Automatic Calibration for a Mutual Insurance System in a Multi-Player Serious Game

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Abstract: In the context of a serious educational game that motivates children to adopt more sustainable home-to-school mobility habits, we designed and implemented a collaborative multi-player mutual insurance system, with the intent to support low-performing players with the help of high-performing ones. As a preliminary step towards a field study evaluating this new game mechanic, in this paper we present the design and the development for an automatic calibration of the system, simulating the effects of the choices for each parameter in the player's game progression.

Keywords: Serious games, Playful education, Design methods, Gamification in education

1. Introduction

Serious games can be defined as "games in which education, in its various forms, is the primary goal, rather than entertainment" (R. Michael & L. Chen, 2006).

Serious games are routinely applied for learning, education, and training, and this research topic has been rapidly growing over the last years (Hooshyar et al. 2018, Jagušt et al. 2018, Kickmeier-Rust et al. 2014, Marconi et al. 2018, Ferron et al. 2019). In particular, Games-Based Learning (GBL) helps students develop skills and knowledge and strengthens their ability to handle the learning experiences provided by the games. (Al-Azawi et al, 2016).

In all games with a purpose, keeping the player engaged for longer may result in a more permanent and significant behavior change, and thus player retention becomes particularly relevant (Berkovsky et al. 2010, Vassileva 2012, Kaptein et al. 2012, Jacobs 2016).

For this purpose, it is paramount to design the game adaptivity and personalization (Streicher & Smeddinck, 2016): that is, being able to adjust the content and interaction schemes of games, as virtual environments, to the knowledge level, skill, preferences, and experience of the users.

Recent studies conducted on the effects of serious games show that also in this domain, personalization and adaptivity can promote user acceptance, motivation, and retention (Hooshyar et al. 2018, Jagušt et al. 2018, Kickmeier-Rust et al. 2014, Legaki et al. 2019, Monterrat et al. 2017, Stuart, Serna, Marty, Lavoué & Lavoué 2019, Orji, Nacke & Di Marco 2017, Orji, Mandryk & Vassileva 2017, Scanagatta et al. 2020).

This paper focuses on KidsGoGreen, a serious game that motivates children to perform daily trips from home to school in a sustainable way. Teachers can define personalized virtual journeys across the world and associate to each stop multimedia educational material. The sustainable km performed by each pupil through home-to-school trips contributes to the advancement of the whole group in the virtual journey. The educational material is unlocked when the group reaches each stop. In this manner, the entire school community (children, teachers, and families) is involved in a collective playful educational experience.

The KidsGoGreen experimentation in schools highlighted the need for continuous monitoring and re-calibration of the game during operation. The teachers program each stage in the team's route to be reached in a specific time frame, yet a high variance might affect the performance of the children.

For this reason, a class could miss the deadline by several days, which could be particularly problematic for a mid-game stage set before the Christmas holiday season or the final stage set before the end of the school year. The factors responsible for the performance variance might be external (weather, road conditions) or internal (class overall motivation and dedication, school schedule).

To reduce this variance, we designed a multi-player mutual insurance system. A high-performing team (class of pupils) can donate the excess gained game points (virtual km) to a shared mutual fund. On the other hand, a low-performing team can withdraw from the mutual fund the game points required to reach the next stage.

As a preliminary step towards a field study evaluating this new game mechanic, it was necessary to calibrate its inside workings carefully. After we obtained real-world data from the previous iteration of the serious game, we designed a simulation procedure. We then evaluated different approaches and the values of the different parameters governing the mutual insurance system to analyze the effects on the game progression.

Furthermore, with the introduction of this shared fund, we also introduced in the KidsGoGreen game basic economics principles such as *inflation* and *deflation* to keep the overall system in equilibrium. This exploration constitutes (as far as we know) the first exploration of this research topic.

In Section 2 we first present relevant work in the literature. In Section 3 we detail the context of the gamified system. In Section 4 we explain the details of the multi-player mutual insurance system. In Section 5 we discuss the insights we gained from its simulation and tuning. Section 6 concludes our paper.

