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Abstract

This paper focuses on the physiological identification of Clutch-Flow states in real-world educational scenarios. By using the Eduflow scale and Polar H10 wearable devices, we develop two STEAM face-to-face project-base teaching-learning experiences with students in 5th and 6th grade of primary education. Based on Heart Rate Variation (HRV) recorded for 18 one-hour sessions and their comparison to responses obtained in 181 EduFlow questionaries filled in by students after each session, a Kubios-based analysis was performed, obtaining a total of 127 reports about HVR. The main findings of this study reveal multiple and meaningful correlations between physiological data and the flow phenomenology in group of students; and a proposal to identify clutch states based on the EduFlow scale results.

Introduction

The study of optimal learning experiences, particularly through Flow Theory (Csikszentmihalyi, 1975), has garnered considerable attention in educational contexts (Csikszentmihalyi, 2014). Flow, described as a state of deep engagement and satisfaction that arises when challenge and skill are balanced, plays a pivotal role in fostering intrinsic motivation and learner well-being (Heutte, 2021). This engagement occurs without expecting a tangible reward, but the well-being of the same task (Csikszentmihalyi, 1975). The most commonly mentioned dimensions involved in the flow state are concentration, loss of self-consciousness, and loss of sense of time (Peifer et al., 2021), although 39 dimensions describing the phenomenology have been identified (Rosas, Padilla-Zea & Burgos, 2023).Grounded in the principles of positive psychology, Flow Theory addressed research on how technology can support not only learning outcomes but also the flourishing of students in educational environments (Seligman & Csikszentmihalyi, 2000; Heutte, 2020). Specifically, the concept of "positive technologies" has emerged, emphasizing the use of digital tools and environments that support emotional well-being, social connection, and cognitive engagement (Riva et al., 2012).

In educational settings, technology-enhanced environments offer unique opportunities to create conditions that support flow states, enhancing motivation, emotional resilience, and sustained focus (Heutte, 2019; Riva et al., 2012). This is especially relevant in project-based and STEAM (Science, Technology, Engineering, Arts, and Mathematics) education, where complex, interdisciplinary tasks require students to engage deeply and adaptively with their learning material (Daugherty, 2013). Positive computing and positive technology frameworks advocate for tools that can foster such states by aligning instructional design with the principles of positive psychology, aiming to build not only knowledge but also psychological strengths within learners (Calvo & Peters, 2014; Heutte et al., 2022). As a consequence, STEAM methodology has been studied in Flow Theory (Andersen, 2016).

The EduFlow-1 scale, developed by Heutte et al. (2014, 2016a), provide a validated approach to measuring flow in educational contexts, allowing researchers to assess 4 flow dimensions: cognitive absorption (D1), transformation of time (D2), loss of self-consciousness (D3), and autotelic experience-well-being (D4). This scale has shown efficacy across varied learning environments, including face-to-face and e-learning platforms, and serves as a bridge between self-reported experiences and empirical measures of engagement (Heutte et al., 2016a). Later, Heutte et al. (2016b, 2021) proposed an evolution of the EduFlow-1 model (EduFlow-2), suggesting that D1 dimension (cognitive absorption) must be referred to as cognitive control.

However, limited research exists on the physiological correlates of flow in group educational settings, particularly in the intersection of flow and "clutch" states— a term used to describe high-engagement experiences that are effortful and performance-driven, as opposed to the effortless engagement (Csikszentmihalyi, 1975; Moneta, 2021), typical of traditional flow states (Swann et al., 2022). Although Swann et al. (2022) validated a scale in English to differentiate Flow-Clutch states in sports and exercise for individuals, we here consider the use of the EduFlow-1 scale, more suitable for educational real-word contexts, to elaborate an alternative definition of the clutch states, also contributing to the need of clarifying the behavior of flow in groups (Zumeta et al., 2016). Actually, among 34 statistically validated scales identified by Rosas, Padilla-Zea & Burgos (2023), the EduFlow-1 scale is effective for evaluating students' flow in both e-Learning and face-to-face environments (Heutte et al., 2016a), which widen the possibilities of its application in different educational contexts.

