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Stuart Hallifax

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Stuart HALLIFAX

Adaptive gamification of digital learning environments

Ludification adaptative d'environnements pédagogiques numériques

Devant le jury composé de :

Martin Jean-Claude, Professeur à l'Université Paris Sud
Calvary Gaëlle, Professeure à l'INP Grenoble
George Sébastien, Professeur à Le Mans Université – IUT Laval
Vanden Abeele Vero, Professeure à KU Leuven
Nacke Lennart, Maître de conférences à University of Waterloo
Lavoué Elise, Maître de conférences à l'Université Jean Moulin Lyon 3
Marty-Jean Charles, Maître de conférences à l'Université de Savoie
Serna Audrey, Maître de conférences à INSA Lyon

Président
Rapporteuse
Rapporteur
Examinatrice
Examineur
Directrice de thèse
Co-directeur de thèse
Co-directrice de thèse

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ABSTRACT

Gamification, the use of game elements in non game contexts, is becoming widely used in the educational field to enhance learner engagement, motivation, and performance. Many current approaches propose systems where learners use the same game elements. However, recent studies show that learners react differently to different game elements, and that learner motivation, engagement, and performance can vary greatly depending on individual characteristics such as personality, game preferences, and motivation for the learning activity. Results indicate that in some cases game elements that are not adapted to learners can at best fail to motivate them, and at worst demotivate them. Therefore, adapting game elements to individual learner preferences is important. This thesis was part of the LudiMoodle project, dedicated to the gamification of learning resources to enhance learner engagement and motivation. In this thesis, I propose a new system that adapts relevant game elements to learners using individual characteristics, as well as learner engagement. This work is based on previous results in the general gamification field, as well as more specific results from gamification in education. Our main goal is to propose a generic adaptation engine model, instantiated with specific adaptation rules for our educational context.

This manuscript presents four major contributions: (1) A general adaptation engine architecture that can be implemented to propose relevant game elements for learners, using both a static and dynamic adaptation approach; (2) A design space and design tools that allows the creation of relevant and meaningful game elements, in collaboration with the various actors of the gamification process (designers, teachers, learners etc.); (3) A static adaptation approach that uses a compromise between both learners' player profile (i.e. preferences for games) and their initial motivation for the learning task; (4) A dynamic learner model built on a trace-based approach to propose an adaptation intervention when an abnormal decrease in engagement is detected.

The adaptation engine was implemented in a prototype for the LudiMoodle project, that was used by 258 learners in 4 different secondary schools in France for learning mathematics. To build this prototype we ran a real world study, where learners used this tool as a part of their normal mathematics course. From this study, we ran multiple analyses to better understand the factors that influence the motivational variations of the learners, and how their interaction traces could predict their engagement with the learning task. These analyses served to evaluate the impact of the adaptation of game elements on learner motivation and engagement, and to build the trace based model used for dynamic adaptation.

This work represents a significant advancement for the adaptive gamification field, through a generic model for static and dynamic adaptation, with the former based on individual learner characteristics, and the latter on observed

learner engagement. I also provide tools and recommendations for designers, to help explore different game element designs. Finally, I discuss these findings in terms of research perspectives, notably with regards to further possible advancements in the dynamic adaptation domain.

Keywords: Gamification, learning, engagement, motivation, tailored gamification, adaptive gamification, meaningful gamification, meaningful design, behaviour, learner model.

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INTRODUCTION

This first chapter introduces the context and motivations for my research. I first present the general origins of gamification as well as the first waves of research into this field. From this general overview, we quickly focus on the topic at hand, adaptive gamification to individual users. I then present the LudiMoodle research project that framed my PhD. Finally I present the three research questions that guided my research, and the structure of this present manuscript.

1.1 GENERAL CONTEXT

1.1.1 Gamification origins

Gamification as a term first appeared in the early 2000s¹, however it was not until 2011 that a formal definition emerged, proposed by Deterding, Dixon, Khaled, and Nacke [31]. These authors propose that gamification be defined as: "*the use of game elements in non-game contexts*". A recent literature review of gamification research [83] showed that the most commonly used game elements included "*Points, score XP*", "*Challenges, quests, missions*", "*Badges, achievements*", and "*Leaderboards, rankings*".

Gamification has been used in many domains. From sport [1, 84], to health [10, 113, 120, 122], and education [33, 73, 89, 90, 105], to help foster user engagement, motivation, and performance. A well-known commercial example of gamification is the language learning application Duolingo². In this online tool, learners have a wide variety of game elements to keep them motivated to continue learning. Figure 1 shows an example of the application interface, where learners can see the proposed game elements. In this example learners have a daily XP goal, displayed via a progress bar. They also have a leaderboard where they can compare their progress with other learners, and a badges system, where each language lesson is represented by a level and badge. Another interesting example of gamification is the piano stairs presented in figure 2. In 2009 Volkswagen ran a marketing campaign in Sweden aimed at promoting how "Fun can obviously change behaviour for the better". A short video available here³ shows how these stairs behave like a normal piano, making sounds when users stepped on the keys. The goal behind these piano stairs is to entice people to use the stairs more (instead of the escalator next to them), thus promoting physical activity. The video shows how users in general preferred to use this new fun interactive tool than the normal escalator. In

1 it has been said that it was coined as early as 2003 by Nick Pelling <http://www.nanodome.com/conundra.co.uk/>

2 <https://www.duolingo.com>

3 <https://www.youtube.com/watch?v=SByymar3bds>

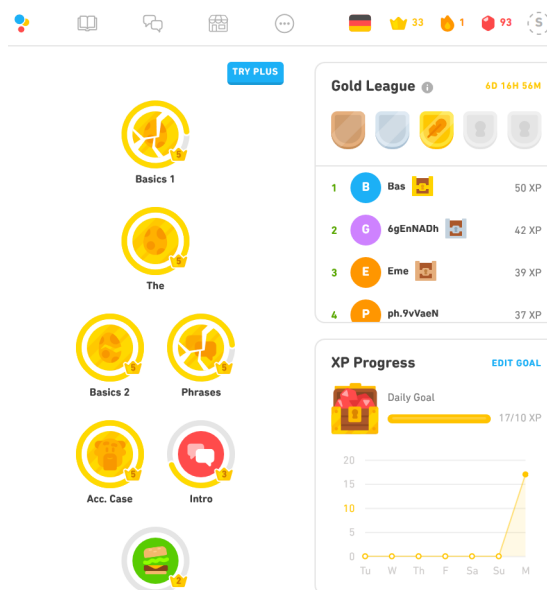


Figure 1: A screenshot from the Duolingo app. Here learners can access a leaderboard where they can compare their progress with other learners. Progress bars for each individual lesson, an experience system with daily goals that they can achieve, and finally a weekly schedule where they are encouraged to do at least one lesson per day.

this example the gamification is applied as a layer over the top of the principal activity (i.e. the physical activity of taking the stairs). The gamification layer has one goal: to motivate users to participate in the activity, without modifying it. These two examples show the wide variety of gamification approaches that exist.

In both of these examples, all users are expected to interact with the same game elements. The two systems do not adapt for different expectations or preferences in their users. This could be a problem, as recent research shows that to be effective, gamification should be adapted to individual users preferences and expectations [41, 61, 108, 122]. This recent research shows that game elements that are not adapted to users may (at best) fail to motivate, or worse, demotivate them entirely.

Users are not all motivated by the same game elements, as these game elements have different motivational affordances. It is generally thought that gamification works by eliciting the same motivational and psychological experiences and affordances as games do [68]. Therefore the individual game elements should provide different specific motivational affordances. Other work posits that gamification helps to fulfil basic needs described in Self Determination Theory [129] (SDT). SDT supports three basic psychological needs that must be satisfied to foster well-being and health:

- Autonomy: desire to be in control of ones life.
- Competence: desire to experience mastery, and to control the outcome.
- Relatedness: desire to interact with, and connect to others.



Figure 2: A set of piano stairs designed to incite and motivate users to exercise and use the stairs instead of the escalator.

Ryan et al. [130] described how video games can provide satisfaction of these needs. They found that solitary gameplay generally supported autonomy and competence satisfaction, and that multiplayer environments support the satisfaction of all three needs. Gamification therefore attempts to extract and isolate the elements of games that support each need, and reapply them to non-game contexts. For example game elements designed to provide personalisation such as personalised avatars should provide a sense of autonomy for users. Game elements designed to provide a challenge, such as quests and timers, provide a sense of competence to users when they complete said challenges. Relatedness could be provoked through game elements that involve other users, such as leaderboards, teams, or guilds.

1.1.2 *Research in the gamification field*

1.1.2.1 *Generalities*

The first research in the gamification field was mainly concerned with three things: (1) defining, identifying and classifying game elements for gamification; (2) describing systems, designs, and architectures for gamifying; and (3) analysing the effects of gamified systems on users. Nacke & Deterding stated in an editorial on the maturing of gamification research [112], that : "*the first wave of gamification research was held together by fundamental questions of "what?" and "why?"*". The first *studies* in gamification were mainly concerned with observing and describing effects on users, comparing them to non gamified situations. They generally showed that gamification *can* work, and *can* help motivate and engage users, when compared to non gamified situations, and provided some ideas as to *why* it worked. The question of "*what*" was tackled by more theoretical and exploratory work into game element design and classification frameworks, to provide structured classifications of game

elements, and design practices to help create game elements better suited to users [30, 67, 114, 148].

As stated previously, one of the core problems with earlier gamification approaches is the fact that all users are presented with the same game elements, thus ignoring the individual user preferences and expectation. The second wave of research identified by Nacke & Deterding [112], aimed at understanding *how* gamification works, and *when* it should be applied (and when it should *not* be applied). This recent research generally focused on understanding individual differences in users, and how these individual differences translate to preferences for game elements. This is still an emerging field, and work has been mostly turned towards identifying different personality traits [41, 72] or preferences for video games [105, 119] as a basis for adaptation.

1.1.3 *Gamification in education*

Education is one of the most used domain for applying gamification, as pointed out by multiple literature reviews [61, 83, 96]. As with other general applications of gamification, gamification in education attempts to leverage the motivational affordances of games to motivate and encourage learners to engage with the learning content. However it is also important to avoid the possible demotivating effects of unadapted game elements (I dive more into the possible adverse effects of unadapted gamification in Chapter 2, section 2.1). The educational domain does offer some rather interesting challenges towards gamification, Harviainen [63] presented a review of the "critical challenges" that gamifying education poses. For example they state that "not everyone attending a classroom is a digital native" and that "not everyone likes games, [...] an unwilling player may disrupt the game". This shows that the challenges linked to tailoring gamification are just as important in the educational field, as in many cases when gamification is applied to classrooms, it is mandatory. Meaning that even the less willing learners still have to participate and could therefore be subject to the more negative effects of gamification. Harviainen also raises problems due to the framing of gamification in the classroom. For example more competitive game elements could induce cheating to get higher rankings. Finally they state that "To promote its intended learning goal, a game has to be geared for that task, either through design, pre-play briefing, or both." Meaning that the learning content must be considered strongly during the design and implementation of the gamification. These challenges identified here show the slight, albeit important, specifics when gamifying education.

1.2 RESEARCH CONTEXT: LUDIMOODLE PROJECT

The work presented in this manuscript was conducted within the LudiMoodle project financed by the *e-FRAN Programme d'investissement d'avenir*⁴.

⁴ <https://www.gouvernement.fr/e-fran-1-ecole-change-avec-le-numerique>

The main goal of this project is the design, testing, and validation of a tailored gamification approach, applied to digital teaching resources (Moodle [107]) to increase secondary school learner motivation. More specifically, we applied our gamification model to secondary school mathematics using a gamified Moodle platform developed with the project partners. During the project we worked in collaboration with researchers in educational sciences from the ECP⁵ (*Éducation, Cultures, Politiques*)⁶ lab in the Lyon 2 University, pedagogical designers from the PAPN (*Pole d'Accompagnement à la Pédagogie Numérique*)⁷ from the Lyon 3 University, and Edunao, a company in digital learning technologies. During this project we ran a study in real world conditions, where learners used a gamified learning platform during their mathematics lessons. This experiment was carried out in six secondary schools in the Auvergne-Rhone-Alpes region of France with the help of the "Rectorat de l'Académie de Lyon". A total of 5 teachers and 258 students took part in the project. The teachers involved in this project participated to the development of both the learning content and the game elements used (see chapter 4 for how we involved them during the design of the game elements).

1.3 RESEARCH QUESTIONS

In this manuscript we will generally be answering the questions identified in this "second wave" of gamification research [112], specifying them to our context (education):

- **Who** are we adapting our gamification to? I.e. How can we categorise learners, and what preferences are linked to these categorisations?
- **What** game elements can we adapt to these different learners? How can we design these game elements with both the learners and the learning context in mind?
- **How** can we adapt these game elements to learners? How can we select appropriate game elements for different learners?

The work presented here is centred around the proposition of an adaptation engine for the LudiMoodle project. The adaptation engine should serve as a tool that proposes appropriate game elements for learners. The basis for this adaptation engine is presented in more detail in section 1.5. Each chapter in the manuscript serves to present and improve different parts of the adaptation engine architecture, through the studies and analyses presented.

1.4 RESEARCH APPROACH

During my thesis we adopted an empirical approach, first using theory to build adaptation models, and updating them with successive field results. Our

⁵ <https://recherche.univ-lyon2.fr/ecp>

⁶ Education, Cultures, Politics

⁷ The digital pedagogy support Team

first adaptation model was based on a study of the related literature. This first model was updated using general results (i.e. uncontextualised) obtained from a crowdsourced study. Crowdsourcing is commonly used in HCI research (e.g., [65, 118, 120]), to recruit a large number of participants from diverse backgrounds. These general findings were then tested in our specific educational context during the LudiMoodle study. The results from this experiment allowed us to update our generalised model to a more context-specific version. Finally using a log analysis approach [13] to analyse user behaviour from the LudiMoodle experiment, we were able to evaluate and finalise our adaptation model.

1.5 CONTRIBUTIONS

In this manuscript, I present four major contributions linked by a generalised adaptation engine architecture. This serves as a framing device for the rest of this work, as the different modules that compose it are the subject of the following contributions and studies (see figure 3 for a simplified version of the architecture).

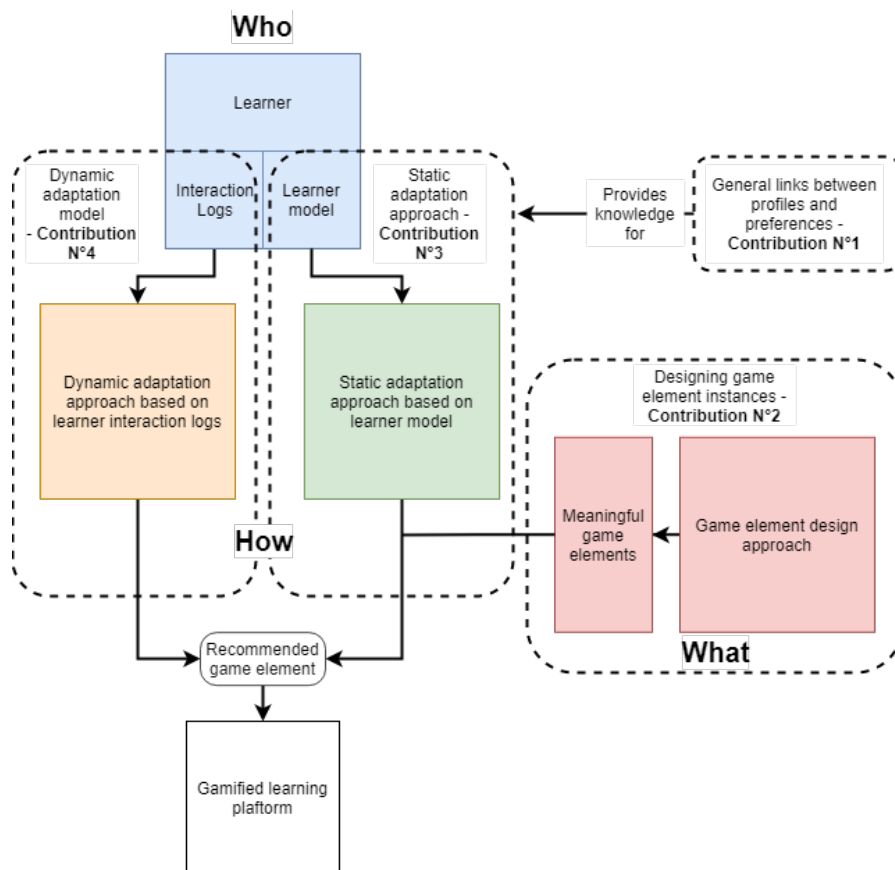


Figure 3: The general adaptation engine architecture. All the contributions are identified here.

First, the work presented in chapter 2 is a study of the related work in the adaptive gamification in education field, that identifies four research gaps. These gaps motivate the research in the following chapters. I first present an overview of the research and applications of gamification in education highlighting the need for adaptive gamification in this context. Secondly I present an in-depth literature review on the subject of adaptive gamification in education, with a focus on understanding the current state of the research in this field. I then present a brief analysis of previous work into the classification and taxonomy of game elements, as well as different design practices for game elements. The four research gaps that emerged from this review are

1. a gap in game element nomenclature and design
2. a gap in comprehensive learner models
3. a gap in the evaluation of adaptation methods
4. a gap in dynamic adaptation methods.

My first contribution is a study of the links between learner models and game elements in a de-contextualised setting. Chapter 3 presents a crowd-sourced study that investigates links between different user models and game element preferences, in a de-contextualised setting (i.e. not linked to a specific context). Our goal was to obtain generalisable results that could be applied to any context. We compared three different user models, related to game preferences and general personality traits. We also compared the impact of different game elements that implement the same motivational strategies, using a game element abstraction framework designed to fill **Gap 1**. Finally we compared our results from this study to those from studies that were carried out in specific contexts (health, education etc.). Our results highlighted the importance of game element selection and design, and helped inform the choice of user model that would be used for the Ludimoodle adaptation engine. The comparison of our findings to those obtained in different contexts, showed the importance of context on the motivational impact of game elements. The work in this chapter served a first answer all three questions, by showing how we can categorise based on user profiles, use these categories to select appropriate game elements, and that different game elements issued from the same motivational strategies have different impacts. This contribution represents a first step in filling *Gaps 1 & 2*.

My second contribution is a game element design space and design cards to explore said space, aimed at facilitating the creation of relevant game elements in co-design sessions with the various actors of the gamification process. Research [115] shows that game elements are more effective when they "make sense" to learners, and that when game elements make meaningful connections to the context and content, they motivate and engage learners better. We therefore decided to involve all the different actors of the gamification process (teachers, learners, designers etc.) in the design of the game elements. In chapter 4 I present the design space and method as well as a usage scenario in the LudiMoodle project. These tools helped the actors by

providing a common language and by prompting questions that some of the less experienced actors would not have naturally considered. This contribution serves to fully answer the "What" question, by demonstrating a way to create meaningful game elements. In the context of the LudiMoodle project the game elements designed during the design sessions were used in the final adaptation engine model. This contribution also fills the first research **gap** by providing an simplified in-depth game element design method.

My third contribution are domain specific adaptation rules for recommending appropriate game elements based on a learner model composed of a contextualised (motivation for learning) and de-contextualised (game preferences) profile. These rules serve to create a *static* adaptation approach. My approach proposes a compromise between the two profile recommendations in the specific learning context. Chapter 5 presents the LudiMoodle field study. A total of 258 learners from four different secondary schools in France participated in our study, and used our gamified learning platform for about six weeks. From the results of this study, we created a first set of adaptation rules based on learner profiles. We then simulated different adaptation approaches using the different learner profiles, and compared the effectiveness of adaptation vs. randomly assigned game elements. These results allowed us create learner model, the adaptation rules, and compromise algorithm. This contribution serves to fully answer the "Who" and "How" questions, through the dual profile learner model for the former, and the compromise algorithm for the latter. This also serves to fill the **second** and **third gaps**.

My fourth and final contribution is a *dynamic* adaptation approach based on the study of learner interaction logs to determine when an adaptation intervention is required. Chapter 6 presents how we tracked and analysed learner behaviour using a trace based approach. From these analyses we show how we can propose adaptation interventions when necessary to avoid the loss of learner engagement during the use of the gamified learning platform. These losses could come from ill-adapted game elements, or shifting learner preferences and expectations. This contribution serves to fill the **fourth research gap**: the gap in dynamic adaptation methods.