2. Literature review

Serious games have proven successful in raising awareness, increasing participation, and promoting sustainable behavior in social, environmental, and health domains (Seaborn & Fels 2015, Deterding et al. 2011, Bielik et al. 2012, Ferron et al. 2019).

However, game content adaptivity and personalization in a multiplayer setting, particularly relevant for non-competitive and collaborative games, is a well-recognized and still uninvestigated problem (Streicher & Smeddinck, 2016).

In the presence of several players with very heterogeneous performances and preferences, adaptive algorithms need to properly calibrate the game to meet their expectations and skills (Stuart, Serna, Marty & Lavoué 2019).

Moreover, if not carefully designed and properly implemented, automatic game adjustment can have a substantial impact on the balancing and the perception of the balancing by the players, which may interfere with their game experience.

It is essential to render the game adaptation transparent to players. In Gerling et al. (2014), the authors compare visible and transparent adjustment strategies in an established motion-based game.

The study revealed that explicitly observable calibrations might negatively impact players' self-esteem and feelings of relatedness in player pairs. In contrast, transparent adjustments seemed to improve self-esteem and reduce performance differences without affecting the player experience.

As a recent example, in Scanagatta et al. (2020), the authors committed to promoting a more even player experience across players without overly rewarding high-performing ones or penalizing low-performance ones. The study focused on an educational game targeting primary school children whose goal was to raise their awareness towards the reduction and correct disposal of e-waste. In this work, the modification of the game mechanics was *transparent*, as the children were not made aware of its existence and did not discover it during the game's execution.

Mutual insurance is a well-known concept (Cass et al. 1996, N. O'sullivan 1998). Its goal can be defined as "*to provide its members with insurance coverage at or near cost*".

Figure 1: Virtual journey in KidsGoGreen, programmed by the teachers for the school year. The educational material associated with each stop is unlocked when the whole class collects enough real-world kilometres travelled with a sustainable mode of transportation

While mutual funds hold a strong position in the market, they and the implications of the organisational form have attracted limited interest among academics (Talonen 2016). Our purpose is to help in this matter, with regards to their application to the context of educational games.

3. Application context

KidsGoGreen is an educational game that targets primary and secondary schools, and aims to induce a collective shift towards sustainable home-to-school mobility habits. It involves the entire school community (children, teachers, and families) in a playful educational experience based on a virtual educational journey around real-world stops.

3.1 KidsGoGreen experimentations

KidsGoGreen has been deployed in primary and secondary schools in various Italian regions for several years. During 2020-2021, 62 KidsGoGreen virtual journeys were activated in 54 schools, involving more than 3,000 students.

These experiments showed an impact on home-to-school mobility that exceeded all expectations: a 56% percent reduction in car trips to school.

The system has also shown a high educational and didactic value. Teachers and school managers testify how KidsGoGreen has been for them "a completely new way of teaching", which has enabled interdisciplinary and inclusive paths, intra- and inter-class collaboration, and enthusiastic participation of teachers and students.

Families also see a significant impact of KidsGoGreen in terms of children's awareness of environmental sustainability issues and autonomy in home-school trips and during free time.

3.2 KidsGoGreen current limitations

In the post-game evaluation, some pupils and teachers reported their frustration when proceeding too slowly in the virtual journey. Others report that they were proceeding too fast, that the unlocking of some stops was too frequent, and that they did not have enough time to use and elaborate the associated educational material properly.

This comments, in general, regards the broad issue of calibration. At the moment, it is performed with the following steps: The game's duration is decided in advance (typically from 2 months to the whole school year). Then it is necessary to decide the number of journey's legs, and their distance (the amount of virtual kilometres needed to unlock them).

Teachers have to make an educated guess on the estimated whole class *travel speed,* based on the current home-school mobility habits of the children, and an estimation of their possible behavioural improvement.

Firstly, the initial calibration might be optimistic or pessimistic, leading to a growing distance between the game's supposed execution, and the observed team's performance.

Furthermore, during the game operation, the children's performances may vary, due to external factors (weather, road conditions) or internal (class overall motivation and dedication, school schedule).