Basides, physiological techniques in Flow Theory are rare (Kotler et al., 2022), and lab settings often lack real-world authenticity in Flow Theory (Rosas et al., 2022; Rosas et al., 2025; Heutte et al., 2021a) some attempts have been developed (Knierim et al., 2018). There is great heterogeneity of physiological techniques, both in its foundations, instruments, parameters extracted and in the way in which they are combined (Khoshnoud et al., 2020). Several techniques have been identified to identify flow (see (Knierim et al., 2018), (Khoshnoud et al., 2020)), such as heart rate (HR) and its variability (HRV). Nevertheless, wearable devices increasingly measure Heart Rate Variability (HRV) accurately in real-world settings (Speer et al., 2020; Naranjo, et al., 2015), becoming them into gold-pattern to be used in this study and addressing potential issues with relying solely on questionnaires (Gilgen-Ammann, Schweizer & Wyss, 2019).

This paper explores the physiological basis of flow and clutch states within real-world, project-based STEAM learning activities, utilizing the EduFlow-1 scale alongside Heart Rate Variability (HRV) measures obtained through wearable Polar H10 devices. Through this dual approach, we aim to validate EduFlow-1 from a physiological perspective and clarify the nuanced interplay between flow and clutch states within group learning contexts. Our work builds on Heutte´s integration of positive psychology and educational technology by examining how such tools and frameworks can optimize student engagement and well-being in active, technology-enhanced classrooms.

Our research questions are:

(RQ1) Are there coherent statistically significant correlations between group measures of HRV parameters and the EduFlow-1 scale and its dimensions, for in-person groups of primary school students?

(RQ2) Are there recalled flow states as measured by flow questionnaires compatible with physiological clutch states phenomenology?

The rest of the paper is structured as follows: Section 2 introduces general concepts on Heart Rate Variability (HRV), Section 3 presents the methods, Section 4 discusses the results, with an emphasis on the physiological validation of the EduFlow-1, Section 5 provides a discussion of the results, and finally, Section 6 concludes the paper.

The Heart Rate Variability (HRV)

This section highlights the devices used and tools developed in this research. We just include here the most basic information to justify what we measure and what it means.The human heart is an extremely complex organ, located on the left side of the rib cage, with a size similar to that of a fist. Anatomically, it is divided into 4 chambers of different sizes (2 atria and 2 ventricles) that contract (systole) and recover (diastole) cyclically, pumping blood through the veins and arteries.

Likewise, the heart has its own pacemaker, represented by the sinoatrial and atrioventricular nodes but, in turn, the cardiovascular center of the brain is capable of modifying its cadence through the Autonomous Nervous System, balancing the flow coming from the Sympathetic and Parasympathetic systems (Shaffer & Venner, 2013). In very general and simplified terms, the Sympathetic Nervous System accelerates the heart rate, while the Parasympathetic Nervous System relaxes it and allows its recovery (Saturno Chiu, 2017; Shaffer, McCraty & Zerr, 2014).

It should also be noted that the intrinsic nervous system of the heart has its own neurons and short and long-term memory functions (Verkerk et al., 2012) that can influence cardiac pressure, rhythm and cadence, associated with hormonal factors (Shaffer, McCraty, & Zerr, 2014). The functioning of the heart has a close connection with breathing, the limbic system and the frontal cortex (Shaffer, McCraty, & Zerr, 2014; Torres et al., 2015; McCraty & Shaffer, 2015) and, therefore, with the cognitive processes [34], primitive emotions, long-term memory processes, complex emotions (Torres et al., 2015), attention and motivation (Schandry & Montoya, 1996). Moreover, the intervals between cardiac pulses suffer variations due to breathing, baroreflexes and environmental factors (Kleiger, Stein & Bigger, 2005).

Furthermore, when we listen to normal heart sounds, we hear two beats with different cadences that are generated by the opening and closing of the heart valves (e.g. McCraty & Shaffer, 2015). By recording heart sounds over time, we obtain phonocardiograms, where these two highest intensities sounds approximately coincide with the maximum electrical potentials of the electrocardiographic wave (Wiggers, 1923; Mitchell & Wang, 2014), which we can measure with devices and, with this, establish the times that elapse between cardiac pulses in milliseconds. Likewise, aortic, ventricular and atrial pressure, as well as ventricular volume fluctuate as the heartbeats occur

(Wiggers, 1923; Mitchell & Wang, 2014). Additionally, the normal cardiac function is possible thanks to the production of a series of cyclic electrical potentials that, when recorded graphically over time, gives rise to an electrocardiogram.

