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Studying the Flow Experience in Computer-Supported Collaborative Learning: A Study with PyramidApp

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Abstract

Computer-Supported Collaborative Learning (CSCL) is recognized as an effective methodology for fostering social interaction mediated by technology in ways that potentially trigger learning. The successful implementation of CSCL hinges on factors such as the scripting mechanics for activity sequencing proposed by Collaborative Learning Flow Patterns (CLFP). Yet, research in CSCL scripts has not studied if CLFPs achieves the so-called notion of "flow experience," defined as an optimal state in which individuals are engaged and absorbed in an activity. This study proposes an approach to measure flow in the case of the Pyramid CLFP and studies the factors that influence the flow experience in the PyramidApp tool. The study tests a model that uses analysis of the Flow Short Scale and data logs. The findings show that there is a relationship between factors such as the speed of individual contributions and active participation in groups with the flow experience. Notably, the quantity of participation does not exhibit a discernible impact on the flow. The study emphasizes the interest of the modelled factors and the proposed approach for learning analytics to understand the flow experience in CLFP implementations.

Notes for Practice

- Our study examines the factors that influence students' flow experience (or deep engagement) during collaborative learning activities, specifically in the Pyramid CLFP. Using a backwards stepwise regression model, it identifies efficient individual contributions (submission speed), effective peer review processes (rating speed), and high-quality group discussion as key factors that significantly enhance the flow experience.
- The study finds that the quantity of participation, as indicated by the number of characters in a collaborative editor, does not have a significant impact on the flow experience. This confirms the expectation that the quality of participation is more crucial in facilitating flow experiences in collaborative learning activities.
- The findings of this study contribute both to the practical aspects of designing engaging collaborative learning activities and to the theoretical understanding of the flow experience in educational contexts. The results emphasize specific factors that could be promoted or should be monitored towards more immersive and satisfying learning experiences. As expected, rich social interaction leads to flow while quantity in participation does not. Interestingly, speed in individual submissions, but not speed in peer review submissions, is shown to be an indicator of flow.

Keywords: Flow experience, collaborative learning, pyramid collaborative learning flow pattern, learning analytics

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1. Introduction

The incorporation of educational methodologies into digital environments has highlighted collaborative learning as a tool for achieving meaningful learning. Recognized for its effectiveness in fostering discussion and participation, collaborative online learning has proved its ability to facilitate learning experiences, surpassing the traditional classroom discussion and empowering students to own their learning (Barkley et al., 2014; Scager et al., 2016; Theophilou et al., 2024). Notably, the importance of collaborative online learning is underscored by its ability to promote active engagement and knowledge creation (Qureshi et al., 2023). However, the successful implementation of collaborative online activities relies on factors such as those influencing the activity's flow patterns (Amarasinghe et al., 2021; Patel et al., 2012).

The concept of the flow experience, as introduced by Csikszentmihalyi (1990), refers to an individual's perceived state of optimal experience, in which learners are deeply engaged and absorbed in an activity. This notion of flow holds significant relevance within collaborative online learning environments, as it has been recognized to enhance learning outcomes (Buil et al., 2019), increase motivation (Boudreau et al., 2020), and improve overall satisfaction (Lee et al., 2019).

It is crucial to distinguish between this psychological concept of flow and another usage of the term in the context of collaborative learning: the "flow" in Collaborative Learning Flow Patterns (CLFPs). While Csikszentmihalyi's flow refers to a learner's subjective state of optimal engagement, in CLFPs, "flow" denotes a structured sequence or pattern of collaborative learning activities. CLFPs are designed to orchestrate these activities in a way that potentially fosters effective collaboration and social interaction mediated by technology (Hernández-Leo et al., 2005a).

As technology continues to evolve, shaping learner motivation, researchers are increasingly exploring strategies that promote psychological flow experiences to enhance online learning environments (Gao et al., 2019; Doğan et al., 2022). Yet, it is critical to understand that this experiential flow is a complex construct, interacting dynamically with various aspects of the learning environment, including the structured activity sequences in CLFPs. Although CLFPs are not designed to directly target an individual's psychological flow state, the way they organize activities (their structured flow) can significantly impact the factors that either facilitate or impede learners in achieving these states of optimal engagement. Among various CLFPs in online learning, the Pyramid pattern stands out for fostering active learning, knowledge construction, and problem-solving skills. Its multilayered collaborative structure encourages a hierarchical exchange of ideas, with each layer building upon the insights of the previous one, facilitating a comprehensive exploration of the subject matter (Hernández-Leo et al., 2005b). The pyramid pattern shares similarities with certain game mechanics as participants advance through progressively more complex levels, gaining deeper understanding and mastery (Lobo-Quintero & Hernández-Leo, 2020). The structure of the pyramid pattern provides a scaffolded framework that not only supports the acquisition of domain-specific knowledge but also nurtures critical thinking skills (Kloos & Alario-Hoyos, 2021).

Despite its potential benefits, there is a lack of understanding on how to effectively measure the flow experience within CSCL scripts and CLFPs. Current research has focused on measures using self-reported questionnaires, software logs, interaction traces (i.e., activity heatmaps), and even physiological measures (Choe et al., 2015; de Manzano et al., 2010; Jackson & Marsh, 1996; Jackson & Eklund, 2002). However, there is still a gap in the research regarding the effective measurement of the flow experience within collaborative learning scenarios with scripting mechanics, such as those in the Pyramid CLFP. More specifically, there is a need for research on how to measure the flow experience within this framework to fully understand its impact and effectiveness in collaborative learning environments. Therefore, this paper aims to address this research gap by investigating our main research question:

- RQ1: To what extent are the features of the Pyramid CLFP related to the flow experience?

To answer this question, two sub-research questions need to be answered:

- sRQ1: How can the flow experience be measured in the context of CLFP implementations, such as in PyramidApp?
- sRQ2: Which factors in Pyramid CLFP activities contribute more to a flow experience?

The present study introduces an approach to measure the flow experience in the Pyramid CLFP specifically within the context of the PyramidApp tool (Manathunga & Hernández-Leo, 2018). The PyramidApp tool is a digital platform designed to facilitate and support collaborative learning when structured according to the Pyramid CLFP, which also shares common scripting mechanics with other CLFPs (activity sequence, changing group formation across the sequence of activities, peer review, knowledge building). The platform offers an opportunity to capture the flow experience through its data logs and user interactions, offering learning analytics that help us to understand student performance and actions during collaborative online activities. By incorporating measurements obtained from student experience and data logs, the study tests a model to determine the factors that influence the flow experience in the collaborative online tool PyramidApp.

