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Dynamic gamification adaptation framework based on engagement detection through learning analytics

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ABSTRACT: Most current adaptive gamification approaches use what is often called a “static” adaptation approach – i.e. game elements are adapted to users once, generally before using the gamified tool, based on a static user profile. On the other hand, dynamic adaptation proposes to adapt game elements based on user behaviour in real time, reacting to variations in user engagement. In this paper, we propose an adaptation framework using an initial static adaptation based on learner profiles, and a dynamic adaptation that uses learning analytics to refine the static adaptation recommendations. The adaptation system is able to observe various learning analytics to estimate learner engagement, to compare to that of other learners, and then to signal to teachers learners that require a change in their gamified environment. We propose a protocol for a future study to test our approach in real conditions, and provide some recommendations for future directions.

Keywords: Gamification, adaptation, interaction log traces, behaviour, engagement, learning analytics

1 INTRODUCTION

Adaptive gamification is the process of tailoring gamification to individual users. Currently, most approaches use “static” adaptation – i.e. they tailor based on individual static user characteristics once. For example in a literature in adaptive gamification for education (Hallifax et al., 2019) found that 13 papers presented some form of static adaptation, and 7 some form of dynamic adaptation. These user characteristics, or profiles, are generally based on information such as preferences for video games (Tondello et al., 2018, 2016), or motivation for education (Hallifax et al., 2020) or even general personality traits (Goldberg, 1992). These approaches only capture the state of the user once, and can fail to take into account differences that occur in users during the usage of the gamified platform. It is particularly true for users’ engagement which is a dynamic process that changes overtime during a course (O’Brien & Toms, 2008). This present research is focused on a dynamic adaptation of game elements integrated in a learning environment based on learner engaged behavior.

In this paper, we propose a learning analytics-based approach to estimate and track learner engagement, and offer the basis of a system that can leverage this engagement tracking to signal to teachers when an adaptation should occur. According to this approach, the teachers make the final decision to adapt game elements to learners during the course.

This paper is structured as such: section 2 presents a brief overview of the related literature on dynamic gamification adaptation approaches and methods and tools to analyze engagement. Section 3 presents our general adaptation framework; section 4 presents an application of the general framework to a specific learning context. Finally, in section 5, we conclude, and present future extensions of this work.

2 RELATED WORK

2.1 General dynamic adaptation approaches

There are a few dynamic adaptation approaches in the related gamification literature (Böckle et al., 2017). For example, (Paiva et al., 2016) modelled learner interactions with their learning platform (MeuTutor) to identify patterns in learner behavior to propose personalized missions. They categorized learner actions into four different categories: collaborative (actions related to helping other learners), individual (watching video classes, answering exercises and tests), social (chatting with other learners, sharing class progress), or gamification (achieving various badges and point ranks) interactions. Teachers then used these “interaction profiles” to adapt the learning goals for each individual (i.e. proposing goals that would entice them to interact with otherwise ignored learning content). This resulted in somewhat mitigated effects on learners: on the one hand, this adaptation led to an increase in individual and gamification interactions, but on the other, it failed to have an effect on social interactions. Another example is proposed by (Jagušt et al., 2018) where they present a simple adaptation system. In a math-learning environment, learners fight against a virus by completing mathematics exercises. The system is setup so that the virus “adapts” its speed so that it is always slightly behind the learners at all time. This adaptive setting showed large increases in learner performance, but the authors noted a negative effect on learner stress.

A different interesting approach was proposed by Monterrat et al. (Monterrat et al., 2017, 2015). In their work, they propose to adapt based on various learner profiles (mostly player types) in a static approach. They would then change these initial profiles based on learner behavior – the idea being that would use some kind of framework to link learner behavior and profiles. When the learner’s profile changes by a significant amount, they would reuse the static adaptation rules – i.e. select another game element based on this new learner profile. This approach would be an easy way to implement dynamic adaptation, by enabling the reuse of a breadth of readily available research into links between various learner profiles and relevant game elements. However, to our knowledge there are no framework that link learner behavior (or interaction log traces) to any of the commonly used profiling systems (player profiles, learning styles etc.).

