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Modeling the physiological response of flow in groups: a mathematical approach

David Antonio Rosas^{1*} , Natalia Padilla-Zea² and Daniel Burgos^{2,3*}

*Correspondence:
david.rosas@udites.es; daniel.burgos@unir.net

¹ University of Design, Innovation and Technology (UDIT), Av. Alfonso XIII, 97, 28016 Madrid, Spain

² Universidad Internacional de La Rioja (UNIR), Av. de La Paz, 137, 26006 Logroño, La Rioja, Spain

³ MIU City University Miami, 111 NE 1St Street, 6Th Floor Miami, Miami, FL 33132, USA

Abstract

This paper advances in the understanding of motivation in terms of flow in groups from a physiological perspective. We use wearable devices to monitor the heart rate variation during a set of sessions of face-to-face STEAM project-based learning. By using Action Research with mixed-methods design, we observed a set of 28 students in real-world settings during 18 classes and used both customized and commercial tools to analyze data retrieved. Based on the cognitive absorption and motivation obtained from EduFlow-scale-based physiological data, we propose mathematical models to predict the Flow that a group will experience in a teaching–learning session. Our preliminary results may challenge the central axiom of Flow Theory, while clarifies the balance hypothesis.

Keywords: Flow theory, Education, Mathematical model, Heart rate variability

Introduction

Flow Theory (Csikszentmihalyi, 1974) explains why individuals engage in activities without immediate or tangible rewards. This is attributed to the enjoyable psychological state experienced during such activities, making the process itself rewarding (Csikszentmihalyi, 1974).

Flow is typically represented by the Flow Channel (Csikszentmihalyi, 1974), meaning that Flow occurs when a balance exists between abilities that a person has and challenges that this person faces. In addition, a set of nine elements define psychological flow: balance Challenge-skill, action-awareness, clear goals, unambiguous feedback, concentration, sense of control, loss of self-consciousness, transformation of time, and autotelic experience (Csikszentmihalyi & Csikszentmihalyi, 1988; Jackson & Marsh, 1996). Similarly, regarding the nine components of Flow, Quinn (2005) suggests classifying them with deep concentration as the core element. That way, deep concentration provokes becoming one with the activity, which makes a kind of chain with feeling control, forgetting yourself and forgetting time (see Beard, 2015). This state is also known as optimal experience, because it is characterized by enjoyment, performance (Privette, 1983) and moderate effort (Swann et al., 2018) which are crucial in educational settings activities (Peifer et al., 2022).

Furthermore, Csikszentmihalyi explains in Beard (2015) how the Flow Theory was born from a completely different approach to the most typical ones at that time: reinforcement to rats in a maze. On the contrary, Csikszentmihalyi realized that many people such as artists were able to be completely absorbed in their work just because of the pleasure of enjoying the process, rather than the final result. This is very similar to the feeling felt by chess players or mountain climbers, for example (Csikszentmihalyi, 1974).

Flow state measurement often employs questionnaires, though not all of them are validated (Moneta, 2021). Among the 34 validated flow questionnaires identified by Rosas et al. (2023), EduFlow (Heutte et al., 2016) and Flow Short Scale (Rheinberg, et al., 2003) were selected for their applicability in primary face-to-face schools with technology-mediated learning processes. Heutte et al. (2016) demonstrated that EduFlow scales effectively evaluate optimal educational experiences in primary school students, both in-person and online. The scales encompass dimensions such as cognitive absorption, altered perception of time, loss of self-awareness, and autotelic experience/well-being, with cognitive absorption significantly influencing the other categories (Heutte et al., 2016). In addition, EduFlow has recently been effective in predicting asynchronous flow in Massive Online Open Courses (Ramírez Luelmo et al., 2024).

However, our interest is in objectively measuring physiological responses of students changes in the flow state by using, in this case, the Heart Rate Variability (HRV). The HRV is affected by various factors, including stress, emotions, and cognitive processes (Saturno Chiu, 2017; Shaffer et al., 2014; Thayer et al., 2009; Saavedra Torres, 2015; Schandry & Montoya, 1996), and it is commonly used to measure biological responses to stimulus (Peifer et al., 2022, Knierim et al., 2018; Khoshnoud et al., 2020).

In this study, as already presented in Rosas et al. (2022), we use EduFlow and Flow Short Scale combined with HRV methods. Specifically, advances in technology now allow non-invasive wearable Polar H10 devices to monitor HRV, considered as a gold standard for such measurements (Gilgen-Ammann et al., 2019).

Given the limited understanding of flow in group settings, natural educational contexts, and from a physiological perspective (Rosas et al., 2023; Zumeta et al., 2016), this study employs a quasi-experimental design with mixed methods. Two groups participated in an action research cycle during 9 sessions each, finding significant correlations among HRV parameters, the EduFlow scale, and its dimensions.

Our research hypotheses are:

H1 The group flow recall representation is described by a mathematical model based on HRV physiological response.

H2 The mathematical model obtained from the HRV physiological response is congruent with the group flow phenomenology.

The rest of the paper is structured as follows: in Sect. 2, we describe the materials and methods used; in Sect. 3, we present the results obtained from the experience, discussing them in Sect. 4; finally, Sect. 5 outlines main conclusions, limitations and further works.

Materials and methods

This research follows the Declaration of Helsinki as well as the Spanish Organic Law 3/2018 about Personal Data Protection. It has also been approved by the UNIR Ethical Committee under the code PI 015/2022. Moreover, the Granada (Spain) Juvenile Prosecutor's Office was informed about the characteristics, purposes and data collection instruments used, since minors were involved in the study. Legal guardians were also informed during a meeting, and informed consent for participation was mandatory. No reward was provided to any participant, being free to dropout the research without any consequences nor explanations. Data gathering was anonymized, and we only use average values in this work in order to avoid any possibility to identify participants.