The structure of this paper is as follows. Section 2 describes the theoretical background of the flow experience, Pyramid CLFP, and existing approaches for measuring flow extracted from the literature. Section 3 describes the methodology of the study, measurements and data analysis. Section 4 presents the results. Finally, the discussion and conclusions are presented in Sections 5 and 6.

2. Background

2.1. The Flow Experience in Education

The concept of flow was introduced to define an "optimal experience," a type of situation wherein individuals achieve an optimal state during a certain activity in which the mind becomes effortlessly focused and engaged (Csikszentmihalyi, 1975). According to Mahnke et al. (2014), absorption and fluency constitute the two principal components of the flow experience. While, absorption entails profound concentration on the task, blocking out irrelevant stimuli and giving rise to various phenomena (i.e., time dissociation, loss of self-reflection, and loss of self-consciousness), fluency is characterized as the sense derived from a smoothly executed action, wherein knowledge of each step leads to continuous activity that, as a whole, appears guided by inner logic (i.e., thoughts and movements occur automatically; Rheinberg, 2008).

While flow experience has primarily been investigated in individual performers (Abuhamdeh, 2020; Sanjamsai & Phukao, 2018), there is a growing interest in studying the quality of flow in social circumstances. Specifically, researchers have shown significant interest in exploring group flow experiences (Sawyer, 2007, 2015; Pels et al., 2018). The shift towards examining flow within social contexts recognizes the dynamic interplay between individuals within a group setting and the potential amplification or attenuation of flow states (Hackert et al., 2023). This evolving emphasis on group flow not only enriches the comprehension of optimal experiences within collaborative environments but also promotes the development of strategies and interventions aimed at fostering positive group learning dynamics.

Sawyer (2007) defines group flow as "an optimal collective experience that occurs when members develop a feeling of mutual trust and empathy, in which individual intentions harmonize with those of the group." According to Van den Hout et al. (2016), group flow creates a state at the group level where all participating team members are entirely immersed in their common activity, working intuitively and synergistically towards a shared goal, thereby increasing team effectiveness, productivity, and performance.

In the educational context, the concept of group flow is characterized by a sense of enjoyment derived from achieving realistic goals and overcoming challenges inherent to the learning process (Csikszentmihalyi & Csikszentmihalyi, 1988; Cesari et al., 2021). Extensive research consistently demonstrates that experiences of flow are closely tied to heightened motivation, improved learning outcomes, and increased satisfaction within educational settings (Engeser & Rheinberg, 2008; Shernoff et al., 2003). This phenomenon holds relevance for engagement and optimal learning experiences across diverse fields, encompassing both formal education and adult learning contexts (Heutte et al., 2021). Furthermore, the theory of flow has found application in gamified learning environments, underscoring its significance in the design of learning experiences and human development (Vann & Tawfik, 2020).

Educators and researchers alike have delved into strategies to promote flow in educational settings, recognizing its role in motivating learners and enriching their educational experiences (Csikszentmihalyi & Larson, 2014). The benefits of attaining a state of flow during the learning process have been explored across various contexts. For example, Hamari et al. (2016) identified a positive correlation between flow and engagement in student learning, particularly in the context of game-based learning. Concurrently, Klein et al. (2010) observed that the experience of flow significantly influences student perceptions of learning and overall satisfaction.

Understanding and applying the concept of group flow is crucial for improving teamwork, creativity, and overall performance in collective efforts. In the context of collaborative learning, incorporating group flow principles fosters a strong sense of unity and shared purpose among participants. When learners experience group flow, the collaborative learning process becomes more efficient and engaging. Identifying and leveraging the elements that contribute to group flow can lead to the design of effective strategies for enhancing collaborative online learning experiences, ultimately resulting in improved outcomes and a more enriching educational environment.

2.2. Assessing the Flow Experience in Pyramid CLFPs

CLFPs are topic-independent structures of potentially effective scripted sequences of learning activities that can be adapted to multiple educational scenarios (Hernández-Leo et al., 2005a). These patterns are designed to facilitate effective collaboration by providing guidance on sequencing learning tasks, defining roles and responsibilities, and supporting group formation (Hernández-Leo et al., 2005a; Dillenbourg & Tchounikine, 2007). CLFPs prestructure collaboration in a manner that promotes productive interactions, enhancing the potential effectiveness of the educational situation (Jermann et al., 2004). This, in turn, fosters individual participation, accountability, and balanced positive interdependence. Other examples of CLFPs are the Jigsaw and Think-Pair-Share (Hernández-Leo et al., 2010). Moreover, CLFPs are broadly accepted patterns describing structures for Computer-Supported Collaborative Learning (CSCL) scripts. CLFPs, and CSCL scripts, share common collaboration mechanics, such as group formation, peer review, sequence of (individual and collaborative) activities, changes in group formation across activities (Dillenbourg & Hong, 2008).

Among the various CLFPs, the Pyramid pattern has been recognized for its efficacy in promoting active learning, knowledge construction, and problem-solving skills through its multilayered collaborative structure (Hernández-Leo et al., 2006). The Pyramid CLFP is typically employed for addressing complex problems that lack a specific solution, requiring participants to gradually reach a consensus (Hernández-Leo et al., 2005b). In the Pyramid CLFP, learners are initially organized into small groups, collaborating to complete a task or solve a problem. As the activity progresses, these groups are combined to form larger teams, compelling learners to integrate their individual contributions and collaborate on developing a more intricate solution (Dillenbourg & Tchounikine, 2007). Moreover, the Pyramid pattern fosters individual participation, accountability, and balanced positive interdependence, resulting in desired positive behaviours in the learning process (Manathunga & Hernández-Leo, 2018).

Several methods have been employed to assess the flow experience. Some of the most common approaches include measuring it with instruments such as self-report questionnaires where individuals reflect on their subjective experiences and provide ratings or responses related to the key components of flow (Jackson & Marsh, 1996; Jackson & Eklund, 2002; Choe et al., 2015). Other approaches have included physiological assessments, like examining heart rate variability and brainwave patterns, providing objective insights into the physiological indicators linked to the state of flow (de Manzano et al., 2010; Wang & Hsu, 2014). However, other approaches — such as the combination of data that capture both student perceptions and interactions within educational software — have remained less explored (Van Schaik et al., 2012; Hou & Keng, 2021).

An initial exploration focused on the combination of different sources of data can be found in some recent works. For example, Oliveira et al. (2021) analyzed behaviour data and its correlation with the flow encountered by students identifying a series of indicators to predict students' flow experience (i.e., speed and frequency of actions, time to complete the tasks, active viewing). Building upon this foundation, in their subsequent research (Oliveira et al., 2022), they employed structural equation modelling to discern how the speed of student actions serves as a predictor for the flow experience. Parallelly, using similar indicators, Ford and Bryan-Kinns (2022) examined student interactions with a musical composition platform, employing logs and video recordings to discern patterns of engagement and flow. Additionally, Semerci and Goularas (2021) introduced a novel approach to evaluating student flow states within educational systems. Utilizing student grades and interactions, the study employed activity heatmaps and deep neural networks in an e-learning environment to meticulously calculate and understand the dynamics of their flow states. Table 1 presents a description of the studies, including insights into the learning analytics indicators employed to gauge the flow state in students.