2.2 Explaining and analyzing engagement

Engagement is a complex process. O'Brien & Toms (O'Brien & Toms, 2008) define it as "a quality of user experience characterized by attributes of challenge, positive affect, endurability, aesthetic and sensory appeal, attention, feedback, variety/novelty, interactivity, and perceived user control". It is particularly a dynamic process of engagement and disengagement. To adapt dynamically we need to be able to estimate engagement in real time. Currently, we can identify two major methods of estimating engagement, subjective and objective methods.

Subjective methods generally rely on questionnaires such as User Engagement Scale (UES - (O'Brien et al., 2018)) to determine engagement. However as previously stated, in a dynamic adaptation setting where we need to be able to estimate engagement in real time (or semi-real time), such tools are not quite adequate (i.e. we would not be able to administer multiple questionnaires between usage sessions). Therefore, we can look to more objective methods based on various learning analytics (such as interaction analysis). For example Bouvier et al. (Bouvier et al., 2014) present a study on the engaged behaviors of players in an online sport game. They present a trace model that categorizes user trace actions into four different categories of engagement that are then linked back to the different categories of the Self Determination Theory (Ryan & Deci, 2000). The four categories of engagement identified in this context are: Environmental (linked to *Autonomy* towards the environment), Social (linked to *Relatedness*), Self (*Autonomy* towards the character or role), and Action (linked to *Competence* and *Autonomy* towards the actions). This method was also used for measuring engagement in serious games for education in (LOUP et al., 2016).

We can also look at the methods presented by (Fincham et al., 2019) , who used factor analysis (FA) methods to establish an engagement model based on various simple learning metrics. They list a total of 18 metrics (inspired by the review performed by (Joksimović et al., 2018)). Of these 18, 7 are derived directly from learner trace logs, and are related to behavioural or academic engagement (i.e. days active, question accuracy etc.). The other 11 are related to either cognitive or affective engagement (i.e. learner feeling towards the content, or their knowledge of it). The different engagement categories presented in this paper refer to those distinguished by (Reschly & Christenson, 2012). From these 18 metrics they distinguish a final engagement model based on three engagement factors (using a factor analysis approach). What is interesting is that their factor model does not show a difference between behavioural and academic engagement (something that the authors state is often present in the related engagement literature (Appleton et al., 2008)).

All of the approaches presented here use “*a posteriori*” methods to determine engagement – i.e. after the end of the experiment or usage, so that the researchers can evaluate the impact of the learning system on learner engagement. The challenge for us is to be able to present a method or framework that can estimate learner engagement *during* the usage of a learning environment so that we might be able to adapt game elements according to its evolution (especially if a disengagement is perceived).

3 OUR PROPOSAL – GENERAL ADAPTATION FRAMEWORK

In this paper we propose to develop the adaptation engine architecture presented in Figure 1. This engine is able to select relevant game elements for learners based on both their learner profile, and their behavior (as observed through a set of learning analytics), as presented in blue. This engine therefore employs both a static and dynamic adaptation approach. The static adaptation uses the learner profile and occurs before using the gamified system. It is highlighted in green and described in further detail in section 3.1. The dynamic uses learning analytics and occurs whilst learners are using the gamified system. It is highlighted in yellow, and fully explained in section 3.2.