The above is summarized in Figure 1, composing a Wiggers diagram (1923), where we are especially interested in the normal pattern that is repeated in an electrocardiogram, which presents peaks and valleys, which are named as P, Q, R, S and T waves. In this present study, we measure the intervals in milliseconds between consecutive P waves, which is a measure of heart rate variability (e.g. Shaffer & Ginsberg, 2017). Also, because in a healthy heart, the existence of abnormal pulses is possible, it is necessary to filter the signal before extracting some cardiac parameters, which are studied from the temporal and frequency domains and through non-linear techniques (e.g. Shaffer & Ginsberg, 2017; Shaffer, McCraty & Zerr, 2014).

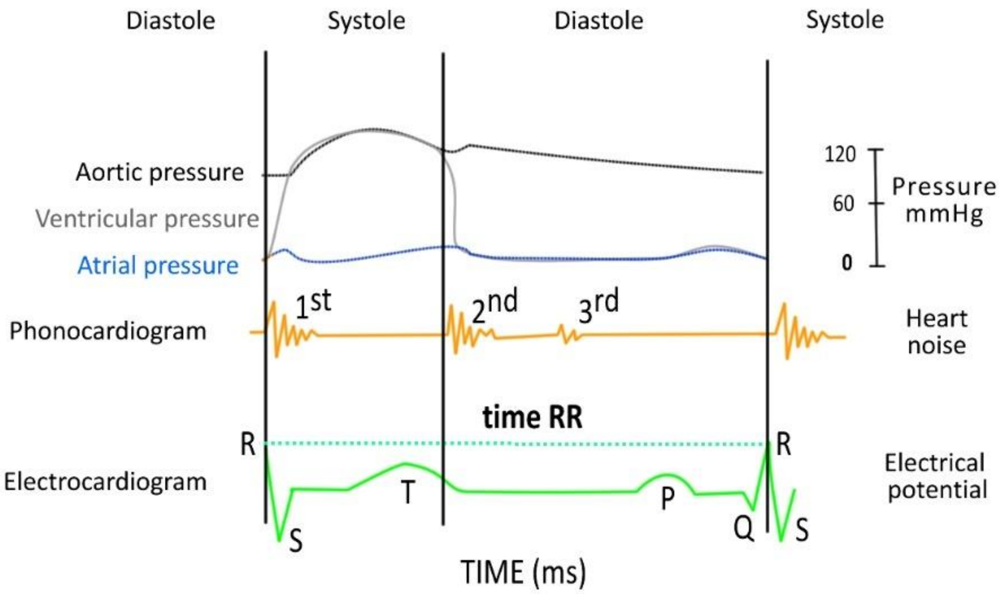

Figure 1. Wiggers Diagram. Simplification of Mitchell & Wang (2014)

Methodology

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. Of course, legal tutors were properly informed and informed consent for participation was mandatory. No reward was provided for any participant. Data was anonymized and we use mean values in this work.

Research Design

This research used a quasi-experimental design with mixed methods (Sampieri, 2018) and two experimental groups by means of research-action (Stenhouse, 1984).

Instruments

We chose the EduFlow questionnaire, which students and the teacher completed on paper after each 60-minute lesson. This survey has been validated and is suitable for evaluating the presence of flow in technology-mediated project-based learning (Heutte et al., 2014; 2016a). EduFlow-1 has 16 items, divided equally in 4 dimensions (D1-cognitive control, D2-time transformation, D3-loss of self-consciousness, D4-autotelic experience-well-being). Every item must be answered with a 7-point Likert scale, in an ascending degree of agreement (Annex I). Students also completed the Swedish Flow Proneness Questionnaire (Ullén et al., 2012), which indicated that all participants were capable of experiencing flow, as reflected in their responses on a 5-point Likert scale (Annex II). Additionally, we utilized TicWris Max watches as data loggers and Polar H10 sports bands, both recognized as gold standards in wearable electrocardiology (Gilgen-Ammann et al., 2019), and suitable for research involving children (Speer et al., 2020). We developed an application in Kotlin (see Jemerov & Isakova, 2018) using Android Studio (Bumblebee v.2021.1.1) to access the watch's accelerometer, interactive screen buttons, and SD card. Through Bluetooth and the Polar SDK v. 3.3.6 library (Oikarinen et al., 2016), the application also collected electrocardiological data from the sports band. We refer to these Kotlin applications as "Polar H10 SDK UNIR-iTED," giving appropriate credit to the library's developers. Figure 1 shows the set composed of the sports band and the smart watch.