Table 1. Flow Indicators from the Literature

Indicator	Description	Source
• Speed of student actions in the system • Frequency of student actions • Active time in the system • Time used to finish a step/mission • Total unique session views	The paper discusses how to predict student flow experiences through behaviour data in gamified learning environments.	Oliveira et al. (2021)
• Active time in the system • Number of completed missions • Number of completed tasks • Number of wrong tasks • Average response time	The paper extends the previous work and, using structural equation modelling, identifies possibilities to predict student flow experiences through the speed of student actions.	Oliveira et al. (2022)
• Interactions with the platform • Time used to complete an activity • Active time in the system	By analyzing the interactions of students with a musical composition platform using logs and video recordings, the authors identified engagement/flow patterns.	Ford and Bryan-Kinns (2022)
• Total time spent • Time spent actively • Number of mouse clicks • Mouse movement paths	The authors proposed a new method for evaluating the flow state of students in educational systems. The study used student grades and interactions using activity heatmaps and deep neural networks in an e-learning environment to calculate their flow states.	Semerci and Goularas (2021)

While current approaches to measure the flow experience have different advantages, including the contrasting of self-reports with data logs, the versatility of these methods in capturing different types of measurements, and the time-and-cost-effective evaluation (Oliveira et al., 2021), there is still a need for more comprehensive and context-specific methodologies, measurement and indicators to assess the flow experience in collaborative learning environments, such as those scripted according to well-known CLFPs such as the Pyramid pattern. Validated scales to measure flow, such as the Flow Short Scale (Rheinberg et al., 2003), when triangulated with learning analytics measurements (data logs) aligned with the context of the study (CSCL mechanics in PyramidApp), offer an opportunity to improve existing flow analytics in this context of study.

The present study, therefore, aimed to address this research gap by exploring how the flow experience can be measured in the context of the PyramidApp platform (Manathunga & Hernández-Leo, 2018). To achieve this, the study tests a model that combines the measurement of student flow states through a validated scale and the CLFP-aligned objective indicators about learner actions in the platform to determine the factors that influence the flow experience in a CLFP specific context.

3. Methodology

3.1. Study Design and Sample

PyramidApp served as the primary research environment in the present study. We therefore designed the study to investigate the flow experience and determine the influencing factors in this platform. The data was collected from three PyramidApp activities with the same task, conducted in three different courses, along with self-reports of students using the PyramidApp. The Pyramid activities took place in already-formed groups during the ordinary classes. The dataset compiled the responses from 69 students (11 males, 58 females; $M_{age} = 19.15$; $SD = 1.38$) who completed the Pyramid activity and delivered the self-report questionnaire (Flow Short Scale, FSS, Section 3.3). All participants whose data is considered in the dataset were informed about the activity and consented to participate in the study according to the research protocol approved by the ethics committee of the institution completing this research.

3.2. Materials: PyramidApp

PyramidApp is a web-based system that incorporates a Pyramid CLFP-based approach to the creation and deployment of educational activities in both traditional and remote learning settings (Manathunga & Hernández-Leo, 2018). The system provides a platform for teachers to design activities and for students to carry them out. Within the PyramidApp enactment tool, individual students are able to submit their responses to the assigned tasks and engage in preliminary discussions in small groups. A common option is agreed upon and subsequently propagated to larger groups at higher levels. These groups deliberate and ultimately reach a consensus on one or a few options at the global level. The tool encompasses an option submission space, a rating mechanism that facilitates the consensus-building process, and an integrated space for discussion (Figure 1).

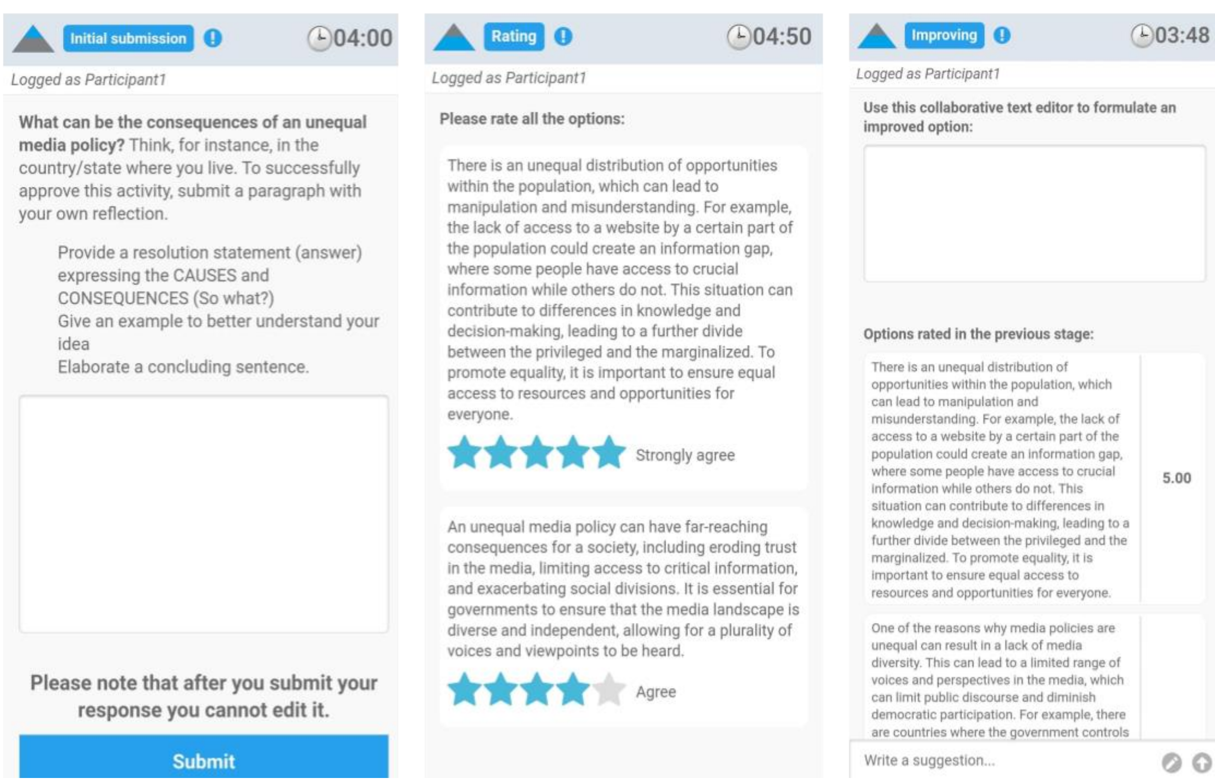

Figure 1. PyramidApp visual mobile interphase.