As depicted in Figure 2, for each KidsGoGreen stop, we can think of a window of arrival. Given the target (dotted blue line) and the estimated daily speed (gray line), it is possible to estimate the arrival date (blue vertical line). The sustainable km performed each day by the group of students may vary (red line).

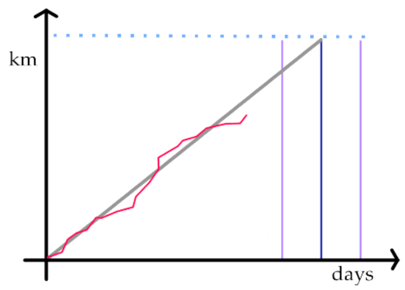


Figure 2: Example of maximum allowed delay / advance of a game

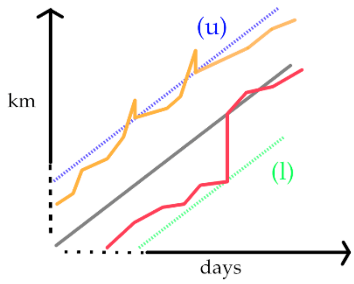


Figure 3: Example of *bounded performance*

While a deviation from the expected arrival date is acceptable (violet lines), significant delays or advances in the game can compromise the overall experience.

The system does provide tools for monitoring (i.e., reporting significant deviations from the estimated daily group speed) and re-calibration (i.e., assignment of group-level challenges to make up for delay). However, the workload required on the teachers to correctly use these tools was found to be excessive.

4. The KidsGoGreen Mutual Insurance System

We thus introduce in the game a new game mechanic, as defined in the MDA framework (Hunicke et al., 2004): the *mutual fund*, a game point concept shared by all the teams.

When a team obtains a number of game points (the virtual kilometres gained through sustainable home-to-school trips) higher than a given threshold, the points in excess are *donated* to the fund.

Vice-versa, when a team falls behind a given threshold with its game points, the required points are *withdrawn* from the fund (given the condition that the fund contains a sufficient residual amount).

This behavior is similar to a basic insurance fund, where the team's deposits are the premiums, and the team's withdraws are the claims. Attention must be given to the evolution of the mutual fund amount. A significant difference in the team's deposits and withdraws leads to either over-performing or under-performing behavior.

This generates a *bounded performance,* as shown in Figure 3. Blue dotted line is the upper bound (deposit threshold); green dotted line is lower bound (withdraw threshold). The orange line is a team's performance that exceeds the maximum allowed advance; the red line instead exceeds the maximum allowed delay. The two parameters can be thought of as "what is the maximum advance/delay allowed to teams in the game?", creating a "channel" for containing the team's performance.

Finding the equilibrium between "premiums" and "claims" is the main goal of insurance research; in this particular application context, we must face the critical limitation that it is impossible to gather sufficient data to predict the team's performances with a sufficient degree of precision.

We decided to circumvent this problem by introducing a parameter with which it is possible to affect the economic behavior of the system directly. When a team donates game points to the system, the amount is multiplied with a given factor before being added to the fund. With a value of the factor higher than 1, this corresponds to a process of *inflation*. Vice-versa, with a value lower than 1, this corresponds to *deflation*.

We note that the particular game context has characteristics that make it suitable for "behind the scenes" adjustment. Firstly, its primary target is children; previous exploratory work in this area showed that they do not perceive such game manipulations (Scanagatta et al., 2020). They are *transparent*, and thus appropriate for reducing performance differences without affecting the player experience (Gerling et al., 2014). Secondly, the game does not feature a competitive aspect, and the narrative is suitable to favor a collaborative aspect (helping each other to reach their journey's destinations).

Therefore, we have identified three parameters that control the execution of the multi-player mutual insurance system: the *deposit-threshold*, the *withdraw-threshold*, and the *economic-adjustment*. The value given to these parameters and how they are handled can radically change the game's course. The next section will show the insights we gained from their calibration.

5. System Simulation & Evaluation

As a preliminary step for a field study, we created a simulation apparatus that could help us understand how different strategies and values for the system's parameters would affect the team's experience.

