# Generating Personalized Challenges to Enhance the Persuasive Power of Gamification

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**Abstract.** While gamification is often effective in incentivizing behavioral changes, well-known limitations concern retaining the interest of players over the long term, and sustaining the new behaviors promoted through the game. To make the gamification user experience more varied and compelling, we propose an approach based on the Procedural Content Generation of personalized and contextualized playable units that appeal individually to each player. We have implemented this approach as a system that generates and recommends personalized challenges, based on the player's preference, history, game state and performance, and we have evaluated it using a smart urban mobility game that proposed weekly challenges to hundreds of citizens/players.

**Keywords:** Gamification, Recommender Systems, Procedural Content Generation, Sustainable Behavior

## 1 Introduction

Over the past decade significant efforts have been undertaken to build various persuasive systems to encourage and promote more sustainable life styles [1, 2]. As a persuasive technology [3], Gamification [4] has shown significant potential, in many sustainability applications, ranging from energy conservation [5], to recycling [6] to mobility [7].

While gamification is often effective to incentivize users to modify their behaviors and achieve certain set goals, an often–observed shortcoming is that its effects tend to diminish in the long term [8,9]. That hampers its persuasive power, since the new behaviors that are being promoted must be reinforced over time to effectively form new habits [10]. To counter that problem, we propose to introduce in gamification the Procedural Content Generation (PCG) [11] of personalized playable content. PCG is used in contemporary electronic games, to computationally generate a wide variety of game elements, which can enhance the user experience and sustain the interest of players, by adapting the game to the personal preferences, abilities and style of each individual player [12]. Our hypothesis is that, by injecting personalized playable content, we can


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analogously improve long–term engagement and retention in a gamified system, and thus amplify the persuasive power of gamification.

To that end, we have devised an approach for the automated generation of challenges, as part of our gamification framework for Smart Cities [7]. Challenges are playable units that set a goal for an individual player, which must be achieved within some constraints (e.g., temporal), in exchange for an in–game reward. We present here a challenge generation system that automatically produces challenges with personalized goals (based on the player's preferences, game history and performance) and rewards (based on the difficulty of the requested goal, the current game state of the player, and her game objectives).

The rest of the paper is organized as follows. We discuss relevant related work in Section 2; we offer an application scenario in Section 3; we describe our technical approach in Section 4; we report on our evaluation and findings in Section 5; and we offer our conclusions in Section 6.

## 2 Related Work

Our proposed framework is rooted in a combination of Procedural Content Generation (PCG) and Recommender Systems (RSs). PCG is an umbrella term for a vast set of techniques devoted to automate the construction of Game Design Elements (GDEs) to be delivered in electronic games. Those GDEs may vary widely, from textures and sounds, to buildings, maps and whole game level layouts, to items, equipment and other virtual goods, to playable units of content such as riddles to solve, obstacles to overcome, encounters with Non-Playing Characters, challenges, missions and quests to complete, and even entire story-lines [13]. Advancements in PCG are driven by very practical considerations (players dislike uniformity and excessive repetition, and the computational generation of diversified content for a game may lead to significant time and cost savings, especially at scale), but also by the possibility to personalize the game experience, thus adapting it to some elicited characteristics of each individual player [12, 14]. For example, Zook et al. have used PCG to tailor the game play to a model that captures the player's current know–how and her measured – as well as predicted – performance, and have applied it to both missions in a role–playing fantasy games and training scenarios in a military serious game [15, 16].

This kind of personalization of game content shows great potential to avoid frustration or boredom for players [17], and keep them engaged, as discussed for example by Sauvik et al. [18].

In order to offer playable units of content that are best–suited for a given player, some PCG approaches aim at leveraging the potential of Recommender Systems (RS), that is, their ability to predict what a user may prefer, choose or accept among a set of items [19]. For example, in [20] a content-based recommender system is used to calculate the most appropriate location and quantity of content for each area of a video game map (in that case, content refers to the number of objects in the game, such as virtual enemies, treasures, etc.).

Although similar combinations of PCG and RS are increasingly being investigated in electronic games proper, to our knowledge their use as a strategy to enhance engagement and ensure retainment of players in gamified applications is novel, and with the proposed framework we intend to explore it and evaluate its potential.