The PyramidApp breaks down collaboration into multiple stages, allowing students to provide answers to a problem through collaborative interaction. In the first phase, students are given an assignment for which they must come up with an individual answer. After the initial individual submission, the system divides the students into small groups so they can view and grade each other's responses. In the following step, referred to as the answer improving stage, students are requested to talk and discuss in order to come up with a better response as a group. Following this stage, the students are divided into larger groups by the system so they can vote on the best responses and continue to discuss and debate until the task is completed. The user interface has been designed for both mobile and desktop screens to allow students to participate from their own devices.

PyramidApp provides an opportunity to capture the flow experience through its data logs and user interactions. The application generates data logs that capture learner interactions and behaviours in the form of metrics on each one of the phases, storing the result of the individual submission, the different submissions scores generated by each student, the chat records, and the number of characters in the collaborative editor, along with the time of each one of these interactions. This information is instrumental in assessing the occurrence of flow experiences within the context of collaborative learning.

3.3. Instruments and Measures

The study approach combined self-report measurement and data logs to provide a better understanding of the flow experience within Pyramid CFLP. The self-report measurement involved administering a questionnaire to users to capture their perceptions of flow, while the data logs recorded PyramidApp activity. The analysis of these assessments and logs facilitated the construction of flow indicators, which subsequently defined the main variables.

3.3.1. Self-Report Measurement: The Rheinberg Flow Short Scale (FSS)

The FSS (Table 2) consists of ten items assessing two essential dimensions crucial to the flow experience: Fluency of Performance and Absorption by Activity. Fluency of Performance gauges the ease and smoothness with which tasks are executed during learning activities, while Absorption by Activity measures the extent of immersion and focus reported by participants. The FSS also includes two additional dimensions, Challenge and Anxiety, evaluated through four questions to assess the perceived difficulty and stress experienced during the learning process. Respondents use a Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree) to rate each item, providing a structured approach that facilitates a better understanding of subjective experiences related to the flow phenomenon.

Table 2. The Flow Short Scale (FSS) Dimensions and Items

Dimension	Items
Fluency	I feel just the right amount of challenge
	I do not notice time passing
	I am totally absorbed in what I am doing
	I am completely lost in thought
	My thoughts/activities run fluidly and smoothly
Absorption	I have no difficulty concentrating
	My mind is completely clear
	The right thoughts/movements occur of their own accord
	I know what I have to do each step of the way
	I feel that I have everything under control
Challenge	For me personally, the current demands are (Too low - Too high)
Anxiety	Something important to me is at stake here
	I must not make any mistakes here
	I am worried about failing

Source: Rheinberg et al. (2003)

3.3.2. Data Logs

To complement the measurement obtained through the FSS, the study also incorporated the analysis of data logs from PyramidApp. The data logs were extracted for each PyramidApp phase and observed as the following learning analytics:

Submission speed: This measurement involved the assessment of the ratio between the length of a student's answer and the time taken to formulate an answer measured since the start of the individual phase. By accounting for both speed and length, this metric offers insights into the engagement levels of individual students during the initial phase of the activity, providing information about the efficiency in formulating the first individual submission.

Rating speed: This metric captured the ratio between the length in characters of answers evaluated by students and the time spent on the evaluation process. The measurement served as an indicator of student engagement during the rating phase, offering insights into their attention levels and commitment to the assessment process.

Quantity of participation: This measurement saw the participation of each student in the collaborative creation of the answer by observing the number of characters in the collaborative editor in the group task phase, collected as quantitative measurement. The number of characters for the three activities was counted N = 634, Mean by student = 12.431.

Chat interaction: This indicator was reflected in the number of messages in the group chat by each student, reflecting the student's active participation and their willingness to share thoughts and negotiate ideas with peers. The measurement was collected as quantitative measurement. During the three activities, N = 1567 messages were exchanged between the students, Mean by student = 12.431.

Quality of discussion: This measurement evaluated the score of the messages exchanged during the group discussion, providing insight into the depth of the conversation and the degree to which students collaborate effectively. This variable was qualitative. More details about its processing are explained in the data analysis section.

3.4. Data Collection

The study was conducted as a workshop activity in three different Public Relations courses. To ensure a consistent and efficient measurement of flow experiences in PyramidApp, the data collection followed a structured procedure. Figure 2 displays the overall procedure.

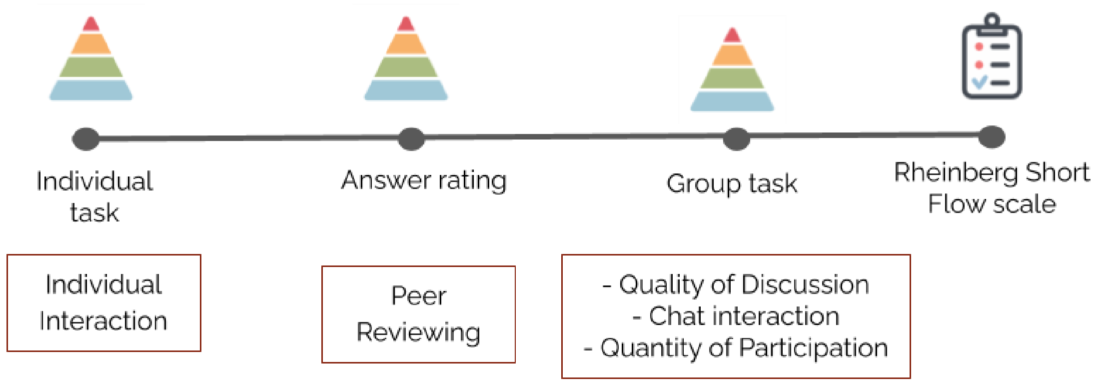

Figure 2. Procedure and variables collected.

A two-level pyramid activity was designed to bring discussion about "the consequences of unbalanced media policies" (a topic appropriate for the class). As part of the initial level, students completed individual tasks. First, they submitted their individual answers to an initial question, aiming to encourage initial reflection and critical thinking on the topic. After submitting their answers, students were instructed to read and rate some of their peers' answers assigned by PyramidApp. This step was designed to expose students to diverse perspectives and ideas on the topic, fostering a sense of connection and mutual understanding among participants. Following the rating phase, students proceeded to the second level. As part of the second stage, students were randomly assigned by the software to small groups (four to five students per group) to discuss their individual answers and peer-reviewed responses. The goal was to encourage collaborative dialogue and negotiation as groups worked together to formulate a new, shared answer based on their collective understanding and insights.