Figure 2. Application Running in a Smartwatch and HRV Wearable Sensor

The application was installed on each device to connect exclusively to a specific Polar H10 band via Bluetooth. The Polar H10 bands recorded cardiac data at a frequency of 1 Hz in smartwatches’ SD cards. Next, we used Kubios software (Tarvainen et al., 2014, 2021) to filter and detrend the signal and remove artifacts like extra, missing, or unaligned beats that distort HRV measurements (Shaffer & Ginsberg, 2017; Seppälä et al., 2014; Shaffer, McCraty & Zerr, 2014). Kubios allowed us to extract multiple cardiac parameters in CSV format, dividing records into time segments and generating reports. To ensure comparability, we configured Kubios to divide each participant's recordings into 5-minute segments, in line with the electrocardiological standard for children (Seppälä et al., 2014). The calculated cardiac parameters for each participant and session were exported in 5-minute batches in CSV files for analysis with Excel, SPSS, or Python, depending on the required analysis. Moreover, two parameters evaluate SNS and PNS activity.

For our teaching content, we created learning designs following the STEAM methodology: educational artistic robotics for 6th grade and 2D/3D graphical design for 5th grade. We followed the Theory of Elaboration (Reigeluth & Stein, 1983), developing educational content in a growing spiral of deepening levels around thematic axes. The difficulty level of each activity was evaluated using Bloom's taxonomy for the digital age (Churches, 2009), which classifies activities into three levels with three sublevels each, ranging from lower to higher thinking skills (Bloom, 1990). Each elaboration level was turned into instructional modules in SCORM format (ADL, 2009), considering that students are in the concrete operations stage (Piaget & Inhelder, 2016). These SCORM modules were integrated into a specially designed web application, which recorded every second (1 Hz) in a MySQL database the activity shown to students on the classroom projector, its Bloom’s taxonomy classification, the time in Universal Unix format, and the teacher's actions (e.g., passing pages, explaining, answering questions).

Participants

This study took place at the public primary school CEIP Natalio Rivas in Huéscar, Granada, Spain, involving 5th and 6th grade students aged 11 and 12. Students were excluded if they lacked signed informed consent, were repeating the grade, had high absenteeism, temporary or declared cardio-respiratory conditions, or diagnosed difficulties in understanding the questionnaires. The research-action cycle was conducted with two groups, whose characteristics are detailed in Table 1.

Table 1 Sample Characteristics of the Groups

Group	N	Boys	Girls	Average Age	SD
E1	14	7	7	10.80	0.44
E2	14	8	6	11.82	0.31

Experimental Procedure

The research was conducted during the academic year 2021/2022. Each group attended 9 lessons, conducted twice weekly for one hour before break time, in the ICT classroom using individual laptops and mice. Participants, who had received prior training, wore sports bands privately in the locker room, as the app verified correct usage of the bands, hence, HRV data were discard in case of incorrect wearing. No physical activities were scheduled prior to the lessons, and participants rested for 10 minutes beforehand. The teacher also completed a class diary with personal impressions. The EduFlow questionnaire was translated into Spanish by two bilingual psychologists. These translations underwent review by interpreters from the Official Languages School and were returned to the psychologists for final adjustments. Participants completed the questionnaire in its final form using pencil and paper at the conclusion of each teaching session, under the supervision of a trained researcher and a schoolteacher. The initial session served as a practice for using the devices and familiarizing students with the classroom structure, and for introducing the teacher to the groups and teaching safe technology practices. The instructional design spanned 9 sessions; however, for accuracy, data analysis only encompassed sessions 2 to 9 for both experimental groups.

Results

Summarized Statistical Validation of the Spanish Translation of the EduFlow Scale

To validate the Spanish-translated EduFlow scale statistically, questionnaires were completed at the conclusion of each of the 18 sessions conducted with both experimental groups. A total of 218 questionnaires were filled out. After excluding incomplete or incorrect submissions, 181 questionnaires remained for analysis (83% valid responses). SPSS software was used for the analysis.The Kolmogorov-Smirnov test revealed a non-normal distribution (D(190) = 0.129, p = .0001). Additionally, the internal consistency, measured by Cronbach's alpha coefficient (alpha = .824, n = 12), did not improve upon removing any of the items in the questionnaires (see Cronbach, 1951).