## 3 Application Scenario

We briefly introduce a scenario, which we will use as a working example through- out the paper, and which derives from a gamification campaign on sustainable urban mobility in which we have experimented with our challenge generation system (see Section 5 for further details).

In our sustainable mobility game, players / citizens make progress and compete with one another by accumulating points and collecting badges, based on their daily transportation choices. Choosing public transportation (e.g., buses) is better rewarded than driving a car on the same itinerary; similarly, choosing any zero–impact mode of transportation (i.e., bicycle, walking, etc.) that does not produce $CO_2$ emissions is even better rewarded than public transportation. The city administration may also consider additional objectives, such as pushing new or under–used transportation services (e.g. a newly rolled out bike sharing service), or encouraging specific alternatives at certain junctures (e.g., instead of taking an over–crowded bus line at peak hours, choose a train, since it offers more capacity), etc. Personalized challenges in such a game must be relevant to the individual user both "as a citizen", and "as a player": as a citizen, because they should stimulate the user to either try new, more sustainable modes of transportation, or to continue – and improve on – any positive mobility habits she has already adopted; and as a player, because the reward offered by a challenge should provide enough of a valuable incentive in terms of the player's game status and advancement goals; moreover, it should be commensurate to the effort required of the player to complete the challenge. In our game campaign, we generated and assigned two challenges per player each week in accord with weekly themes reflecting the priorities of the city administration. Among the themes, we had a "bicycle week", a "public transport week", a "health and fitness week", etc. Challenges were diverse not only on theme, but also on what they required in order to win. We created about a dozen different flavors of challenges: some required to increase by a certain percentage the number of Km. or weekly trips in a certain transportation mode, others to avoid a mode altogether, others to try a mode at least once, others to visit as many park–and–ride or bike sharing facilities as possible, others to invite a certain number of friends into the game, etc. Our challenge generator leveraged this variability, as well as the recorded game and mobility behaviors of players, to propose hundreds of challenges each week, throughout the 9 weeks of duration of the gamification campaign.

## 4 Technical Approach

We developed our challenge generator in two iterations. Each of the two proto- types was integrated in our gamification framework, which uses the DROOLS open source rule engine[1] for the definition, deployment and execution of games.

### 4.1 Challenge definition

To be effective in the specific context of gamification, the generation of playable units of content must fulfill two purposes at the same time: i) enhancing the user experience, proposing playable content that is in accord with the player's preferences, contextually relevant to her current game state and objectives, and of balanced difficulty; and ii) further the gamification goals, that is, persuade players to take action in accord to the behavioral change that is the "ulterior motive" of any gamified system. For that reason, we conceptualize all types of challenges with the following tuple: < P, G, C, D, R, W >, where

- P refers to the individual player to whom the challenge is assigned.
- G defines the goal, that is, a task or a performance target, which should be fulfilled to successfully complete the challenge.
- C is a constraint for reaching the goal; a typical example is a temporal deadline e.g., player PL must achieve goal G within one week.
- D is an estimate of the difficulty of the given challenge for player P. Notice that, the difficulty of the same challenge, that is, with same goal and constraint, may be different for different players.
- R is the in–game reward (a.k.a. prizes) awarded for completing the challenge. We define rewards in terms of existing elements of the game: for example, a reward can be a bonus or booster for points accumulation, a badge in a collection of achievements, etc.
- W is a weight that represents how significant the task represented by the challenge is for the behavior being promoted via gamification, that is, the ulterior motive behind the game.

Our challenge generator works with challenge models and corresponding code templates. To create a challenge model, a game designer must specify the various elements of the tuple above, For example, the combination of goal *G* and constraint *C* can be expressed programmatically as a logical expression predicating on the state of player *P*, which – if satisfied – triggers the awarding of the specified reward *R*. This conceptual scheme can be repeated, and allows the game designer to define the general business logic for a repertoire of challenge types. For example, a challenge model requiring a relative improvement, players must improve by *X%* their performance, quantified with counter *CT*, with respect to a previous game period *GP*. A wide variety of challenges can then be instantiated by the generator, by filling with opportune values the set of

[1] `http://www.drools.org`

parameters that is specific to each challenge model. For instance, the model above, in the context of our sustainable mobility scenario, could be filled for a given player P with values *X = 20*; *CT* = walking *Km*; *GP* = 1 week.