The entire pyramid activity, including individual tasks, peer reviews, and group discussions, was designed to take approximately 15 minutes. This time constraint was intended to maintain a balance between the challenge of the task and the skills of the students, which is a critical aspect of the flow experience (Csikszentmihalyi, 1990). Once students have completed the Pyramid activity, they were asked to respond to the Rheinberg survey, reporting their perceptions of flow and related experiences during their engagement with PyramidApp. Each student was given an anonymous username (a.k.a. unique ID) to match their PyramidApp data with their corresponding questionnaire.

3.5. Data Analysis

Once the data collection was completed, we proceeded to create a dataset. The compiled dataset combined two distinct types of data: self-reports and data logs. The FSS measurement facilitated the calculation of the dependent variable (flow experience), while the PyramidApp data logs were instrumental in analyzing the independent variables (Influencing Factors). Subsequently, we conducted preliminary analysis to establish variables for model testing. Figure 3 displays a summary of the pipeline of the data analysis process, including the statistical tests to validate the model.

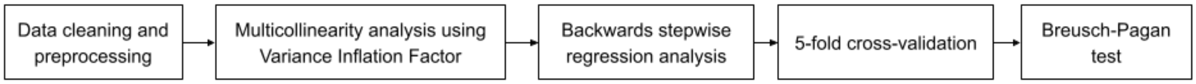

Figure 3. Pipeline of the analysis process.

Following the protocol outlined by Rheinberg et al. (2003), the flow experience was calculated (Table 3) assessing the average value of the "fluency" and "absorption" dimensions. The data analysis showed that the variable "fluency" had a mean value of 4.147 and a standard deviation of 0.676, indicating moderate to high levels of task ease and progression among the participants. "Absorption," measuring the level of concentration and engrossment in the task, had a mean value of 4.234 with a standard deviation of 0.796. The "anxiety" dimension, representing feelings of stress or nervousness, showed a mean of 3.782 and a relatively high standard deviation of 1.416, implying varied levels of anxiety across the participants. The "challenge" dimension, which measures perceived task difficulty and effort, recorded a mean score of 4.367 and a standard deviation of 0.950, indicating that most participants found the task moderately challenging.

Table 3. Results from the Flow Short Scale

Variable	Mean	Standard Deviation
Fluency	4.147	0.676
Absorption	4.234	0.796
Anxiety	3.782	1.416
Challenge	4.367	0.950
Flow	4.191	0.545

The histograms of these variables show the distribution of the responses (see Figure 4).

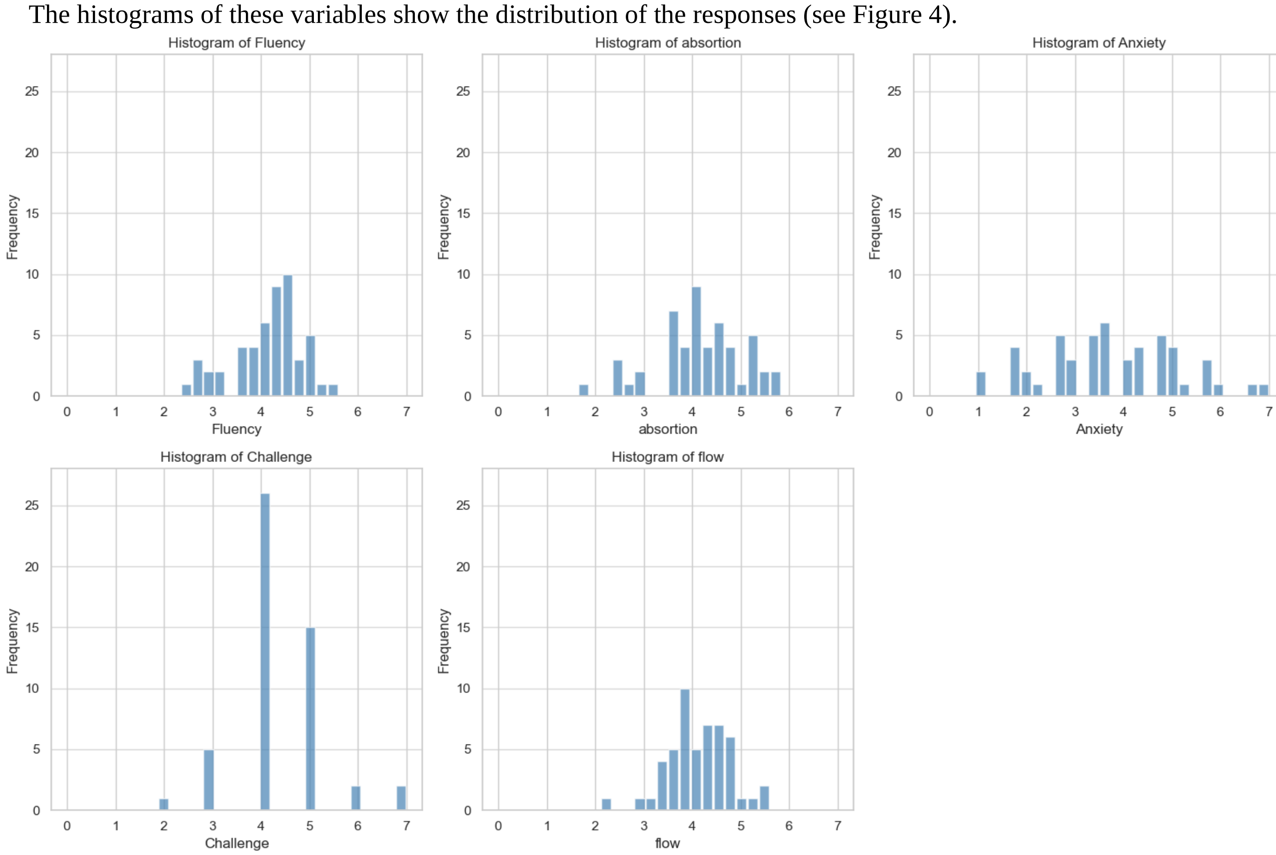

Figure 4. Distribution of the answers to the Flow Short Scale.