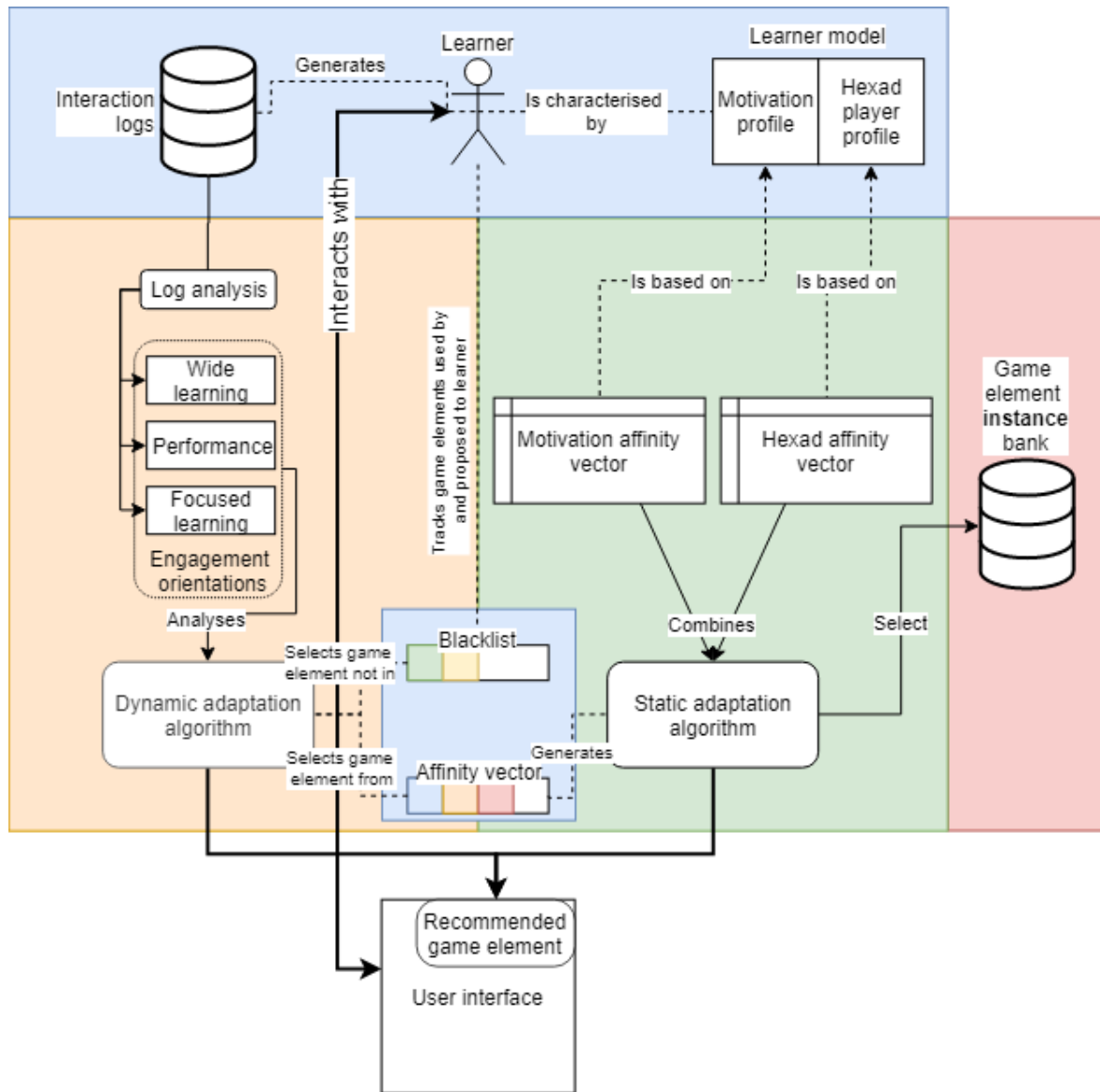


Figure 1 Our adaptation engine architecture. The green section (static adaptation approach) is described in 3.1. The yellow section (dynamic adaptation approach) is described in 3.2. The blue section is the learner information, containing the learner model (combined motivation and player profile), the learner’s interaction logs, their affinity vector (an ordered list that represents the most appropriate game elements for the learner generated by the static adaptation algorithm) and their game element blacklist (a list that tracks all the game elements used by and proposed to the learner).

3.1 Initial static adaptation based on learner characteristics

In our study applied to the educational context, (Hallifax et al., 2020) showed that using the Hexad profile (Tondello et al., 2016) as a learner player profile and initial motivation for mathematics (Ryan & Deci, 2000) to statically adapt game element provided significant positive results. We used partial least squares analyses (PLS (Hair Jr et al., 2016), a technique also used in (Orji et al., 2018)) to establish links between the dimensions of the two profiles and effects on learner motivation and behavior. From these analyses, we create an “affinity vector” for each learner (i.e. a list of game

elements sorted by descending order of affinity for each learner) which represents how each game element can be expected to positively (or negatively) affect a learner's motivation. We propose to use such a system for the basis of our static adaptation (the method for creating an affinity vector is fully described in our previous work (Hallifax et al., 2020)). Before the learner starts using the gamified learning system, we generate their profile (from questionnaires) and provide them with the most appropriate game element *a priori*.