Gamification, the use of game elements in non-game settings, is more and more used in education to foster learner motivation, engagement, and performance. Recent research in the gamification field suggests that to be effective, the game elements should be tailored to learners. In this chapter, I first provide a general overview of the research into gamification in education which highlights the need for adaptive gamification. I then present an in-depth literature review on adaptive gamification specifically in education in order to provide a synthesis of current trends and developments in this field. This literature review addresses 4 major concerns: (1) The different current types of contributions to the field (2) The terminology used to discuss the game elements used (3) What these contributions base their adaptation on, and the effect on the gamified system? (4) The impact of the adaptive gamification on learners, and how this impact is measured. From this literature review, I identify four research gaps that I will be addressing in the following chapters of this manuscript.

2.1 GAMIFICATION IN EDUCATION

Due to its predicted effect on motivation, engagement and performance, it comes as no surprise that gamification has been widely purported as appropriate for use in education. In a literature review performed in 2014, Hamari et al. [61] reported that of the 24 empirical studies they reviewed, 9 of them were in the "educational/learning" field (none of the other contexts presented more than 4 studies). A later literature review by Looyestyn et al. [96] asked the question "Does gamification increase engagement in online programs?". The authors analysed 15 studies with 6 of them specifically in the online learning domain.

For example, Filsecker and Hickey [45] tested the effects of external rewards on motivation and engagement in fifth graders. They expected that the inclusion of external rewards would decrease intrinsic motivation in their learners. They found that, by including these rewards in a gameful like manner, they could avoid the expected decrease in intrinsic motivation and even increase learner conceptual understanding of the studied topic. On the other hand, whilst the external rewards did not undermine motivation, they did not foster disciplinary engagement.

Kyewski and Krämer [86] obtained more nuanced results when testing badges in three different conditions (badges visible to only the learner, to everyone, or no badges at all). They found that badges had *less* impact on learner intrinsic motivation and performance than initially assumed. They

found no effect on intrinsic motivation from either of the gamified conditions, and a general decrease in intrinsic motivation over the three conditions. However, when asked, learners better evaluated the badges which were only visible to the themselves, than those that were visible to everyone.

In addition, in a study on how gamification affects online learning discussion, Ding et al. [32] showed that learners were more interested in the game elements that were directly linked to their grades. Learners showed greater controlled motivation (motivated by grades and instructor opinion) than autonomous motivation (intrinsically motivated for learning). Also, Denny et al. [29] tested the effect of badges and scores on learner behaviour. They found that only badges had an effect on how participants behaved in their experiment, increasing the number of self assessments made. They also found that this directly resulted in better examination performance for those participants.

Several studies compare the impact of gamified and non-gamified learning environments. For instance, Zainuddin et al. [150] tested two versions of a flipped class setting. One with gamification (points, badges and leaderboards) and one without. They found that learners provided with the gamified environment had increased levels of perceived competence, autonomy, and relatedness, better performance, and were able to achieve better results during the tests. On the contrary, Monterrat et al. [106] showed that learners who were free to use a non-gamified learning environment had a higher level of intrinsic motivation after the experimentation, compared to learners using a gamified environment. Finally, Jagust et al. [69] tested two adaptive situations. In the first situation, the time learners had to answer questions changed depending on how quickly they answered the previous question. In the second situation, a target score changed depending on group performance. In both situations, learners completed more tasks than compared to a non-gamified situation, with the first situation providing a larger effect.

Going back to the literature review performed by Hamari et al. in 2014 [61], they point out that "*the learning outcomes of gamification as mostly positive, for example, in terms of increased motivation and engagement in the learning tasks as well as enjoyment over them.*" However they also state that some of these studies show "*negative outcomes which need to be paid attention to*". These mitigated results are shown for example by Hakulien et al. [56] who presented a study where students activity in an online learning environment was analysed to determine whether badges had an effect on their behaviour. Their results showed that whilst badges had a positive effect on learning behaviours, they did notice an increase of "*unwanted*" behaviour from some badges. For example the more competitive badges might have reduced carefulness in learners. Another example is from Dominguez et al. [33] who analysed the results from a study on the effects of game elements on learner motivation and performance in an online university course: "Qualifications for users of ICT". They compared a gamified version of the course to a non gamified version. Whilst learners who completed the gamified experience got better scores in practical assignments, they also performed poorly

on written assignments and participated less on class activities, although their initial motivation was higher. This shows that whilst the gamified version of the e learning course **did** increase performance in some areas, it decreased it in others. Hanus and Fox [62] tested a gamified environment that used a leaderboard and badges, comparing it to a non gamified version of the same university Communication course. They found that learners in the gamified course showed less motivation and lower final exam scores than those in the non-gamified class.

These results tend to show that there is no consensus on the effect of gamification on learners and that these effects may vary depending on the type of game elements used. A more recent literature review of gamification research by Koivisto and Hamari [83] also points out that "while the results in general lean towards positive findings [...] the amount of mixed results is remarkable". It is believed that these mixed results are due to individual differences between learners and contexts (domains, ages etc.). Thus by adapting gamification to the individual learners can be seen as a way to improve the learner experience with gamification.

2.2 ADAPTIVE GAMIFICATION IN EDUCATION

Adaptive gamification in education attempts to improve the mitigated results identified in the previous section, by adapting the gamification experience to individual learners. Generally this is done by identifying different categories of learners (see section 2.2.4.1) and proposing different game elements for these different categories. However other methods of adapting, based on learner behaviour exist. In the rest of this chapter, I present the results of a literature review the research on adaptive gamification in education that was presented at the EC-TEL conference in 2019 [58]. Through this review, I highlight the current research in the field and the research gaps still to fill. The following chapters of this manuscript serve to fill these gaps as described in section 2.5.

This review first identifies three different types of contributions to the field of adaptive gamification in education: 1) preliminary research on recommendations for game elements adapted to learner profiles, 2) technical contributions on architectures that have not been tested yet and 3) studies that look at the impact of adaptive gamification that make use of such architectures, and that provide valuable results into this research approach. The analysis of these three contribution types show the maturity of this field. Following this we then analysed the different terminologies used to describe the different game elements used. We then looked at the different learner characteristics that the different papers base their adaptation systems on, and how the adaptation affects the game elements. We identified two categories of adaptation systems: static adaptation (based on learner profiles) and dynamic adaptation (based on profiles and behaviour). Finally we analysed the impact of the adaptive gamification systems on learners' motivation and performance.

2.2.1 *Review process*

This structured literature review process was based on the guidelines and processes described by Brocke et al. [146], and Webster et al. [147]. First, by defining the review scope, specifying the research questions and therefore explicating the search query (explained in more in detail in section 2.2.1.1). Then, after running the search query through the major scientific digital libraries and filtering the papers that did not fit the review scope (see section 2.2.1.2).

2.2.1.1 *Defining the review scope*

The following search query was designed to fully enclose the scope of the three research questions:

(gamif) AND (learning OR education OR teaching) AND (adapt* OR tailor* OR personali*)*

The first part of the query (i.e. gamif*) was used to capture all terms that start with “gamif” (i.e. gamification, gamified etc.). Note that “gamif*” and “gamif” were used depending on the capabilities of the search engines used as some allowed for wildcard characters and others not. After testing different permutations of “teaching words” the terms “Learning” “Education” and “Teaching” seem the most relevant (when alternatives such as “learn” or “learner” were added the result count did not change, so this more focused approach was favoured). Finally the adaptive part of the query followed a similar reasoning as with “gamif”. The three base words (“adapt”, “tailor” and “personali”) allowed us to capture the different keywords used to describe these works (and also allow for regional variants such as the British “personalised” versus the American “personalized”).

2.2.1.2 *Paper search & filter*

We ran our search query on the major scientific digital libraries (ACM, IEEE, Science Direct, Springer) and Google Scholar. Due to the fairly large nature of our search query, we received a large number of initial hits (370 papers as of Spring 2019, see table 1), which lead to a rigorous filtration process in order to remove false hits.

Papers were first reviewed by scanning the keywords and title, then the abstract, and finally the full text if the paper was not excluded from the previous two steps. Papers were then excluded for the following reasons:

- **Format:** Results that were either abstracts, preview content, posters or workshop papers were removed. We made this decision so that we only studied mature works. Finally, we also removed papers that were not in English (many of the results from Google Scholar had English abstracts or titles, but the rest of the paper is in another language).

Table 1: Number of papers before and after content filtering. The number of papers excluded is given for each filtration step. The search queries were executed in spring 2019.

Filtration step	Source					Sum
	ACM	IEEE	Science Direct	Springer	Google Scholar	
Keyword query	64	94	17	35	160	370
Removed - format	18	8	1	2	49	78
Removed - scope	41	79	13	26	74	233
Removed - duplicate	2	1	1	1	34	39
Final count	3	6	2	6	3	20

- **Scope:** Here we analysed the content discussed in the papers. Papers were excluded due to scope because they did not specifically deal with adaptive gamification in learning. For example papers that discussed adaptive gamification for health or sport were removed.
- **Duplicates:** A few references were found in multiple databases, as some of the databases contain references to papers that are cited by papers that they publish. Furthermore some of the papers found were extended versions of previous papers. The non extended versions were therefore excluded.

After this filtering, we were left with a final total of twenty papers that were included in the final analysis.

2.2.2 Types of contributions identified

We examined the degree of maturity of the research field in light of two criteria. First, we identified the contribution type of each reviewed paper (table 2). Second, we reviewed the vocabulary used to describe the adapted content in each contribution.

Table 2: Type of each contribution. These types are described below.

Contribution type	Recomm.	8	[7, 11, 19, 25–27, 81, 154]
	Architecture	2	[82, 104]
	Study	10	[36, 64, 69, 79, 89, 105, 106, 108, 124, 128]

Regarding the first criterion, we classify the papers into three types of contributions that emerged from the review:

- Recommendations: identification of game elements that would be adapted to different categories or classes of learners, based on literature review, or general surveys (8 papers). These recommendations correspond to preliminary research and they have not been implemented in a system yet.
- Architectures: adaptation engines based on existing theoretical works, that have not yet been tested in real world situations (2 papers).
- Adaptation studies: an adaptation engine, based on recommendations to adapt game elements to learners, tested with learners through a real world study (the combination of an adaptation architecture, theoretical recommendations, and a real world study) (10 papers).

2.2.2.1 *Recommendations:*

We found two major categories of papers: papers that base their recommendations on literature surveys, and those that base their recommendations on user surveys, or feedback. In the first category, Borges et al. [11] review literature on "player types" (archetypal reasons why users seek out game experiences) and link these to learner roles and different game elements based on the motivational aspects they provide. Chalco et al. [19] also link motivational aspects with player types and game elements. Škuta et al. [154] also use player types, but link them to higher level game principles. They then propose a matrix that associates game elements to player types based on how well each game element implements the linked game principles. In the second category, Denden et al. present three user studies, two based on a feedback after using a non adapted gamified tool [26, 27], and one based on a user survey [25] where participants rated statements based on game elements in order to determine their preference. Knutas et al. [81] analysed videos and interviews with learners in a software engineering project to create clusters of learners based on their interactions. These clusters were then linked to Bartle player types and relevant game elements. Barata et al. [7] used a similar approach, creating four types of learners based on their strategies during an online course. They then propose different goals that could be provided to each of the learner types. These studies serve to provide valuable information about what game elements learners might prefer, but still need to be implemented and tested in a real adaptation system.

2.2.2.2 *Architectures:*

We found only two papers that describe adaptation engine architectures without any associated study. They present what the engine takes into account, what it adapts, and how it adapts it. Kuntas et al. [82] describe their process for designing an algorithm based personalised gamification system. They detail learner characteristics on which they base the adaptation of some game elements and the algorithm used to link the two. Monterrat et al. [104] describe

an architecture that presents game elements as "epiphytes", completely separate from the learning content. They can therefore swap out game elements as needed. They also propose a module that tracks learner interactions in order to more finely adapt the game elements. They use a learner model that contains data on learner (gender, age, player type), usage data, and environment data.

2.2.2.3 *Studies:*

Half of the reviewed papers present studies that rely on an adaptive gamification system in an educational setting [36, 64, 69, 79, 89, 105, 106, 108, 124, 128]. These papers provide valuable results about the impact of adaptive gamification on learner motivation and performance. We present them in section 2.2.5.

2.2.3 *Game element vocabulary*

We observed that the papers reviewed have a general consensus about the vocabulary used to name the type of elements used in the gamification systems. Twelve of the papers reviewed [7, 11, 19, 25–27, 64, 69, 79, 124, 128, 154] used the term "game element" to describe the low level implementations they use, such as points, levels, leaderboards, progress. Four papers from the same authors [89, 104–106] use the term "game features" to present the same level of implementation. Knutas et al. [81, 82] use the terms "game like elements". Mora et al. [108] present different gamification "situations" (that combine different game elements). We can therefore observe that the papers reviewed generally agree on the term "game element" to designate what is adapted.

When we actually investigate the different names of game elements used in each of these studies we see that there is an interesting overlap. Table 3 shows the different names for game elements presented in the different studies. We attempted to group them based on similar names, or the descriptions given. Only papers that specifically provided the names and or descriptions of the game elements used were included. From this we can see that whilst the general name for the elements is somewhat stable (i.e. "game elements") the for some elements there is not a generalised naming scheme. For example the concept of "badges" frequently comes up in the related work using that name, whereas the concept of progress bars is somewhat less consistent, with some authors using the terms "experience bars", or "levels". Work still needs to be done to better understand the similarities and differences between game elements that use similar or different names.

In summary, we find the field of adaptive gamification in education to be emergent, as there is a relatively low number of papers, that cover a wide variety of contribution types. Regarding the kind of contributions, twelve papers (two architectures and ten studies) take advantage of the ground work that the eight recommendations papers lay out. Furthermore, we found the vocabulary used to describe what is adapted to be quite stable, pointing towards a general

Table 3: Comparison of all the different names of game elements presented or discussed in the different papers. Some categorisations of similar names or descriptions are given. Papers that use the same name as the category are noted with an X.

Paper	Goals	Rewards			Virtual goods	feedback	Progress	Time	Social			
		Points	Evaluations	Badges					Leaderboard	Collaboration	Self expression	Gifts
[124]	Missions											
[44]		Score										
[103]	Objectives		Stars		Tips	Walker	X	X	X			
[106]			Bright stars		Mnemonics							
[105]			Stars		Tips	Walker	X	X	X			
[89]					X							
[79]		Score			X							
[128]					X							
[19]	Quests system	X		X		X			X	Social Connections	Customisation tool	X
[69]								X	X	Teams		
[71]	Challenges			X		Exp Levels		X			Avatars	
[70]		X			X							
[26]		X		X	X	X			X	Chat	Avatar	
[25]	Achievement	X		X	X	X			X		Status / Self expression	Altruism
[27]		X		X	X	X			X	Chat	Avatar	
[81]										Player interaction		
[154]												
[64]	Challenges	X		X	X	X			X			
[35]		X		Trophies / Badges		X			Ranking		Avatars	

consensus among authors. We do however believe that more work needs to be done in the architectures front, as well as the general design of game elements. The various actors of the gamification process, such as learners and teachers, should be brought into the design of game elements to avoid confusing or alien game elements.

2.2.4 Information used for adaptation and its effect on game elements

In this section we analyse both 1) what information is considered for adaptation (learner profile or activity) and 2) what the effect of the adaptation is (a change of the game element, or a modification of how the game element works). Our review analysis also allowed us to identify two major types of systems: static systems, and dynamic systems (see table 4). In a static system, the adaptation occurs **once**, usually before the learners start using the learning environment. In a dynamic system, the adaptation happens **multiple times** during the learning activity. We first present a short explanation on the different player types, followed by our the analysis of the papers according to whether they present a static or dynamic adaptation.

2.2.4.1 Profiles used to adapt to learners

We observed many different manners to categorise learners. These learner profiles can be based on preferences for video games (i.e. **Player types**), on general personality traits, learner expertise, even things such as age, or gender.

The most used profile (ten papers) is player types: classifying users based on their play style or game preferences. The term "player type" was first coined by Bartle in 1996 [9]. Bartle describes four types of Multi-User Dungeon players (MUDs), the Achievers, the Socialisers, the Explorers, and the Killers, based on what each of these player types prefers to do in the game. For example: "Achievers are interested in doing things to the game, i.e., ACTING on the WORLD", whereas "Explorers are interested in having the game surprise them, i.e., in INTERACTING with the WORLD". Here we will mostly be focused on the Brainhex[110], and Hexad [101] player types.

Developed considering neurobiological findings, the Brainhex [110] player typology proposes seven different player types (Achiever, Conqueror, Daredevil, Mastermind, Seeker, Socialiser, and Survivor). However this player typology was only ever proposed as a general approach to understanding why people chose to engage with and player games. Therefore its direct usage in gamification can be somewhat criticised.

Marczewski [101] proposed the player types Hexad specifically with gamification in mind. It describes six user types (Philanthropists, Socialisers, Free Spirits, Achievers, Players, and Disruptors) that differ in the degree to which they are more influenced by extrinsic (ex rewards, grades etc.) or intrinsic (ex: personal growth, fun etc.) factors. Instead of basing these player types on observed behaviour, they were based on the fundamental universal needs proposed by the Self Determination Theory (SDT) [129]. SDT proposes that humans strive to fulfil three basic needs, *relatedness*, *competence*, and *autonomy*.

Table 4: Classification of the papers according to the kind of information used for adaptation (user profile and/or activity), its effect (game element **change** or **modification** of its functioning) and the kind of adaptation (static or dynamic). The learner activity concerns either context based **performance**, or general **behaviours**. Some papers use multiple types of information, and are present on multiple rows.

		Static		Dynamic	
		Change	Modification	Change	Modification
Profile	Player Type	8 [11, 19, 36, 89, 105, 106, 108, 154]	0	2 [81, 104]	0
	Personality	4 [26, 27, 64, 128]	0	0	0
	Expertise	1 [11]	0	0	0
	Other	2 [11, 25]	0	1 [104]	1 [82]
Activity	Performance	0	0	0	2 [69, 79]
	Behaviours	0	0	2 [81, 104]	4 [7, 82, 124]

Marczewski also drew inspiration from Dan Pink [127] who proposed that people are also motivated by *purpose*. These four intrinsic motivations provided the basis for four of the Hexad player types (philanthropists, socialisers, free spirits, and achievers), with the other two linked to *change* (disruptor) and *rewards* (player).

2.2.4.2 Static adaptation

Systems that use static adaptation all work in a similar manner. They base their adaptation on a learner profile, and adapt by changing game elements. Learners' profiles are identified, learners are sorted into different categories based on these profiles, and different game elements are given to each of the different categories of learners.

For learner profiles, the static adaptation systems generally use player types and more rarely learner personality. The papers reviewed used either the Bartle Player types [9] (used in two papers [19, 154]), the Brainhex player satisfaction model [111] (used in three papers [36, 89, 106]), the Hexad player types [141] (used in one paper [108]), or the categories of players described by Ferro et al. [41] (used in one paper [11]). The papers that use these player types typically use the definitions of the different categories as a basis for their adaptation rules, for example the Hexad classification suggests using badges and levels (amongst others) for Achievers. Brainhex and Hexad provide a questionnaire to determine a player profile, i.e a set of values that define how well the player fits each type. Generally studies adapt using the dominant player type, i.e. the type that scores the highest for a given learner. However, Mora et al. [108] question the precision of only using the dominant type and propose to consider several dimensions of the profile to tailor gamification.

For the personality traits, two of the five papers [26, 27] used the Big Five Factors personality traits [49]. Two papers used a user motivation questionnaire: Roosta et al. [128] used the framework presented by Elliot et al. [38]; Hassan et al. [64] used the questionnaire developed by Chen et al. [20]. Only

a few static systems used other kinds of user characteristics, such as gender and gaming frequency [25], or learner role (tutor or tutee) [11].

2.2.4.3 *Dynamic adaptation*

In dynamic adaptation, systems use learner activity to adapt game elements, either alone or in combination with a learner profile.