Regarding the objective measurement, we extracted and cleaned the logs generated by the PyramidApp tool to build the variables: 1) submission speed, 2) rating speed, 3) quality of discussion, 4) chat interaction, 5) quality of participation. Quantitative variables (1 to 4) underwent processing as specified in the measurement specifications (Section 3.3). While for the quality of discussion, we quantitatively determined the score of chat messages through a content analysis of all messages exchanged by the students (N = 1567). This step followed the approach proposed by Velamazán et al. (2022). The developed scoring system allocates a score of 0.1 to messages in positive subcategories, 0.5 to those featuring light humour/jokes, and penalizes messages in the spam/negative jokes subcategory with a value of –0.1 (refer to Table 4). Given the informal and unrestrained nature of the chat messages, the categorization process needed manual assessment. Moreover, each message was not only examined individually but also within the broader context of the conversation. For instance, a message initially considered a joke might be reclassified as spam if repeated frequently. Additionally, some messages presented a blend of content and social-emotional elements, such as combining feedback with humour or a joke. The first and the second author performed a classification of the messages, assigning each message to a specific subcategory. To measure the inter-rater reliability of the coding system, the calculation of Cronbach's Alpha was used and returned an average value of 0.82.

Table 4. Categories for Chat Messages

Category	Subcategory	Flow score	Reference
Cognitive and content-related categories	1 Ideas/proposals	0.1	Adapted from van Aalst (2009)
	2 Feedback/answers	0.1	
	3 Questions/doubts	0.1	
Social and emotional categories	4 Support of the team	0.1	Adapted from Järvenoja et al. (2017) and Näykki et al. (2014)
	5 Regulation of behaviour	0.1	
	6 Humour and jokes	0.05	
	7 Wasting time, spam, distractions, or negative jokes	–0.1	
	8 Greetings	0.1	
	9 Uncategorized	0	

Once the data from the different measurements was processed, we proceeded to construct and validate the model. To determine the presence of multicollinearity among the independent variables, a variance inflation factor (VIF) analysis was performed (Table 5). The VIF values obtained indicated no significant multicollinearity between the independent variables, as all VIF values excluding the constant were below the threshold value of five (Kim, 2019). This validates that the variables can be included in the regression analysis without causing issues related to multicollinearity.

Table 5. Results of the VIF Analysis

Feature	VIF
Const	6.928
Submission speed	1.197
Rating speed	1.135
Quantity of participation	1.099
Chat interaction	1.662
Quality in discussion	1.591

After assuring that the collinearity between variables was not significant, a backward stepwise regression analysis was performed; this analysis started with all candidate variables and tested them for statistical significance in the regression, deleting any insignificant variable (p-value > 0.05).

A backward stepwise regression analysis was conducted with flow as the dependent variable and the independent variables of submission speed, rating speed, quantity of participation, chat interaction, and quality in discussion. Multiple linear regression methods such as the backward stepwise regression are common statistical techniques used in educational research (Elmore & Woehlke, 1996) and have been previously used in studies related to analyzing the flow experience (Sillaots & Jesmin, 2016; Moral-Bofill et al., 2023). Finally, to test the performance of the model, a 5-fold cross-validation and a Breusch-Pagan test were conducted.

4. Results

The backward stepwise regression analysis (Table 6) revealed a statistically significant model (Prob F-statistic: 1.14e–18), with an adjusted R^2 of 0.836. This finding suggests that four variables (submission speed, rating speed, quantity of participation, and quality of participation) account for approximately 83% of the variance in flow among the sampled individuals. The variable chat interaction was discarded due to its high p-value = 0.203 and negative coefficient = –0.008.

Additionally, the regression results indicate that quality in discussion and submission speed had a significant positive effect on the flow experience during the Pyramid activities (p = 0.026 and p = 0.001 respectively). Looking at the regression coefficients, a change in one unit in the quality in discussion will increase the mean value of the flow variable by 1.407 while a change in one unit in the submission speed will increase the mean value of the flow variable by 0.740.

The variable rating speed (p = 0.001) with a coefficient of 0.014 shows a limited or minimal effect on the flow; however, future studies could further explore the relation of this variable with the flow experience. Finally, the variable quantity of participation was not statistically significant (p = 0.085) with a low coefficient (0.015).

Table 6. Results of the Backward Stepwise Regression Analysis

Dep. variable flow		
Model ordinary least squares		
Adj. R-squared 0.836		
F-statistics 65.84		
Variable	**Coefficient**	**p-value**
Submission speed	**0.740**	**p<0.01**
Rating speed	**0.014**	**p<0.01**
Quantity of participation	0.015	p>0.05
Quality in discussion	**1.407**	**p<0.05**
Chat interaction	–0.008	p>0.05

To assess the performance of the model, we computed the root-mean-square error (RMSE) of the backward stepwise regression. The RMSE is a commonly used metric that quantifies the average discrepancy between the predicted values of a model and the actual observed values. A lower RMSE indicates a better fit of the model to the data. For our particular model, the resulting RMSE was determined to be 0.528. Given that the flow experience was measured on a scale from 0 to 7, this RMSE indicates that the model's predictions are reasonably close to the actual values, suggesting a good fit. Moreover, to ensure the stability and generalizability of the model, a 5-fold cross-validation was conducted, yielding an average RMSE of 0.569. Cross-validation evaluates the performance of a predictive model on new, unseen data, providing a more reliable estimate of its predictive accuracy. The reasonable RMSE values obtained, both from the initial model and the cross-validation, support the use of the identified variables (individual interaction, peer reviewing, quality of discussion, and quantity of participation) as appropriate predictors or indicators of the flow experience in the context of this study. This reasoning highlights the robustness of our model and the relevance of the selected variables in predicting the flow experience, thereby validating our methodological approach and findings.

Following the evaluation of the model, we built the residual plot for the K-fold OLS model (Figure 5). Following the criteria of Tsai et al. (1998), the residual plot showed a random scattering of points around the horizontal line at y = 0, suggesting that the model's errors were evenly distributed and had constant variance. This pattern indicates that the assumptions of homoscedasticity and linearity were reasonably met by the model. The absence of any noticeable trends or patterns in the plot suggests that the model adequately captured the underlying relationship between the predictor variables and the dependent variable "flow" (Tsai et al., 1998).