Sample

This research follows an Action Research design with mixed methods (Hernández-Sampieri, 2018), involving 2 groups of 14 students. These groups used the same versions of digital class diary, teacher's observations diary, EduFlow, and FKS scales. The first group, belonging to the 5th course of primary education, developed a project related to 2D and 3D design while the second group, in the 6th course of primary education, developed a project related to robotics. This experience was developed during the course 2021–2022 (Table 1). Moreover, the teacher was a seasoned professional with 48 years of age and extensive experience in the field.

Instruments

Starting from findings in Rosas et al. (2022, 2023), we selected the Flow Short Scale (FSS) and EduFlow questionnaires. Such surveys are appropriate for assessing flow prevalence in project-based teaching mediated by technology, as several authors agree (Heutte et al., 2016; Rheinberg et al., 2003). FSS has 6 items for the dimension related to course progression, 4 to assess cognitive absorption, and 3 for the relevance of the task. It also contains questions to address subjective challenge (A1), skills (A2), and balance (A3) perceived during the task performance. On the other hand, EduFlow has 4 items for each of the dimensions (D1-cognitive absorption, D2-time transformation, D3-loss of self-consciousness, and D4-autotelic experience-well-being). Additionally, pupils completed the Swedish Flow Proneness Questionnaire (Ullén et al., 2012) to study if these students could experience flow.

In order to record physiological data, every participant wore TicWris Max watches as data-loggers and Polar H10 sports bands to detect physiological responses, since they are considered a gold standard in wearable electrocardiology (Gilgen-Ammann et al., 2019) and are appropriate for research involving children (Speer, 2020). An application in Kotlin (Kotlin Foundation, 2022), in combination with a library called Polar SDK v. 3.3.6 (Oikarinen et al., 2016), was developed with Android Studio (Bumblebee v.2021.1.1) to

Table 1 Sample characteristics

Group	N	Boys	Girls	Average age	SD
5N_1	14	7	7	10.80	0.44
6N_1	14	8	6	11.82	0.31

access the watch's accelerometer, its interactive screen buttons, its SD card and, through Bluetooth to the electrocardiological data generated by the sports band. We call these applications in Kotlin with the generic name "Polar H10 SDK UNIR-iTED", giving the corresponding credit to the developers of the library.

The application was installed in a personalized way on each device, to connect only to a specific Polar H10 band via Bluetooth. Then, Polar H10 sports bands registered cardiac data with a sampling of 200 Hz, which means a set of 200 measures each second. These measures were automatically processed by the API included in the Polar SDK, resulting in data with a frequency of 1 Hz recorded as CSV files in the SD cards included in the watches, saving R waves in milliseconds, beats per minute, and time in Universal Unix format. Data in SD cards were downloaded to a PC after every session. To process the data recorded, we developed a simple Jupyter Notebook application to extract cardiac data into CSV files.

Later, we used the software Kubios 3.5.0 (Tarvainen et al., 2021) to filter the signal, detrend the signal time series, and remove artifacts, such as extra, missing, or unaligned beats, that produce distorted measures of HRV (Shaffer et al., 2014; Shaffer & Ginsberg, 2017; Seppälä et al., 2014). There are previous academic works where a combination of Kubios and precision wearable electrocardiography sports bands is used (Chin & Kales, 2019; Naranjo et al., 2015). Kubios also allows extracting multiple cardiac parameters in CSV format, separating the records by time sections and generating reports. Furthermore, to ensure comparability of the cardiac parameters, this software was configured to divide the recordings of each participant in the study into 5-min segments, aligning with the electrocardiological standard for children as outlined in (Seppälä et al., 2014). Finally, the cardiac parameters calculated with Kubios for each participant and session were exported in 5-min batches in CSV files, for subsequent analysis with Excel, SPSS or Python, depending on the degree or type of treatment necessary. We want to highlight that these 5-min batches reduce granularity but make HRV measures comparable to others, in line with international cardiological standards (see Shaffer & Ginsberg, 2017; Seppälä et al., 2014).

These tools were used in a set of technological-based educational itineraries following the STEAM methodology. In particular, educational robotics for the 6th grade and 2D/3D graphical design for the 5th grade. In this context, we followed the Theory of Elaboration (Reigeluth & Stein, 1983) in which educational contents are developed in a growing spiral of deepening levels, around thematic axes or epitomes. Along with the above, the level of difficulty of every proposed activity was evaluated using Bloom's taxonomy for the Digital Era (Churches, 2009). In Bloom's taxonomy, a gradation of activities is established in 3 levels, with 3 sublevels each, which comprise lower thinking skills until reaching higher thinking skills (Bloom, 1990). Furthermore, each level of elaboration was materialized as instructional modules in SCORM format (ADL, 2024). They were created considering that, due to their age, the students should be in the stage of concrete operations (Piaget & Inhelder, 2016). These SCORM modules were incorporated into a specifically designed web application, able to record in a MySQL data base, every second (1 Hz), the activity shown to the students on the classroom's projector, its Bloom's taxonomy classification, the time in Universal Unix format, and the teacher's

attitude (if he/she was merely passing pages, explaining something for the first time to the group, answering individual or group questions).

Experimental procedure

We followed the research process outlined in (Rosas et al., 2022). The pre-experience was focused on identifying possible non-autotelic students with the SFPQ (Ullén et al., 2012).

During the experience, lectures were scheduled twice a week before any kind of physical activity and started after the students rested for 10 min in the same ICT classroom, using individual laptops and mice. The same teacher taught both groups and kept a diary to gather qualitative information about any incidents during the teaching periods. Additionally, the tutor assigned by the school for each group was present during every lesson, witnessing the processes. Pretrained pupils fitted on themselves the HRV bands in the privacy of the locker rooms, since the apps informed us if the Polar H10 bands were correctly worn. Later, groups attended their scheduled courses (9 lesson-plans of one hour each). SCORM-based materials were displayed by a projector and the digital diary recorded, each second, the activity, time, teacher's attitude, and task difficulty shown, following Bloom's taxonomy for the Digital Era (Churches, 2009). Students also completed EduFlow and FSS scales in paper format after each lesson.

In the post-experience step, interviews with students were conducted to compare quantitative results with the information recorded in the flow scales and in the teacher's diary.