Borrowing from the taxonomy in [21] our approach to challenge generation can be characterized as an On-line, Constructive, Parameterized, and Optional case of PCG applied to gamification, in which personalization is achieved by choosing appropriate values in the parameters space, according to each player's profile.
Moreover, in the first prototype of the challenge generator, a further level of personalization came from assignment criteria attached to each challenge model to be instantiated, which were decided by the game designers, and effectively segmented the players' population based on variables in their profile. In the second prototype, that manual criteria specification has been replaced with a dedicated Recommendation System, which automatically samples a large number of challenge instances across all the available models and their parameters space, and takes finer-grained, individual assignment decisions.

### 4.2 Challenge generation

**Semi-automatic approach** Our first prototype relies on a certain amount of expert judgment by a game designer prior to the proper generation process; therefore, we call it semi–automatic. To support the game designer in that work, we have developed a frontend tool for the challenge generator, which is shown in Figure 1. In the tool, the designer can pick what models she wants to instantiate, specify values for their parameter sets, and define which assignment criteria must be applied. In the example reported in the Figure, only two models are shown: *percentageIncrement*, which sets an improvement goal relative to one's past performance, and *absoluteIncrement*, which asks to reach a set performance goal. Still, the game designer can achieve a lot of variation by applying different value combinations for the parameter set of each model. For example, the *absoluteIncrement* model can be used to provide various goals on the number of zero–impact weekly trips; but it can be used as well to ask to every participant to refer the game to at least one potential new player. Further variation and personalization come from specifying what assignment criteria – logical clauses that predicate on the game state and profiling variables collected for each player – will decide the assignment of each parameterized model to different segment of the player population.

On the right-hand-side of the tool, a chart representing the distribution of challenges over the player population enables the game designer to understand the effect of the selection criteria she has written. The game designer may go through some iterations of this specification process, and try different assignment options, until she is i) certain that each player will receive the planned number of challenges (2, in our case); and ii) the challenge distribution reflects well the behaviors the game wants to push at that time (for example in accord to the theme of the week). At that point, she can decide to instantiate all challenges, which results in the PCG of new game code and its deployment onto the run-time of our gamification framework. The new code applies uniquely to each individual player, and – as outlined above – differentiates her game experience using her current game stated, as well as her accumulated game performance, and her track record in terms of gamified behaviors.