4.2 Physiological Validation of the EduFlow Scale in Groups

The physiological validation was conducted using group mean values to ensure data anonymity. Following international cardiological standards (Shaffer, McCraty & Zerr, 2014; Seppälä et al., 2014), each lesson was segmented into 5-minute intervals to assess HRV parameters, adhering to a maximum lesson duration of 1 hour. Table 2 summarizes the initial 5 minutes of all lessons, regardless of group or activity, and provides a summary of the Annex III. It identifies statistically significant Spearman correlations (Spearman, 1904) between each mean HRV parameter, extracted using Kubios (see Tarvainen et al., 2021), and the dimensions of the EduFlow scale. The scale's dimensions were categorized as follows: D1 - cognitive control, D2 - time transformation, D3 - loss of self-consciousness, D4 - autotelic experience-well-being, and overall EduFlow (Sum of Scale). We observed positive correlations between HRV parameters associated with sympathetic nervous system (SNS) activity and D1, D2, and D3. However, parameters linked with parasympathetic nervous system (PNS) activity showed negative correlations. Conversely, D4 exhibited opposite correlations. Because of this, we indicate in the column "Sign/Activity" if there is or not physiological coherence within each dimension of the EduFlow scale and the corresponding HRV parameters, where correlation sign were identified and matches (yes/no). Instances where correlations did not clearly align with either sympathetic or parasympathetic activity were marked as (N/A).

Table 2 Relation among HRV Parameters and EduFlow Scale

EDUFLOW SCALE X HRV						
	DATA				COHERENCE	
VARIABLE CODE (TARVAINEN ET AL., 2021)	Sign	Spearman coef. without sign	Alpha	Activity	Sign/ Activity	Sign / EduFlow dimensions
SNSINDEX	-	0.185	0.05	SNS	Yes	D1, D2
MEANRRMS	+	0.238	0.01	SNP	yes	D1, D2
MEANHRBPM	-	0.238	0.01	SNS	yes	D1, EduFlow
MINHRBPM	-	0.262	0.01	SNS	yes	D1, D2
MAXHRBPM	-	0.247	0.01	SNS	yes	D1, D2, D3
VLFPOW_FFTMS2	+	0.221	0.05	T-H	N/A	D1
VLFPOWFFTIOG	+	0.187	0.05	T-H	N/A	D1
HFPEAKARHZ	+	0.174	0.05	SNP	yes	D3
D2	+	0.187	0.05	SNP	yes	D2

D1 X HRV						
	DATA				COHERENCE	
VARIABLE CODE	Sign	Spearman coef. without sign	Alpha	Activity	Sign/ Activity	Sign / EduFlow dimensions
PNSINDEX	+	0.258	0.01	SNP	yes	Only case
SNSINDEX	-	0.291	0.01	SNS	yes	D2, EduFlow
STRESSINDEX	-	0.273	0.01	SNS	yes	Only case
MEANRRMS	+	0.298	0.01	SNP	yes	D2, EduFow
SDNNMS	+	0.249	0.01	SNP	yes	Only case
MEANHRBPM	-	0.298	0.01	SNS	yes	D4, EduFlow
MINHRBPM	-	0.319	0.01	SNS	yes	D2, EduFlow
MAXHRBPM	-	0.271	0.01	SNS	yes	D2, D3, EduFlow
RMSSDMS	+	0.225	0.05	SNP	yes	Only case
NNXXBEATS	+	0.227	0.05	SNP	yes	Only case
PNNXX	+	0.25	0.01	SNP	yes	Only case
HRVTRIANGULARINDEX	+	0.247	0.01	SNP	yes	Only case
TINNSMS	+	0.253	0.01	SNP	yes	Only case
DCMODMS	+	0.21	0.05	SNP	yes	Only case
ACMODMS	-	0.217	0.05	SNS	yes	Only case
VLFPOW_FFTMS2	+	0.265	0.01	T-H	yes	EduFlow
LFPOW_FFTMS2	+	0.236	0.01	P	yes	Only case
VLFPOWFFTIOG	+	0.247	0.01	TH	N/A	EduFlow
LFPOWFFTLOG	+	0.227	0.01	SNP	yes	Only case
TOTPOWFFTMS2	+	0.222	0.05	SNP	yes	Only case
VLFPOW_ARMS	+	0.297	0.01	T-H	N/A	Only case
LFPOWARMS	+	0.28	0.01	SNP	yes	Only case
VLFPOWARLOG	+	0.308	0.01	T-H	N/A	Only case
LFPOWARLOG	+	0.289	0.01	SNP	yes	Only case
TOTPOWARMS2	+	0.246	0.01	SNP	yes	Only case
RESPHZ	+	0.209	0.05	R	yes	D2
SD1MS	+	0.224	0.05	SNP	yes	Only case
SD2MS	+	*0.251*	*0.01*	*SNS*	*NO*	*Only case*