5.1 Evaluation indicators

To compare different strategies for the parameters' calibration, it was necessary to define the *objective function*: the set of goals that could allow evaluating each combination. First, we identified the two main fundamental indicators of the overall mutual insurance system's goals.

The first was the <u>mean teams' delay</u> (computed regarding their *expected performance*), which indicated the mean number of days a team would need to continue playing to reach the end of their virtual journey.

The second was the <u>total number of withdraws</u>. From the point of view of a children's team, each withdraw represents an event in the game where their under-performance is compensated through the mutual fund. Limiting the number of withdraws is of utmost importance to maintain the team's motivation high - withdraws need to be perceived as exceptional events in the game.

The same cannot be said of deposits, which represent a positive event in the game in which the team, having accumulated more game points than expected, donates the excess to the mutual fund.

The <u>mean teams' delay</u> and the <u>total number of withdraws</u> indicators are directly linked. In the proposed mutual insurance system, the withdraw mechanic is the primary means to alleviate the teams' delay. Thus the two parameters have to be taken into consideration simultaneously.

5.2 Simulation

We now define the simulation procedure we implemented. The basic concept is to choose one combination of parameters' values, simulate the execution of many games, and collect precise statistics on the overall game's progress. Comparing those statistics allows us to understand better the effect of choosing different strategies and values for the parameters.

First, we collected performance from the previous executions of KidsGoGreen, obtaining data from 69 real-world classes. In each simulation, we randomly choose 40 of them.

From each real-world data, we defined a synthetic team, randomly choosing the start date of its game (in a period ranging across 365 days). The corresponding real-world data sampled its journey goals, performances, and journey duration.

For each day of the simulation (lasting a year), we then simulated the performance of each synthetic team. We then computed the *expected performance* (based on the target of the next leg of the journey, and the number of remaining days), the *deposit-threshold* and the *withdraw-threshold* (based on the expected performance and the different approaches that we will outline in the following subsection). We followed these guidelines:

1. If the synthetic team's game points total was higher than the *deposit-threshold* at the end of the day, all the game-points over that threshold were removed from the team's points pool, multiplied by the *economic-adjustment* parameter, and added to the shared mutual game points fund.
2. If instead at the end of the day the synthetic team's game points total was lower than the *withdraw-threshold*, an amount of game points equal to the difference between the *withdraw-threshold* and the *expected performance* were removed from the mutual fund, and this difference was added to the team's points pool.

Notice: The withdrawal was executed on the condition that the mutual fund had a residual amount higher than the required amount - the mutual fund was not allowed to be overdrawn.

5.3 Economic Adjustment

We now analyze the parameter of *economic-adjustment*, which regulates the inflation/deflation economic behavior of the mutual insurance system. At the start of our research, we treated it as an independent parameter like the others. We then realized that we could instead treat it as a *dependent* parameter, thus removing the need to calibrate it independently, reducing the search space of the parameter calibration of one dimension.

The reason is that it refers to a mechanic that is by design *transparent*; if the change on the raw numbers is performed in such a way that the players are made not aware of it, then the actual value governing the change is not relevant (apart from being constrained inside some reasonable hard-limits).

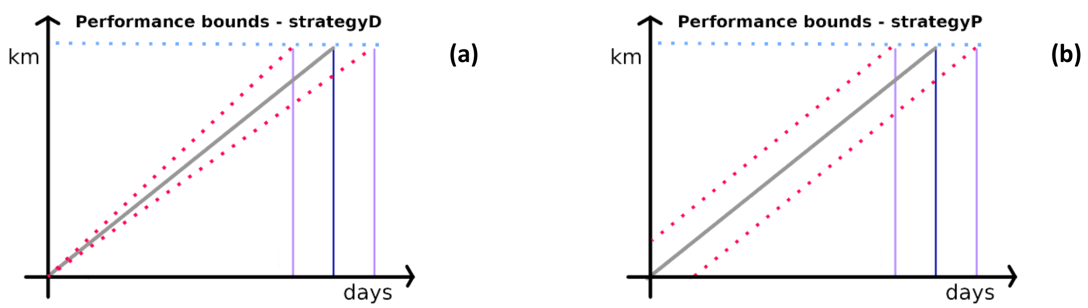


Figure 4: Representation of the approach for *deposit-threshold* and *withdraw-threshold* (red dotted lines) as a percentage of the player's performance, for either <u>strategyD</u> (a) and <u>strategyP (b)</u>

The *economic-adjustment* affects the fund size directly, since each deposit by the teams is multiplied by its value. Consequently, it affects the withdrawal rate, as the fund is not allowed to be overdrawn.