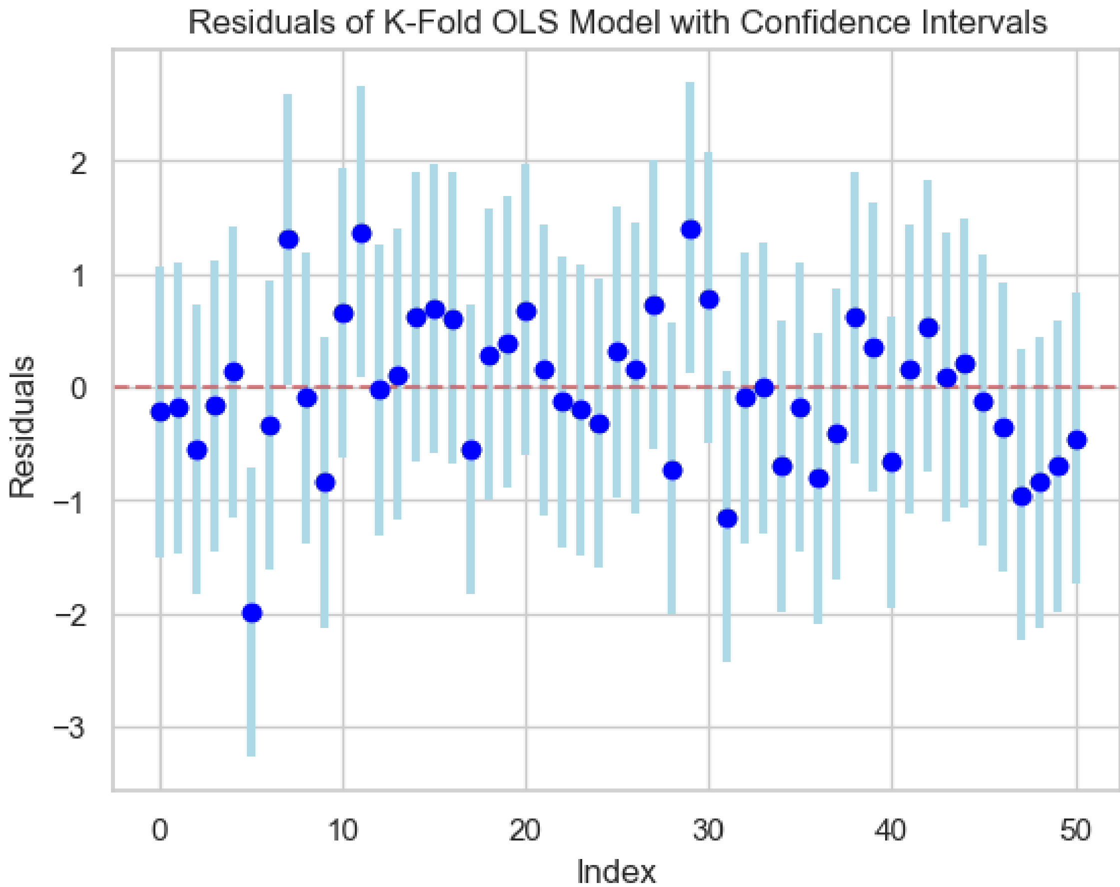

Figure 5. Residual plot of the 5-fold cross-validation.

Additionally, a Breusch-Pagan test (also known as the Cook-Weisberg test) was used to check for heteroskedasticity (nonconstant variance of the errors). The test is based on the idea that if the variance of the errors is not constant, there should be a systematic relationship between the residuals and the predicted values.

The test uses the following null and alternative hypotheses:

- Null Hypothesis (H0): Homoscedasticity is present (the residuals are distributed with equal variance)
- Alternative Hypothesis (HA): Heteroscedasticity is present (the residuals are not distributed with equal variance)

If the p-value of the test is less than some significance level (i.e., $p = 0.05$) then we reject the null hypothesis and conclude that heteroscedasticity is present in the regression model.

The results of the Breusch-Pagan test were as follows:

- LM Statistic: 3.882
- LM-Test p-value: 0.422
- F-Statistic: 0.950
- F-Test p-value: 0.443

In this case, both p-values (0.422 and 0.443) were greater than the significance level of 0.05. This means that the null hypothesis (Homoscedasticity is present so the residuals are distributed with equal variance) cannot be rejected, and it can be concluded that there is not enough evidence to suggest that the errors have nonconstant variance (heteroskedasticity) in the model.

The partial regression plot (Figure 6) displays the relationship between each predictor variable and the dependent variable "flow" while controlling for the effects of other predictor variables. The plots reveal positive but small slopes for the predictor variables, indicating that they have a weak but positive association with flow experience. This supports the notion that these variables are relevant in predicting flow experience, although their individual contributions to the model might be limited.