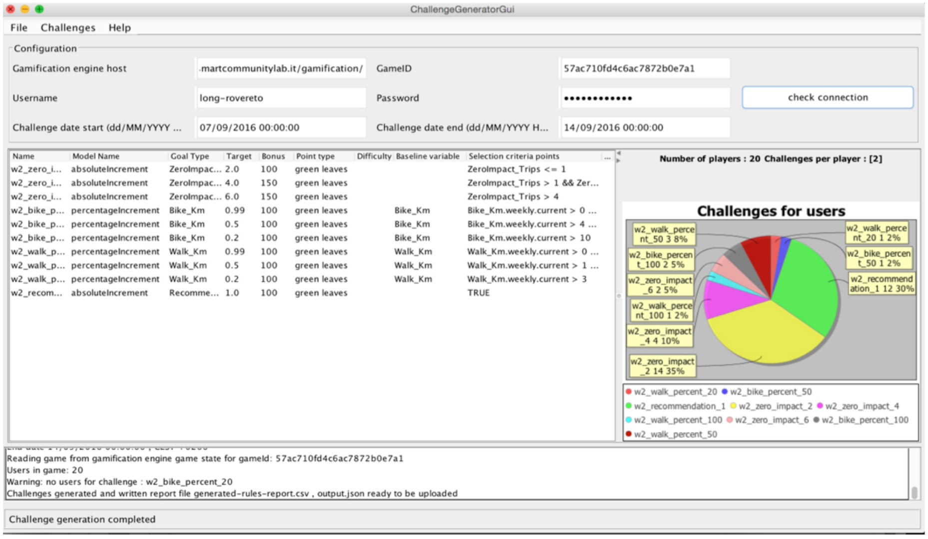


Fig.1: The Challenge Generator Frontend

It is worth noticing how this semi–automatic process can be fairly time– consuming for game designers. Moreover, they must gather significant experience with the gamified domain and the game itself, in order to produce challenge assignments that can be well accepted by most players and enhance their game experience, and at the same time push them to further the underlying goals of the gamification campaign. Also, in games with large number of players an approach that strongly relies on this kind of expert judgment is hard to scale. Therefore, for the second iteration of our challenge generator, we have investigated the use of a recommender system that can automatically produce and assign challenges, looking at each player individually.

**Automatic approach with individual recommendations** The design of the recommender system at the basis of our second prototype is depicted in Figure 2, and has three main modules: *Challenge Generation*, *Challenge Valuator*, and *Filtering and Sorting*.

The Challenge Generation module constructs a set of challenges, by enumerating all parameter combinations of each challenge model that the game designer intends to introduce in the game. That results a large number of partially–filled instantiations of the challenge tuple introduced in Section 4.1. The tuples, at that stage, do not contain information about *Reward*, *Difficulty*, *Weight* and of course the assigned Player. All those instances are stored in a challenge repository.

The Challenge Valuator module is in charge of implementing a set of procedures for each of those instances, and is broken down in the difficulty estimation and computing prize sub–modules. The former module estimates the level of *difficulty D* for the challenge goal, by comparing it with the distribution of the performance of the whole player population so far on the same kind of task, comparing it to the distribution of all active players in the game (in each particular means of transport). The latter module calculates, a fair *reward (R)*, which is commensurate to the effort necessary to the player to complete the challenge, based on the goal and its level of difficulty.

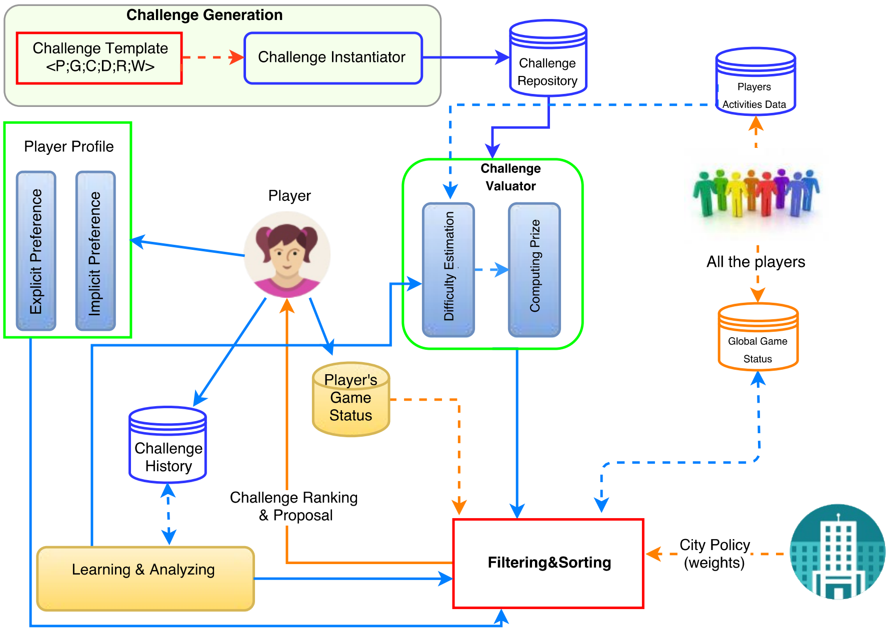


Fig.2: The conceptual view of the proposed system

In the *Sorting and Filtering* module, a multi-criteria recommendation algorithm ranks the generated challenges for each individual player. The intent of this algorithm is to balance the interest of the player to earn rewards that help her to progress towards her objectives in the game (e.g., collect enough points to reach a new achievement or a certain leaderboard position, etc.) while not requesting goals that are too difficult, and the interest of the city to push more strongly specific citizen behaviors and choices at any given juncture. Requested improvement, difficulty, amount of reward, distance to the next game objective, and *weight W*, which captures the city administration perspective, are therefore the dimensions that our algorithm considers to find a "*sweet spot*", and suggest challenges that are well suited to the user both "as a citizen" and "as a player".