Keeping in mind those considerations, we then produced a procedure to define the parameter's value. The parameter *economic-adjustment* was set to the starting value of 0.6. A first simulation was performed in which the total number of withdraws was noted.

The value of the parameter was then increased of 0.2. A new simulation was performed, and again the total number of withdraws was noted, and compared with the moving average of the last ones recorded. If higher, the new value for *economic-adjustment* was confirmed, and the loop continued. Otherwise, the calibration ended.

5.4 Deposit and Withdraw threshold

We now describe how we calibrated the *deposit-threshold* and the *withdraw-threshold* parameters, which govern the corresponding mechanics. For the calibration of those parameters, we tested two strategies.

The first is to define them as a percentage of the team's performance. For example, we tested the set of values (1.10, 1.05, 1) for the *deposit-threshold* and (0.95, 0.9, 0.85) for the *withdraw-threshold*. This approach corresponds to defining upper and lower bounds divergent from the performance line. We gave this approach the name of <u>strategyD</u>. We present a visual explanation in Figure 4a.

The second strategy is to define the threshold as a percentage of the expected team's total performance. For example, we tested the set of (0.1, 0.2, 0.3, 0.4, 0.5) for both the parameters - to be added or removed to the current expected team's performance. This approach corresponds to defining upper and lower bounds parallel to the expected performance line. We gave this approach the name of strategyP. We present a visual explanation in Figure 4b.

We observed the effect of the two strategies on the two indicators that have been chosen as evaluation criteria. About the total number of withdraws, we recognized that its distribution in the majority of the simulations performed with the first strategy was heavily skewed. This was because the bounds are very close at the start of the game, and it is thus frequent for the team's performance to fall out. We provide an example in Figure 5a. Across all the simulations, the mean of the medians of the distribution was 7.48.

Instead, with the second approach, we observed that the distribution of teams' withdraws was more evenly distributed during the game's duration, thus solving the problem outlined before. We provide an example in Figure 5b. Across all the simulations, the mean of the medians of the distribution was 31.26. However, we also recorded a very high variance in the team's statistics. We found that journeys length distribution also showed a high variance; thus, this disparity influenced the parameter's effect, as it was directly involved in their calculation.

To solve this problem, we thought to define the threshold of the parameters using as a unit of measurement the number of days (based on the team's expected daily performance) - meaning that the deposit threshold indicated now the maximum allowed number of days of advance on the expected journey's end (for the withdraw threshold, it indicated the maximum delay). The values tested were (1, 2, 3, 4, 5, 6, 7) for both parameters.

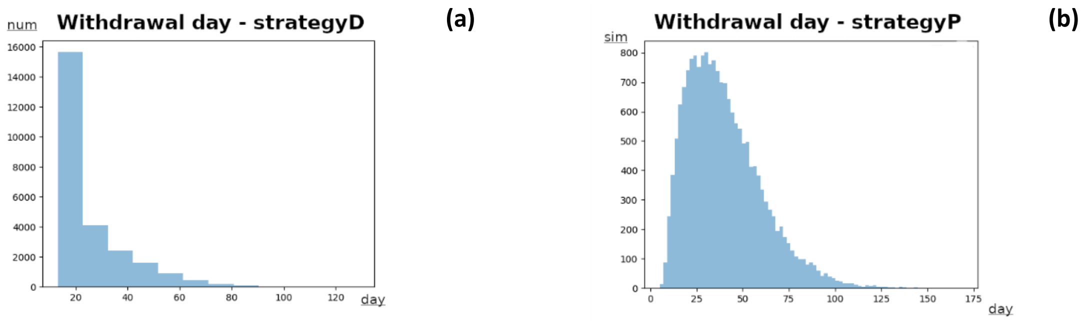


Figure 5: Example of the distribution of the game day on which withdraws have been performed, for either strategyD (a) and strategyP (b)

5.5 Insights

We now present the main insights we gained from the simulations.