Systems that only use learner activity make adaptation by modifying the functioning of the game element. Two papers adapt the goals presented to learners. Paiva et al. [124] categorise all learner actions as either collaborative, gamification, individual or social interactions; the system adapts the kind of goals the learner receives according to the kind of actions they perform. Barata et al. [7] propose a system that varies the goals and rewards given to learners based on their behaviours, by distinguishing four types of learners: achievers, disheartened, underachievers, and late bloomers (a learner is not fixed into a specific category, as their behaviour may vary over time). Jagušt et al. [69] present two dynamic adaptation situations, both of them using learner activity. In the first situation, learners are timed in a maths quiz. Each time the learner gets a question right, they are given less time for the next question, essentially increasing the difficulty based on the learner's performance. In the second situation, the learners are shown a target score that changes depending on how they respond to questions: the more correct answers they give, the more the target score increases. Kickmeier-rust et al. [79] change the types of badges presented to, and feedback received by the learner based on the mistakes they make.

Two systems use both learner activity and profile. Monterrat et al. [104, 105] aim to modify the learners' profile based on their activity. The system then uses previously established static adaptation rules. When the learners' profile changes significantly, a different game element is given to the learner. The learner profile is based on the Ferro player types in earlier versions of their work [104], and in more recent work [105] they propose to use the Brainhex model (in [104] they also use gender and age for adaptation). This is a straight forward way of implementing dynamic adaptive gamification using static adaptation rules. The systems proposed by Knutas et al. [81, 82] use an algorithm that also uses learners' profile and interactions. In both systems, they use the Hexad player profile, and in the more recent one [82] they also use learner skills. In [81] they analysed videos of students during project meetings and classified their interactions and propose different game elements based on a combination of profile and interaction types. They lay the ground rules for a dynamic adaptation based on learner activity, but do not offer a method to detect these actions in real time. In [82] they use learner chat activity and profile to provide personalised goals.

In summary, adaptation of game elements is made using two major categories of information: static adaptation mainly relies on learners' profile (mainly their preferences and motivations), dynamic adaptation is based on how learners perform with regards to the learning content, or how the learners

Table 5: Impact of the reviewed studies. The numbers show how many studies are present in each category.

Duration	Static		Dynamic	
	Positive	Mitigated	Positive	Mitigated
Short	0	0	2 [69, 79]	0
Long	4 [64, 106, 108, 128]	2 [89, 105]	0	1 [124]

interact with the system in general. The majority of systems then use this information to select which game elements would be the most appropriate for learners. Only a few (five) adapt by modifying how the game elements function.

2.2.5 Impact of adapted gamification on learners

We examined the impact of adaptive systems reported in the "study" papers identified in section 2.2.2. We found that the results could be split into two categories (see Table 5) those that show a general positive impact on learner's motivation or performance, and 2) those that show more mitigated results. We also split the studies based on 1) whether they used a static or dynamic adaptation, and 2) the duration to investigate whether these factors influence the impact of adaptive gamification on learners. We identified short studies as those lasting less than two weeks, and long studies as lasting more than two weeks (with an experimental process that is closer to real world learning practices).

2.2.5.1 Short studies

We found two studies that lasted less than two weeks [69, 79], with both of these studies using a dynamic adaptation. All of these studies reported positive results on learners. In [79], learners used the adaptive system over two sessions, for a total possible time of thirty minutes. According to the authors the personalised system reduced the amount of errors that learners made. Learners with the adaptive situation showed a larger decrease in errors made in the second session when compared to learners that used the non adaptive situation. In [69] Jagust et al. test two adaptive situations that learners used for 15 minutes each. In the first situation, the time learners had to answer questions changed depending on how quickly they answered the previous question. In the second situation, a target score changed depending on group performance. In both situations the authors report an increase in learner performance (learners completed more tasks than compared to a non gamified situation), although the first situation caused a larger increase than the second one.

2.2.5.2 Long studies

Seven of the reviewed studies lasted more than three weeks [64, 89, 105, 106, 108, 124, 128]. Four studies showed generally positive results [64, 106, 108, 128]. Roosta et al. [128] presented learners with a different game element based on their motivation type. Learners used an online tool for one month. The authors find that learners who had game elements that were suited to their motivation type showed significant differences in motivation, engagement, and quiz results when compared to learners who had randomly assigned game elements. They used learner participation rates in the online activities as a metric to gauge motivation and engagement. Monterrat et al. [106] split learners into three different groups: one group received game elements adapted to their Brainhex player type, one group received counter-adapted game elements, and the third group received random game elements. Learners were then free to use the learning environment as they wanted over a three week period. The authors found that learners with the adapted game elements spent more time using the learning tool than those with the counter adapted elements. Hassan et al. [64] also showed a widely positive result in their study: learners who used game elements adapted to their learning style showed a higher course completion rate than those who used random game elements. This impact was also observed with learners' self-reported motivation using a questionnaire. Finally Mora et al. [108] also report a general positive impact from their adaptation, with an increase in behavioural and emotional engagement in learners, reported using a questionnaire that was given to learners after using the tool. In this study, university learners were sorted into different groups based on their Hexad profile (the groups contained users that had similar Hexad profiles) and used a learning tool over a period of 14 weeks, with each of the different Hexad groups receiving different game elements. However, the authors themselves point out that these results are not significant due to the small sample size.

The other three studies showed more mitigated results [89, 105, 124]. In Monterrat et al. [105] learners used the learning environment during 3 structured learning sessions, each lasting 45 minutes set over a three week period. The learners were middle school students, and used the learning environment as normal part of their lessons. The results show that learners with counter-adapted game elements found their game elements to be more fun and useful than learners with adapted or random elements. The authors performed a similar study reported in [89], with adults who used the learning tool voluntarily. Learners were free to use the learning tool over three weeks. They found little to no difference for the majority of learners. They found that adaptation had an influence only on the more invested learners: learners with adapted game elements showed less amotivation (calculated using a questionnaire [53]). They did not find any difference in learner enjoyment for those particular learners. Paiva et al. [124] analysed the usage data during the month after the introduction of tailored goals in their learning tool. Learners received personalised goals to encourage them to increase the number of specific learning actions they performed (for example learners who performed a low number of indi-

vidual learning actions were shown goals designed to increase their number of individual learning actions). The authors found that the social and collaborative goals were effective in increasing the number of related actions. However this effect was not observed with individual learning goals (they do not observe an increase in the number of individual learning actions).

In summary we can see that shorter studies tend to show positive results from adaptive gamification, where as the longer ones show more mitigated results. The two short studies compared the impact of the adaptive gamified situation to a non adaptive gamified situation, this does not allow us to understand if the impact on learners is due to the adaptive nature of the gamified system, or due to the introduction of a novel gamified system itself. With the longer studies, we can assume that the novelty effect wears off, thus leading to more mitigated results, as the static adaptation tested in the longer studies may not be precise enough to take learner variations into. This novelty effect was also identified by Hamari et al. in [61]. Furthermore, we can see that there is some contradictory results from the different papers. [106] and [64] both report an increase in learner motivation for all learners in their studies, whereas [89] only show an increase in the more invested learners. This could be due to the nature of the metrics used to gauge learner motivation. In [64] they use a questionnaire to establish this, but [89, 106] both use the time learners spent using the tool.

2.3 CLASSIFICATIONS OF GAME ELEMENTS AND DESIGN PRACTICES

Coming from the observations made in section 2.2.3, it is important to note that there has been some work done on proposing classification frameworks of game elements, which should provide a common understanding of game elements. The MDA framework proposed by Hunicke et al. [67] proposes three levels of game element description:

- Mechanics which describes the particular components of the game, at the level of data representation and algorithms
- Dynamics which describes the runtime behaviour of the mechanics acting on player inputs and each others' outputs over time
- Aesthetics which describes the desirable emotional responses evoked in the player when they interacts with the game)

These three levels link players and designers in how they experience and interact with them. Players experience Aesthetics when they interact with the various game Dynamics generated by the implemented game Mechanics. Designers design game Mechanics, that interact with each other and players to form game Dynamics, that in turn generate an emotional response from players, in the form of Aesthetics. Whilst this is a useful tool for decrypting video games and understanding how they function, its applications in gamification are somewhat lacking. For example this framework does not propose how

these game mechanics might be affected by the context in which they would be deployed.

Werbach and Hunter [148] take a more concrete approach for describing game elements using their framework, albeit in a game design centred manner. The DMC framework proposes three "levels" :

- Dynamics: the big picture aspects of the gamified system that have to be considered and managed but which are not directly implemented in the game. Ex: Constraints, Emotions, Narrative, Progression, Relationships. These aspects should be implemented by the next level.
- Mechanics: the basic process that drive the action forward and generate player engagement. Ex: Challenges, Chance, Cooperation, Competition, Feedback, Resource acquisition, Rewards, Transactions, Turns, Win States. These processes should be composed by the elements in the next level.
- Components: Specific elements that compose various mechanics. Ex: Points, badges etc.

This framework is mainly focused on game elements from a design perspective. Werbach and Hunter are concerned with how these game elements are *designed*, and not the *effects* that they have on users.

On the topic of how these game elements were designed (or selected for use in the different studies). None of the papers in the literature review explicitly state that presented studies employed game elements that were co-designed with learners, or teachers. This could be an issue, because game elements should function better in their role of fostering engagement and motivation if they make sense, or meaning to learners. This is the basis of the concept of "Meaningful gamification" defined by Nicholson in 2012 [114]. In this idea, game elements should make sense to users, creating explicit connections to the given activity, and supporting feelings of competence, autonomy and relatedness, identified as essential in Self-Determination Theory [114, 129, 140]. On the contrary, non-meaningful elements may be ignored or worst may demotivate users [30, 114]. Therefore, whilst designing game elements with the specific learners and learning activity in mind might be challenging, it may also provide a better gamified experience [114].

2.4 IDENTIFIED RESEARCH GAPS

Adaptive gamification in education is a novel and cutting edge research field, that has been gaining in popularity in the past few years. In order to better understand the current state of research in this field we performed an in-depth literature review that included twenty papers. Our analysis highlights a strong theoretical base, with eight papers that present recommendations for game elements, two that propose architectures that use these recommendations, and ten papers that test various adaptation engines in real world learning settings. We observed a variety of information used as a basis for adaptation, with both

static and dynamic approaches to adaptation. This shows that this is a wide and diverse research field. From this literature analysis we present four research gaps that should be addressed to help further the adaptive gamification research field. These research gaps are addressed in the following chapters of this manuscript, as described in section 2.5.

2.4.1 *Gap in game element nomenclature & design*

As shown in section 2.2.3 there is a certain confusion in the general nomenclature of game elements, and a gap in how they are designed. First the terms that define each of the game elements needs to be standardised and better defined. What are the differences between the Missions used by Paiva et al. [124] and the Quest system presented by Chalco et al. [19]? From studying the descriptions, we can see that there is little difference. A general framework should describe each game element along different abstraction levels (i.e. Points, Badges and Virtual goods are all forms of rewards and have somewhat similar functionalities. Points are more similar to badges than they are to Goals for example. And Self set goals are closer to forced goals than they are to Leaderboards).

Frequently game elements are selected without consideration for the learners that are going to use them. However as pointed out by Nicholson [114], game elements are more effective if they make sense to users. Thus came about the idea of meaningful gamification. We believe that by designing game elements specifically for the learning context, in collaboration with the different actors that will either be using or overseeing the use of the gamified tool (i.e. learners and teachers), we can achieve better and more effective game elements.

2.4.2 *Gap in comprehensive learner models*

As pointed out in 2.2.4.2, half of the reviewed papers use learner player types to adapt game elements. Generally they use the dominant player type identified to classify the learners. Mora et al. [108] question this in their study and show promising results when adapting to more than the dominant player type (although as the authors state, their results are not significant). Furthermore very few systems (only two) take learning characteristics into account, such as learner expertise [11] or learning styles [64]. We believe that the mitigated results identified in 2.2.5 could be partly due to the complex nature of learner preferences that are not represented in these simplified learner classifications. We therefore firstly advise taking into account more complex learner profiles, that include more specific learning data, such as learner expertise, learner skills as well as learner player types. Furthermore, learner activity should also be better explored as a means for adapting game elements. A similar research gap was identified in a literature of Tailored gamification in 2020 by Klock et al. [80], where they propose that research should consider "*all of the aspects of a users characteristics*".

2.4.3 *Gap in the evaluation of adaptation methods*

As identified in section 2.2.5, we advise that future adaptive gamification studies should aim for longer durations, as the results from short studies may be affected by the novelty effect of introducing gamification and not the adaptive nature of the gamified system. Furthermore, studies should compare the effectiveness of the adaptive system to that of a non adaptive system, which would also help with identifying if the impact on learners is due to gamification in general or to the adaptive nature. We also observed two ways for studies to quantify the effectiveness of the tested systems: either as an impact on learner performance or learner motivation. For learner performance it is fairly straightforward, using metrics such as course completion rate [64], or test results [79]. However, for learner motivation, the process was somewhat more complex, as studies used ad-hoc metrics to infer learner motivation (for example [89] used time spent on the learning tool, [105, 124] used learner feedback). This makes the comparison of the results from different studies difficult to make. We therefore advise that more research be performed into a more structured manner to estimate learner motivation levels. For example O'Brien et al. [116] propose a the User Engagement Scale (UES) to estimate user engagement, which has been shown to be somewhat robust and effective.

2.4.4 *Gap in dynamic adaptation methods*

We identified in section 2.2.4 how adaptation of gamification may affect the gamified learning environment by changing the game element itself, or by modifying its functioning. In their current state, most adaptation systems work in a static way. We highly believe that there is more to be explored in the domain of dynamic adaptation. For example the question of how and when a dynamic adaptation presents itself to a learner still has to be addressed. If the change brought on by the adaptation is not explained or presented to the learner in a clear and understandable manner this could confuse and could distract the learner from his/her learning activity. In the field of user interface adaptation Bouzit et al. [15] show that change needs to be observable, intelligible, predictable and controllable for the user. We believe therefore that research needs to be done into how these concepts can be applied to educational settings. Going back to the general literature review by Klock et al. [80], they also propose to consider dynamic modelling, stating that "*users, systems, and contexts change over time*". On the question of "when" only a few studies show methods for tracing user behaviour. For example Bouvier et al. [12] present a trace based approach for estimating user engagement and adapting when engagement is low.

2.5 CONCLUSION

In this chapter we presented an in depth literature review in order to better understand the field of adaptive gamification in education. We identified that

the field is emergent, with a theoretical base that several studies in real world learning settings build upon, and a general consensus on the language used. There is still room for this field to grow and develop, especially regarding dynamic adaptation that has been studied only once on a long term. From the shortcomings identified in the related literature, we identified four research gaps that should be addressed in adaptive gamification research. The following chapters in this manuscript all aim to fulfil these gaps. First, we highlighted a research gap in game element nomenclature & design. Second, we identified a gap in comprehensive learner models that combine both contextual (i.e. related to the education domain) and non-contextual (i.e. unrelated to the educational domain) information. Third, a research gap into the evaluation of the effects of adapted gamification on learners. Finally a gap in the research into dynamic adaptation methods

Adding to these research gaps, we can observe a distinct lack of generalised adaptation architectures. In section 2.2.2.2 we observed that only two papers presented generalised architectures of systems that can be used to tailor game elements to learners. However of these two, one [82] only described an algorithm for choosing appropriate game elements. The other does present a more generalised approach [104], and whilst they do propose a model to take learner behaviour into account in parallel to a learner profile, the work is still in a preliminary stage.

The main goal of this manuscript is therefore to expand on these ideas for an architecture to adapt gamification to learners, and to provide answers to fill in the identified research gaps. Generally the architecture is structured around three questions : **Who** are we adapting to? **What** are we adapting? and **How** are we adapting?. Each of these three questions is represented by a module in the architecture. In this vein, Chapter 3 presents a first look into associating user profiles with different game elements, and provides the results of a study that sought to compare various user models. The results of this chapter served to answer (in part) the first two research gaps: classification of game elements & better learner models. Chapter 4 expands on the work provided in Chapter 3 for the first research gap. A comprehensive game element design space, with tools to explore and create meaningful game elements linked both the learners and context serve to fulfil this first research gap. Chapter 5 fills the second gap by testing the effectiveness of adding user motivation to the learner model. This Chapter also serves to start to fulfil the third gap by analysing the effects of gamification on learners in a long form study. The final research gap, (exploring dynamic adaptation approaches) is covered by the proposal presented in Chapter 6. I present a trace based model in this chapter that proposes to quantify and clarify how learner engagement and motivation evolve over time through the usage of gamified tools, and that allows to identify when an adaptation is required.

All of the various examples and studies presented in this manuscript are from the Ludimoodle project, unless specified.

GAME ELEMENT RECOMMENDATIONS BASED ON USER MODELS

*Based on the study of the related work, we see that it is important to provide adapted and tailored game elements for learners. A first approach commonly observed in the related literature is to categorise learners based on their video game preferences (i.e. player profiles). However findings are very heterogeneous, and somewhat difficult to reuse due to different contexts, different profiles used to characterise users, and different implementations of game elements. This chapter presents a first study that investigated the links between different profile models and different preferences for game elements, how different implementations of similar game elements can affect users differently, and how the context of the gamified application can change the effect of game elements on users. The goal of this study is to provide insight into how we can generate recommendations for appropriate game elements, based on individual user characteristics. For this purpose, we ran a crowdsourced study with 300 participants to identify the motivational impact of game elements. Participants were asked to select which game elements they believed would motivate them more to complete an unspecified task in a pairwise comparison manner. This study differs from previous work in three ways: first, it is independent from a specific user activity and domain; second, it considers three user typologies; and third, it clearly distinguishes motivational strategies and their implementation using multiple different game elements. Our results reveal that (1) different implementations of a same motivational strategy have different impacts on motivation, (2) dominant user type is not sufficient to differentiate users according to their preferences for game elements, (3) Hexad is the most appropriate user typology for tailored gamification and (4) the motivational impact of certain game elements varies with the user activity or the domain of gamified systems. This study was the subject of a paper that was awarded with an honourable mention at the CHI Play conference in 2019: *Factors to Consider for Tailored Gamification* [59]. This chapter presents a first step in fulfilling the need for "richer learner models".*

3.1 INTRODUCTION

As shown in Chapter 2 users can be more or less receptive to different game elements [17, 75, 105, 106, 122]. Personality and preferences have a great influence on the effect that game elements have on user motivation. Appropriate game elements can lead to higher levels of user motivation, whereas

inappropriate game elements can demotivate users. Recent work on tailored gamification [41, 72, 108, 118] has provided valuable results that identify links between user types and relevant or motivating game elements. However, these results are very heterogeneous due to three reasons.

First: the studies are generally carried out in different and particular domains (usually in health [118, 119] or education [72, 108]). Even with studies that are in similar domains, we can sometimes observe different results (see Chapter 2, section 2.1).

Second: they rely on specific and different user typologies or personality models, mainly BrainHex [110], Hexad [141], or Big Five [50].

Third: they do not consider the same game elements or study different levels of abstraction of motivational strategies. For example the Rewards used in [118, 120, 121] are considered Points by [41] and [72]. Furthermore the concept of rewards systems can vary greatly based on what kind of rewards, and how they are used in the system. Similar issues can be raised for other game elements such as the game elements called cooperation in [118, 120, 121] which show up as Teamwork in [71] and Guilds or Team in [101, 141].

Thus, it is difficult to isolate and identify which game elements provoke which effects on

Thus, the motivational impact of game elements considered in these studies is difficult to isolate making it is quite difficult to identify which game elements are appropriate for which user profiles. Furthermore as appropriate game elements are subject to change when the context or activities change, re-using in different contexts is somewhat flawed. Finally as pointed out in chapter 2 studies in tailored gamification generally only use dominant types, which can prove problematic as we can question how well these dominant types are at capturing individual differences in learners. This line of questioning is also present in Orji et al. [120] where they consider each dimension of the player profile independently.

The goal of this chapter is to present a study that investigates factors to consider to support gameful design choices for tailored gamification, and proposes more generalizable findings on the links between game element preferences and user profiles. The study conducted investigates the motivational impact of game elements according to user types. It differs from existing works in three major ways: first, it is context-independent meaning that the scenarios that illustrate the game elements are not related to a specific user activity or domain; second, it compares two different user typologies (BrainHex [110], Hexad [101]) and a personality trait model (Big Five [49]); and third, it makes use of an abstraction level framework to describe the different game elements tested (see section 3.3).

