few studies investigated facial muscle activity in relation to flow, it is too early to draw conclusions. Our results provide references for further clearing inconsistence.

Integrating our findings on relations between flow experience and physiological parameters, we conclude that flow value is closely associated with ANS activation. It means that other physiological parameters associated with these aspects may also be effective to predict flow experience. HR, IBI, HRV, LF-HRV, HF-HRV, and RR are all effective indicators which can be served as physiological parameters of flow in VR game of this study. These results in the VR game are mostly consistence with previous study. Whether other indicators (ZM EMG, LF/HF, and RD) can predict the flow or not needs to be further tested in more VR games. In a word, the results supported that the evaluation model proposed by us is an effective reference.

Following this research, there are many directions that worth further studying. First direction of future work is to investigate flow more widely with EEG or imaging techniques (fMRI, PET scan) [32]. Although flow experience can be reflected in a number of physiological indicators, i.e., ANS activities, the most essential and accurate physiological reflection may be observed in brain activity. Therefore, investigating the flow with EEG and brain imaging technology will better reveal the nature of flow experience. The second direction is to explore contributions of different physiological indicators, because different indicators may have different weights in predicting flow experience. To clarify this issue will contribute to computing and evaluating flow more accurately. Thirdly, flow can be affected by many factors (antecedents), and it can also further affect many subjective experiences or behavioral outcomes (consequences). In further research, the evaluation model should be improved and used to fully understand the antecedents and consequences of flow. Fourthly, the complexity of previous results may imply that it is better to treat flow as a process rather than just an overall state in the future [60, 61]. In particular, we should study the relationships between flow and various physiological parameters over time. On this issue, the size of samples in the previous study was small, so there might be sample differences, which led to inconsistent results. Big data analysis may be an innovative research method to clarify these issues in flow study [62–64]. Fifthly, the physiological flow in VR game has its own particularity. After all, except for being activated by flow state, these physiological parameters may also be affected by the VR environment to some extent. Therefore, whether previous conclusions can be stable across various situations needs to be further investigated. Finally, future study should conclude practical implications, e.g., how to reach the state of flow, how to switch from stress or bore state to flow state. The studies of physiological flow can contribute to more intelligent game interaction and optimal UX. For instance, when engaging a VR game, physiological data of the player can be captured in real time. Based on these data, flow experience of the player can be evaluated and input to the game system. Then, the system can provide feedback to player through adjusting the device or the game parameters to optimize the UX in VR game by automatically adapting to player's state. Through solving these questions, the physiological study of the flow can be effectively used to achieve better VR game design.

6 Conclusion

In conclusion, we provide a comprehensive physiological evaluation model for measuring flow experience in VR games. The model consists of five first-level indicators and their respective second-level indicators. An empirical study is conducted to test the effectiveness of partial indicators to predict flow. Most results support the model and reveal that HR, IBI, HRV, LF-HRV, HF-HRV, and RR are all effective indicators. Flow experience is closely associated with ANS activation, and an inverted-u-shaped function between flow and HRV, LF-HRV, HF-HRV is found. These indicators could be further served as physiological parameters of flow experience to optimize the VR game design.

Further research is needed to improve the evaluation model and conclude practical implications in optimizing UX in VR games in the future.

Acknowledgments We would like to thank all reviewers for their valuable comments. This work was supported by the Special Funds of Taishan Scholar Construction Project, the China National Key Research and Development Project (2016YFB1001400), the National Natural Science Foundation of China under Grant (61272243, 61472225), the Shandong Provincial Science and Technology Development Program (2013GSF11802), and Shandong Province Natural Science Foundation (BS2009DX003).

References

1. Zaharias P, Mehlenbacher B (2012) Exploring User Experience (UX) ind virtual learning environments. Int J Hum Comput Stud 70(7):475–477
2. Hassenzahl M, Tractinsky N (2006) User experience—a research agenda. Behav Inf Technol 25(2):91–97
3. Csikszentmihalyi M (1990) Flow: the psychology of optimal experience. Harper & Row, New York
4. Csikszentmihalyi M (1975) Beyond boredom and anxiety: experiencing flow in work and play. Jossey-Bass, San Francisco
5. Sweetser P, Wyeth P (2005) GameFlow: a model for evaluating player enjoyment in games. Comput Entertain 3(3):1–24
6. Jegers K (2007) Pervasive game flow: understanding player enjoyment in pervasive gaming. Comput Entertain 5(1):9