To show the different effects of changing the value of one parameter with respect to the other, we produced *pivot* graphs: meaning that the value of one parameter was fixed, and we superimposed the distributions obtained by all the possible values of the other parameter.

We will present the graphs pivoting on only one value for both parameters to have a meaningful exposition. To this end, we choose the value of 4 as a middle ground. We report that the graphs' upcoming remarks were also observed pivoting over other values.

We start with pivoting *deposit-threshold*. In the following paragraphs, we will show the observed effects of varying the value for *withdraw-threshold* from 1 to 7.

As the threshold increases in value, the total number of withdraws becomes more skewed to the lower values on the left - meaning that fewer withdraws are performed in general. This behavior is reasonable, as a high value for the parameter indicates a farther bound which activates the withdraw, decreasing their frequency. We report this in Figure 6a.

As the threshold increases in value, the distribution for the withdrawal's game execution day exhibits a lower kurtosis but a similar skewness. The explanation for the first finding is a direct consequence of the previous point, as there are a lower number of withdraws in general. We report this in Figure 6b.

As the threshold increases in value, the mean teams' delay distribution shows both a higher skewness and a higher kurtosis. It is interesting also to observe a sharp decline of the distributions close to the threshold value, with nonetheless a small tail representing the cases in which teams who fell behind the threshold could not activate the threshold due to the mutual fund having insufficient capital. This could be improved by manually increasing the *economic-adjustment* parameter. We report this in Figure 6c.

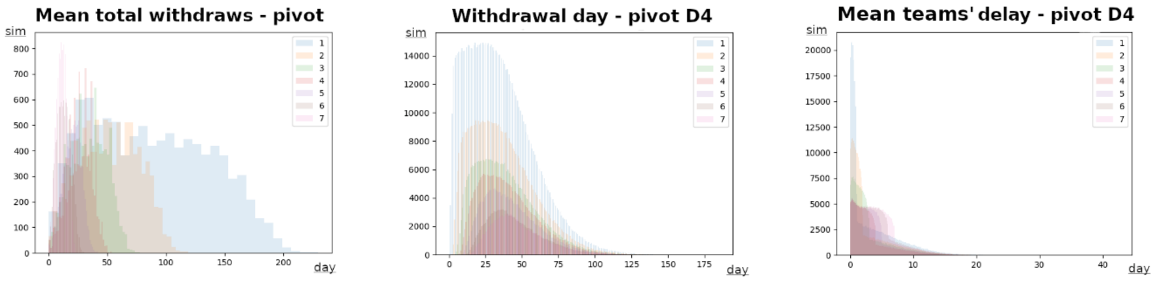
We now proceed with pivoting on *withdraw-threshold* and showing the effects of varying the value for *deposit-threshold* from 1 to 7.

As the threshold increases in value, the distribution of the total number of deposits shows a higher skewness to the left, meaning that fewer deposits are performed in general. This behavior is reasonable, as moving away from the threshold makes reaching it less frequent. We report this in Figure 7a.

As the threshold increases in value, the deposits' game-day execution distribution shows a lower kurtosis and a similar skewness (similar to what was observed with the withdraws). We report this in Figure 7b.

As the threshold decreases in value, the number of withdraws decreases, as a bound for this parameter too strict will prevent teams from ever being in advance, and thus more at risk in the future of falling behind. We report this in Figure 7c.