Results

From our previous works (Rosas et al., 2022), we know that FSS and EduFlow scale correlate with very high values ($r_s = 0.692$, $p < 0.0001$, $n = 200$). However, in this paper we chose just one of them to avoid redundancy. The one selected was EduFlow scale, which is more specific to the STEAM methodology and is suitable for both online and face-to-face environments (Heutte et al., 2016). Additionally, Rosas et al. (2022) report that the internal coherence of the EduFlow scale ($\alpha = 0.827$, items = 11) is adequate and higher than that of the FSS scale ($\alpha = 0.812$, items = 12) in terms of Cronbach's alpha (Cronbach, 1951). However, we retained the dimensions A1 (skills), A2 (challenge), and A3 (skills-challenge balance) from the FSS scale, which are not present in the EduFlow scale, to address the perceived difficulty of any lesson. Neither the scales nor their extracted dimensions exhibit normal distributions (Rosas et al., 2022), leading to the further preference for non-parametric statistics.

Among several HRV parameters extracted using Kubios software, we selected Heart Rate (HR) and its standard deviation (SD) for a phenomenological model intended for low computational settings applications, like the one available in our setting. Additionally, they are intuitively interpretable, and provide insights into the dynamics of Sympathetic (SNS) and Parasympathetic Nervous System (PNS) heart modulation (Shaffer et al., 2014; Speer, 2020). Moreover, we present three additional robust group flow models based on SNS and PNS indexes, designed for high-computational-cost environments and aimed at improving the educational performance.

Furthermore, to be able to represent different kind of activities, we considered all sessions in both groups (16 sessions) and divided them in 5-min periods, due to international cardiological standards (Speer, 2020). In order to concentrate data from all the sessions, we limited the time to 25 min, since sessions could have different duration (different time to wear the devices, to go to calm, etc.). This way, we consider 5 periods of 5 min for each session, having data from all the participants in all the defined time spans. Since we are interested in group flow, intended to safeguard the anonymity of participants, and combine the different activities that can take place during the sessions, we computed mean values of the HRV measurements in every time span of all the sessions. That means that we obtain an average value for {minute5session1, minute5session2, minute5session3, etc.}, {minute10session1, minute10session2, minute10session, etc.}, {minute15session1, minute15session2, minute15session, etc.}, and so on until minute 25. In particular, we calculated the mean HR in beats per minute (bpm, represented as HR_f in tables) to address mean SNS activation in every span from all the participants, in all the sessions. Next, we computed the mean cognitive absorption (D1_f) because that is the corner stone of EduFlow model, as well as the mean EduFlow scale score (Flow_f), from all the questionnaires responded at the end of every lecture. Later, we obtained the Spearman correlations among D1_f and HR_f, as well as among Flow_f and HR_f, on every 5-min period ($p < 0.01$), to address correlational variations through sessions in each span, as summarized Fig. 1.

The correlations between HR_f and cognitive absorption (D1_f) has a maximum after the first 5 min of all the lessons ($r_s = 0.364$, $p < 0.01$, $n = 16$) and decreases thereafter. We can see it in Fig. 3, period 2, where both D1_f and Flow_f have a maximum absolute value, meaning a maximum Flow, since HRV and Flow has negative correlation. A similar behavior is shown for Flow_f scale and HR_f. Therefore, the teacher may anticipate an educational response to manage group flow expectations after the first five-minute period.

In Table 2, we calculated the mean parameters for the 5 first minutes of each lesson (ID), for cognitive absorption (D1g), heart rate in bpm (HRg), its standard deviation

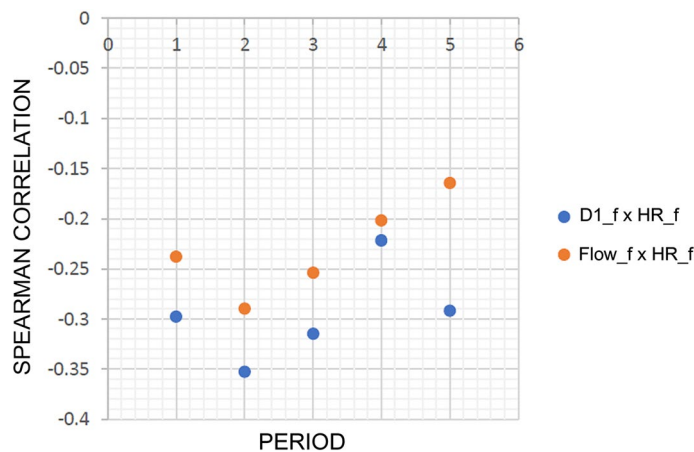


Fig. 1 Spearman correlations among HR_f, Flof_f, and D1_f on every 5-min spans for all lessons ($p < .01$)

Table 2 Group average of the first 5 min of the sessions of control groups

ID	D1g	HRg	SDg	A1	A2	A3	Flow	%D1g	%Flow
2N5	10.83	77.81974157	6.46964171	2.25	6.00	5.25	49.40	51.5714286*	58.8095238
3N5	12.64	98.02736845	6.86027909	3.64	5.82	5.45	51.82	60.1904762	61.6904762
4N5	10.4	85.4850352	6.1290678	3.20	6.00	5.00	41.25	49.5238095*	49.1071429*
5N5	11.63	96.55322213	6.22246775	3.38	4.88	5.25	44.57	55.3809524	53.0595238*
6N5	12.67	84.691319	7.04047022	2.78	5.89	5.22	49.67	60.3333333	59.1309524
7N5	13.82	88.02391827	6.92081855	3.64	4.27	4.55	52.91	65.8095238	62.9880952
8N5	13.36	84.17523191	6.92782691	3.64	4.55	4.55	48.82	63.6190476	58.1190476
9N5	10.5	85.3676189	6.987784	4.10	5.40	5.70	48.00	50*	57.1428571
2N6	16.43	76.5451436	6.52791743	2.29	7.43	4.71	62.71	78.2380952	74.6547619
3N6	16.33	74.09460278	6.7404624	3.20	6.00	5.00	56.33	77.7619048	67.0595238
4N6	14.7	76.19841067	7.1827317	4.20	6.44	4.60	58.00	70	69.047619
5N6	15.5	77.7063	6.29030743	3.43	6.71	4.57	57.67	73.8095238	68.6547619
6N6	16	73.6696434	6.50298363	2.89	6.89	4.89	55.75	76.1904762	66.3690476
7N6	13.56	84.76313525	6.51502822	4.11	5.33	5.44	49.88	64.5714286	59.3809524
8N6	14.78	81.987991	6.47760044	3.78	7.44	5.00	54.44	70.3809524	64.8095238
9N6	13.67	86.56288083	7.10632983	4.67	6.67	4.67	51.33	65.0952381	61.1071429