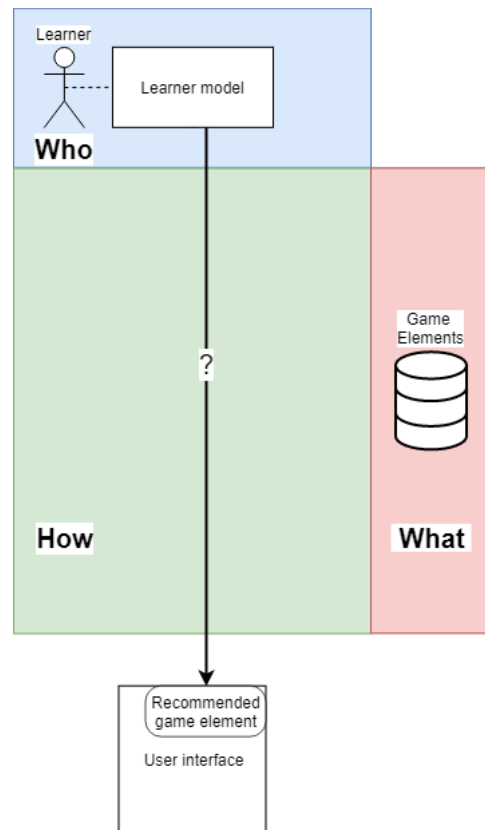


Figure 4: Step one of designing our adaptation engine, determining how to link users to appropriate game elements.

3.2 RESEARCH QUESTIONS

This study seeks to identify the factors that will support design choices when tailoring gamification to user profiles. These choices underline a general question which is how we can identify users' preferences for game elements. Thus, we address the following research questions:

RQ1: *Considering the game elements*, Do game elements implementing a same motivational strategy have different impacts on user motivation?

RQ2: *Considering the user typologies*

a: Is the dominant user type sufficient to discriminate users' preferences?

b: Which typology should be chosen for tailored gamification?

RQ3: *Considering the user activity and domain*, To which extent does the context influence the motivational impact of game elements?

Through these questions we will attempt to elucidate the first step of adapting game elements to users. In short we will create a first simple user model that we will use to select appropriate game elements (see figure 4).

3.3 ABSTRACTION LEVEL GAME ELEMENT FRAMEWORK

To help identify which game elements to test in this study, we designed a simple abstraction level game element framework that categorises game elements into overarching motivational strategies. This framework represents a first step in covering the need for better designed game elements (presented in 2.4 by dealing with the general confusion in the naming and implementation of game elements presented in section 2.2.3).

This framework drew inspiration from similar tools that propose a description of the different abstraction levels of game elements, such as MDA (Mechanics Dynamics Aesthetics) [67] and DMC (Dynamics Mechanics Components) [148], described in the previous chapter (section 2.2.3).

We expand on previous models by proposing a more structured framework, linking different game elements to their higher level motivational strategies. We also propose a more motivation oriented manner to describe game elements, focusing on how they can affect users rather than how they are designed. Finally our most concrete level also takes the specific domain where the game elements are deployed into account. We propose three abstraction levels:

- **Motivational Strategies:** high-level abstract concepts that motivate and engage users that are too abstract to be directly implemented. This is somewhat akin to the Dynamics level described in the MDA framework [67], and the Mechanics level in DMC [148]. However in our framework, the focus is on how these different strategies can motivate and engage users.
- **Game elements :** specifications of the motivational strategies that provide general rules on how they function. Here we are close to the Mechanics levels of MDA [67], and Components level of DMC[148].
- **Game element instances:** specific instances of game elements - created for a specific domain, users, task etc. (for example the badges system from Duolingo). This final level takes the context specifics into account to create the game element. instance.

To better understand how a game element can be described using this framework, I propose to decompose the Points game element from the Ludimoodle project (full descriptions of all the game elements used in the project are provided in Chapter 5 section 5.3.2). The Points game element in the Ludimoodle project rewarded learners with a set amount of points for each correctly answered question. Learners could see how many points they could gain in each quiz. Points were represented by a little gold coin stack. The points game element implements the "*Reward*" **motivational strategy**. This tells us that it should provide some kind of reward for completing an action / activity. In this case, the reward is given when correctly answering a question. For the **Game element** level, we use *Points* which implies that the reward is a numerical format. Finally the Instance level provides the contextual informa-

tion, relevant design (visible maximum, coin design), and functionality rules (how many points awarded per correct answer).

Table 6 presents the full framework, along with the corresponding storyboards designed for this experiment.

Each of the motivational strategies provokes one of multiple of the motivations provided in the self determination theory (SDT) [129]. The majority of these motivational strategies promote *competence* (rewards, goals, time, progress), however *Self Goals* also promotes *autonomy*. *Social interaction* game elements promote *relatedness*. Each of the game elements are commonly found in gamification literature using a wide variety of names. See table 7 for an overview of the different references of game elements in the relevant literature.

3.4 STUDY DESIGN

To explore these questions we ran a crowdsourced study that asked participants to evaluate the motivational impact of the 12 different game elements present in the abstraction level framework (see section 3.3). The game elements are illustrated using storyboards that show an implementation independently from any specific user activity and domain. The perceived motivational impact of each element is evaluated using a paired comparison protocol which has been shown to be more reliable than direct rating [126, 134]. Participants were asked to select which of two storyboards they found to be more motivating. We compare variations based on users' profiles according to the three most commonly used user models: BrainHex [110], Big Five Personality Factors [49] and Hexad [101]. This study reached 616 participants that were then filtered down to a set of 300 high-quality and consistent participants.

3.4.1 Materials

We designed a storyboard for each game element independent of any activity and domain (see an example in figure 5). This methodology was inspired by other studies in this vein [119–121]. Each of the storyboards depicts three panels where a user completes a generic "task" with the game element changing accordingly. The full storyboards are provided in the annexes at the end of this manuscript.

Rewards game elements

In the *Points* storyboard (figure 38), the user receives points each time they complete a task, their total score is shown in the game element area. For *Badges* (figure 39) the user gains a badge for completing the task, they can see a list of the badges they have obtained, as well as the badges they can still obtain in the game element area. For *Useful rewards*, the user completes a

Table 6: The Strategy-Element-Instance framework. Each of the game element instances is shown in a different storyboard example used in the following study.

Strategy	Game Element	Instance explanation
Rewards	Badges	One time rewards that are given to users based on specific actions they perform (medals, trophies etc.) See figure 39
	Points	Numeric rewards that are given to users based on general actions (performance, bonuses etc.) See figure 38
	Useful	Rewards that have an effect on the system (bonuses, power-ups etc.) See figure 40
Goals	External	Goals that are set by the system, or by some other 3rd party. See figure 41
	Self	Goals that are self defined by the user, either through direct input or selection. See figure 42
Time	Schedule	Game elements that keep the users coming back on a regular schedule (daily rewards / challenges for example). See figure 43
	Timer	Game elements that keep track of the time the user spends performing an action (increasing, decreasing timers etc.) See figure 44
Social Interaction	Trading	Being able to exchange goods / tools with other users. See figure 45
	Teams	Being able to work with other users to achieve common goals. See figure 46
	Discussion	Being able to exchange information with other users. See figure 47
Progress	Compared	Game elements that compare a users' progress to that of other users (leaderboards, ranking systems etc.) See figure 48
	Task	Game elements that display a users' progress in the task, independently from other users (progress bars etc.) See figure 49

Table 7: The 12 game elements from the abstraction framework as represented in previous studies.

Strategy	Game element	Equivalent to
Rewards	Badges	Badges [41, 72] Rewards [72] Badges or Achievements [101, 141]
	Points	Points [41, 72], Reward [119–121], Points [101, 141]
	Useful	Reward [119–121]
Goals	External	Goal setting & Goal suggestion [119, 120]
	Self	Clear goals [72]
Time	Schedule	Reward Schedule [41]
	Timer	Timer [89]
Social Interaction	Trading	Collection & trading [101, 141]
	Teams	Cooperation [119–121] Teamwork [71] Guilds or Team [101, 141]
	Discussion	Social network [101, 141]
Progress	Compared	Leaderboards [41, 72, 89] Competition and Comparison [121] Comparison [119, 120] Social Comparison [101, 141]
	Task	Bars [41] Progress [72] Self-monitoring and suggestion [121] Self-monitoring and feedback [119, 120] Advancement [71] Levels or progression [101, 141]

task and gains a "Give example" power. The area on the right shows the users inventory, with items such as "Skip task" and "Help" that suggest their usage.

Goals game elements

Both of the Goals storyboards have the same general structure: the game element area on the right shows a list of goals that the user has to complete, each one has a checkbox that shows whether a given goal has been completed or not. For *External Goals* (figure 41), the storyboard shows the user completing a task, after which a popup informs them that the system has given them a new goal. A new goal and checkbox appear in their goal list. For *Self Goals* (figure 42) there is a button in the game element area that opens a window where the user can add a new goal themselves.



Figure 5: An example of one of the 12 storyboards created to illustrate the game elements that implement the 5 motivational strategies. This particular one depicts the Badges game element related to the Rewards strategy.

Time game elements

The *Schedule* storyboard (figure 43) shows a five day calendar. The user has to complete at least one task per day. Each day that a user completes a task, a check mark is placed in the corresponding day. After completing five days, the user receives a bonus. For the *Timer* storyboard (figure 44), the user is timed to see how quickly they can complete a task. In the game element area, they are shown a table of their previous times. After completing a task the table updates, and the user is informed if they performed faster than before.

Social Interaction game elements

In the *Trading* storyboard (figure 45), a user selects a task to complete in the task area. A popup informs them that they need a "key" to start that particular task, which they acquire by using the "chat" on the right to trade another user for it. For the *Teams* storyboard (figure 46), the user acquires points each time they complete a task, the user can see their team score. A set of notifications on the right show when another user in their team completes a task and increases the team score. The *Discussion* storyboard (figure 47) shows a user stuck on a task. They use the chat on the right to ask other users for help. Another user provides a solution to their problem and they can complete the task.

Progress game elements

Both of the Progress game element storyboards have a similar design. They both use a progress bar in the game element area that fills up when a user completes a task. In the *Compared Progress* storyboard (figure 48), the bar shows the class average on the side and opens a popup when the user advances into the top 50% of their class. In the *Task Progress* storyboard (figure 49) the class average is replaced by a simple marking to show how much of the task the user has completed (50%, 60% etc.).

3.4.2 Storyboard validation

To ensure that these context-independent storyboards would be understood by all participants, we ran a pre-study comparing them to similar storyboards

for a maths learning activity. We asked participants to describe in their own words each storyboard. The descriptions were then reviewed by two different evaluators and graded out of 3.:

- 0: the participant does not understand the panels
- 1: they understand what is happening in the panels but not how the system works
- 2: they understand the panels but show minor confusion on how the system works
- 3: they understand the panels and how the system works perfectly

After an initial set of evaluations using 8 participants, we iterated on our storyboard design, and validated the final design using a further 2 participants. We found that the descriptions given for the context-free storyboards matched those given for the task-specific ones. Furthermore, to ensure that the comprehension of the storyboards was not influenced by age, or familiarity with video games (or game mechanics in general), we calculated the correlation between these factors. We found a very low correlation (0.10) between participant age and understanding, and a low correlation (0.28) between video game familiarity and understanding. We therefore judged that our storyboards could be understood as well as context-specific storyboards by all participants.

3.4.3 Procedure

As stated previously, we used a paired comparison technique to evaluate the perceived motivational impact of each game element. Participants were shown pairs of storyboards, and were asked to choose which one they estimate "*would motivate them more to use the system*" (forced-choice methodology). Such paired comparison protocol offers 3 advantages over Likert-type rating [126]: (1) the experimental task is less cognitively demanding [22] (choosing a preference between two items is easier than providing an ordinal rating); (2) it avoids normalization issues which occur, for instance, when some users avoid extreme response categories; (3) it has been shown to provide higher sensitivity and lower measurement error [134].

We opted for a *full* paired-comparison design, meaning that each participant evaluates *all possible* pairs of storyboards, i.e. $\binom{n}{2} = n(n-1)/2$ pairs with n the total number of storyboards. In our experiment $n=12$ leading to 66 comparisons. This full design, as opposed to incomplete ones, is more time consuming for individual participants but allows a complete evaluation of participant agreement and consistency. Note that the order of pairs is randomised for each participant.

3.4.4 Data collection

As commonly used in HCI research (e.g., [65, 118, 120]), we leveraged the power of crowdsourcing to recruit a large number of participants. Our study

used the Figure Eight platform ¹ and proposed a task divided into two parts: firstly, participants were asked to complete the paired-comparison experiment described above; secondly, they were asked to fill questionnaires allowing us to determine their BrainHex, Hexad and Big Five profile. For the first two, we used the official questionnaires [141, 153], for the last one, we used a simplified version of traditional big five questionnaires called TIPI (Ten Item Personality Measure) [51]. Using the tools provided by the crowdsourcing platform we ensured that our participants came from a wide variety of different countries and that they could respond to our task only once. Participants were paid a total of US\$1.25, and spent between 15 and 25 minutes to complete the surveys.

3.4.5 Data filtering

As with all crowdsourced studies, certain measures are required to ensure that the responses given by participants are genuine. We employed two mechanisms to filter careless participants (we did not filter any of the answers to the personality or player type questionnaires):

(1) In the pairwise comparison task, we inserted four "test" questions where participants were expected to answer a certain way. For example, one "test" question presented a situation where a user would gain 20 points, and another where the user would lose 10 points for performing the same actions. Participants were therefore expected to choose the first one as the more motivational. Participants with less than three correct answers to these four test questions were rejected.

(2) To evaluate the reliability of each participant, we checked their individual consistency, by calculating the number of cyclic triads occurring in their choices. A cyclic triad occurs when a pair comparison is intransitive, (e.g., A is preferred to B , B is preferred to C and C is preferred to A). The coefficient of consistency [77] is then computed as follows for each observer: $\zeta = 1 - \frac{24c}{n^3 - n}$ where n is the number of stimuli (12 in our experiment) and c the number of cyclic triads. $\zeta = 1$ when there is no circular triads (i.e. perfect consistency) and will decrease to zero as the number of circular triads, and thus the inconsistency, increases. Participants' results were rejected if their coefficient of consistency was inferior to 0.75, as in [92]. This limit was decided to allow for some degree of input error (i.e. clicking on the wrong button) whilst still removing the most inconsistent participants.

A total of 616 participants performed the whole task; 180 were rejected according to (1) and 136 were rejected according to (2) giving a final set of 300 valid and consistent participants. This strict filtering insures a high reliability of our results. Participants came from a wide variety of backgrounds, a summary of the demographic information and distribution of the different user types is presented in table 8.

¹ The website has since undergone a rebranding <https://appen.com/>

Table 8: Participant demographic information

	Total participants (300)
Gender	Male (203), Female (97)
Age	<20 (9), 20-30 (124), 30-40 (93), 40-50 (45), 50-60 (24), 60+ (5)
Origin	Europe (131), Africa (17), The Americas (106), Asia (44), Oceania (2)
Big five dominant type	Agreeableness (73), Conscientiousness (104), Emotional Stability (46), Extraversion (17), Openness to Experiences (60)
Brainhex dominant type	Achiever (32), Conqueror (48), Daredevil (21), Mastermind (118), Seeker (35), Socialiser (33), Survivor (13)
Hexad dominant type	Achiever (49), Disruptor (5), Free Spirit (71), Philantropist (61), Player (85), Socialiser (29)

3.4.6 Data Analysis

We describe in this section the different tools used for data analysis. Note that we used Bonferroni's correction to compensate for the multiple comparisons in our statistical tests.

3.4.6.1 Perceived motivation score

As explained in the Procedure, each participant provides a "vote" for a storyboard for each of the 66 possible pairings. Results per participant can be recorded in a 12×12 preference matrix. These per-participant preference matrices are then summed into a single one. In this summed matrix P , each element $P_{i,j}$ represents the number of times the storyboard i was judged to be more motivating than storyboard j . An example of such a matrix is given in table 9.

Table 9: Example preference matrix for one participant and five storyboards. In this example the participant voted *Story1* more motivating than *Story2* when presented with the pair *Story1* – *Story2*. However *Story1* and *Story2* scored the same in total. The participant also voted for *Story3* each time they were shown it, and never voted for *Story5*.

	<i>Story₁</i>	<i>Story₂</i>	<i>Story₃</i>	<i>Story₄</i>	<i>Story₅</i>	Score	Normalised
<i>Story₁</i>	-	1	0	0	1	2	0.4
<i>Story₂</i>	0	-	0	1	1	2	0.4
<i>Story₃</i>	1	1	-	1	1	4	1
<i>Story₄</i>	1	0	0	-	1	2	0.2
<i>Story₅</i>	0	0	0	0	-	0	0

As classically done with pairwise comparison experiments [126], we can then consider the number of votes received by each storyboard as its score of perceived motivational impact, which may then be divided by the number of comparisons per storyboard for normalisation purposes. This score computation can be done either for each individual participant, or for groups of participants (e.g., for calculating the preference scores for each dominant user type). In the example matrix (table 9) *Story₅* had a final score of 0 (it was voted 0 times out of a possible 5). *Story₁* had a normalised score of $2/5 = 0.4$

Note that more sophisticated statistical methods exist for inferring scale values from a preference matrix [16, 137]. However they were not shown to give a better representation of perceived motivational impact score than the vote counts. Using the data gathered in this study we observed an average correlation of 0.999 (SD: 0.0002) between scores obtained by vote counts and Thurstone’s Law of Comparative Judgements, Case V [137].

3.4.6.2 Participant agreement

Beyond motivational scores, it is also interesting to analyse the agreement of participants in their choices, i.e. the similarity of their votes. The coefficient of agreement u was defined by Kendall and Smith [77] as: $u = \frac{2\Sigma}{\binom{s}{2}\binom{n}{2}} - 1$ where s is the number of participants and Σ is the sum of the number of agreements between all $\binom{s}{2}$ possible pairs of participants and $\binom{n}{2}$ possible pairs of stimuli. It ranges from 1 (perfect agreement) to $-1/s - 1$, if s is even, and $-1/s$, if s is odd.

3.4.6.3 PLS-PM

To calculate how well each user type affects the scores for each implementation we used a method called *partial least squares path modelling (PLS PM)* [55]. PLS PM is a method of structural equation modelling which allows estimating complex cause-effect relationship models with latent variables, that has been previously used in studies on the effects of gamification on user motivation [119–121, 141]. Essentially we use it to see how the values for each

user type influence the scores for each game element. The influence values vary between -1 and 1 depending on how strong the effect is. As this is a statistical evaluation we use the calculated p-value to determine the validity of the given influences.

3.5 RESULTS

3.5.1 *RQ1: Perceived motivation for different implementations of motivational strategies*

As presented in table 7, a given motivational strategy can be implemented in the form of different game elements. To investigate if different implementations of a same motivational strategy lead to different levels of perceived motivation, we analysed the motivation scores obtained for the game elements on the entire set of participants. Scores are computed from the preference matrix as explained in Section 3.4.6.1. Instead of a single score per game element, we compute a score distribution using a bootstrap technique [37]: scores are computed 200 times, each time on a random set of participants of the same size as the original set, generated by sampling with replacement. The bootstrap distributions allows for statistical testing and their percentiles provide the 95% confidence intervals.

Figure 6 illustrates the perceived motivation scores. The corresponding scores are given in table 10. For each motivational strategy, we performed pairwise paired t-tests over the score distributions to assess if significant differences exist between game elements. The results of these tests are given in table 11.

The Rewards strategy shows highly significant differences among the motivational impact of its implementations. Badges is the best perceived, followed by Useful Rewards and finally Points (Badges-Points $t:137.56$, Points-Useful $t:-60.25$, Useful-Badges $t:-114.23$, $p<.001$). Similar results have been found by Denny et al. [29] who showed that in educational settings their badge system was more effective than their points system. They attribute the differences to the fact that the points setting "lacked clear targets". Several other studies have also reported the efficacy of badge systems [3, 28, 52]. Studies that show an effectiveness of Points [21, 40] integrate this game element with others like leaderboards or badges, thus preventing an isolated impact of this particular game element.