7. Berta R, Bellotti F, De Gloria A, Pranantha D, Schatten C (2013) Electroencephalogram and physiological signal analysis for assessing flow in games. IEEE Trans Comput Intell AI Games 5(2):164–175
8. Tozman T, Magdas ES, MacDougall HG, Vollmeyer R (2015) Understanding the psychophysiology of flow: a driving simulator experiment to investigate the relationship between flow and heart rate variability. Comput Hum Behav 52:408–418
9. Harmat L, de Manzano Ö, Theorell T, Högman L, Fischer H, Ullén F (2015) Physiological correlates of the flow experience during computer game playing. Int J Psychophysiol 97(1):1–7
10. Shin D-H, Biocca F, Choo H (2013) Exploring the user experience of three-dimensional virtual learning environments. Behav Inf Technol 32(2):203–214
11. Engeser S (2012) Advances in flow research. Springer, Verlag, New York
12. Goleman DJ (1995) Emotional intelligence. Bantam, New York
13. Marr AJ (2001) In the zone: a biobehavioral theory of the flow experience. Athletic insight. Online J Sport Psychol 3(1). Elektronische Ressource: http://www.athleticinsight.com/Vol3Iss1/Commentary.htm
14. Dietrich A (2003) Functional neuroanatomy of altered states of consciousness. The transient hypofrontality hypothesis. Conscious Cogn 12(2):231–256
15. Rheinberg F (2008) Intrinsic motivation and flow experience. In: Heckhausen H, Heckhausen J (eds) Motivation and action. Cambridge University Press, Cambridge, pp 323–348
16. Peifer C, Schulz A, Schächinger H, Baumann N, Antoni CH (2014) The relation of flow experience and physiological arousal under stress—can u shape it? J Exp Soc Psychol 53:62–69
17. de Manzano O, Theorell T, Harmat L, Ullén F (2010) The psychophysiology of flow during piano playing. Emotion 10(3):301–311
18. Fairclough SH (2009) Fundamentals of physiological computing. Interact Comput 21(1–2):133–145
19. Rani P, Sarkar N, Liu C (2005) Maintaining optimal challenge in computer games through real-time physiological feedback. Paper presented at the 11th Human–Computer Interaction International, Las Vegas, NV
20. Prinzel LJ, Freeman FG, Scerbo MW, Mikulka PJ, Pope AT (2000) A closed-loop system for examining psychophysiological measures for adaptive task allocation. Int J Aviat Psychol 10(4):393–410
21. Schüler J, Engeser S (2009) Incentives and flow experience in learning settings and the moderating role of individual differences. In: Wosnitza M, Karabenick SA, Efklides A, Nenninger P (eds) contemporary motivation research: from global to local perspectives. Hogrefe, Göttingen, pp 339–358
22. Csikszentmihalyi M, LeFevre J (1989) Optimal experience in work and leisure. J Personal Soc Psychol 56(3):815–822
23. Moneta GB, Csikszentmihalyi M (1996) The effect of perceived challenges and skills on the quality of subjective experience. J Personal 64:275–310
24. Takatalo J (2008) Components of human experience in virtual environments. Comput Hum Behav 24:1–15
25. Takatalo J, Kawai T, Kaistinen J (2015) User experience in 3d stereoscopic games user experience in 3D stereoscopic games. No. August 2015
26. Hwang M-Y, Hong J-C, Hao Y, Jong J-T (2011) Elders' usability, dependability, and flow experiences on embodied interactive video games. Educ Gerontol 37(8):715–731
27. Cheng LK, Chieng MH, Chieng WH (2014) Measuring virtual experience in a three-dimensional virtual reality interactive simulator environment: a structural equation modeling approach. Virtual Real 18(3):173–188
28. Phillips L, Interrante V, Kaeding M (2012) Correlations between physiological response, gait, personality, and presence in immersive virtual environments. Presence Teleoper Virtual Environ 21(2):119–141
29. Hamilton JA, Haier RJ, Buchsbaum MS (1984) Intrinsic enjoyment and boredom coping scales: validation with personality, evoked potential and attention measures. Personal Individ Differ 5(2):183–193
30. Dietrich A (2004) Neurocognitive mechanisms underlying the experience of flow. Conscious Cogn 13(4):746–761
31. Austin JH (2010) The thalamic gateway: how the meditative training of attention evolves toward selfless transformations of consciousness. In: Bruya B (ed) Effortless attention: a new perspective in the cognitive science of attention and action. MIT Press, Cambridge
32. Davis CA, Levitan RD, Reid C, Carter JC, Kaplan AS, Patte KA et al (2009) Dopamine for 'wanting' and opioids for 'liking': a comparison of obese adults with and without binge eating. Obesity 17(6):1220–1225
33. Goldberg II, Harel M, Malach R (2006) When the brain loses its self Prefrontal inactivation during sensorimotor processing. Neuron 50:329–339
34. Gusnard DA, Akbudak E, Shulman GL, Raichle ME (2001) Medial prefrontal cortex and self-referential mental activity: relation to a default mode of brain function. Proc Natl Acad Sci USA 98:4259–4264
35. Raichle ME, MacLeod AM, Snyder AZ, Powers WJ, Gusnard DA, Shulman GL (2001) A default mode of brain function. Proc Natl Acad Sci USA 98:676–682
36. Sheikholeslami C, Yuan H, He EJ, Bai X, Yang L, and He B (2007) A high resolution EEG study of dynamic brain activity during video game play. In: Proceedings of 29th annual international conference IEEE Engineering in Medicine and Biology Society, pp 2489–2491
37. de Manzano Ö, Cervenka S, Jucaite A, Hellenäs O, Farde L, Ullén F (2013) Individual differences in the proneness to have flow experiences are linked to dopamine D2-receptor availability in the dorsal striatum. Neuroimage 67:1–6
38. Peifer C, Schachinger H, Baumann N, Schulz A, Antoni CH (2010) The relation of the stress-hormone cortisol and the flow-phenomenon. In: The concept of flow: toward a scientific integration, Braunschweig
39. Keller J, Bless H, Blomann F, Kleinbohl D (2011) Physiological aspects of flow experiences: skills-demand-compatibility effects on heart rate variability and salivary cortisol. J Exp Soc Psychol 47(4):849–852
40. Peifer C, Schachinger H, Antoni CH (2011) Cortisol and flow experience—an experimental approach. Paper presented at the 2nd world congress on positive psychology, Philadelphia, July, 2011
41. Peifer C, Schächinger H, Engeser S, Antoni CH (2015) Cortisol effects on flow experience. Psychopharmacology 232(6):1165–1173
42. Larsen JT, Berntson G, Poehlmann KM, Ito TA, Cacioppo JT (2008) The psychophysiology of emotion. In: Lewis M, Haviland-Jones JM, Barrett LF (eds) The handbook of emotions, 3rd edn. Guilford, New York
43. Kivikangas JM (2006) Psychophysiology of flow experience: an explorative study. Master's thesis, University of Helsinki
44. Nacke LE, Lindley CA (2010) Affective ludology, flow and immersion in a first-person shooter: measurement of player experience. J Can Game Studies Assoc 3(5):1–21
45. Keller J, Bless H, Blomann F, Kleinböhl D (2011) Physiological aspects of flow experiences: skills–demand–compatibility effects on heart rate variability and salivary cortisol. J Exp Soc Psychol 47:849–852