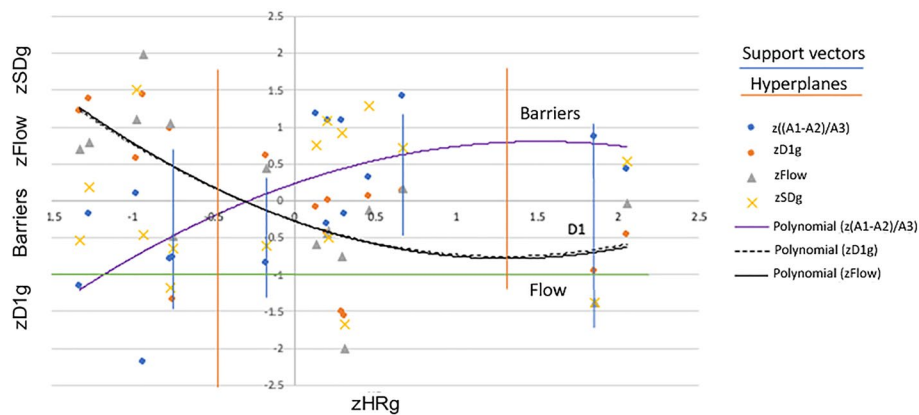


Fig. 2 Computational model representing the first 5 min of physiologically measured sessions

(SDg), A1, A2, A3, the sum of the EduFlow scale (Flow), and the mean D1g and Flow as a percentage of the scale.

Figure 2 shows a scatter plot from data in Table 2, with mean group normalized variables as Z values, to understand how the model features are related. In particular, we use HR in bpm (HRg hereinafter), its standard deviation (SDg hereinafter), cognitive absorption (D1g), EduFlow scale (Flow) and a feature called as Barriers, calculated with Eq. (1), which uses the averaged value of FSS scale variables called as Challenge (A1), Competences (A2), and Balance (A3). The Barriers variable addresses the asperities found in any task while using three items from the same questionnaire to compute a dimension.

$$Barriers = \frac{\overline{A1} - \overline{A2}}{\overline{A3}} \tag{1}$$

Following this idea, by using second-grade polynomial regression, three adjustment curves are obtained for features *zHRg*, *zD1g* and *zBarriers*. These curves draw a figure with mirror symmetry with respect to the X axis, which have great significance from the point of view of the Flow Theory postulates, as we will see later.

From this result, we can identify *zones for high, medium and low flow*. In these zones, the average standard deviations have a differential behavior (moderate in the high flow zone, high in the medium flow zone and very low or extremely low in low flow zones). Even a no flow zone is defined when *zSDg* is very low. This parameter would not be used for any other purpose, since it does not seem as good a classifier as the Flow or *D1g* features, for example. Likewise, if we delete from the model the points where flow is not verified (marked with an * in Table 4), we find Eq. (2) through quadratic regression, where an estimate of the manifested group flow is obtained as a percentage of scale. The values corresponding to sessions third and fourth of the 5th grade are not included in the regression, as they are located in the area where flow is not verified. In addition, we calculated the quadratic fit in terms of R^2 (0.4678, Desv. Est. Error=4.062). Likewise, we present the fitted model in Eq. (2) ($r=0.684$, $df=13$, $F=4.835$, $Sig.=0.031$), when we consider groups of people and eliminate cases where flow is not verified.

$$Flow = 0.0361HRg^2 - 6.5270HRg + 354.37 \tag{2}$$

Furthermore, we can study the *expected average group flow* by applying the k-means algorithm (MacQueen, 1967), once the experimental points where no flow exists was obtained (meaning that $zSDg < -1$). Table 3 shows the 3 clusters identified.

From this result, we can identify 4 phenomenological zones (high flow, medium flow, low flow and absence of flow), which considers the 3 previous clusters, together with another one in which flow is zero or very low (Fig. 3).

To establish the segmentation of Fig. 3, the characteristics *zSDg* and *zEduFlow* are simultaneously casted on the ordinate axis, with respect to *zHRg* (on the abscissa). Two vertical lines of separation (hyperplanes) are defined for an area of low average group pulsations (L1) and another one for high average group pulsations (L2), based on Z values with maximum separation between adjacent clusters. There is also a

Table 3 Cluster analysis with K-means algorithm when eliminating no flow points

Iteration history			
Iteration	Changes in the cluster centres		
	1	2	3
1	0.000	0.481	2.993
2	0.000	0.000	0.000

a. Convergence achieved. The maximum absolute coordinate change for any center is 0. The current iteration is 2. The minimum distance between initial centers is 13.969

Variable	Clusters		
	1	2	3
HRg	98.0273684500	85.0340793767	75.6428200900
D1g (%)	60.190476190	64.968253968	75.200000000
Points in each of the clusters	1	6	5