Figure 2 shows an additional *Learning and Analysis* module, which is in progress. That module uses Machine Learning on the performance with challenges over the history of the game, to assess what challenges are most likely to be accepted and successfully taken up by a player.

# 5 Evaluation

Our evaluation addresses both of the approaches described in Section 4. The semi–automatic approach was at the basis of an open–field urban mobility gamification campaign; we can also evaluate the recommendation–based, fully automated approach comparatively to the semi–automated one, using the same experimental data set.

## 5.1 Semi-automatic approach evaluation

We introduced the procedural generation of challenges for the first time within a sustainable urban mobility game in the city of *Rovereto*, Italy (about 40,000 citizens).

**Study setting.** We carried out this gamification campaign as an open–field study that lasted nine weeks in the Spring of 2016. The game was open to all residents of Rovereto, as well as commuters from the surrounding areas of Trentino. Citizens could participate to the game by using a mobile App available at the principal mobile app stores, which was advertised through an extensive, multi–channel advertising campaign that went on throughout the game duration and tried to cover the whole territory, and an audience as diverse and general as possible. About 400 citizens

Through the App, which combines multi-modal journey planning capabilities for planned trips, with user–activated tracking in case of impromptu trips etc., we collected detailed statistics about the itineraries recorded its users when playing the game, such as, Km, trips and trip legs travelled in each transport mode, and so on. Almost 400 citizens downloaded our *App*, 300 actually registered for the game, and 110 were active players, who interacted and competed with the game. The principal findings on the effects of the gamification campaign are detailed in [7]; here we only discuss challenge–related findings.

**Main findings.** The 110 active players were given a total of 1,308 challenges; they succeeded in 212 of them, and worked towards 83 more challenges, without managing to complete them within their 1-week deadline (overall, a challenge acceptance ratio of 24%).

As discussed, the city administration set specific mobility–related themes for several game weeks. The way the game designers implemented those themes was by generating challenges that could persuade players to increase their use of the corresponding transportation options. What emerged is that the thematic weeks by and large had the intended effect: for instance, in the "*public transport week*" the combination of bus and train modes of transportation peaked at 70% of all Km. travelled by players, i.e., the highest percentage in all game weeks; in the "zero–impact week" the combination of modes that do not produce $CO_2$ emissions, i.e., walking, private cycling and bike sharing, jumped to 38% (from 28% in the previous week); analogously, later on, in the "health and fitness week", those same modes reached a combined 62%, again highest among all weeks. Overall, these results suggest that using challenges was effective to nudge players towards the specific mobility choices pushed by the city administration via the thematic weeks.

We also gathered the opinions of players at end of the game, using an in–App survey, which was administered as a challenge itself, with a significant in–game reward, and which was fulfilled by 36 of the 110 active players (about 33%).
The survey included a number of questions about players' change of habits, as well as their opinion on the game and the underlying sustainable mobility campaign. Related to the scope of this paper, one question aimed to assess which game mechanics were considered most effective. The question was: *"How important was the following game element to keep you active in the game and encourage you to keep moving in a sustainable way?"* The options available included all major mechanics in our game (points, leaderboards, badges, badge collections, and challenges); we also included for comparison the material prizes given out weekly to top performers by the city administration and some sponsors. The results are shown in Figure 3. From it, it is evident that respondents had a highly positive consideration of our procedurally generated challenges as an effective persuasive mechanics, even better than material prizes, and on a par with the main competitive game mechanics, i.e., points and leaderboards.