Regarding the Goals strategy, the difference between the two implementations is also significant ($t:70.34$, $p<.001$). Externally set Goals are perceived as more motivating than Self set Goals. This could be explained by the fact that users may find it more difficult to set their goals by themselves, especially without a specific (and meaningful) task to carry out. The studies in [34, 88] also show that External Goals are effective means for user performance and motivation.

Regarding the Time strategy, Timers score less than Schedule ($t:-84.22$, $p<.001$). We believe this to be due to the fact that Timers are usually seen as

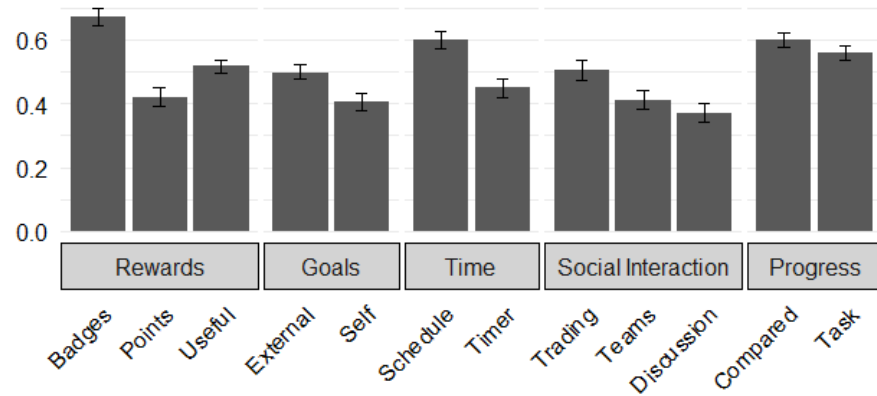


Figure 6: Perceived motivational impact scores of all game elements, for the whole set of participants. The error bars show the 95% confidence intervals. Full values are provided in table 10

Table 10: Perceived motivational impact scores of all game elements, for the whole set of participants (contains the values for Figure 6).

Mot. strategy	Game Element	Avg.	5th %-ile	95th %-ile
Rewards	Badges	.67	.64	.70
	Points	.42	.39	.45
	Useful	.52	.50	.54
Goals	External	.50	.48	.52
	Self	.41	.38	.43
Time	Schedule	.60	.57	.63
	Timer	.45	.42	.48
Social Interaction	Trading	.51	.47	.54
	Teams	.41	.38	.44
	Discussion	.37	.34	.40
Progress	Compared	.60	.58	.62
	Task	.56	.54	.58

Table 11: Results of the t-test comparisons of average scores between implementations of a same strategy.

Mot. strategy	Comparison	t	p
Rewards	Badges-Points	137.56	<.001
	Points-Useful	-60.25	<.001
	Useful-Badges	-114.23	<.001
Goals	External-Self	70.34	<.001
Time	Timer-Schedule	-84.22	<.001
Social Interaction	Discussion-Teams	-24.34	<.001
	Teams-Trading	-45.33	<.001
	Trading-Discussion	75.67	<.001
Progress	Compared-Task	46.42	<.001

stressful for most users. In our storyboard, the Schedule game element shows the tasks accomplished on a week, users have more time to carry out their tasks and could perceive it as less stressful.

The three implementations of Social Interaction scored differently, with Trading scoring the highest, and Discussion scoring the lowest (Discussion-Teams t:-24,34, Teams-Trading t:-45.33, Trading-Discussion t:75.67, $p<.001$). Teams and Discussion are in the three least motivating game elements. Young [149] showed that discussion based interventions can be effective in situations where the users are intrinsically motivated by the task.

Finally the Progress implementations rank closely but still show a significant difference in scores (t:46.42, $p<.001$), with Progress Compared scoring higher. It is noteworthy that both game elements are ranked in the top four. Some previous studies also show the effectiveness of social comparison [60] and of progress bars [39].

As a conclusion, regarding **RQ1**: our results demonstrate that **user motivation varies significantly with the different implementations of a same motivational strategy**.

3.5.2 RQ2 a: Reliability of dominant user type

Many studies in tailored gamification or adaptive games consider only the dominant user type [19, 41, 48, 89, 136] defined as the type that scores the highest for a given user profile.

To evaluate the reliability of the dominant user type for tailored gamification, we looked at how they affect the perceived motivational impact of the game elements. To do so, we clustered participants according to their dominant user type (for both of the player typologies, as Big Five cannot be considered in this manner) and calculated the Kendall Coefficients of Agreement

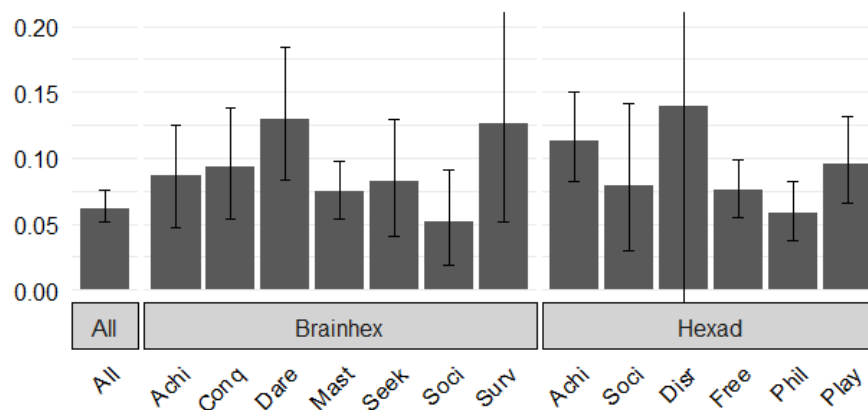


Figure 7: Coefficients of agreement for each dominant type. The error bars show the 95% confidence intervals. Full values are provided in table 12

u within each group and compared to the global value (obtained on the whole set of participants). The idea is to study if users sharing the same dominant type perceive the same motivational impact of game elements (and thus show a higher agreement than whole set). Figure 7 shows the results.

Table 12: Average agreement scores for each user type.

Typology	User Type	Avg. Agre.	5th %-ile	95th %-ile	n
	All	0.06	0.05	0.07	300
Big Five	Agree.	0.06	0.04	0.09	73
	Consc.	0.09	0.06	0.11	104
	Emot. stab.	0.08	0.04	0.12	46
	Extra.	0.10	0.06	0.16	17
	Open.	0.08	0.06	0.12	60
	Brainhex	Achiever	0.09	0.05	0.13
Conqueror		0.09	0.05	0.13	48
Daredevil		0.14	0.08	0.19	21
Mastermind		0.07	0.05	0.10	118
Seeker		0.08	0.05	0.13	35
Socialiser		0.05	0.02	0.09	33
Survivor		0.13	0.06	0.21	13
Hexad	Achiever	0.11	0.08	0.16	49
	Disruptor	0.13	-0.07	0.44	5
	Free spirit	0.08	0.05	0.10	71
	Philanthropist	0.06	0.04	0.08	61
	Player	0.09	0.07	0.12	85
	Socialiser	0.08	0.03	0.13	29

We find the coefficients of agreement within each dominant user type cluster to be low (no group scored an agreement greater than 0.15). While most of these values are nevertheless higher than the global one (0.062), this still shows that, regarding RQ2 a: **dominant user types cannot be considered sufficient to differentiate users according to their game element preferences.**

3.5.3 RQ2 b: Comparing user models

In this section we investigate more precisely the relationships between the user models (both player types and personality model) and game elements to identify which user typology is the most relevant to identify user preferences for game elements. Table 13 shows the PLS path coefficients that reflect the influence that each user model dimension has on the motivation score of the different game elements.

Table 13: PLS Path coefficients for each user type of each typology. Values in grey are not significant ($p > .05$), highlighted in dark grey are significant ($p < .05$), and highlighted in black are highly significant ($p < .001$).

(a) BrainHex								(b) Hexad					
GE	Seek	Surv	Dare	Mast	Conq	Soci	Achi	Phil	Soci	Free	Achi	Disr	Play
Badges	.01	-.01	.13	.11	.07	-.07	.02	-.08	.07	.04	.05	-.06	-.07
Points	-.12	.02	.01	-.02	-.08	-.05	-.06	-.06	-.14	.06	-.16	.00	.10
Useful	.11	-.04	.13	-.03	-.08	.02	.10	.03	-.13	.09	-.07	-.02	-.08
External	-.07	.04	-.04	.09	-.16	.02	.02	.13	-.30	.05	.10	-.05	-.01
Self	.06	.10	-.09	.01	-.10	.10	.01	.12	-.08	.05	.09	.00	-.08
Schedule	-.02	.03	-.05	.02	.04	-.07	-.00	.07	-.10	-.07	.03	-.08	-.04
Timer	-.08	.01	.02	-.05	.04	-.07	-.14	-.03	-.04	-.15	.13	.06	.01
Trading	.01	.06	.02	-.05	.10	.11	.04	-.06	.26	.05	.03	-.01	-.06
Teams	.02	-.09	.01	-.05	.16	.04	.09	-.05	.34	.01	-.10	-.07	.03
Discussion	.08	.07	-.10	.01	.01	.18	.06	.02	.24	.13	-.11	-.07	-.01
Compared	.01	-.13	.03	.04	-.01	-.08	.01	.02	-.14	-.14	.08	.16	.08
Task	.02	-.09	-.06	-.06	-.09	-.15	-.12	-.07	-.16	-.11	-.06	.17	.07

(c) BigFive					
GE	Extr	Agre	Cons	Emot	Open
Badges	.00	-.01	.04	-.02	.00
Points	.05	-.07	.04	.04	-.06
Useful	-.02	.01	-.12	.03	-.04
External	.00	.03	.07	-.03	-.04
Self	.06	.05	.03	-.03	-.02
Schedule	-.05	.04	.06	.03	-.07
Timer	.03	-.05	.08	-.03	.06
Trading	.03	.12	-.15	.10	.04
Teams	-.05	-.04	-.06	-.06	.19
Discussion	-.03	.14	-.06	-.02	.04
Compared	-.02	-.14	.02	.02	-.05
Task	-.02	-.12	.07	-.06	-.10

We present our results grouped by user typology, and we discuss the extent to which our results are in line with the definition of each user type (the full definitions are provided at the end of this chapter ??).

3.5.3.1 *BrainHex*

Daredevil affects *positively* two game elements of the Rewards motivational strategy: **Badges** and **Useful Rewards**. According to the definition, Daredevils appreciate "rushing around at high speed whilst still in control" [110]. Badges may reinforce the feeling of control and knowledge on the system, and Useful Rewards may help them to speed up progression.

The **Socialiser** type influences two game elements: **Discussion** *positively*, and **Progress Task** *negatively*. Nacke et al. [110] define Socialisers as "liking hanging around with, and helping people". This definition therefore tends to confirm that Socialisers are motivated by discussion. However, it does not explain the influence of this type on Progress Task.

The **Conqueror** user type has a significant *positive* influence on **Teams**, as well as a significant *negative* influence on **External Goals**. These influences are unrelated to the definition as conquerors are people who "like defeating impossibly difficult foes, struggling until they eventually achieve victory" [110]. Although an argument could be made that teaming up with others (in an alliance strategy) to defeat difficult foes, could appeal to conquerors.

The **Achiever** user type has two *negative* influences: **Timer** and **Progress Task**. Achievers "like collecting anything they can collect, and doing anything possible" [110]. The presence of a **timer** could hinder their abilities to achieve this. However the definition of Achiever does not provide any explanation for the negative influence on Progress Task.

The **Survivor** user type shows a significant *negative* influence on the **Progress Compared** game element which is unrelated to the definition stating that survivors enjoy "escaping from terrifying situations" [110].

Seekers, defined as people who have interest in "finding strange and wonderful things" [110], have no significant influences on any of the game elements tested.

Finally, **Mastermind** have also no significant influences. Nacke et al. [110] define them as people who "like solving puzzles and devising strategies", meaning that they might be more motivated by the task itself than the game elements used.

As a conclusion, for BrainHex, five user types have significant influences on the different game elements. Some of our results can be explained using the definition of BrainHex typology [110], especially for **Daredevil**, and partially for **Socialiser** and **Achiever**. However most of our results cannot be backed up by the definitions given in the typology. In addition, Mastermind and Seeker user types definitions seem not well suited for gamification. This result is in line with recent empirical investigation on the psychometric properties of BrainHex that has shown low reliability scores [18, 47]. This typology was built for games and there is no evidence of the generalizability of game motivation models to gameful design [138].

3.5.3.2 Hexad

The **Socialiser** player type affects *positively* the three Social Interaction game elements (**Trading**, **Discussion** and strongly **Teams**) and *negatively* **External Goals** and **Progress Task**. Regarding social interactions, our results are consistent with the definition that states that Socialisers "like to interact with others and create social connections" [101].

Disruptor has significant *positive* influence on both **Progress Compared** and **Progress Task**. This could be explained as disruptors seek to change a system [101]. Perceiving the boundaries of the system thanks to progress elements could help them to expand beyond these limits.

The **Achiever** user type has only a significant *negative* influence on **Points**. Some authors point out that reward systems (specifically points) can be perceived as useless if their implementation is not linked to the context [72]. As Achievers are motivated by competence [101], we can assume that they do not appreciate points as illustrated in our scenarios.

Free Spirit has only a significant *negative* influence on **Timer**. According to the definition, Free spirits are motivated by autonomy. They like to explore within a system and act without external control [101]. In this case, Timer can be perceived as constraining their freedom by time.

The **Philanthropist** user type has no effect on the motivation scores given for the different game elements. According to the definition [101], philanthropists are motivated by purpose. Thus we can think that this user type does not influence any preferences for our elements that are not connected to a specific user activity and domain.

Finally, we did not find any significant influences for the **Player** user type. Players are defined as being motivated by extrinsic rewards. They will do anything to earn a reward within a system, independently of the type of the activity [101]. Players seem to be able to appreciate anything, and therefore will react positively to almost any game element used, explaining that we do not find any particular influence.

As a conclusion regarding Hexad, four user types have significant influences, among which one is highly significant. Moreover, most of our results are consistent with the definitions of the Hexad typology [101]. This result reinforces the fact that this typology was designed especially for gamification and most of its player types are based on SDT [129], the major theoretical foundation for gamification research.

Seeing as our results with Hexad are the most consistent with the definitions of its user types, and that its types have more influence on the perceived user motivation than those from BrainHex and Big Five, we can state that, regarding **RQ2 b: Hexad is the most relevant typology to identify user preferences for game elements and thus should be used to tailor gamification.**

3.5.3.3 *Big Five*

The **Openness to experiences** trait has a significant *positive* influence on **Teams**. The appreciation for new ideas and curiosity [50] are two characteristics of this personality trait that can explain this result.

Regarding the **Agreeableness** trait, we observe a *positive* influence on **Discussion** and a *negative* influence on **Progress Compared**. The positive influence on social interactions is consistent with the definition stating that people with high agreeableness are generally generous, cooperative and helpful [50]. However the definition of this trait cannot explain why these people are demotivated by game elements related to the progression in the task.

Emotional stability shows no significant influences on any of the game elements. People with high emotional stability have a tendency to resist negative emotions such as anger or anxiety [50]. We can assume that people with this personality trait are not responsive to the game elements in terms of motivation.

The **Conscientiousness** trait influences significantly only one game element, **Trading** *negatively*. This result is not related to the definition of this trait since conscientious people are defined as self-disciplined and well organised. Finally, **Extraversion** shows no significant influences. **Extraversion** is defined as a "pronounced engagement with the external world and enjoyment from interacting with people" [50]. To fit the definition, we would have expected a positive influence for game elements that implement the Social Interaction strategy.

As a conclusion regarding Big Five personality model, three traits have significant influences. As with BrainHex some of our results can be partially explained by the definition of the personality traits (**openness to experiences** and partially **agreeableness**), but most of them are not directly in line with the definitions. This result was predictable since Big Five is a general personality trait model and not specifically developed for games or gamification.

3.5.4 *RQ3. Activity and domain influence on the motivational impact of game elements*

We finally compare our results to the findings of previous studies when their game elements or persuasive strategies are similar to ours (see table 7 for correspondences). Previous studies were conducted in specific contexts (specific domain and user activity), with possible influence of users' intrinsic motivation for the activity and/or domain on the observed user motivation. It is noteworthy that whilst the study in [121] focuses on a serious game, it uses game elements in a similar way as a gamified system. In our study, we use storyboards that show implementations of motivational strategies independent from any specific context. Our analysis in this section aims to identify the extent to which the context has an influence on the motivational impact of game elements according to user types.

3.5.4.1 *BrainHex*

Our results are *consistent* with other studies for the **Socialiser** type, for which Orji et al. [121] also found a negative influence on self-monitoring (vs. Progress Task).

Three of our results on the **Achiever** and **Survivor** user types *contradict* the previous studies. Regarding **Achievers**, Orji et al. [121] found a positive influence on self-monitoring, whereas we find a negative influence on Progress Task and Lavoué et al. [89] predict a positive link with timer, whereas we find a negative influence. Concerning **Survivors**, Orji et al. [121] found a positive influence on competition & comparison, whereas we find a negative influence on Progress Compared.

We also find influences for game elements that are *not identified* in previous work for the **Daredevil** type. Finally, other studies also found *other influences* for the 7 user types.

We can conclude that our results obtained with the BrainHex user typology are quite different from the other studies conducted in specific contexts (gamified health system [121] and experts' recommendations in education [89]).

3.5.4.2 *Big Five*

Regarding the Big Five personality model, the positive influence we find of the **Agreeableness** trait on Discussion *is consistent* with the results of Orji et al. [119] on cooperation. Regarding **Emotional stability**, Orji et al. [119] studied people with a low emotional stability and also did not find any influences for those people. They stated that persuasion may not be effective for people who are emotionally unstable. In the same domain (health) but for a different activity, Jia et al. [72] found negative influence on points, badges, progress and rewards and they argued that for people with high emotional stability gamification may not be an effective approach.

Our results *contradict* previous studies only for **Openness to experiences**, Orji et al. [119] found a negative relation with cooperation, whereas we find a positive influence on Teams.

We also find a negative influence of **Conscientiousness** on Trading that is *not identified* in previous studies.

The three comparable studies also found *other influences* for **Extraversion**, **Agreeableness** and **Conscientiousness**, and the two studies held in the health domain do not find similar results. For instance for **Agreeableness**, Orji et al. [119] found influences on four game elements (self-monitoring & feedback, comparison, competition and reward) whereas no influences were found for these in Jia et al. [72].

Regarding the Big Five personality model, the comparisons with other studies highlight the differences in the results obtained both (1) between our study and studies conducted in a specific context, and (2) between the studies conducted in different contexts, even in the same domain like health.

3.5.4.3 *Hexad*

Our results are *consistent* with other studies for the **Philanthropist** user type, which do not find any influence on the motivational impact of game elements. Our results are *partially consistent* both for the **Socialiser** and **Disruptor** user types. Regarding **Socialisers** and positive influences on social game elements, [141] also suggest positive influences on Teams, Social Network and Social Comparison, while Orji et al. [120] also found positive influences for Cooperation. Regarding **Disruptors**, all studies including ours observed positive influences for the **Progress Compared** element (Competition in [120, 141]). We observe *contradictions* only with [120] for these two player types regarding the **External Goals** and **Progress Task** elements. Our results are different from previous studies regarding three player types. We find influences for game elements that are *not identified* in previous works and other studies found *other influences* for **Achiever** and **Free Spirit** (previous work do not show any influence for elements comparable to the timer). Finally, regarding **Players**, we do not find any influences whereas [141] found positive influences for every game elements and [120] for most of game elements (except for Self-Monitoring & Feedback and Goal Setting & Suggestion).

As with Big Five, the results with the Hexad types are quite different from those found in studies conducted in specific different contexts (education [141] and health [120]), except for three user types (Philanthropist, Socialiser and Disruptor).

In conclusion, for all user typologies (BrainHex, Hexad) and the personality model (big five) we can see that, regarding **RQ3: the motivational impact of certain game elements varies according to the activities or the domain of gamified systems**. In fact, our results are quite different (especially for BrainHex) from those found in contextualised studies. We also observe differences between the studies conducted in different contexts, even between two studies conducted in the same general domain (Health) with the Big Five user typology.