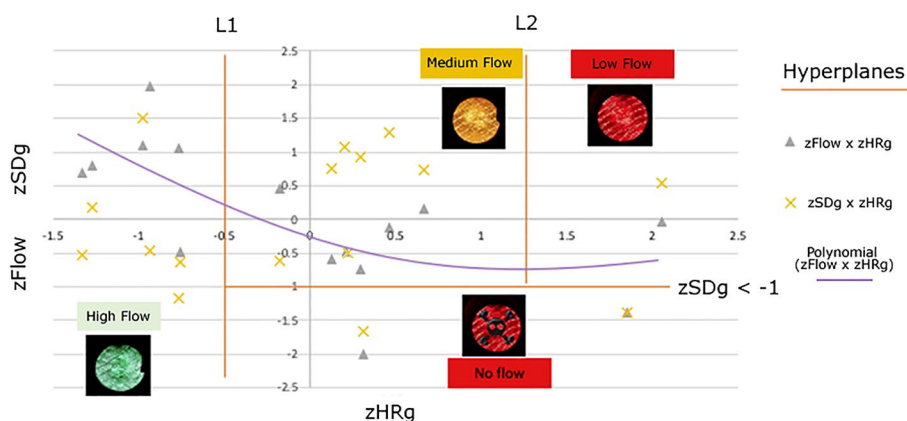


Fig. 3 Phenomenological zones defined from zFlow, zSDg, and zHR, with icons and semaphore color code

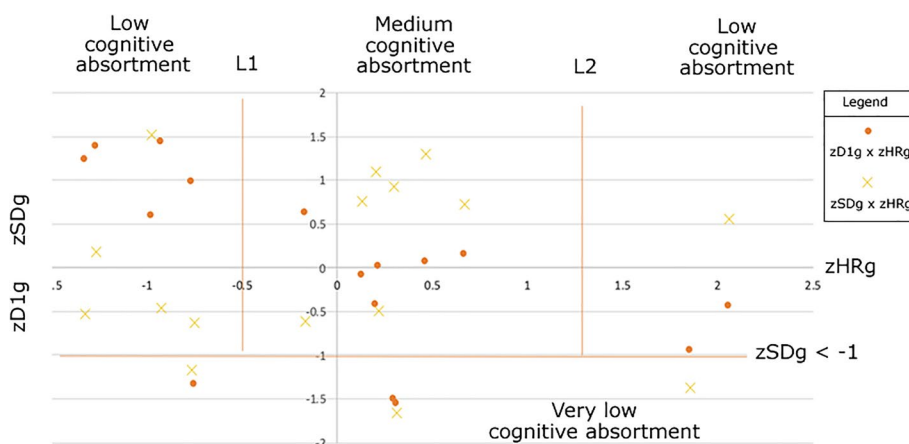


Fig. 4 Cognitive absorption phenomenological zones defined on zSDg, zD1g and zHRg

horizontal line separating points with low standard deviation from the average group heart rate ($zSD < -1$). Therefore, the high flow zone is that with $zHRg$ values $< L1$. The medium and low flow zones are above the $zSDg$ value ≥ -1 and they are separated by $L2$. A zone with insignificant or no flow experienced is identified by values $zHRg > L1$ and $zSDg < -1$.

Once this segmentation is established, the second-degree polynomial in Eq. (2) fit curve between $zHRg$ and $zFlow$ is calculated, excluding the points where no flow or very low flow is expected.

Once described the flow score behavior, we are going to characterize cognitive absorption ($zD1g$) (Fig. 4), as it is also shown in Fig. 2 (orange dots). Vertical limits are stated to separate areas of high, medium and low cognitive absorption, depending on $zHRg$ ($L1$ and $L2$). These lines are found by calculating the midpoint between the $zHRg$ coordinates of the closest points of adjacent clusters, giving the same result as an SVM classifier (Vapnik, 1999) with vertical support vectors. A horizontal line is also represented to separate the cases where the $zSDg$ standard deviation is lower than the average value ($zSDg < -1$).

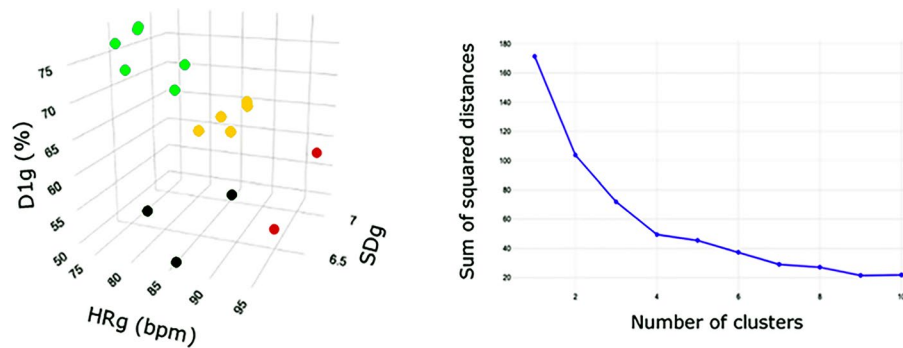


Fig. 5 Clusters obtained by using the K-means algorithm with HRg (bpm), D1g (%) and SDg (left). Scree plot (right)

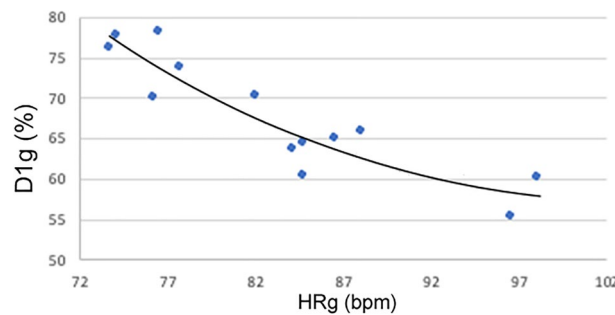


Fig. 6 Quadratic regression for HRg (bpm) and D1g(%) without atypical values

To statistically prove what we see in previous figures, the K-means algorithm is applied. The initial clusters are split into 4 new clusters according to HRg, D1g, and SDg. It can also be seen in the scree plot and distribution of experimental points (Fig. 5).

This way, the 4 zones defined for cognitive absorption (high, medium, low or non-existent) are explained.