3.2 Real time dynamic adaptation based on learning analytics

From the initial static adaptation, we can go one step further, and refine these *a priori* predictions and affinities. As previously stated, we can propose a dynamic adaptation that takes into account learner behaviour (tracked using learning analytics) to provide an estimation of learner engagement with the learning environment. We propose a dynamic adaptation approach that tracks various types of engagement over the course of the learning experience to suggest an adaptation of the game element when learner engagement decreases. To properly describe how this dynamic adaptation approach should work, we can use the PDA/LPA framework proposed by (Bouzit et al., 2017) – see Figure 2. The PDA/LPA framework describes two adaptation cycles on both the user and the system sides. Users **perceive** an adaptation change, make a **decision** about this change, and **perform** an action (PDA). They then **learn** from this cycle, use this new knowledge to **predict** how the system will react, and **adapt** their behaviour (LPA). This new adapted behaviour flows back into their perceptions and the cycle starts again. On the system side, the system **perceives** learner actions, makes a **decision** based on these perceptions, and performs an adaptation **action** (PDA). The system then **learns** from this adaptation, **predicts** how this will affect the user, and **adapts** its adaptation system (LPA). In our adaptation engine, we propose a simplified version that does not follow all of the PDA/LPA steps, providing a simplified version that allows for future expansion. Notably we do not leverage co-evolution between learner and system, neither does the system predict or adapt to the learner's behaviour. These could be further explored in future expansions of the system. The system works as follows:

1. The learner interacts with the learning platform, generating the interaction log traces (or learning analytics) – **Action**
2. The system analyses these log traces and estimates learner engagement – **Perception**
3. The system decides whether a game element adaptation is required (i.e. if learners show a decrease in engagement) – **Decision**
4. The system proposes a new relevant game element for this learner – **Action**
 - a. The learner sees this new game element – **Perception**
 - b. They interact with this new game element generating new interaction logs – **Action**
 - c. This new game element has an effect on their behaviour and engagement - **Adaptation**
5. On the system side: the proposed game element is blocked for the learner (i.e. it is not reoffered in future) – **Learning**
6. The system then analyses the new log traces generated by the learner and estimates his/her engagement – **Perception** - (restart from step 2)

This adaptation system raises a few questions that need to be answered: (1) How can we control that these adaptations are effective? ((Bouzit et al., 2017) propose that: “controllability is essential to enable the end-user to be actively involved in any adaptation activity”) (2) How can we ensure

that these adaptations do not occur too often (creating an unstable environment for the learner), and how can we ensure that adaptations do not occur too *rarely* (and therefore not reacting quickly enough to losses of engagement)? We provide first answers to these questions within the framework of the LudiMoodle project described in next section.

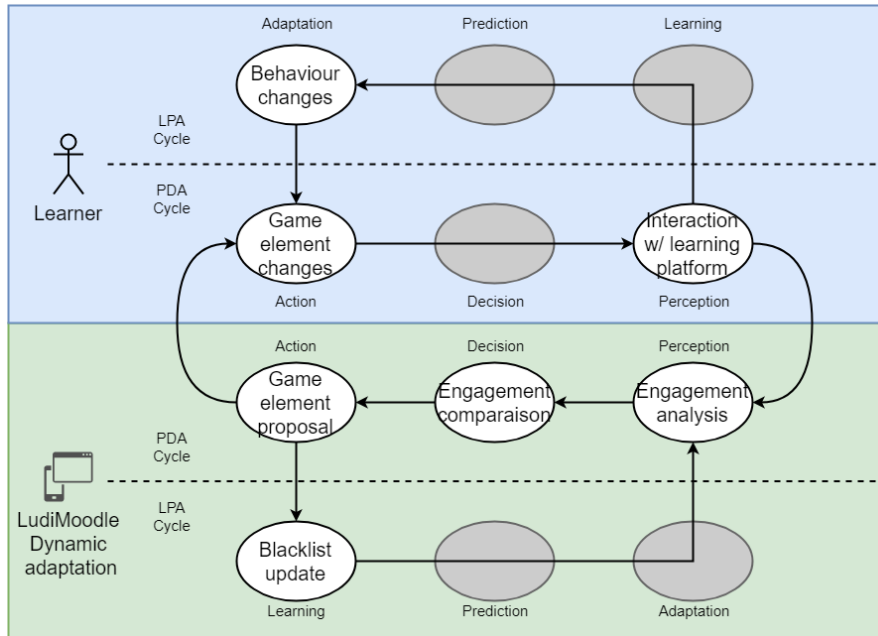


Figure 2 PDA/LPA framework applied to our proposed dynamic adaptation model.