3.6 LIMITATIONS

3.6.1 *About the experimental protocol*

Regarding the experimental protocol, one major difference with previous studies deals with how we collected our data. We used forced-choice paired comparison instead of declarative statements to identify the perceived impact of game elements on user motivation. As stated in Section 3.4, this protocol has been shown to be less cognitively demanding [22] and to provide higher accuracy [134] as compared with Likert-type rating. We notice that it also impacts our results as it forces the users to choose which game elements they prefer. We therefore obtain a ranking of game elements (meaning that a user could not vote all game elements as equally motivating). We believe this has a direct consequence on two profile dimensions (Hexad-Player, and Big Five-Extraversion) for which people will tend to appreciate most of game

elements, leading to no specific significant influences when applying the PLS PM method. In addition, using PLS PM allows us to observe negative influences on the perceived motivational impact of game elements whereas some of the other studies only measure positive influences [89, 141]. This could be a limitation to the comparisons we make in Section 3.5.4.

3.6.2 *About the context-independent scenarios*

We use context-independent scenarios to evaluate the motivational impact of game elements independently from a specific context. However certain game elements may be less motivating for users shown without a concrete task to carry out. We suppose this to be especially true for External Goals, Self Goals and Useful Rewards that are not perceived as the most motivating elements in our study and Progress Task that is negatively influenced for three user types. Furthermore, for some user types, no significant preferences can be shown without a specific task to carry out. We think this is especially true for the philanthropist who is motivated by purpose.

3.6.3 *About the implementation of motivational strategies*

Finally, the results we obtain may differ from other studies due to the fact that the implementations of our motivational strategies may be quite different from those used in other studies. For instance, the Rewards strategy in [120] is implemented in the form of points that can be used to unlock new customisation options. This implementation can be considered as a combination of our Points and Useful Rewards (see Table 1). We believe that our approach allows us to study the isolated motivational impact for each game element more precisely.

3.7 IMPLICATIONS FOR DESIGN: GENERALISED ADAPTIVE GAMIFICATION

According to our findings, we recommend to consider two main factors when designing tailored gamification: the choice of the user typology and the implementation of the motivational strategies. In this section we discuss both factors, considering also the influence of the context of the gamified system.

3.7.1 *User typology recommendations*

First, we recommend using **Hexad user types** when designing tailored gamification. Our results reinforce the fact that Hexad was created especially to address gamification (compared to BrainHex which focuses on player types in games and Big Five which focuses on personality traits).

Second, our results show that considering only the dominant player type is not sufficient to discriminate users' preferences. We thus advise designers to consider users' profiles as a combination of several player types, espe-

cially the four that identify the most significant influences: **Socialiser**, **Disruptor**, **Achiever** and **Free spirit**. The **Philanthropist** type does not appear to identify motivating game elements in any of the studies in a discriminant way. The **Player** type is similar as it either shows no significant influences (in our study) or significant influences for all [141] or most game elements [120].

Finally, the comparison of our results with contextualized studies reveals that the motivational impact of game elements for the Hexad user types is more or less influenced by the context. For Socialisers, designers should preferably implement social interactions (recommendation also found in the other context-independent study [138]). For Disruptors, progress compared is recommended. The design of these game elements can be made independently from the context. Achievers and Free-spirits have contradictory preferences according to the different studies. This can be explained by the fact that these two user types are highly dependent on the activity or on the environment of the gamified system, meaning that the design of game elements should take into account the context of the gamified system for these types of users.

3.7.2 *Game element recommendations*

First, care needs to be taken when implementing a motivational strategy. As shown in Section 3.5, different implementations of a same motivational strategy have different impacts on user motivation. **Rewards** is a good illustration of this: **Badges** is the highest rated of any of the implementations, whereas **Points** is one of the lowest rated ones (the same can be said for **Timer** and **Schedule**).

Whilst we cannot precisely recommend game elements for each user profile, we can make recommendations based how user motivation should vary with a game element using Hexad types. **Badges** and **Schedules** can be used as motivating game elements for all users. These were two of the highest scoring game elements and had no negative influences from any user types in both our study and related studies. Designers can therefore feel confident that these game elements will have no adverse effects on user motivation.

Progress game elements (**Compared** and **Task**) and **External Goals** are generally considered as motivating and could be used for various user types. In particular, **Progress compared** game element is recommended for users who have a high score in the *Disruptor* type. At the contrary, we recommend to carefully use **Progress Task** for high *Socialiser* users, as a negative influence was observed and also for high *Disruptor* users since we found contradictory results with previous studies. All three of the social interaction game elements (**Trading**, **Teams**, and **Discussion**) are generally perceived as less motivating, except for the *Socialiser* type which shows positive influences in all studies. We thus recommend to attribute these game elements only to high *Socialiser* users. **Points** and **Timer** show low motivation scores and the only influences they have from the various profile types are negative ones. We can therefore

advise against using these game elements to motivate users. Finally, no influences were found for **Self goals** and **Useful items** which means that these elements are probably highly dependent from the context. They should be designed closely with the activity to be perceived as motivating game elements.

3.8 CONCLUSION

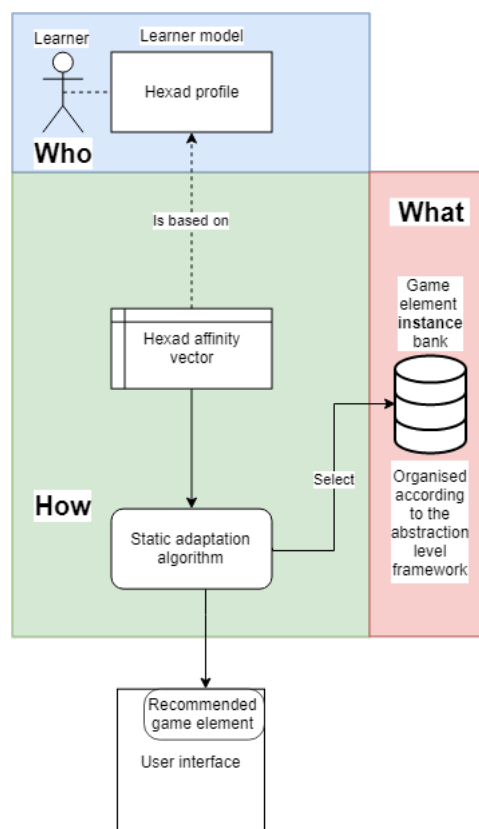


Figure 8: The first step of creating the adaptation engine. Based on the *generalised* results from this study, we create a learner profile based on a Hexad player profile, generating game element recommendations through an affinity vector, and select the most appropriate game element. From figure 4 we update the learner model, affinity vector, simple adaptation algorithm and, sorted game element instance bank. The findings from this chapter are still quite general, and do not yet take the educational context into account.

In this chapter we showed that three major factors influence how tailored gamification affects user motivation: the implementation of a given motivational strategy, the choice of the user typology, and the gamified context. In short the choice of user typology allows to highlight different preferences, and therefore propose different game elements, that implement different motivational strategies. We found valuable insights on how to tailor gamification, notably by showing that the Hexad user typology seems the most relevant to identify user preferences for game elements. However, the results found here also show that the context in which these game elements are used has an

important effect on their impact. Care should therefore be taken when designing tailored gamification in education as the findings (i.e. links between various learner profiles and game elements) found in other domains may not be directly applicable in this field. For example the appropriate game elements found by Orji et al [118, 120, 121] in a health setting were found to not be appropriate for the same profile types in this decontextualised setting, and will probably not be appropriate in an educational setting either. This is why in chapter 5 we use preliminary results from the LudiMoodle project (i.e. from a specific learning context) to establish the different adaptation rules that we implemented in the adaptation engine (which would be used in a very similar specific learning context) instead of reusing these decontextualised results. The method of obtaining the links between profile and game elements however *is* something that we can reuse. We can also conclude that seeing as the context has an importance on the effects of game elements, it would be important to ensure that the context be taken into account in the design of game elements and choice of game mechanics used. In Chapter 4 we provide a method to design game elements that takes the context and various actors into account.

Following these results, a first generalised version of the adaptation engine used the Hexad profile as a sole basis for adaptation (see figure 8). However it became rapidly apparent that some kind of domain related information was required for a better adaptation. This echoes one of the findings of the literature review presented in 2 where we showed the need for richer learner models for adaptation. Chapter 5 shows how initial motivation for the learning domain (i.e. contextualised information about the learner) can serve as a richer learner model for adaptation.

DESIGNING DOMAIN APPROPRIATE GAME ELEMENTS

From the results of the previous chapter, we can see that different implementations of game elements affect learners differently. Furthermore the context in which these game elements are deployed has an important role in motivating and engaging learners. It therefore appears important that both the context and learners are taken into account when designing game elements. For this, we it felt important to be able to unite all actors of the gamification in education process (designers, teachers, researchers, engineers, learners) during the designing of game elements. More specifically the learning actors (i.e. teachers and learners) as they should have better insights into how game elements would better fit into the learning context. However many issues arised when reuniting these multiple actors in design sessions. Notably the lack of common language and different levels of design expertise. To address this, and facilitate co-design sessions, we proposed a design space designed to foster and increase creativity in our actors. We also created a set of design cards to help explore the design space as well as a board that guided and structured the design process. During design sessions we found that both teachers and designers were able to consider multiple different implementations of common game elements, and were able to rapidly achieve a general consensus on design decisions.

The work presented in this chapter, along with the general game element abstraction level framework presented in the previous chapter, serves to fulfil the need for "better designed game elements" presented in Chapter 2.

4.1 INTRODUCTION

As shown in Chapter 2, to be effective, the motivational affordances of gamified systems (properties that allow users to satisfy their psychological needs[140]) should be designed with a deep understanding of human motivation [30, 140] and the expectations of the target audience of said gamified system. Recent studies emphasise the importance of meaningfulness in the design process [30, 100, 114]. Section 2.2.3 explains how and why game elements should make sense to users, and how poorly designed, non-meaningful game elements can have adverse effects on learners.

In practice, even if gameful design methods have emerged recently [30, 140], affording engaging experiences in non-game interactive systems remains challenging. During design sessions designers, developers and other stake-

holders, who may not have the same level of expertise regarding gamification, have to select relevant game elements and decide how to implement them for a concrete situation. They lack guidance on choosing among a huge number of elements considering their impact on motivational affordances. As a result, they are often confined to use only a subset of predefined well-known elements. Various lists of game mechanics are proposed mainly by professional game designers^{1 2} [98, 133] and more recently in academic research works such as [138], but the high number of elements in these lists make their usage difficult, which, as pointed out by Tondello et al. [138] can reduce creativity in the design process. Furthermore it can be ill advised to use game elements not specifically designed for the learning context. As shown in the previous chapter, the context has an important impact on how game elements affect learners. It is therefore important to somewhat adapt game elements to the different context.

Finally, different learners have different preferences for game elements (as shown in the previous chapter), and that these preferences can be linked to their profiles. Guiding designers to consider a wider variety of game elements could help them to take into account a wider variety of profiles and preferences.

Different approaches have emerged from practitioners and researchers, either from HCI or gamification, to support and structure the gamification design process. Many state-of-the-art papers present existing gamification design processes [30, 109, 140]. Global design processes generally offer high-level guidelines to consider the context and suggest the following steps: define the main objective, understand the user motivation, identify the game mechanics and analyse the effect of gamification [85, 148]. However, lower-level design decisions (i.e. interface design and visual aspects) are poorly supported although they can also play an important role in improving user experience [100]. Deterding introduced more operational aspects with the concept of design lenses and skill atoms [30]. However, these approaches offer poor guidance regarding customisation and implementation of elements for a given context.

To guide design sessions, Marache-Francisco and Brangier [100] provide designers with a toolbox for gamification that support two design steps: the context analysis and the iterative conception of the gamification experience. Designers can rely on a conception grid and decision-trees consisting of questions which guide element selection. Other works provide design cards, traditionally used in design practice to foster creativity insuring a common vocabulary and shared understanding among participants [97]. These cards often correspond to design steps (such as [42]) or at fairly high abstract level.

In all, lower-level design decisions (i.e. interface design and visual aspects) are poorly supported although they also play an important role in improving

1 Manrique (2013): <http://www.epicwinblog.net/2013/10/the-35-gamification-mechanics-toolkit.html>

2 Schonfeld (2010): <https://techcrunch.com/2010/08/25/scvngr-game-mechanics/>

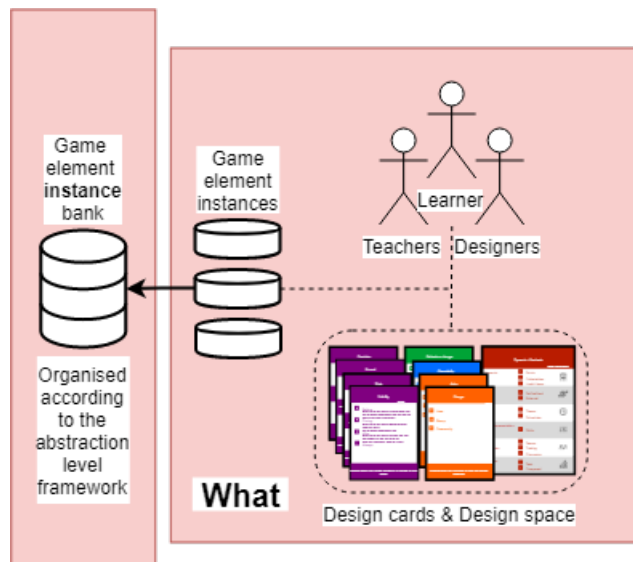


Figure 9: Designing appropriate game element instances for adaptive gamification of learning. On the left the current state of the adaptation engine. On the right the design process that involves all the actors of the gamification process. The designed game element instances are then organised following the abstraction framework and injected into the adaptation engine.

user experience. Marache-Francisco and Brangier [100] showed the importance of visual aspects in the perception of gamification.

This chapter presents work that aims to overcome these limitations by providing a design space that can be used to guide stakeholders during collaborative design sessions. We propose to extend the emerging concept of meaningful gamification to operational and visual aspects, bringing together HCI practices and gamification. This design space, along with a set of design cards used to explore it, were used in the Ludimoodle project with teachers, designers, pedagogical engineers, and to a certain extent students in order to design the game elements used in the final experiment, thus creating the "game element bank" present in our adaptation engine architecture (see figure 9). The game elements in this bank are organised following the framework presented in Chapter 2 section 3.3. The tools presented here serve to create the actual game element **instances** that will be stored and recommended to learners.

4.2 DESIGN SPACE FOR MEANINGFUL GAME ELEMENTS

Design spaces are traditionally used in HCI for identifying alternatives and structuring decisions in the design phase [135]. We present a design space that encapsulates nine dimensions to consider regarding operational and visual aspects of elements for meaningful structural gamification (see table 14 for a summary). This design space is centred around 4 questions that designers have to consider [114]

- **Why:** Why should the game element be used?

- **What:** What part of the learning activity should this game element gamify?
- **How:** How should this game element work? *and* How should this game element look?
- **Who:** Who should use this game element? *and* Who should be able to see this game element?

Table 14: Overview of the game element design space

Question	Dimension	Possible values
Why	Behaviour Change	Autonomy, Behaviour Encouragement / Discouragement, Performance
What	Granularity	Activity, Action, Operation
How (Content)	Strategy & Element	Rewards, Goals, Time, Self Representation, Social Interaction, Progress
Who	Actor	User, Group, Community
	Range	User, Group, Community
How (Presentation)	Visibility	Before, During, After, Always
	Style	Literal, Related
	Format	Relative, Absolute
	Precision	Precise, Fuzzy

4.2.1 Behaviour change (*Why should this game element be used?*)

Gamified systems aim to engage users in changing their behaviour or achieving their goals. This dimension helps designers reflect upon the **design rationale** behind the game element. We identified from the related works four commonly cited behaviour changes according to designers' goal: Autonomy [5], Behaviour Encouragement, Behaviour Discouragement [91], and Performance [148]. By directly mentioning the **design rationale** of the game element, it serves as a reminder for analysing the effect it had on learners, allowing us to understand why this game element was created in this way. For example Kickmeier-Rust et al. [79] implemented a gamified feedback system that had the goal of helping learner performance by providing feedback

on the errors made. They showed that with this feedback learners could avoid these errors in future. We can also consider the streak mechanic from the commercially available gamified language learning app: Duolingo³. This game element shows learners how many consecutive days they have completed a lesson on the platform, with the counter resetting to zero as soon they skip a day. In this example the game element is designed to encourage a repetitive behaviour in learners (i.e. behaviour encouragement).

4.2.2 *Granularity (What part of the learning activity should this game element gamify?)*

According to the Activity Theory [93], an activity is performed by a subject in response to a specific need or motive in order to achieve an objective. By inciting designers to reflect on the granularity level, we lead them to question if the game element should address the main motive of the users (linked to the activity; i.e. running), their sub-goals (linked to actions; i.e. a 5km run) or conditions to realise the actions (linked to operations; i.e. stretching before running or breathing exercises). When using this design space with teachers for example, it is important to first identify in a general sense what each of the granularity levels correspond to in the given context.

4.2.3 *Strategy & Element (How should this game element work?)*

Here designers have to make a choice of which motivational strategy the game element should implement, in order to decide which kind of gamified experience they wish to provide. This design dimension makes use of the Abstraction framework proposed in Chapter 2, section 3.3. Each of these levels provide some kind of idea as to how the final game element instance should function. For example, choosing to implement a badges reward system indicates that designers should think about what kind of actions should be rewarded with badges, what those badges would look like. An external goals system requires to decide what kind of goals, when they are given to the learner.

4.2.4 *Actor and Range (Who should use, and who should be able to see this game element?)*

These two dimensions refer to the actor who uses the element (*actor*) and who can see the game element (*range*): an individual user, a group of users, or a community. These design choices are crucial as they impact the type of regulation intended [54]. Individual users can self-regulate their activity individually (range as individual), or by comparison with others (range as group or community) to achieve personal goals. [151]. Game elements shared by a group of users can help them co-regulate their own activities according to

³ <https://www.duolingo.com>

their own personal goals but also support shared regulation [145]. In such regulation, individuals can take turns assisting with separate actions, but the overall goal is for each member of the group to self-regulate their own activity. Socially shared game elements can also support shared regulation that requires interdependency and the complete cooperation of participants toward a common goal. [54]. Furthermore, a group of users who can see socially shared game elements can compare their progress or performances with all users (the community). This can provide users with a sense of relatedness, as described by self determination theory [129].

4.2.5 *How should this game element look?*

This question provides four separate design dimensions, *Visibility*, *Style*, *Format*, and *Precision*.

4.2.5.1 *Visibility*

Schön [132] assumed that reflection can occur both during the activity being performed (reflection-in-action) and after the activity, e.g. when mentally re-considering it (reflection-on-action). The timing in which the game element is shown to the user can have an impact on the reflection process. We add a third value "before" since we can also incite users to establish goals and plan strategies. For example a goal feature that is visible to the actor before the activity would have a different impact if it were shown during or after the activity. According to the SRL model of Zimmerman [151], if shown before, the element could be used to help the actor analyse, establish goals and plan strategies (forethought phase of SRL). If shown during the activity (performance phase), it could help them monitor and control their activity. If shown after, it could help the actor reflect on the outcome of the activity and try to explain successes or failures.

4.2.5.2 *Style*

Visual aspects of the gamified system play an important role in the perception of gamification affording an appealing and immersive experience [99]. The Style dimension helps designers decide whether the game element should have a simple literal form (e.g. a basic progress bar) or one more related to the domain (e.g. a heart that fills up when you go to the gym to promote healthy living). Using domain-dependant metaphors can favour explicit connections with the given activity as recommended by Nicholson [114]. However, the choice depends on users' intrinsic motivation for the domain and an independent style can reduce the risk of user' amotivation. Studies have shown that more playful designs could be detrimental for users' who have high intrinsic motivation for the domain [62, 89]. However these findings are highly dependant on the individual users. Generally it can be beneficial to ask the target learners for their input on the idea.



(a) The set of cards used to explore, and present the different dimensions of the design space. Some suggestions of values are given for each dimension.



(b) The design board used to structure the design process. The high-level decisions about users and context are presented here.

Figure 10: The tools used to explore the design space. These are the original versions that were used with the teachers and therefore some of the terminology does not reflect the final version presented in this Chapter.