D3 X HRV						
	DATA				COHERENCE	
VARIABLE CODE	Sign	Spearman coef. without sign	Alpha	Activity	Sign/ Activity	Sign / EduFlow dimensions
MAXHRBPM	-	0.180	0.05	SNS	yes	D1, D2, Eduflow

HFPEAKARZ	+	0.227	0.01	SNP	yes	EduFlow

D2 X HRV

	DATA				COHERENCE	
VARIABLE CODE	Sign	Spearman coef. without sign	Alpha	Activity	Sign/ Activity	Sign / EduFlow dimensions
SNSINDEX	-	0.179	0.05	SNS	yes	D1, EduFlow
MEANRRMS	+	0.231	0.01	SNP	yes	D1, EduFlow
MINHRBPM	-	0.229	0.01	SNS	yes	D1, EduFlow
MAXHRBPM	-	0.259	0.01	SNS	yes	D1, D3, EduFlow
RESPHZ	+	0.215	0.05	R	yes	D1
D2	+	0.238	0.01	SNP	yes	EduFlow
DFA2	-	0.184	0.05	SNS	yes	Only case

D4 X HRV

	DATA				COHERENCE	
VARIABLE CODE	Sign	Spearman coef. without sign	Alpha	Activity	Sign/ Activity	Sign / EduFlow dimensions
SDHRBPM	-	0.307	0.01	SNP	yes*	Only case
HFPWFFTLOG	-	0.185	0.05	SNP	yes*	Only case
VLFPOWFFT	+	0.243	0.01	T-H	N/A	Only case
LF_HFRATIOFFT	+	0.179	0.05	SNS/SNP	yes*	Only case
HFPOW_ARLOG	-	0.196	0.05	SNP	yes*	Only case
LFPOW_AR	+	0.178	0.05	SNP	yes*	Only case
HFPOW_ARN.U	-	0.175	0.05	SNP	yes*	Only case
LF_HF_RATIO_AR	+	0.216	0.05	SNS/SNP	yes*	Only case

*THERE WOULD BE NO COHERENCE IF WE CONSIDER AS A SIGN CRITERION THOSE IN EDUFLOW, D1, D2 AND D3, BUT THERE WOULD BE INTRADIMENSIONAL

Moreover, due to its length, Annex IV includes a table illustrating Spearman correlations between mean HRV parameters and the scale, categorized by dimensions, for the initial 5-minute learning segment. This analysis separates participants into thematic groups (E1 and E2). Significant correlations are highlighted in blue for $\propto<$ 0.01 and in orange for $\propto<$ 0.05, while non-significant correlations are shown in white. This method generates color-coded tables that facilitate a clear visual assessment of both the quantity and significance of correlations identified. It aims to elucidate the influence of group and thematic factors, such as those related to robotics or graphic design courses.

In Annex V, similar color-coded tables present correlation data between mean HRV parameters and EduFlow scales across individual sessions (eight for the E1 group and eight for the E2 group), for the initial 5 minutes span

(S1). We maintain consistent terminology for the parameters correlated, as seen in Table 1. This approach allows us to evaluate how specific tasks and participant groups impact the strength of the Spearman correlations observed.

In Table 3 (students) and Table 4 (teacher), we include Spearman's correlations considering all valid responses for each participant in every lesson. These tables use cognitive control (D1) as the reference. They also show the EduFlow scale score and its dimensions, extracted from questionnaires completed at the end of each lesson. PNS activation (-4 to +4) and SNS activation (-4 to +4) were extracted from Kubios software reports, as an average value for the session, according to Tarvainen et al. (2014, 2021). Additionally, AVG represents the average energy expenditure, while MIN and MAX are the minimum and maximum energy expenditure in the session, as calculated by Kubios software following Keytel et al. (2005). No height, weight, or age measurements were gathered, as anonymizing the data would not make sense; thus, we considered a normotypical 10-year-old female person.