4 APPLICATION TO THE LUDIMOODLE PROJECT

4.1 LudiMoodle project: general approach

In the context of the LudiMoodle project (<https://ludimoodle.universite-lyon.fr/>), we provided 5 French secondary schools with a gamified learning environment for teaching basic algebra. Data was gathered from 258 learners aged between 13-14 years old over the course of 3 weeks. They used a randomly assigned (i.e. not adapted to their individual profile) game element during 10 lessons. Each of the lessons was composed of between 4 and 10 quizzes of various lengths depending on the complexity of the lesson. The main goal of this project is to compare the effects of (1) statically adapted game elements (2) dynamically adapted game elements and (3) non-adapted (i.e. randomly assigned) game elements. Each of the game elements were chosen to cover one or multiple of the Hexad types as proposed by (Marczewski, 2015). The game elements used in this system are as follows:

- Avatar: Learners have a small goblin character and they can unlock various clothes and accessories for it. Game elements like this one are generally recommended for **Free Spirits**, as these avatars provide them with a personalized representation of themselves.
- Badges: Learners can win various badges based on their lesson progression, individual quiz progression, and longest correct answer streak. Badges are generally shown to be motivating for all users, but should particularly be effective for Players and Achievers, as they represent clear-cut goals for them to achieve with attractive rewards.

- Score: Learners gain points for each correct answer and are shown the maximum point total they can win in each lesson. As this game element gives learners a clear representation of how well they are doing in the course, and rewards them for performing better, it should be attractive to **Players**.
- Timer: Learners are timed for each question. Every time they answer a question correctly, their time is saved. During the next questions of that quiz they are tasked with answering faster, each time that they do, a character runs faster and faster. Here learners are challenged to beat themselves in a race, meaning that **Achievers** should be interested by it.
- Progress Bar: Learners progress in each lesson is represented using a rocket ship that travels towards a planet in space. Each new lesson shows a new planet. This game element should be particularly interesting for the **Achiever** player type as with badges, we also have a clear goal
- Ranking: Learners are placed in a “race” against other learners. Their final position in the race is determined by the number of questions they answered correctly. As this game element allows learners to compare themselves to others, (even if fictional) it should be motivating for **Socializers**

Both the learning content (i.e. quizzes) and game elements were designed in direct collaboration with the teachers who used this tool in their classrooms. This meant that concerning controllability, we proposed that teachers, with their knowledge of: the game elements, the learning content, and the learners; would be the most knowledgeable to understand if the proposed game element is appropriate for a specific learner or not. Between two lessons, teachers are given a table showing the game element each learner is currently using, a suggestion for a new game element that would be more engaging for the learner (if relevant), as well as the previous decisions they made for each learner (if they exist) (see Figure 3).

There are two learners in the test Class

- Learner01
- Learner02

Learner01

Lesson	Proposition	Used	Choice	Comment
L1	Timer	Timer	✓	Based on profile
L2	X	Timer		
L3	X	Timer		
L4	Ranking	Ranking	✓	Learner seems to lack challenge from timer

Learner02

Lesson	Proposition	Used	Choice	Comment
L1	Avatar	Avatar	✓	Based on profile
L2	X	Avatar		
L3	X	Avatar		
L4	Badges	Avatar	✗	Learner said they really enjoy the avatar!

Figure 3 Teacher control interface. In this example, the teacher accepted the proposal for Learner01 (Ranking) and refused the proposal for Learner02 (Badges).

The learning environment automatically stored all learner interaction traces (page visits, question answers, etc.) which we then analysed to determine learner engagement following a similar approach to that proposed by (Bouvier et al., 2014). Our main goal in tracking learner engagement is to be able to detect abnormal decreases, alert the teacher to these decreases and propose a game element adaptation so that we might counter this loss of engagement.