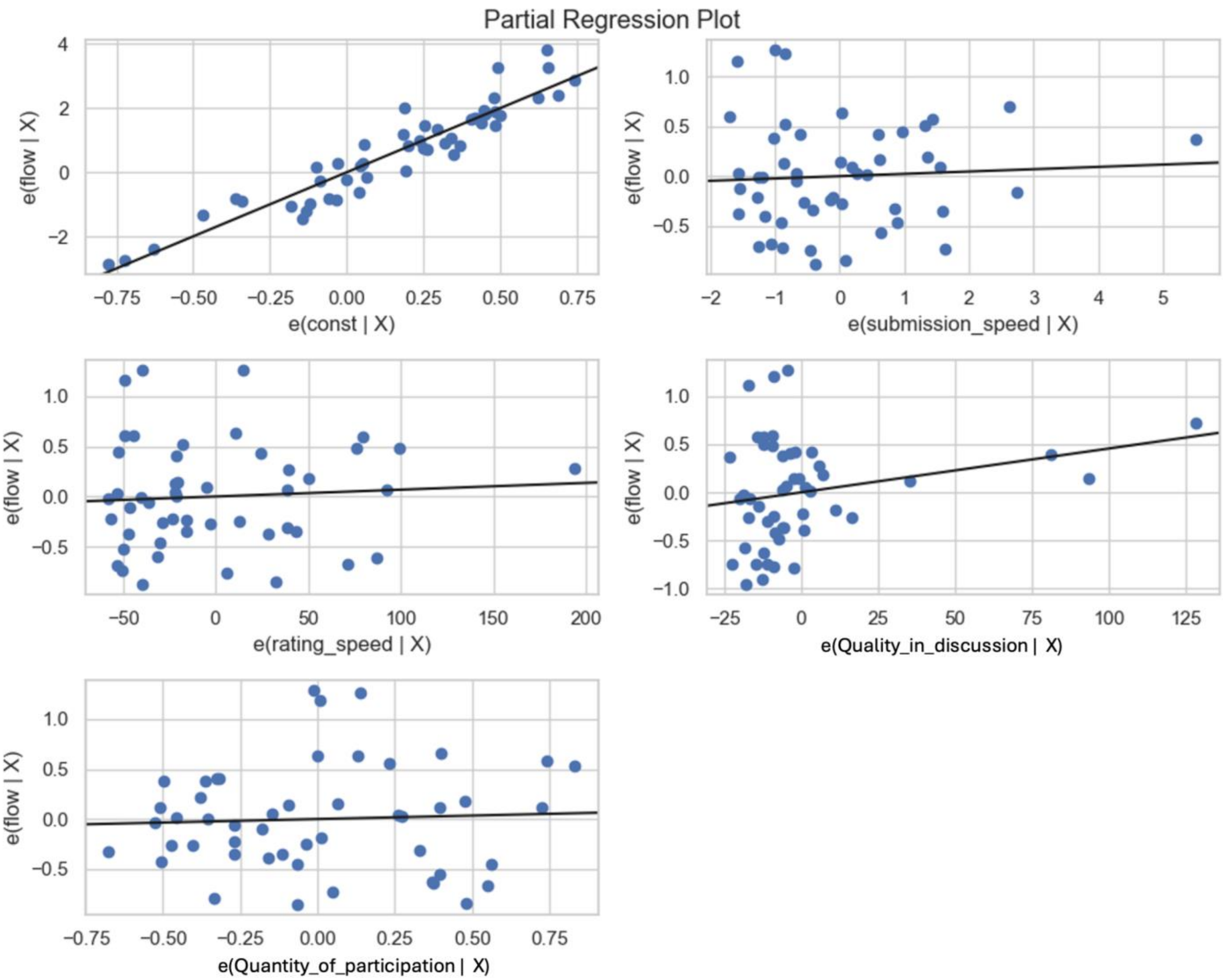

Figure 6. Partial regression plot showing the relationship between each predictor variable and the dependent variable flow.

The plot for the constant term demonstrates a well-distributed pattern of points, which suggests that the model appropriately captures the overall mean of the flow experience. The absence of any noticeable trends or patterns in this plot further corroborates the notion that the assumptions of linearity and homoscedasticity are reasonably met by the model. To compare the results with other techniques, principal component regression (PCR) analysis was performed with four principal components. The average RMSE for the four-component PCR model was 0.516, slightly lower than the backward stepwise regression model.

5. Discussion

In this study we explore the relationship between Pyramid CLFP features and learners' flow experience. Our findings provide evidence that such a relationship indeed exists. By integrating self-reports from the Flow Short Scale with data logs from PyramidApp, we propose an approach to measuring flow in CLFP contexts, offering a more holistic and accurate assessment.

Our analysis pinpoints which Pyramid CLFP features contribute most to a flow experience. Notably, efficient individual contributions emerged as the strongest predictor, suggesting that activities balancing individual challenge with skill level are crucial for creating this kind of experience. Additionally, effective peer review processes and high-quality group discussions were identified as significant contributors, highlighting the importance of constructive social interactions in the Pyramid pattern's higher levels.

These findings stress the importance of fostering an environment that strikes an optimal balance between challenge and skill level for individual learners. The strong link between efficient individual contributions and flow aligns with

Csikszentmihalyi's notion of this balance. Consequently, educators should carefully design individual activities and prompts that provide appropriate challenges, allowing learners to engage deeply without inducing frustration or boredom.

Furthermore, the significance of effective peer reviews and high-quality group discussions emphasizes the value of promoting constructive peer interactions. To support flow experiences in collaborative contexts, instructors should implement strategies that encourage active participation, respectful feedback exchanges, and thoughtful idea negotiation. This could involve providing clear peer review guidelines, facilitating structured discussions, and fostering an environment of mutual respect. Incorporating tools that enable seamless communication within collaborative platforms can further enrich these interactions.

Importantly, our results stress focusing on the quality, not just quantity, of social interactions. This insight has significant implications for developing collaborative learning technologies and designing educational strategies seeking (psychological) flow experiences. Educators and designers should prioritize features that foster meaningful peer-to-peer interactions, constructive feedback, and in-depth discussions, moving beyond mere participation metrics.

This study makes several significant contributions to the CSCL field. Theoretically, it extends our understanding of how specific CLFP features, particularly in the Pyramid pattern, relate to learner flow experiences. The findings show that certain features enabling efficient individual work and fostering rich group interactions are key flow predictors, enriching our comprehension of the interplay between collaborative structures and psychological states. These findings correspond with the Self Determination Theory (SDT; Ryan & Deci, 2000), which states that autonomy, competence, and relatedness are fundamental psychological needs that, when satisfied, lead to enhanced self-motivation and mental health. In our study, the balance between challenge and skill in individual tasks supports competence, while high-quality group interactions foster relatedness.

Practically, our findings translate into evidence-based guidelines for designing engaging collaborative environments. By identifying balanced individual challenges, constructive peer interactions, and rich social dialogues as flow contributors, the study provides strategies for crafting collaborative learning experiences that deeply engage learners. These guidelines are useful in the context of PyramidApp, where some of the previous studies have focused on learning outcomes. For example, Amarasinghe et al. (2021) showed PyramidApp's effectiveness in facilitating learning gains among students. Furthermore, integrating these guidelines can enhance PyramidApp (and similar CSCL scripting tools) to foster an immersive learning experience that encourages the development of the flow state.

In sum, this work significantly advances CSCL by bridging CLFPs with the psychological flow experience. In line with Qureshi et al. (2023), the insights from this study reshape how we conceive and design collaborative spaces, prioritizing not just structural efficiency but learner engagement. As online collaboration becomes increasingly central to education and professional life, these findings will guide the creation of environments that are deeply engaging, motivating, and satisfying for all participants.

6. Conclusion

This study aimed to propose an approach to measure flow in the context of the Pyramid CLFP and to investigate the factors that influence the flow experience in CSCL scripts, such as those implementing the Pyramid CLFP through the PyramidApp tool. By incorporating the assessment of student experience and the analysis of data logs, the study captured the complexity of flow, providing a list of factors that influence the flow experience in PyramidApp.

The obtained results from a backward stepwise regression model showed that factors such as the speed of individual contributions, effective peer-review processes, and thoughtful discussions can enhance the flow experience. However, the effect of speed in peer reviewing is low, and notably, the quantity of participation did not exhibit a discernible impact on the flow.

The study emphasizes the interest of the modelled factors and the proposed approach for learning analytics to understand the flow experience in CLFP implementations. The findings contribute both to the practical aspects of designing engaging collaborative learning activities and to the empirical understanding of the flow experience in educational contexts.

Furthermore, this research offers methodological contributions by proposing an approach that combines self-reports and data logs, providing a comprehensive and context-specific methodology for assessing the flow experience in collaborative learning scenarios. This approach can inform future research efforts in this domain, promoting a more holistic understanding of the factors influencing flow states in technology-mediated collaborative learning environments.

While this study has limitations that should be addressed in future research, such as exploring diverse educational environments and expanding the findings to other collaborative learning contexts, it provides valuable insights and recommendations for educators, instructional designers, and researchers alike. By prioritizing features and activities that foster meaningful interactions, constructive feedback exchanges, and in-depth discussions, collaborative learning experiences can be designed to enhance the potential for flow states, ultimately resulting in more immersive, satisfying, and potentially effective learning outcomes.

Declaration of Conflicting Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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