Table 3. Spearman's Correlation with the Flow Scale and Theoretical Energy Expenditure (Students)

		D2	D3	D4	EduFlow	PNS	SNS	AVG	MIN	MAX
D1	rs	.417**	.375**	.471**	.705**	.280**	-.321**	-.287**	-.290**	-.271**
	Sig	<.001	<.001	<.001	<.001	.001	<.001	.001	<.001	.002
	n=127									

Table 4. Spearman's Correlations with the Flow Scale and Theoretical Energy Expenditure (Teacher)

		D2	D3	D4	EduFlow	PNS	SNS	AVG	MIN	MAX
D1	rs	.388	.111	.363	.486	.404	-.459	-.227	-.439	-.225
	Sig.	.137	.682	.168	.056	.135	.085	.417	.102	.421
	n=16									

Note that Table 4 pertains to the teacher's measurements, which cover 16 sessions, with data collected from the first 5 minutes of each lecture. Next, in Figure 3, we show a three-dimensional plot of Z-normalized variables PNS, PNP, and D1 for the teacher and the students.

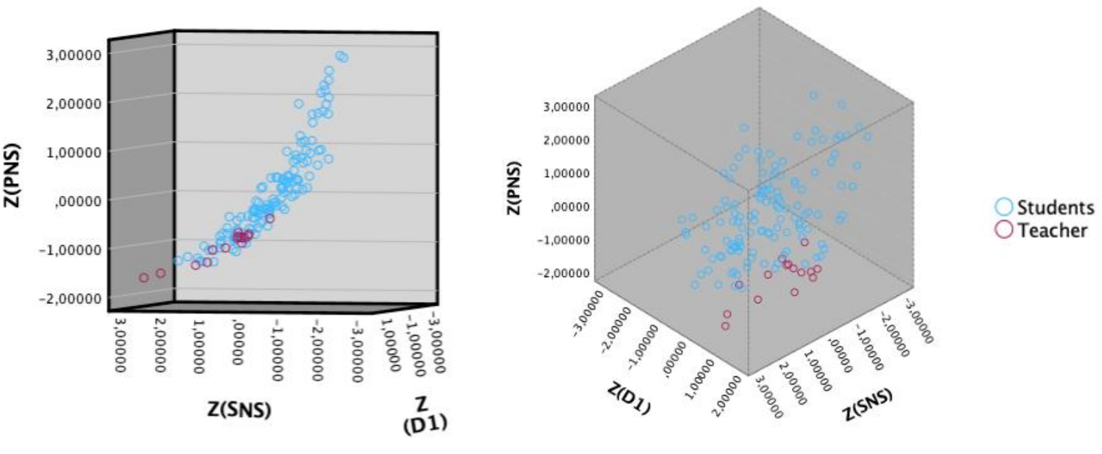

Figure 3. Three-Dimensional Plot of Z-Normalised Variables SNS, PNS, and D1 for Teacher and Students

Discussion

While the EduFlow scale is already validated statistically in other languages, its validation in Spanish was essential for our research purposes. Following the translation of the scale, a preliminary statistical validation was conducted. The standard-item based ∝-Cronbach value (alpha = .824, n= 12) was slightly above 0.80, indicating strong internal consistency Cronbach, 1951).

Regarding RQ1 (Are there coherent statistically significant correlations between measures of group heart rate variability and the EduFlow scale and its dimensions among in-person groups of primary school students?), we identified numerous statistically significant correlations for the EduFlow scale across different group analyses (refer to Annexes III, IV, and V). Upon closer examination, each dimension of the EduFlow scale displayed one or more significant correlations with HRV parameters after 5 minutes of each lesson, which may indicate a physiological validity of the scale and dimensions. Initially observed as weak when considering all groups together (as shown in Table 2), these correlations strengthened when groups were analyzed separately (as seen in Annex IV) and became pronounced when individual lectures were examined (Annex V). This pattern suggests that group composition, thematic content, and task nature influence the flow state significantly, because the correlation coefficient increases as decreases contextual factors (see Cohen, 2013).

Furthermore, consistent coherence in the direction of correlations between HRV parameters and the scale's dimensions is evident, considering SNS or PNS activity, as depicted in Table 2. This consistency may indicate stable and physiologically meaningful correlations.Next, Table 2 highlights that the EduFlow scale and its dimensions exhibit 54 significant correlations with HRV parameters, with 32 of these correlations achieving a significance level below 0.01.