Our analysis proceeded in three steps; first, we reviewed and collated the data available from the LudiMoodle project study using a log trace approach. Second, we ran two factor analyses to create and verify an overarching engagement model that identified the three engagement factors. Finally, we used these factors to track the variation of learner motivation and engagement, and signal to teachers when an adaptation would be necessary. Each step is described in the following sections.

4.2 Determining engagement factors

By analyzing the data that was available from the use of the LudiMoodle platform, we extracted a set of learning analytics that we believed would allow us to follow the evolution of learner engagement and motivation throughout the usage of the system. We then performed two factor analyses (Exploratory FA and Confirmatory FA) to create our final engagement factor model that identifies the following three factors (as calculated in (Hallifax, 2020)):

- **Wide learning engagement (F1)** in figure 4) - This relates to how quickly a learner progressed through the various learning content for a lesson. The more quizzes they passed, the more distinct quizzes they could attempt. Furthermore, the faster they completed each question, the more time they had to attempt other quizzes
- **Performance engagement (F2)** - This directly links to a learner's performance, how well they answered each question and completed each quiz.
- **Focused learning engagement (F3)** - This relates to how much a learner tried to achieve a perfect (100%) score for each quiz, or how much they strived to improve a quiz score.

By calculating these three engagement factors after each lesson, we can estimate how learner engagement varies over time and, more importantly, pinpoint when learners lose engagement. Figure 4 presents an overview of how the different log levels are structured, as well as which operations are used to calculate the different engagement metrics. The final engagement factors along with the metrics that compose them are also displayed. For example, the **performance engagement** factor is computed using the ratio of correct questions (i.e. the percentage of correct questions) and the lesson ratio (i.e. percentage of completed quizzes in a given lesson). The question ratio metric is counted using the complete question operations, which are an aggregation of the *QuizPageView*, *QuestionGradedWrong/Right*, *QuizPageView* log traces.

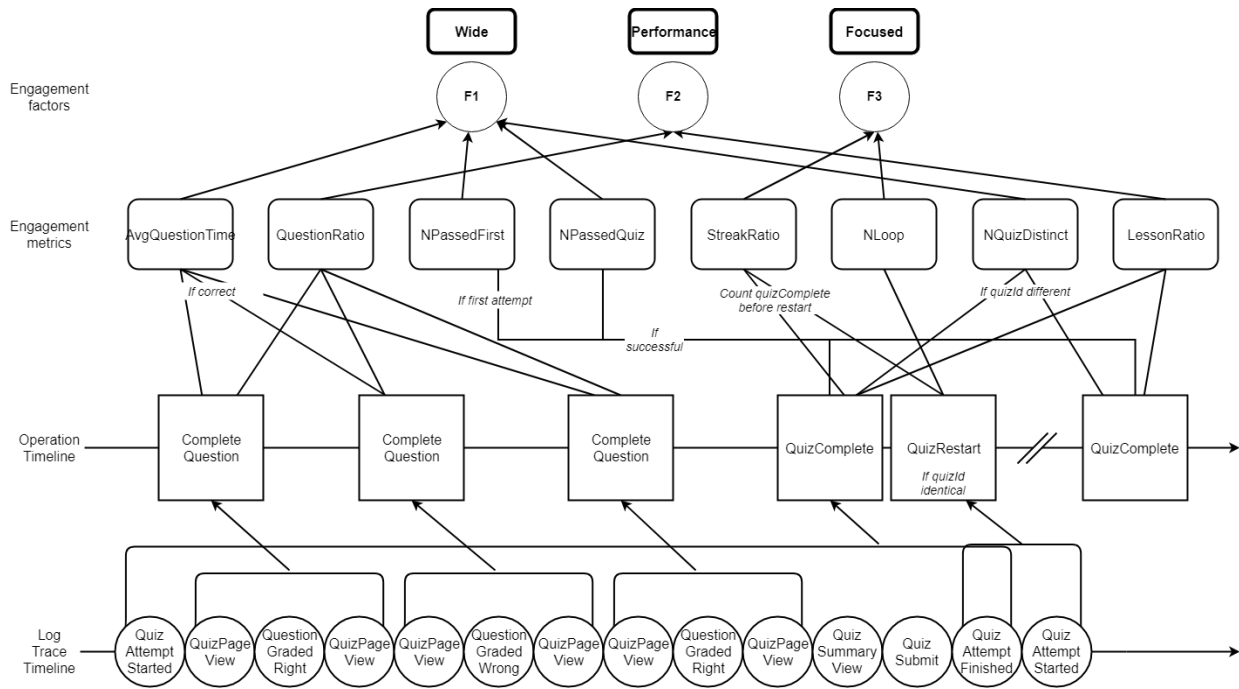


Figure 4. Full log trace analysis model, with the engagement factors (F1, F2, F3) discovered through the EFA/CFA analysis.