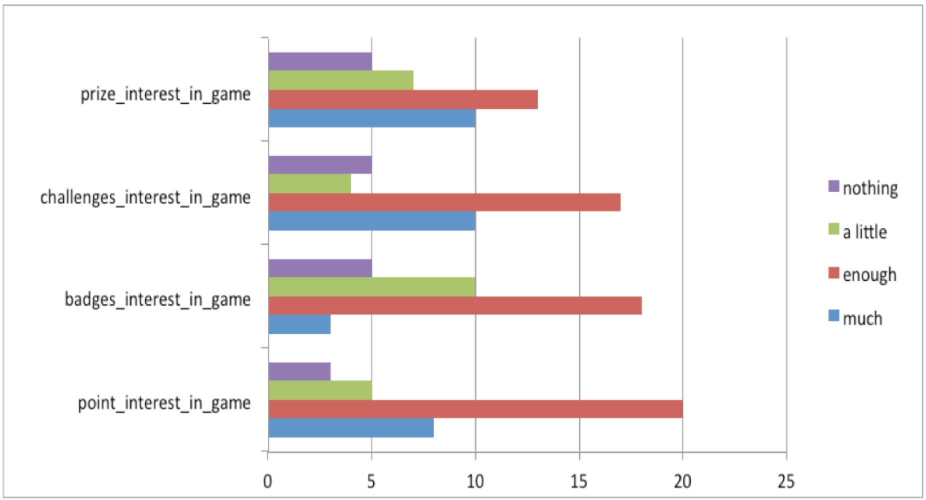


**Fig.3:** Players' opinion on effectiveness of game mechanics (n=36)

### 5.2 Individual recommendation system evaluation

In the second step of the experiment, we evaluate the quality of the challenges automatically produced by our system, based on the player data collected during the Rovereto gamification campaign, and we compare them to the "*historical*" challenges that were actually proposed to its players by means of expert judgment. Our evaluation addresses the following two questions:

- **RQ1:** to what extent the challenge recommendations that are automatically produced for a player are similar to the challenges selected and administered by means of expert judgment for the same player at the same point in the game?

- **RQ2:** whenever the automatically generated and recommended challenges differ from those administered by experts, do they represent more (or less) acceptable and viable alternatives for that given player at that given time?

We considered for our evaluation only challenges that asked players to carry out at least a certain at least a certain number of trips or KM in a given transport mode, or to improve by a certain percentage those counters vis-a-vis- the previous week; moreover, we included in the evaluation only players who were active in a given game week, for a total of 298 challenges. We used the cumulative data from the extensive log collected throughout the game, to reconstruct each player's state at the beginning of each week, and feed that data to our generation and recommendation system. We repeated this procedure for all weeks, and instructed the generator module to consider five different improvement percent- ages: *10%, 20%, 30%, 50%* and *100%* for each sustainable transport mode, since those were the improvements used by the gamification experts.
To gain insight on RQ1, we looked at a measure of similarity between the challenges generated and recommended by our system, and the "historical" challenges (those devised during the P&G game through expert judgment) for a given player in a given week. We defined challenge similarity based on three features: mode of transport promoted, amount of improvement requested, and amount of reward (points) offered. The formulas for similarity computation are shown below.

$$SimM = w_m * Sm(0|1)$$

$$SimR = w_p * \left(1 - abs\left(\frac{fHch - fAch}{R(max - min)}\right)\right) \tag{1}$$

$$SimPI = w_{pi} * \left(1 - abs\left(\frac{fHch - fAch}{PI(max - min)}\right)\right)$$

$$TotalSimilarity = SimM + SimPI + SimR$$

where *fHch* and *fAch* refer to the features of historical challenges and the RS challenges, respectively. *w* symbols are weights for the features: since correspondence of the transportation mode is critical in our scenario, we set $w_m = 0.5$ in case of the same transportation mode *(SimM),* otherwise 0. $w_{pi}$ and $w_p$ are the weight of improvement percentage *(SimPI)* and reward *(SimR),* and are set to *0.25.*

We consider similar only pairs of historical (*H*) vs. recommended challenges (R) with a score $\geq 0.75$, otherwise they are considered dissimilar. The results are reported in Table 1, which show a matching percentage of about 73% (with $p < 0.001$). Related to RQ1, that shows that our automated approach can be used to produce and recommend challenges that are largely analogous to the ones developed manually by gamification designers.