Considering RQ2, we start by discussing Table 3. Weak but significant correlations (sig. <0.01) are demonstrated among D1, D2, EduFlow, SNS, PNS, AVG, MIN, and MAX, where students are considered. These may suggest an influence of groups and activities on Spearman's Rho coefficients. However, a coherence in sign is observed among D1, SNS (+), and PNS (-), as well as a positive correlation with energy expenditure parameters (AVG, MIN, and MAX).Moreover, no significant correlations were found among cognitive control (D1) and the EduFlow scale or its other three dimensions, nor with HRV parameters or energy expenditure for the teacher (Table 4), which may indicate an invariant situation for the psychological state of the lecturer, in opposition to the variability shown by the students. Additionally, the teacher always demonstrated high concentration in demanding tasks (teaching and researching at the same time). He also reported a prevailing feeling of stress in every session in the class diary. The combination of flow recall, cognitive control, and physiological activation may show key characteristics of clutch states, as defined by Swann et al. (2021).

Experimental points in Figure 2 describe a parabolic surface, where the teacher's points occupy the lower-right zone (Figure 2-right). This corresponds with high SNS activation, very low PNS activation, and high cognitive control, in contrast with the more dispersedly distributed experimental points for students. Because the teacher's experimental points are clustered in a small area of the curved surface, it may justify why no significant correlations were observed in Table 4. Conversely, this area is prone to Clutch states.On the other hand, most experimental points belonging to students' responses cover a wider area of the curved plane in Figure 2. This zone may be prone to flow rather than clutch states. This is due to the greater spread of the experimental points compared to the teacher's (in an invariant clutch state) and the more variable psychological states recalled by pupils. However, the prevalence of flow for pupils also varies in degree when the SNS and PNS parameters change, since cognitive control (D1) changes as well. In lines 233 and 250 of Annex V, corresponding to group E2, a very strong correlation is observed between "Loss of self-consciousness" (FlowD3) and up to 25 different HRV parameters (e.g., $rs = -.932$, $p < .001$ between D3 and MeanRR). Such strong and frequent correlations are not present in other sessions or groups. Notably, D3 is associated with social interaction (Heutte et al., 2021b), which aligns with the context in which students were working on free, collaborative robotics projects in small groups.

Conclusions, Limitations and Future Research Work

This study undertakes the physiological validation of the EduFlow scale in student groups through a research-action process at a primary school in Granada, Spain.Following the statistical validation of the scale, we proceeded with group validation, revealing a clear cardiologic correlation among groups using the EduFlow scale in response to RQ1.Key contributions of this study include an objective examination of Flow Theory beyond post-experience assessments. We enhance precision in studying this intricate, non-linear, and dynamic phenomenon in real-world settings, moving beyond laboratory experiments with limited samples and time constraints. Additionally, we validate the EduFlow scale from a physiological perspective for groups of individuals. Regarding RQ2, we found a parabolic surface describing the relationships among SNS activation, PNS activation, and cognitive absorptment (D1), where clutch states are prone when $zPNS<0$, $zSNS>0$, and $zD1>0$. Addressing criticisms raised by Swann et al. (2018), which advocate for a paradigm shift due to similar states to flow (e.g., clutch), conceptual ambiguities, and methodological inaccuracies, we acknowledge the need for further research. Nevertheless, we underscore the profound insights gained from flow phenomenology, coupled with advances in its conceptualization and methodological refinement as demonstrated by Kotler et al. (2022) and others.

This work also acknowledges its limitations. For instance, our methodology exclusively employs STEAM, recognizing the existence of other methodologies. Temporally, while our study duration and session count exceed those of comparable works, further extension could enhance insights. Cardiological standards restrict our analyses to 5-minute intervals, and the complexity of tasks limits our sample size. Cultural biases may exist despite flow experiences being culturally universal. Participant age introduces biases related to developmental stages. We conducted our study in a well-equipped environment conducive to these findings, which may not be universally applicable. Participant selection relied consistently on a teacher-researcher with substantial professional experience. Equipment limitations due to budget constraints necessitated devices with limited computational power, influencing data recording and analysis costs. Future research will explore leveraging this information to predict student behavior when monitored for their flow experiences. Moreover, the very strong correlations observed between D3 and many HRV parameters in collaborative groups need further research into flow in group settings.

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Annexes

Annex I : https://acortar.link/EBpNK8
Annex II : https://acortar.link/3NvxmY
Annex III : https://acortar.link/2BdIt3
Annex IV : https://acortar.link/DdMIG1
Annex V : https://acortar.link/TfqdW1

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