Next, we adjust the quadratic model to adjust cognitive absorption and HRg. Again, we do not consider cases where flow prevalence was too low or not verified (Fig. 6). The goodness of the adjustment was calculated in terms of $R^2 = 0.8363$ (Desv. Est. Err. = 3.219). In Eq. (3) the regression model is presented ($r = 0.915$, $df = 12$, $F = 25.554$, $Sig. < 0.001$), considering D1g and HRg characteristics.

$$D1g = 0.024HRg^2 - 4.9362HRg + 310.75 \tag{3}$$

Next, in Fig. 7, we show the quadratic regression among Barriers [1] and HRg ($r = 0.673$, Desv. Estim. Error = 0.210, $df = 15$, $F = 5.388$, $Sig. = 0.020$) from Table 2, and the polynomial Eq. (4).

$$Barriers = -0.001HRg^2 - 2.39HRg - 11.532 \tag{4}$$

Next, we show (Fig. 8) three models including 5N1 and 6N1 individual measures in groups, focusing on three key characteristics: SNS (Sympathetic Nervous System

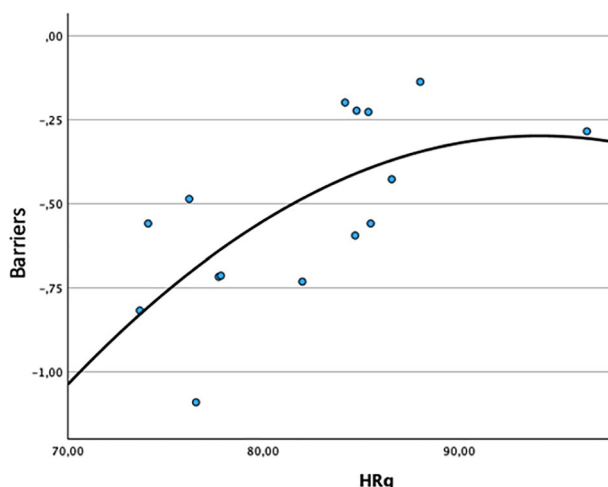


Fig. 7 Quadratic regression for HRg (bpm) and Barriers

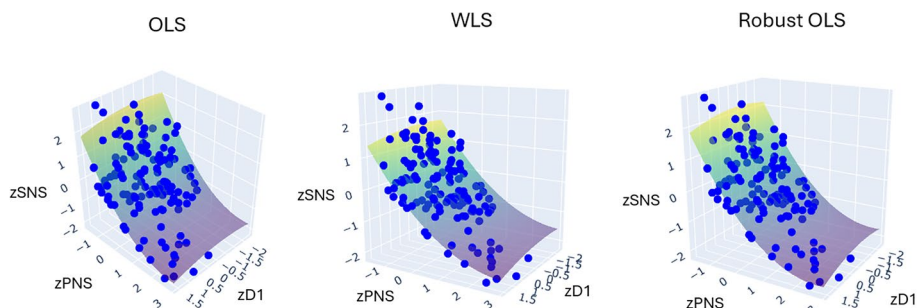


Fig. 8 Alternative 3D plots and adjustment among SNS, PNS, and D1 with OLS, WLS and robust OLS

activation index), PNS (Parasympathetic Nervous System activation index), and D1 (Cognitive Absorption). The PNS is analyzed using Mean RR, RMSSD, and SD1 (derived from Poincaré plots), while the SNS is characterized by Mean HR, the Stress Index (calculated as the square root of Baevsky’s stress index), and SD2 (Poincaré plot), extracted with Kubios (see Tarvainen et al., 2021).

It is crucial to highlight that the models are developed using data from the first 5 min of the lecture sessions, offering an unprecedented adjustment in Flow Theory. HRV parameters are calculated over a five-minute time segment to ensure comparability with established standards. Cognitive absorption (D1), a central element of this analysis, is derived from the four dimensions obtained through EduFlow questionnaires completed by participants after the sessions. All values are normalized to Z-scores to allow for standardized comparisons. Additionally, both the initial data and the Python (Python Software Foundation, 2024) calculations are presented in Annex I. The study explores multiple modeling techniques, including Ordinary Least Squares (OLS), Robust OLS, and Weighted Least Squares (WLS), showing interactive graphs with a Google Colaboratory notebook (Binsong, 2019).

In Table 4, we show a comparative summary of OLS, WLS, and robust OLS regression models.

Table 4 Comparative summary of OLS, WLS, and robust OLS regression models

Metric/variable	OLS coefficient	OLS P> t	WLS coefficient	WLS P> t	Robust OLS coefficient	Robust OLS P> z
R-squared	0.941		0.809		0.941	
Adj. R-squared	0.940		0.804		0.940	
F-statistic	525.5		139.0		474.0	
Prob (F-statistic)	1.34e-79		3.87e-46		7.57e-77	
AIC	9.274		67.64		9.274	
BIC	23.84		82.20		23.84	
const	-0.1421	0.000	-0.1959	0.000	-0.1421	0.000
zD1	-0.1074	0.000	-0.1080	0.000	-0.1074	0.000
zPNS	-1.1053	0.000	-0.9011	0.000	-1.1053	0.000
zD1_squared	-0.0573	0.003	-0.0344	0.047	-0.0573	0.000
zPNS_squared	0.2004	0.000	0.1394	0.000	0.2004	0.000

Discussion

This paper establishes two hypotheses, which have been positively solved. Regarding H1, we showed that equations (Csikszentmihalyi, 1974) and (Csikszentmihalyi & Csikszentmihalyi, 1988) model the Flow phenomenology and Cognitive Absorption phenomenology, respectively. Moreover, adjustments obtained can be considered very good comparatively with respect to the state of the art reported by (Tordet et al., 2021). In their state of the art, they inform that the correlations between physiological measurements and flow scales for isolated individuals reached the best fits at $r=0.45$, also being consistent with those found using a flow measurement scale by direct observation. Consequently, we go from obtaining moderate to high correlations (Rowntree, 1984), since we obtained ($r=0.684$, $df=13$, $F=4.835$, $Sig.=0.031$), when we consider groups of people and eliminate cases where flow is not verified. Moreover, from data represented in Fig. 4, we obtain an interpretable model (Murdoch, 2019), since it is predictive, descriptive, and relevant. This interpretability is a criterion to evaluate the bias of an algorithm (Boyd & Crawford, 2012; Datta, Sen, & Zick; 2016), which seems consistent with the scientific literature, since:

- HR is a parameter related to the Sympathetic Nervous System (SNS) activation. If it is very high, the student may be stressed and he or she will have difficulties to achieve the flow (de Manzano et al., 2010).
- Flow takes place at moderate or low HR values, as indicated by (Tian et al., 2017).
- If the heart rate (HR) standard deviation is low, it may indicate little variability, meaning permanent boredom or permanent stress, depending on the HR, which is not beneficial for the flow state (Csikszentmihalyi, 1974).
- There is a mirror symmetry with respect to the X axis among the flow correlation curves and the “barriers” factor. Barriers factor is built from parameters related to the balance of the task (a precondition to achieve Flow, according to Csikszentmihalyi & Csikszentmihalyi, 1988). Since the divisor (A3) is very close to 5 on average in our dataset (mostly, students appreciate balance in the proposed tasks), the difference between A1 and A2 (Challenges-Skills) is a factor that measures the subjective ease of carrying out activities. For this reason, we call this factor “barriers” or difficulties

so that “the task is performed fluidly and without apparent effort” (Csikszentmihalyi & Csikszentmihalyi, 1988).

- Once discarded the cases where flow is not verified in the model ($SDg < 1$), we find that the goodness of fit of the polynomial equation between HRg and D1g is high ($R^2 = 0.8363$, $df = 12$, $F = 25.554$, $Sig. < 0.001$). This exceeds the correlation reported by (Tordet, 2021) ($R^2 = 0.25$) in the state of the art between physiological measurements and flow scales, comparable to that obtained through direct observation. We must also remember that these calculations are made based on the first 5 teaching minutes group averages per session. Consequently, concentration on tasks is greater when students appear relaxed, without extreme standard deviations in terms of the group mean HR, which seems to suggest that they are not bored or stressed, continually.
- Both mean group flow and cognitive absorption correlation curves (Fig. 4) show a negative correlation with mean group heart rate (HRg).
- The teacher’s diary reflects that students in both experimental groups did not want to leave the classroom, even when a break or their favorite subject, Physical Education, was scheduled next. This indicates a high level of engagement with the courses.
- The assistance in 2 groups were similar, and no student dropped the courses, even when participation in this activity was voluntary.

For environments with higher computational demands, we developed three models using OLS, WLS, and robust OLS regression techniques. These models incorporate complex HRV parameters, such as SNS and PNS indexes, along with cognitive absorption, a key dimension of the EduFlow scales (Fig. 8). A comparison of the models in Table 3 revealed that OLS and robust OLS provided identical results in terms of R^2 , AIC, BIC, and model coefficients. However, the robust OLS model is preferred as it effectively addresses heteroskedasticity issues. Both OLS and robust OLS outperform WLS, as indicated by their lower AIC and BIC values. Notably, the adjustment achieved by the robust OLS regression model ($R^2 = 0.941$; $F = 474.0$; $p. = 7.7 \times 10^{-77}$) represents an unprecedented improvement in Flow Theory, particularly when compared to the state-of-the-art findings by Tordet et al., (2021), who reported $R^2 = 0.2025$.

Regarding H2, as represented in Figs. 2, 3, 6, and 7, we showed that the mathematical models obtained from the HRV physiological response is congruent with the group flow phenomenology. Both Eqs. (2) and (3) exhibit similar polynomial curves with negative slopes, when eliminating experimental points with insignificant flow or cognitive absorption, and overlap when normalized as z-values (Fig. 2). Moreover, we introduced the concept of barriers, based on the axiom of perceived balance among person’s skills and challenges related to the task performed as a precondition to flow states (Csikszentmihalyi, 1974). Even if this axiom is under revision (Løvoll & Vittersø, 2014; Swann et al., 2018), it remains important because barriers draw a meaningful symmetric curve with HRg [4] concerning the relationship described between flow and cognitive absorption (Fig. 2). In this regard, Flow is enhanced when barriers are low, which is consistent with the flow phenomenology.

Moreover, for high-demanding computational environments, we propose a quadratic adjustment in Eq. (5), based on a robust OLS model:

$$zSNS = -0.1421 - 0.1074 \cdot D1 - 1.1053 \cdot PNS - 0.0573 \cdot D1^2 + 0.2004 \cdot PNS^2 \quad (5)$$

These unprecedented models to date challenge the central axiom of Flow Theory. They demonstrate that not all students experienced physiological flow, yet none left the classroom, despite being fully entitled to do so and even having desirable alternatives, such as going to recess. Moreover, these results can be obtained after just five minutes of lecture, and correlations among flow and HRV decreases as the lessons advance (Fig. 1). Considering these two observations, we propose, as a hypothesis for future research, that it is the mere expectation of experiencing this pleasurable state, rather than the physical experience of flow itself, that motivates individuals to continue engaging in activities.

Additionally, we have introduced a concept termed "barriers," which clarifies the meaning of the equilibrium hypothesis. To the best of our knowledge, no physiological models have previously been identified that justify the relationship between perceived flow and constructs related to the concept of equilibrium between task difficulty and participants' skills, although with room for improvement in the adjustments (see Fig. 2 and 7).

Finally, regarding the sample, an additional novelty of this study is the evaluation in long-term real-scenario-based group experiences. This makes the process more difficult and involves a high number of measures to define each of the experimental points (in particular, in this case, each of the experimental points requires 840.000 electrocardiological measures), which sufficiently supports the findings.

Conclusions, limitations and further works

This paper focuses on the mathematical representation of physiological manifestations of Flow. To achieve this challenge, we designed and developed an experience with 2 groups of primary education, more precisely, 5th and 6th grade students in a real context, along with the same teacher, participated in 2 different STEAM projects. To develop this experience, we used the wearable devices H10 Polar band and a smartwatch, which acted as monitoring systems. Data recorded were downloaded into a PC after every session, in order to process and analyze them. This process was developed by using both commercial and ad-hoc tools to obtain 5-min span data, mathematically operate them to fully anonymize information, and compute the mathematical approaches.