For a more in-depth analysis, we looked at the players' acceptance of proposed challenges. We say that a challenge was accepted by a player if either the player successfully completed it, or she took sufficient action to fulfill at least *50%* of the challenge goal during its time span. Table 2 shows the relation- ships between historical challenges, recommended challenges and acceptance. The first row discriminates the 106 accepted historical challenges in two sub- sets: 68 of them were also analogous (i.e., similarity $\geq 0.75$) to recommended challenges, while 38 where dissimilar. Correspondingly, the second row reports that, among the 192 historical challenges that were not accepted, 150 have an analogous recommended challenge, while 42 do not.

**Table 1.** Similarity and Dissimilarity.

| Total # of recommended challenges | 298 | Condition |
|---|---|---|
| Total # of Matched Challenges | 218 | >=0.75 |
| Total # of not Matched Challenges | 80 | <0.75 |
| | | |
| Total Similarity | 73.10% | |
| Total Dissimilarity | 26.80% | |

That matrix can be interpreted as a standard Confusion Matrix, to assess the performance of the RS in recommending challenges that were analogous to accepted historical challenges (and therefore would be likely to be accepted as well by the same players). Consequently, we can compute precision (31%), recall (64%) and accuracy (37%) for our approach. Although 37% total accuracy may seem low in absolute terms, it is important to remark that it is almost identical to the acceptance ratio of historical challenges administered by experts (i.e., 36%), and therefore in line with a positive response to RQ1.

For gaining insight on RQ2, it is useful to focus on the 42 true negatives in Table 2. These are cases of historical challenges that were not accepted by players, and in whose place our system proposes some dissimilar alternatives. By looking at the traveling activities of the corresponding players, we can examine whether the automated recommendations could have been in some cases more appropriate than those devised using expert judgment.

During this analysis, we had to eliminate 24 out of the 42 cases above, since these regard players who, although active in the previous week, chose to not participate in the game at all during the week in which those challenges were active. Unfortunately, no comparison based on their activity can be done in those 24 cases. The remaining cases involve 18 different players; 8 out of the

36 challenges proposed by the RS to those players would have been accepted, according to our definition (fulfillment of at least 50% of the challenge goal), and 5 of the 18 players (27%) carried out travel activities in line with accepting at least one of the two recommended challenges. Although this amount of data is not sufficient for statistical significance, the results seem encouraging with respect to the quality of the recommendation produced and as a preliminary result on RQ2. This is especially true when

one considers that there is an intrinsic negative bias against the automated recommendations in this retrospective test, since those 18 players could not be exposed to the challenges produced by the RS, and, in fact, were asked to spend effort on different challenges, often involving different transport modes.

The evaluation above has allowed us to validate the design of our challenge generation and recommendation system, and to demonstrate the suitability of the approach. The results show that our approach (using RS) can automatically generate and propose challenges, which are analogous in kind and quality to the ones devised by experts with knowledge of the application domain and the design of the game.

**Table 2.** Confusion Matrix

| | Recommended By RS | Not-Recommended By RS |
|---|---|---|
| Historical Accepted | 68 (TP) | 38 (FN) |
| Historical Not-Accepted | 150 (FP) | 42 (TN) |

## 6 Conclusion

We have presented an approach and system for procedural generation of playable content units in gamification. Our system generates challenges that are personalized with respect to the history and habits of each individual player, and contextualized with respect to her game state, as well as the objectives, principles and policies that underlie a gamification solution. We have developed our generation and recommendation system as a component of a comprehensive Gamification Framework for the Smart Cities domain. In our framework, we have been using the injection of personalized and contextualized challenges to provide a varied and interesting experience to each individual player, as well as direct their behavior towards specific priorities of importance to the Smart City.

We have evaluated our challenge generation and recommendation system in an open–field case study on sustainable urban mobility [7]. That evaluation suggests that such personalized units of playable content may have a significant effect on persuading players to embrace the behaviors promoted by the gamification campaign.

We are currently using our challenge generator prototype that incorporates the recommender system in a larger and longer Smart City game in an A/B test fashion, i.e. to administer challenges to a subset of the player population, whereas other challenges are still administered by experts. In the longer run, we will also develop an automated learning algorithm, which will augment our recommendation components, in order to optimize the selection of challenges to the individual player also based on her track record with challenges that had been proposed in the past.

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