46. Bruya B (2010) Effortless attention: a new perspective in the cognitive science of attention and action. MIT Press, Cambridge
47. Peifer C (2012) Psychophysiological correlates of flow experience. In: Engeser S (ed) Advances in flow research, ch 8. Springer, New York, pp 139–165
48. Fridlund AJ, Cacippo JT (1986) Guidelines for human electromyographic research. Psychophysiology 23(5):567–589
49. Larsen JT, Berntson GG, Poehlmann KM, Ito TA, Cacioppo JT (2008) The psy- chophysiology of emotion. In: Lewis M, Haviland-Jones JM, Barrett LF (eds) The handbook of emotions, 3rd edn. Guilford, New York
50. Van Boxtel A, Jessurun M (1993) Amplitude and bilateral coherency of facial and jaw-elevator EMG activity as an index of effort during a two-choice serial reaction task. Psychophysiology 30(6):589–604
51. Porges SW (1995) Cardiac vagal tone: a physiological index of stress. Neurosci Biobehav Rev 19(2):225–233
52. Uijtdehaage SH, Thayer JF (2000) Accentuated antagonism in the control of human heart rate. Clin Auton Res 10(3):107–110
53. Lehrer P (2003) Applied psychophysiology: beyond the boundaries of biofeedback. (Mending a wall, a brief history of our field, and applications to control of the muscles and cardiorespiratory systems). Appl Psychophysiol Biofeedback 28(4):291–304
54. Redondo M, Del Valle-Inclán F (1992) Decrements in heart rate variability during memory search. Int J Psychophysiol 13(1):29–35
55. Thayer JF, Hansen AL, Saus-Rose E, Johnsen BH (2009) Heart rate variability, prefrontal neural function, and cognitive performance: the neurovisceral integration perspective on self-regulation, adaptation, and health. Ann Behav Med 37(2):141–153
56. Kilpatrick DG (1972) Differential responsiveness of two electrodermal indices to psychological stress and performance of a complex cognitive task. Psychophysiology 9(2):218–226
57. Siddle DA, Lipp OV, Dall P (1996) The effects of task type and task requirements on the dissociation of skin conductance responses and secondary task probe reaction time. Psychophysiology 33(1):73–83
58. Tarvainen MP, Niskanen JP, Lipponen JA, Ranta-aho PO, Karjalainen PA (2014) Kubios HRV—heart rate variability analysis software. Comput Methods Progr Biomed 113:210–220
59. Welch KC, Lahiri U, Liu C, Weller R, Sarkar N, and Warren Z (2009) An affect-sensitive social interaction paradigm utilizing virtual reality environments for autism intervention. Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics), vol 5612 LNCS, no. PART 3, pp 703–712
60. Kawabata M, Mallett CJ (2014) Flow experience in physical activity: examination of the internal structure of flow from a process-related perspective. Motiv Emot 35:393–402
61. Pearce JM, Ainley M, Howard S (2005) The ebb and flow of online learning. Comput Human Behav 21(5):745–771
62. Sun YC, Jara AJ (2014) An extensible and active semantic model of information organizing for the internet of things. Pers Ubiquitous Comput 18(8):1821–1833
63. Sun YC, Yan H, Lu C, Bie R, Zhou Z (2014) Constructing the web of events from raw data in the web of things. Mobile Inf Syst 10(1):105–125
64. Sun YC, Song HB, Jara AJ, Bie R (2016) Internet of things and big data analytics for smart and connected communities. IEEE Access 4:766–773