4.3 Engagement variations tracking

In our system, we propose to adapt the game element when we detect an abnormal decrease in learner engagement. For each lesson completed, we calculate the intensity of three engagement factors (**Wide learning**, **Performance**, and **Focused Learning**) for each learner, and the variation of these factors with those of the previous lesson. As there is no baseline, or "standard values" for each of these engagement metrics, we decided to compare them to the rest of the learners' class. The idea is that if a single learner displays a decrease in any of the engagement, it is difficult to interpret if it is "normal" or "expected". For example, in the LudiMoodle experiment the later quizzes were harder and more complicated than the earlier ones. This means that it we could expect a slight decrease in performance from all learners, resulting in a decrease in **Performance Engagement**. Therefore, this decrease should not be seen as *exceptional*, and should not trigger a change. This is why we decided to compare learners' variations to those of their classmates. When a change is triggered the system selects the highest game element from the learner's affinity vector that the learner has not yet used. All game elements that the learner has used in the past are blacklisted as to ensure that they are not proposed again in the future.

It is important to note that when a game element is changed, we impose a short cool-off period, where a learner will not be subjected to another adaptation. This is to allow learners to experience their new game element, and get used to it, before a new change could occur. Changing the game element too often could result in confusion in learners. As the teachers in the LudiMoodle project planned to use the platform during ten lessons, we decided to use a cool-off period of three lessons between adaptations as this would results with a maximum of 2-3 game element changes for the least engaged learners. A too short cool-off period could result in an unstable learning environment

(frequent changes) and might distract the learner, and too few changes might reduce the system's capacity to react to learner behaviour. Furthermore we use a *blacklist* system to ensure that learners are not offered the same game elements over and over. An example of this approach is presented in Figure 5. During the first three learning sessions, the learner uses the same game element (*blue*). At this time no adaptation is possible, and their blacklist contains one element: *blue* (the one they are currently using). Between the third and fourth learning sessions the system can generate a new game element recommendation: this is the first possible adaptation for this learner. The system computes the variations of the learner's engagement factors (noted ΔW , ΔP , ΔD) between session one and two and between session two and three. These variations are then compared with those of the other learners in their class. In this example, an adaptation is proposed, and the system recommends that the learner use the *purple* game element. The learner's blacklist is therefore updated to contain both *purple* and *blue* meaning that these game elements will not be proposed in the future. In the first timeline, the teacher accepts the adaptation, and the learner is assigned the new game element. They are therefore protected from a further adaptation for the next three sessions. In the second timeline, the teacher refuses, and the learner uses the same game element for session four. The system then uses the variations between S3-S4 and S4-S5 to determine whether an adaptation is required. In this example the system also detects a decrease in engagement, and proposes the *orange* game element. The teacher accepts this new proposal, and the learner is assigned a new game element for the next session.