4.2.5.3 *Format*

Barata et al. pointed out [6] that having a clear end state (i.e. a "win point") can increase performance, as it allows to set goals, and better understand general progress. However, for some users "learning stops when goals are achieved" [5], as once the goal is achieved, some users perceive little interest in continuing. Therefore we suggest to consider presenting the game element in a relative (e.g. a score that shows four points out of a possible ten) or absolute format (e.g. a score that only shows four points) depending on the motivational context (users' profile or type of activity).

4.2.5.4 *Precision*

Designers have also to consider the precision of information presented in the game element. For some users, giving precise feedback on the activity performance can be motivating [4]. However for less competitive users, showing exact information can be demotivating [119, 138] (say for example a leaderboard situation where the actor is dead last).

Thus we suggest to consider two possible values: precise (e.g. a leaderboard where the actor is shown to be 6th out of 14 users) and fuzzy (e.g. a leaderboard where actor is shown as in the "Top Half" of users). We recommend that precise presentations should be used when there is no risk of demotivating the user, for example when used for a group of particularly competitive users.

For example in the Ludimoodle context, in France teachers are advised to not provide precise rankings of learners at the secondary school level, as they do not wish to demotivate learners who are "the last in class". Therefore when designing a ranking game element, the participating teachers were somewhat opposed to the idea. However when presented with the precision dimension, they realised that they could simply present the game element with a fuzzy representation, only showing a general idea of where the learner is with regards to the class.

4.3 TOOLS TO EXPLORE THE DESIGN SPACE

The design space presented allows for a systematic consideration of possible choices when designing game element instances. This task may remain complex, especially if the different stakeholders involved in collaborative design sessions do not have the same expertise in gamification. To support the design process and to guide designers in the design space exploration, we created a set of design cards.

Each card represents a particular dimension and contains the possible values, examples, or explanations of the choices and possible impacts on users' motivation (see figure 10a for the full set of design cards).

The cards are designed to be used with a board structuring the different steps to perform during the definition of a game element (see figure 10b). In addition to the properties defined by the design space, the board supports high-

level decisions such as users and context considerations of the given activity (also identified in [42, 100]), and lower-level specifications such as visualisation (final design mock-ups) and operational rules. We decided to integrate these aspects only on the board since they are closely linked to the domain to gamify and would have too many forms or values to be represented by specific cards. These domain-dependant elements are thus instantiated during design sessions for each context and game element.

4.4 TESTING THE DESIGN TOOLS

To test the design space and its exploration with cards and board, we conducted a design session with the various actors of the Ludimoodle project. This workshop took place with four secondary school teachers, two teaching engineers, and a game design expert working on the various game elements that would then be implemented in the final Ludimoodle project (see figure 11). The teachers knew each other and had previously worked together to create maths exercises, but not game elements directly. The workshop lasted four hours. After a quick introduction of the materials, roughly 50 minutes were dedicated to context specification: determining the users' profiles and reviewing the exercises previously created to define actions and operations within the activity. The rest of the session was dedicated to defining game elements to be used. Participants discussed and agreed on game elements using the cards and following the steps on the board. For each game element, participants used a different board and set of cards. In total seven game elements were designed.

We observed that participants rapidly took ownership of the design materials, sharing common ground on the gamification process and favouring communication. As the workshop progressed, participants were able to converge on design agreements faster. Discussions turned towards both at considering the impacts on students' motivation and fulfilling the different stakeholders' interests. The teachers and game designers succeeded in making decisions regarding operational and visual aspects of each game element, so that all of the information required to start the elements' development was provided. Regarding creativity, we observed that participants were able to reuse well-known game element tropes such as points or badges, but also to design unique game elements. In this usage example we chose to identify an activity as a complete learning session on the tablet, an action as the completion of a quiz on the Moodle platform, and an operation as the completion of a question.

For example one of the game elements designed to encourage learners' perseverance implemented the task progression game element. However instead of using a simple progress bar, the participants decided to opt for a more "metaphorical" design. They decided on a tree that grows with each question answered, with a different branch for each exercise. Teachers stated that visuals such as progress bars are generally common in their teaching experience and they wanted to avoid this, and aim for a more playful design,



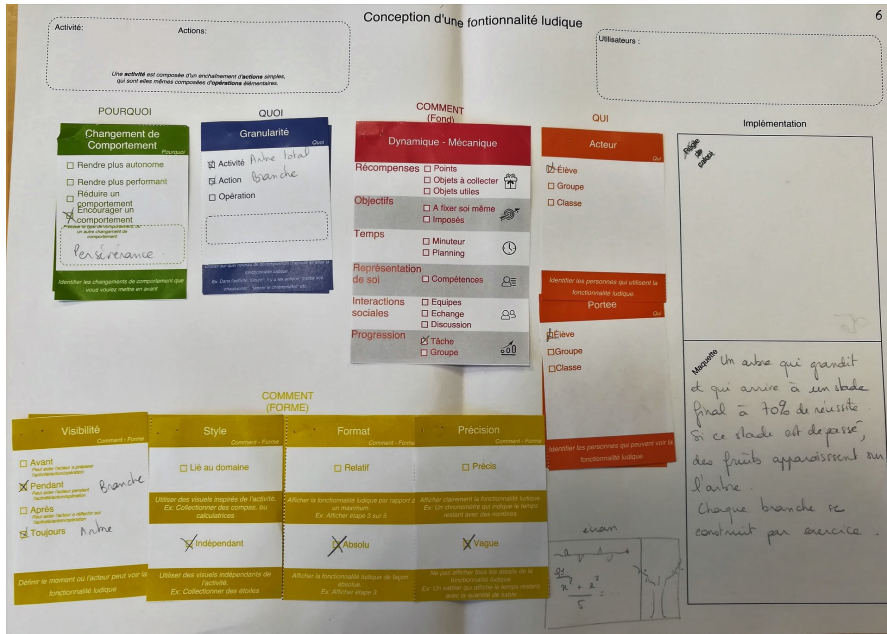
Figure 11: Photo of the co design session held with the various actors of the Ludimoodle project.

which they thought would better engage their learners. Furthermore, as the platform presented multiple quizzes for each maths subject, that were not specifically linked, they felt that the metaphor of the branching tree would resonate well with the learners (this was a way to include the context in the game element design). Figure 12a shows the design tools used, and table 15 shows the full description of the game element designed through the lens of the design space.

Generally participants manipulated the cards with ease, however we observed that the participants had difficulties using the "Behaviour Change" dimension as they always selected the same behaviour. A further iteration of these cards could provide examples of the different behaviour changes possible. We initially did not want to include too many examples of implementations, as we were worried about the participants copying pre-existing designs, and not thinking about how they can articulate with the context. Further workshops should certainly be held in order to improve the material, and to think upon the integration within a larger gamification process. For example incorporating questions from Deterding's design lenses [30] or decision trees from [100].

4.5 CONCLUSION

In this chapter I presented a design space to enable co-design sessions for the creation of meaningful game elements. By implicating the various actors of the gamification process we could achieve the creation of game elements that are better suited to the specific context in which they are deployed, and



(a) An example of one of the boards produced during the workshop. This photo displays a previous version of the design cards, therefore the design is slightly different to the final one presented in this Chapter. The design space description is given in table 15



(b) The final design of the progress game element designed.

Figure 12: An example of one of the game elements designed. Both the original design board created during the co-design sessions, and the final implementation are presented.

Table 15: The values chosen by the workshop participants for each design dimension

Behaviour Change	Encourage a behaviour
Granularity	Activity (Tree) Action (Branch)
Strategy - Element	Task - Progression
Actor	User
Range	User
Visibility	During (Branch) Always (Tree)
Style	Literal form
Format	Absolute
Precision	Fuzzy

that make *meaningful* links to learner needs and profiles. This design method makes use of the abstraction levels framework, and fulfils the "*need for better designed game elements*" presented in Chapter 2.

To better explore this framework and promote creativeness in the design sessions, I proposed a set of design cards and board that exhibit this design space. This set of simple tools can facilitate the design task for non expert designers, and provide a common language for the different actors. When tested, we found that both the design space and tools provided useful guidance in creating unique and interesting game elements, and allowed all participants to reflect on the context and individual learners that would in the future use these game elements. The designs showed a large level of re contextualisation rather than simply rehashing old designs.

APPROPRIATE GAME ELEMENT RECOMMENDATIONS FOR EDUCATION

*How can we generate appropriate adaptation rules? As shown in a previous chapter (chapter 3), the preferences linked to the different player types offer a certain idea as to what game elements can be appropriate for particular learners. From these preferences we could establish a rudimentary set of adaptation rules. However as shown in the same chapter, these preferences (and therefore rules) vary greatly depending on the context. Therefore, it is necessary to look at the specifics brought by the current education domain (i.e. secondary school mathematics) to identify relevant adaptation rules. Furthermore, we also require an effective way to evaluate the recommendations for appropriate game elements we found in the context of the LudiMoodle project. In this chapter, we propose a first set of adaptation rules based on the results from a real world study with secondary school learners (as a part of the LudiMoodle project). These results confirmed our findings from the related work that an untailed gamification approach **generally** demotivates learners. A more thorough analysis revealed that the impact of game elements on learners' motivation varies greatly depending on their initial motivation for mathematics and their Hexad player profile. This highlights the necessity to adapt our gamification approach based on **both** learner player profile and initial motivation.*

From these results we simulate different adaptation rules based on three different learner models (initial motivation, player profile, and dual profile) and analyse the impact of these different adaptations on engagement, motivation and performance. All tests and simulations were made using the data from the LudiMoodle experiment that was carried out in spring 2019. The results of these analyses and simulations could then later serve as a basis for the adaptation rules deployed in the prototype of LudiMoodle static adaptation engine presented at the end of this chapter.

5.1 INTRODUCTION

In education, Kapp [73, 74] argues that gamification serves several purposes such as making learning easier from a cognitive and emotional point of view, enabling automatic feedback, personalising and individualising learning, and changing behaviours, but above all, encouraging learner's engagement in the task, thus making them more active in their learning.

According to Nacke and Deterding [112], the first studies in gamified education were essentially focused on the effect of a set of game elements on users, which did not enable identification of the impact of each game element taken separately. Furthermore, these studies did not take into account the individual characteristics of learners, which can explain the different and sometimes contradictory impacts of gamification observed on learner motivation and engagement (see chapter 2, section 2.1).

Several studies focus on the relationships between user player type and game elements or game mechanics [8, 101, 111, 119]. Some studies also consider that motivation can greatly affect the effects of gamification [89]. However, no study has yet considered a combination of these two aspects when evaluating the impact of different game elements on learner motivation. In this chapter, we propose to study the impact of gamification according both to learners' initial motivation and player profile. For this, we ran a large scale field study in 4 secondary schools in France. 258 learners used a gamified mathematics learning environment in their habitual classroom activities, representing 10 lessons and 45 exercises in literal calculation. We integrated six game elements (points, badges, ranking, timer, progress, and avatar) in the learning environment, that were designed using the method and design tools presented in Chapter 4. We analysed the usage data, as well as learners' responses to the AMS (academic motivation scale [143]) in order to determine the impact of the six game elements used. As each learner was randomly assigned one of these game elements, we could study the impact of each game element according to learners' initial motivation and player profile.

Using these results, we created different adaptation rules based on either a learners' Hexad player type, initial motivation, or a combination of both. We then used these rules to create three different adaptation simulations. By studying different subsets of learners that used an adapted game element based on one of these simulations we were able to compare the three adaptation techniques.

The goal of this chapter is to expand on the previously established adaptation engine (see figure 13). From the results of these two analyses we can enrich the learner model and adaptation rules presented in Chapter 3 (changing our answers to the "**Who**" and "**How**" questions), by providing context relevant information about the learner, as well as context relevant adaptation rules created using the LudiMoodle data.

The studies and analyses presented in this chapter are adapted from two papers, one submitted to the journal *Computers in Human Behavior* that was written in collaboration with the PhD student Stéphanie Reyssier, and the Pr. Stéphane Simonian from the ECP research lab (partners of the Ludimoodle project), and another one published as a long paper at the International Conference on Artificial Intelligence in Education 2020 (AIED) [57].

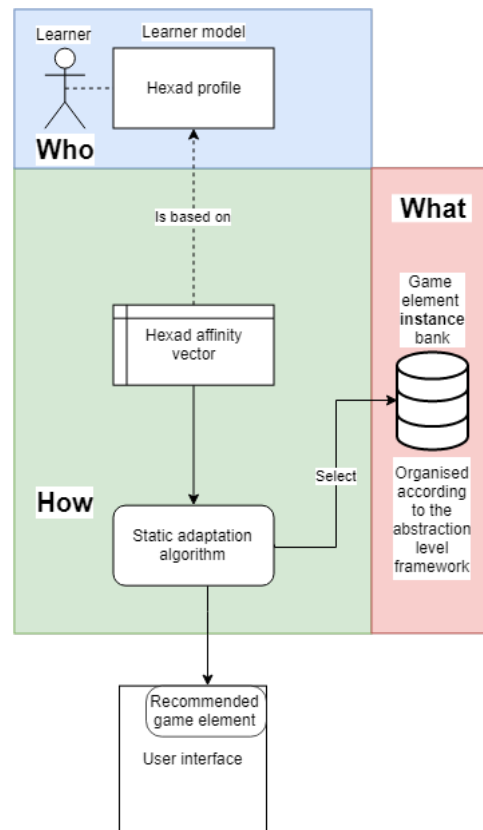


Figure 13: The current state of the new Ludimoodle adaptation engine prototype architecture. In this chapter I update the learner model and the adaptation algorithm (the "**Who**" and "**How**" questions) based on the results of the two studies presented.

5.2 RESEARCH QUESTIONS

In this study, we proposed to answer the following three research questions. The first two by observing and analysing the effects of randomly assigned game elements, and the final one by simulating different adaptations based on the results obtained from the first two analyses:

- RQ1:** How does gamification affect learner motivation? We studied the variation of learner motivation from the beginning to the end of the course. We split learners into subgroups based on which game element they used in order to evaluate how each game element affected their motivation, as well as the motivated behaviours generated.
- RQ2:** How do individual learner characteristics influence the impact of each game element on their motivation? We more particularly studied the influence of the player profile dimensions and the initial level of motivation scores on the variation of motivation, as well as the motivated behaviours they generated.
- RQ3:** Are the effects of tailored gamification dependent on the user model chosen for tailoring game elements? Especially when considering motivation and player types?



Figure 14: The LudiMoodle platform: example of a gamified quiz. The upper half shows the learners game element (here timer), while the lower half shows the the quiz questions. In the title bar, the learner has a set of buttons that they can use to navigate through the learning content and select a different quiz.

We will first answer and discuss RQ1 and RQ2 as the results these two questions are tightly linked. Furthermore the results they provide offer context and justification for RQ3.

5.3 LUDIMOODLE LEARNING ENVIRONMENT

The experiment within the Ludimoodle project ran from March to April 2019. The goal was to observe and evaluate the effects of a gamified mathematics learning environment on the motivation and engagement of secondary school learners in a real world setting. The participants used a gamified version of the Moodle [107] Learning Management System called "LudiMoodle" (see Fig. 14), that was developed specifically for the project. In total, it proposed six different game elements that were designed in collaboration with the teachers involved in the project and that were improved thanks to learners' feedback, following the methods described in Chapter 4. The six game elements are described in section 5.3.2: *Avatar, Badges, Progress, Ranking, Score, Timer*.

5.3.1 Learning content

We built the learning content using the co-design method presented in Chapter 4 in order to keep as close as possible to teachers' usual teaching practices. In total, ten lessons were designed to cover the topic of basic algebra (*calcul littéral* in French). Each lesson covered a different concept in this topic, such

as variables, equation simplification, distributively, or simple demonstrations. Each lesson was composed of 4 to 10 quizzes. The content proposed in the LudiMoodle system was not the entirety of the lesson plan as it was only used for reinforcement exercises (as designed by the teachers during the early conception phases). Teachers had observed that generally these reinforcement exercises were not well appreciated by learners, as they found them to be boring, or too repetitive. Teachers therefore wanted to use this experiment to try and make these types of exercises more fun by introducing something new.

Each of the lessons was conducted in the same way: 10-15 minutes of written notes (handed out by the teachers to ensure that learners had access to the same learning content), followed by 25-30 minutes for answering quizzes related to the lesson topic, using the LudiMoodle tool. To successfully complete a quiz and progress to the next one, learners had to answer at least 70% of all questions correctly. The learners used an individual tablet to access the quizzes. During this time teachers answered questions asked by learners individually. Half way through the experiment (during the fifth lesson), learners had a short exam to evaluate their understanding of the topics covered during this first half. This lesson did not involve the LudiMoodle platform at all, and learners were not told their grade until the end of the experiment to avoid altering their motivation based on their grade. In the second half of the lessons, learners had another lesson without the LudiMoodle platform (lesson 7) where teachers presented some of the more complex concepts that the final lessons would cover (factorisation and double distribution). In total learners therefore used the LudiMoodle platform during eight mathematics lessons.

Learners answered both the AMS and Hexad questionnaires at the beginning of the experiment during an introductory session where teachers presented the platform, and showed learners how to login. At the end of the experiment (post-test), they answered the AMS questionnaire a second time to measure the variation of motivation in an in class session.

5.3.2 *Game elements*

All of the game elements that were deployed as a part of the LudiMoodle system were co-designed with the participating teachers using the methods described in Chapter 4.

5.3.2.1 *Avatar*

The avatar game element showed a goblin-like character that explored different universes (a different universe for each lesson, see figure 15). As the learner progressed in a lesson they would unlock a different piece of clothing, or item that the character was holding. There was one object to unlock per quiz (that was unlocked after the learner correctly answered at least 70% of the questions in the quiz).



Figure 15: The avatar game element in the LudiMoodle system. Each of the different lesson categories has a different universe.

5.3.2.2 Badges

The badges game element proposed three levels of badges per quiz (see figure 16). When the learners correctly resolved three different levels of questions in the quiz (generally 70-85-100 % of each quiz), they would unlock a new level of badge (bronze-silver-gold). An icon on the left-hand side showed how many badges the student unlocked for the current lesson.

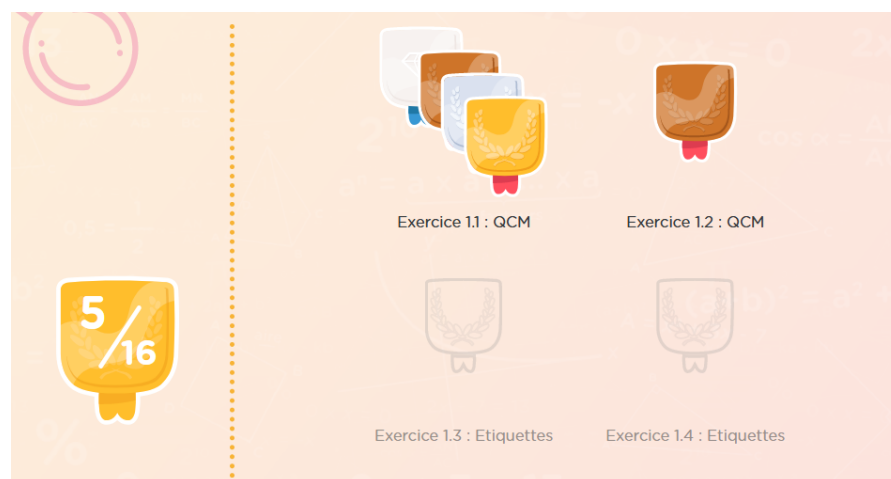


Figure 16: The badges game element. In this situation, the learner has acquired all badges for the first quiz, and only the bronze badge for the second quiz. The icon on the left shows that they have unlocked 5 of the 16 possible badges for this lesson (there is a 5th quiz not shown here).

5.3.2.3 Progress

This game element showed different coloured spaceships that travelled from the earth to the moon (see figure 17). Each lesson launched a new spaceship, and if the learner could complete at least 70% of the lesson, the spaceship would land on the moon.



Figure 17: The progress game element. In this example, the learner has fully completed lesson 3 (the green rocket), and has only partially completed lessons 1 and 2 (orange and yellow rockets).

5.3.2.4 Ranking

The learners who were assigned to this game element could compare themselves to a fictional class of learners. The ranking game element showed a "race" where, as the learners answered questions correctly, they would progress in the race at the same pace as the other fictional learners (see figure 18). If they failed to answer a question correctly they would fall back in the ranking. We calibrated the ranking system to ensure that a learner who completed at least 70% of a lesson would finish in the top 50% of the ranking to ensure they were not demotivated.