From this process, we can highlight 4 main findings in the Fig. 1 model: 1) we were able to define a regression curve for the physiological response of heart rate to Flow, which fits better ($r=0.684$, $df=13$, $F=4.835$, $Sig.=0.031$) to the approaches reported in (Tordet et al., 2021) ($r=0.45$) as the state of the art; 2) similarly, a regression curve for the physiological response of HR to Cognitive Absorption was obtained, also going further the state of the art (Tordet et al., 2021) for observational and physiological flow ($r=0.915$, $df=12$, $F=25.554$, $Sig.<0.001$); 3) a correlation ($r=0.673$, $Desv. Estim. Error=0.210$, $df=15$, $F=5.388$, $Sig.=0.020$) over the state of the art (Tordet et al., 2021) among barriers and HRg is also found 4) we defined zones of high, medium, low, and insignificant Flow state prevalence from the heart rate standpoint. This model is suitable for phenomenological approaches in low computational cost environments.

Additionally, a high computational cost model is presented based on Eq. (5) ($R^2 = 0.941$; $F = 474.0$; $p. = 7.7 \times 10^{-77}$), which significantly outperforms the state of

the art (see Tordet et al., 2021). This model integrates SNS, PNS, and the cornerstone of the EduFlow model (cognitive absorption-control), with potential applications for evaluating advanced educational contexts aimed at improving academic performance.

Thus, we can positively solve our research hypotheses: the group flow recall representation is described by a mathematical model based on HRV physiological response; and these mathematical models are congruent with the group flow phenomenology.

Important future research may be derived from this work, since it sheds light on group flow. Firstly, Flow recall may be more strongly correlated with the initial moments of lessons than with later phases of lectures, which may be counterintuitive. This deserves further study to confirm (or not) this hypothesis. Related to that, Flow Theory may be a motivational theory of expectations: the expectations of experiment flow, not just the physiological flow experienced, strongly influence flow recall and hence the memory of any experience.

This work has limitations stemming from our quasi-experimental research design. We selected real full classrooms in a specific context with primary education students and the same teacher. Although the experiments varied in difficulty levels according to Bloom's taxonomy and were further than those in laboratory settings (Knierim et al., 2018), only STEAM didactic methodology was used, covering two themes. Budget and time constraints also necessitated the use of hardware and software with limited computational power. Space limitations and the teacher's capacity to attend meant small groups of students participating, but this limitation may be mitigated by the size effect and statistical power of our results.

Appendix 1

Dataset and python model in Google Colaboratory. https://colab.research.google.com/drive/1cqAqCfL0P_dmmNnIS53v98NMrWjquS-j?usp=sharing.

Abbreviations

A1	Challenge
A2	Skills
A3	Balance
bpm	Beats per minute
D1	Flow cognitive absorption dimension
D1_f	Mean cognitive absorption
D1g	Mean group cognitive absorption for the first 5 min of each lesson
D2	Flow time transformation dimension
D3	Flow loss of self-consciousness dimension
D4	Flow autotelic experience-well-being dimension
FSS	Flow short scale
Flow_f	Mean EduFlow scale score
HR	Heart rate
HR_f	Mean HR in beats per minute
HRg	Heart rate in bpm for the first 5 min of each lesson
HRV	Heart rate variability
PNS	Parasympathetic nervous system
SD	Heart rate standard deviation
SDg	Heart rate standard deviation for the first 5 min of each lesson
SFPQ	Swedish flow proneness questionnaire
SNS	Sympathetic nervous system
STEAM	Science, technology, engineering, arts, mathematics
zBarriers	Normalized barriers as Z values
zD1g	Normalized D1g as Z values
zHRg	Normalized HRg as Z values

zSDg Normalized SDg as Z values

Acknowledgements

The authors would like to thank Natalio Rivas school from Huescar students, and their legal guardians for their collaboration. Special thanks to UNIR administrative staff for their support during the research process.

Author contributions

David Antonio Rosas conceptualized the study, conducted the experiments, collected the data, and performed the statistical analysis. Natalia Padilla-Zea and Daniel Burgos provided guidance and supervision throughout the research process, contributed to the interpretation of the results, and to the writing and reviewing of the manuscript. All authors read and approved the final manuscript.

Funding

This research and the APC were funded by the Research Institute for Innovation & Technology in Education (UNIR iTED) at the Universidad Internacional de La Rioja (UNIR), ref: PR-2020-03.

Data availability

Data supporting the findings of this study will be made available upon reasonable request, except for data containing personal or sensitive physiological information, which are subject to confidentiality and privacy protections.

Declarations

Ethics approval and consent to participate

This study adheres to the Declaration of Helsinki and complies with the Spanish Organic Law 3/2018 on Personal Data Protection. Ethical approval was obtained from the UNIR Ethical Committee (approval code PI 015/2022). Additionally, the Juvenile Prosecutor's Office of Granada, Spain, was notified about the study's characteristics, purposes, and data collection methods. Legal guardians of participants were thoroughly informed about the research, and informed consent was obtained before participation. Participants were made aware, both orally and in writing, that they could withdraw from the study at any time without providing a reason and without facing any negative consequences.

Consent for publication

This manuscript does not contain any individual person's data in any form (including individual details, images, or videos). Therefore, consent for publication is not applicable. Competing Interests The authors declare that they have no competing interests, either financial or non-financial, related to this study. Funding This research was supported by the Research Institute for Innovation & Technology in Education of UNIR (UNIR iTED) by funding the research and the APC and by a scholarship from the Doctoral School of UNIR. The funding body had no role in the design of the study, data collection, analysis, interpretation of results, or writing of the manuscript.

Conflicts of interest

The authors declare no conflict of interest.

Received: 9 December 2024 Accepted: 4 February 2025

Published online: 05 March 2025

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