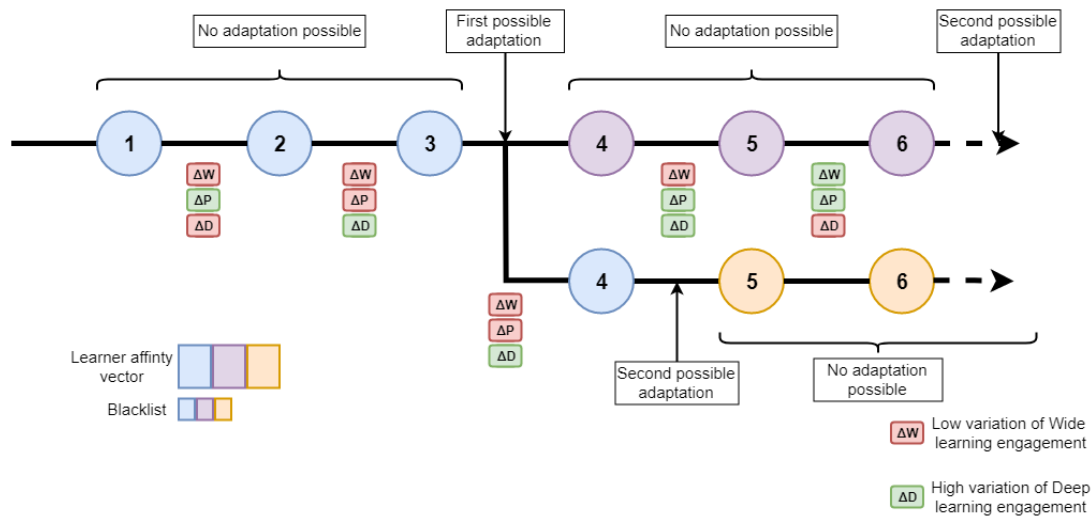


Figure 5. Proposed dynamic adaptation protocol to be used in a real classroom setting

5 CONCLUSION AND FUTURE DIRECTIONS

In this paper we have presented a simple architecture for a game element adaptation engine based on a previously studied static adaptation method (Hallifax et al., 2020) that generates affinity vectors for learners based on their profiles and on a dynamic method that analyses learner behaviour through various learning analytics to estimate learner engagement and refine these static adaptations. Thanks to its controllability property, the system involves teachers directly in the adaptation process, by signalling learners who require an adaptation of the game element they use and suggesting another game element to reengage learners. We believe this approach could be

applicable to many contexts, as illustrated within the LudiMoodle project. In its current state, this system is fairly simple and can be expanded in future work to provide recommendations taking into account the context. It would require the system to be able to collect data on the context of the learner activity, and to integrate them in the analysis of their engagement. Currently, this system has not been tested yet in real conditions (the initial field tests had to be interrupted due to pandemic), we plan to conduct an experiment in March-April 2021.

This work opens new avenues for future research. First, the teacher currently only receives a simple notification of which learners need a game element change and a relevant game element proposition for that learner. We could imagine a future version that shows how each learner's engagement evolves over time. This could help teachers reflect on other types of adaptations they could make to the learning system, for example by changing the learning content to better suit the learners. Research in the learning dashboard field could be interesting for example to represent how engagement varies over time (Carrillo et al., 2017).

Second, we could consider a situation where we give control over adaptation to the learners directly. It would allow them to possibly better understand how the adaptation system works and to better predict when adaptation would occur based on their behaviour, and react to it better (i.e. expect the change). This does raise further questions however, for example on the observability and intelligibility of the system. Currently we ask teachers to control adaptation as they have full knowledge of both the game elements and the gamified system, whereas learners will not necessarily be capable to judge which game elements would motivate them more. (Monterrat et al., 2017) showed that learners' appreciation of game elements differs from the observed impact of these game elements on their motivation and engagement. Such a change would also allow us to observe the extent to which the system understands learner preferences.

Third, we could consider improving our learner model by adding more pedagogical related information such as learning styles. (Zaric & Scepanovic, 2018) showed links between various learning styles and different game elements. Our initial static adaptation (that creates the affinity vector) could take into account learning styles. Thus providing our dynamic adaptation through trace analysis a better affinity vector to select game elements from.

Finally, we can enrich our dynamic adaptation approach by including the other steps of the PDA/LPA framework cycles (Bouzit et al., 2017). Currently the dynamic adaptation does not make use of the **Prediction** or **Adaptation** steps. One way we could improve our system is by making it automatically *adapt* to learners. The system could take note of which of the engagement factors decreases the most for each learner (if any) and weight these higher. Currently the system considers each engagement type equally. For example, if a learner loses more **Wide Learning** engagement than the other two, the dynamic adaptation could weight it higher when comparing it to the rest of the class. This means that if the learner lost **Wide Learning** engagement the system would be more likely to propose an adaptation than if they lost **Performance** engagement. This could provide the learner with a more personalised adaptation. However, we would need to be careful as this might result in "uniformising" learners. A solution could be to consult teachers to better understand which factors could be more important to target for adaptation after analysing the interaction data from learners.

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