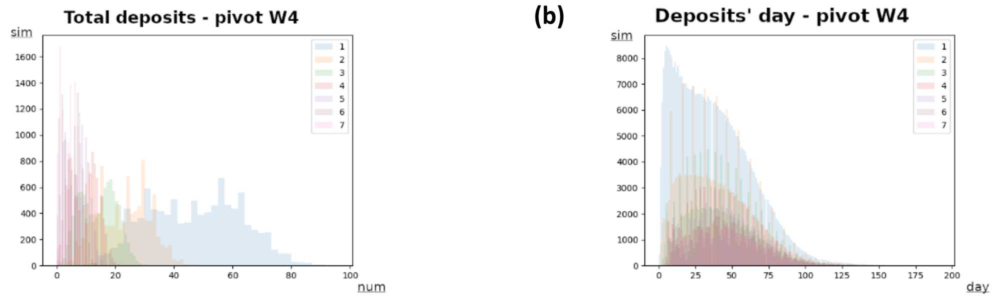
Finally, in Figure 8, we report the values for the parameter economic-adjustment, automatically computed from the other two parameters. We first observe that the value for *economic-adjustment* was always higher than 1. In all cases, an inflation mechanism was needed to keep the mutual fund in equilibrium. We then observe that low values of *withdraw-threshold* (WT, on the x-axis) and *deposit-threshold* (DT, on the y-axis) lead to low value of *economic-adjustment*. This behaviour can be explained by the fact that low inflation is sufficient when there are frequent deposits and withdrawals. Instead, the calibration needs high inflation when deposits and withdraws are rarer (high values for WT and DT - meaning further correction bound).



(a) (b) (c)

Figure 6: Distributions for withdrawal's mean total number (a), withdrawal's game execution day (b), mean teams' delay (c). Pivot on *deposit-threshold* = 4

(a) (b)



(c) **(d)**

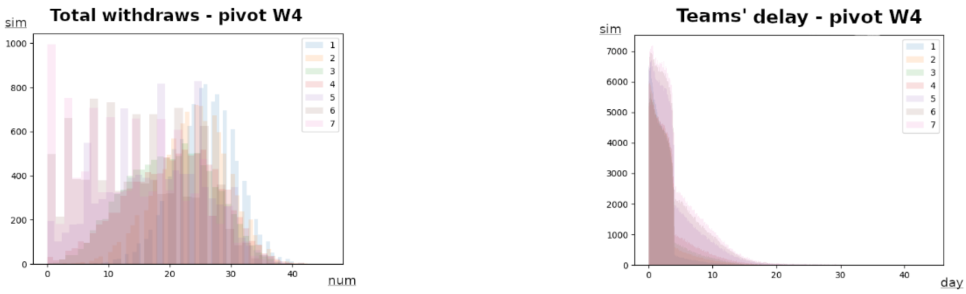


Figure 7: Distributions for the deposits' total (a), deposits' day (b), withdraws' total (c), teams' delay (d). Pivot on *withdraw-threshold = 4*

6. Conclusion & Future Works

This paper presented the design, the development and the initial calibration of a mutual insurance system for a multi-player sustainable mobility educational game.

As a future work, we will conduct a field study for the evaluation of this new game mechanic. In particular, we will (i) investigate whether and how it affects students' motivation towards the goal of promoting sustainable home-to-school mobility habits; (ii) analyze its efficacy in terms of reduction of the variance of the teams' progression; (iii) evaluate its impact in terms of educational value as a mean to introduce and reflect in-class about the key concepts and principles of mutualism and cooperation in general.

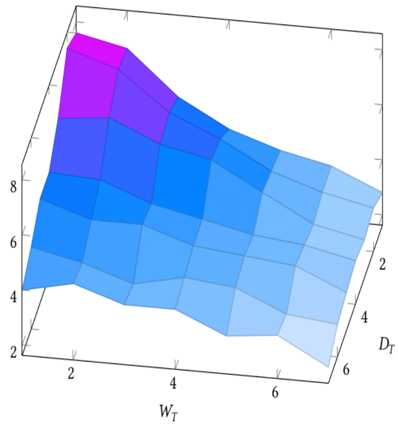


Figure 8: Distribution of the values for the parameter *economic-adjustment*, automatically computed from the values of *withdraw-threshold* (W_T, on the x-axis) and *deposit-threshold* (D_T, on the y-axis)

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