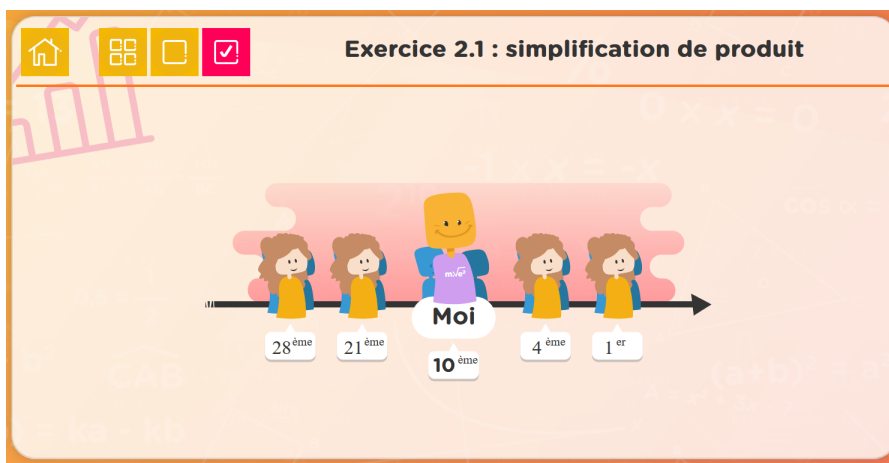


Figure 18: The ranking game element. In this example the learner is part way through the first quiz of the second lesson. They are currently ranked 10th.

5.3.2.5 Score

Each correct answer given by the learners awarding them 1000 points. Each lesson had its own score counter, with a detailed view that showed how many points they had scored for each quiz, so that the learners could pinpoint where they were missing points (see figure 19).

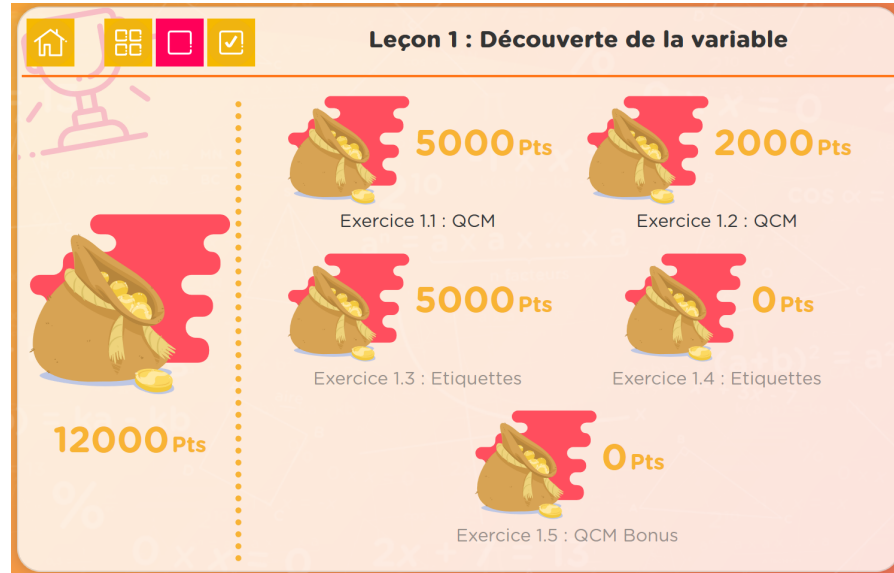


Figure 19: The score game element. In this example the learner has completed quizzes 1, 2 and 3 from the first lesson, earning them a total of 12,000 points.

5.3.2.6 Timer

This game element showed a timer for each quiz (see figure 20). Learners were asked to try and beat a "reference time" for each question. The reference times were calculated based on the times for their previous questions in the same quiz. Each time a learner beat their reference time, an animation changed, with a character that would run faster and faster.

5.4 STUDY DESIGN

5.4.1 Participants

A total of 5 teachers and 258 students (13-14 years old) in twelve classes (an average of 25 students per class), from 4 different secondary schools, participated in the study (for a total duration of 6 weeks). Teachers were involved in the co-design of the game elements and in the construction of the course content.



Figure 20: The timer game element. In this example the learner has completed at least one question correctly, and has a reference time of 14 seconds that they must beat in following questions to make their character run faster.

5.4.2 Profile questionnaires

We used the motivation scale proposed by Vallerand et al. [143] (inspired by SDT [24]). This scale, called the Academic Motivation Scale ("AMS"), evaluates seven dimensions of motivation (three for intrinsic motivation (IM), three for extrinsic motivation (EM) and one for amotivation). Each of these dimensions identifies the reasons why someone would perform an activity (we provide an example of one of the questions asked for each dimension):

- **Intrinsic Motivation for Knowledge** (IM Know.), i.e. performing an activity for the pleasure and satisfaction of doing something new: *"I like learning new things"*
- **Intrinsic Motivation for Accomplishment** (IM Acco.), i.e. performing an activity for the pleasure of overcoming a challenge: *"I like to see that I am able to solve problems"*
- **Intrinsic Motivation for Stimulation** (IM Stim.), i.e. performing an activity for fun or excitement: *"I really like maths"*
- **External Regulation** (EM Ext. Reg.), i.e. performing an activity to gain some kind of external rewards: *"I want to get a good grade"*
- **Introjected Regulation** (EM Intro. Reg.), i.e. performing an activity to avoid shame or increase self-esteem: *"I want to prove that I can do well in maths"*
- **Identified Regulation** (EM Id. Reg.) i.e. performing an activity in order to achieve precise objectives: *"I will be able to choose my future studies thanks to maths"*
- **Amotivation** (Amot.), i.e. the absence of intention to perform an activity: *"I don't know why I go to maths class, I feel like I'm wasting my time"*

We identified the learner player profile using the original Hexad questionnaire [141] that we translated into french. As a reminder the six player types are defined in the player types Hexad [101]:

- **Socialiser**, motivated by social contact: *"Interacting with others is important to me"*
- **Free Spirit**, motivated by creation and exploration: *"It is important to me to follow my own path"*
- **Achiever**, motivated by challenges: *"I like overcoming obstacles"*
- **Philanthropist**, whose goal is to help others: *"It makes me happy if I am able to help others"*
- **Disruptor**, motivated by change: *"I like to provoke"*
- **Player**, motivated by his/her personal success: *"I like competitions where a prize can be won"*

5.5 HOW GAMIFICATION AFFECTS LEARNER MOTIVATION

5.5.1 Analyses

To answer our first research question (RQ1), we compared the score of each motivation subscale (see section 5.4.2) between the pre-test and the post-test, using a non-parametric Wilcoxon Signed-Rank Test.

5.5.2 Results

Our first analysis shows a significant decrease in intrinsic motivation to knowledge (IM Know.), in external regulation (EM External) and a significant increase in amotivation (Amot.), at the end of the experimentation (see Table 16).

We then investigated the variations of motivation splitting learners into groups based on the game element they used, using a non parametric Wilcoxon test. All of the game element presented the same losses of motivation as the general results, except for the ranking and score game elements. For those elements, we do not notice a significant decrease in external regulation. Finally, we observed a decrease in intrinsic motivation for accomplishment and identified regulation with the badges game element (see Table 16).

We also noted significant differences in motivated behaviours, depending on the game elements used. Regarding the *question ratio*, results highlight a significant difference ($p=0.04<.05$) between learners who used a Timer and those who used Badges, with a higher ratio of correct answers with Badges (see Figure 21a). Concerning the *restarted quiz count*, we noted that learners who used a Timer restarted significantly less often than learners who used the Progress, Ranking, or Score game elements (see Figure 21b).

Table 16: Motivational variations in total and per game element. Values in grey are not significant ($p > .05$), values highlighted in light grey are significant ($p < .05$), and values highlighted in dark grey are highly significant ($p < .01$), and highlighted in black are very significant ($p < .001$).

		Game Element						
		All	Avatar	Badges	Progress	Ranking	Score	Timer
Intrinsic motivations	Know.	-9.769	-4.627	-4.22	-3.747	-4.629	-3.829	-2.969
	Acco.	-1.235	-0.121	-2.217	-0.415	-0.703	-0.621	-0.197
	Stim.	-1.261	-0.414	-1.278	-0.019	-1.882	-0.763	-0.33
Extrinsic motivations	Id. Reg.	-0.128	-0.082	-2.259	-0.197	-0.685	-1.211	-1.322
	Intro. Reg.	-0.659	-0.54	-1.917	-0.534	-0.354	-0.209	-0.809
	Ext. Reg.	-6.209	-2.976	-3.363	-4.007	-1.448	-0.83	-2.536
Amotivation	Amot.	10.78	4.125	5.225	3.683	5.397	4.523	3.561

Table 17: R squared values for each of the motivational variations, and the motivated behaviours

	R ²
IM Var	0.343
EM Var	0.120
AMOT Var	0.451
Motivated behaviours	0.026

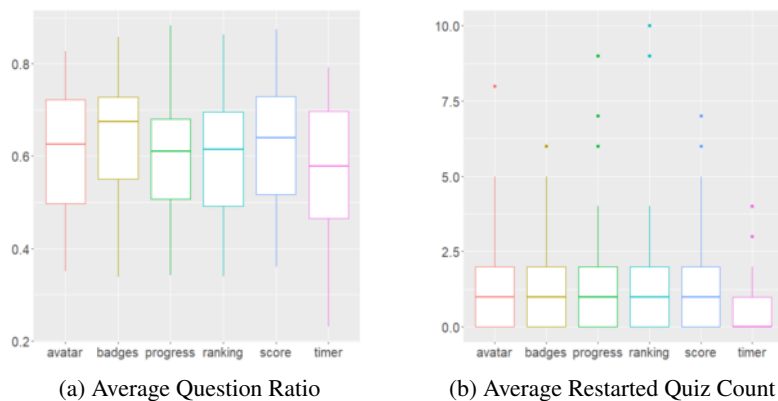


Figure 21: Distributions for the motivated behaviours metrics per Game Element

5.5.3 Discussion - a randomised gamification approach that generally demotivates

These results allow us to draw meaningful conclusions regarding the impact of gamification on learner motivation. Notably randomly assigned game elements generally result in a decrease in motivation. We found that the *external regulation* of learners was lower after the experiment. One possible explanation is that learners motivated by their mathematics grades were frustrated that they did not receive any grades for the quizzes completed during the experiment (a choice made by the teachers for the experiment).

We also noticed a general decrease in *intrinsic motivation for knowledge*, which raises questions about the perceived value of the learning activity. It seems that learners perceived the exercises more as a game than as a serious learning activity, which echoes the findings by Barata et al. [8]. This may also be due to the duration of the study, as teachers testified that some learners were a little bored after ten quiz sessions.

We then showed that learner *amotivation* generally increased for all learners regardless of the game element they used, meaning that they found less reasons to do mathematics with the gamified learning environment. This is a similar result to that found in a previous study conducted with a gamified learning environment dedicated to learning French grammar [89]. Learners provided with game elements that were not adapted to their player profile showed a higher level of *amotivation*.

Regardless of the game element used, we noticed a decrease in *intrinsic motivation for knowledge* and *external regulation*, except for learners who used the **ranking** and the **score** game elements. This may be due to the fact that these game elements closely emulated the feeling of receiving a grade for their work (i.e. the **score** gave a numerical rating of their performance, and the **ranking** showed them if they were performing better than others). With **badges**, we observed that more types of motivation were negatively impacted compared to other game elements (*intrinsic motivation for accomplishment* and *identified regulation*). This corroborates the results presented by Hanus et al. [62] which suggest that **badges** and other rewards are considered as controlling rewards, since they encourage action but constrain it to the objectives proposed by the badges. This perception could degrade learner *intrinsic motivation*.

5.6 HOW INDIVIDUAL CHARACTERISTICS INFLUENCE THE IMPACT OF EACH GAME ELEMENT ON LEARNER MOTIVATION

5.6.1 Analyses

To answer our second research question (RQ2), we used the *Partial Least Squares Path Modelling (PLS PM)* method [55] to calculate the influence between the learner profile scores and both the variations of motivations and number of motivated behaviours. As a reminder this is also the method used

in Chapter 3 to establish links between the various user profile dimensions tested and the game element ratings.

Learners' interactions with the learning environment were tracked using the Moodle data logging system. From these interactions we distinguished two metrics that were used for answering (RQ2) (these metrics were calculated for the entire experiment duration):

- **Restarted Quiz Count:** we identified the number of quizzes they re-tried *after* having completed them. Learners were required to correctly answer at least 70% of each quiz to access the next one. If a learner successfully completed a quiz, and then re-tried to achieve more than 70%, it showed that they were particularly motivated to achieve more.
- **Question Ratio:** we looked at the question ratio of correct and incorrect answers given by the learners as a measure of how well they performed during the task.

Our model is illustrated in Figure 22. The intrinsic and extrinsic motivation subcategories are grouped together in the overarching motivational categories. For example, the three intrinsic motivation scores : Knowledge (Know.), Accomplishment (Acc.) and Stimulation (Stim.) were linked to create a general Intrinsic Motivation construct. We verified that our intrinsic motivation indicators (Know.-Acc.-Stim.) and our extrinsic motivation indicators (Id.Reg.-Int.Reg.-Ext.Reg.) actually measured these constructs (indicator reliability >0.70; internal consistency reliability >0.7 or 0.6 in an exploratory research; mean >0.5).

5.6.2 Results

5.6.2.1 PLS Model

We performed a PLS Path modelling in order to look at the influence of the "initial motivation" and "Player profile" factors on the motivational variations and motivated behaviours during the experiment. Based on the PLS Path analysis we noted the importance to take into account the initial motivations and the learners Player profile, as 34.3% of the variation of intrinsic motivation, 12% of the variation of extrinsic motivation and 45.1% of the variation of amotivation, could be explained by the level of initial motivations and the learners Player profile (see table 17). Finally we generated T-statistics to test the significance of both the inner and the outer model (see Table 18), using a bootstrapping method [37].

5.6.2.2 Effect of initial motivation on the variation of motivation

Results (cf. Table 19a) show a negative influence of the level of amotivation on the variation of amotivation. Moreover, the initial level of amotivation has a positive influence on the variation of intrinsic motivation. These two influences mean that the more amotivated a learner is initially, the less amotivated

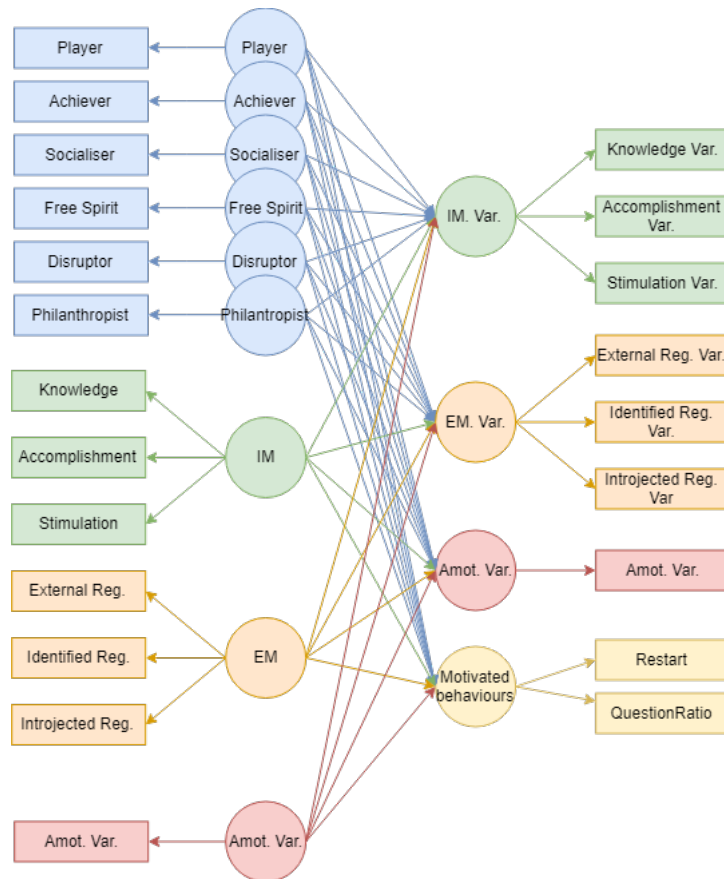


Figure 22: Partial Least Squares Path Modelling Analysis diagram. In blue the Hexad player profile, in green the intrinsic motivation, in orange the extrinsic motivation, in red the amotivation, and in yellow the motivated behaviour markers.

Table 18: Results summary for our reflexive outer models

Latent variables	Indicators	Loadings	Composite reliability	AVE	Rho A
IM	Knowledge	0.922	0.919	0.791>0.5	0.868>0.7
	Accomplishment	0.851			
	Stimulation	0.893			
IMVar	Knowledge Var	0.874	0.803	0.580>0.5	0.760>0.7
	Accomplishment Var	0.639			
	Stimulation Var	0.752			
EM	Identified Regulation	0.770	0.818	0.603>0.5	0.705>0.7
	Introjected Regulation	0.878			
	External Regulation	0.688			
EMVar	Identified Regulation Var	0.679	0.795	0.566>0.5	0.635<0.7
	Introjected Regulation Var	0.842			
	External Regulation Var	0.725			

and the more motivated intrinsically s/he is at the end. We also notice that the level of initial intrinsic motivation negatively influenced the variation of intrinsic motivation, and that the level of extrinsic motivation also influenced negatively the variation of extrinsic motivation. This means that the more a learner is intrinsically or extrinsically motivated initially, the less motivated s/he is at the end for this motivation type.

5.6.2.3 *Effect of Player profile dimensions on the variation of motivation*

Results (cf. table 19a) show contrasting effects depending on the Player profile dimension considered. We noted a significant increase in both intrinsic and extrinsic motivation for the *Achiever*, with a significant decrease in amotivation and a positive influence on motivated behaviours. The *Player* dimension seems to increase both intrinsic motivation and extrinsic motivation. The *Free Spirit* dimension also increases extrinsic motivation. Finally, the *Socialiser*, *Disruptor* and *Philanthropist* dimensions show no significant influence.

5.6.2.4 *Different effects depending on the game element*

For each game element used, we ran a PLS path modelling to identify the influence of both the initial motivation scores, and the learners' Hexad Player profile on both the variations of each motivation type and the motivated behaviour markers (see Figure 22). These models were calculated using groups of learners that had the same game element when using the learning environment. We can thus get a more precise insight on how each of these game elements impacted the variations in motivation types, and which Player profile dimensions contributed to these variations.

- **Avatar**

We found four statistically significant influences (see table 19b) for learners with the avatar game element. Learners' initial **amotivation** score influenced positively the variation of their intrinsic motivation, and negatively the variation of their amotivation. The **Player** dimension also positively influenced the variation of intrinsic motivation, while the **Socialiser** one influenced negatively this same motivation variation.

- **Badges**

We only found two statistically significant influences for learners who used badges (see Table 19c). Learners initial **intrinsic** motivation negatively influenced the motivated behaviours, whereas their **Disruptor** score positively influenced these behaviours.

- **Progress**

We observe three significant influences for learners who used the progress game element (see Table 19d). Each of the initial motivations negatively influenced the variation of the same motivation type.

Table 19: Results of the different PLS Path analysis. Each table shows the results for a different sub group of learners. Values in grey are not significant ($p > .05$), values highlighted in light grey are significant ($p < .05$), values highlighted in dark grey are highly significant ($p < .01$), and values highlighted in black are very significant ($p < .001$).

(a) Results for the entire learner base

	IM	EM	AMOT	Achiever	Player	Socialiser	Free Spirit	Disruptor	Philanthropist
IMVar	-0.698	0.098	0.156	0.247	0.193	-0.048	-0.006	-0.022	-0.064
EMVar	0.041	-0.528	0.004	0.230	0.132	-0.025	0.174	-0.119	-0.074
AMOTVar	0.113	-0.040	-0.656	-0.179	0.095	0.047	0.087	0.086	-0.042
Mot. Beha.	0.107	-0.044	-0.014	0.193	-0.015	-0.129	-0.003	0.048	0.104

(b) Results for the Avatar game element

	IM	EM	AMOT	Achiever	Player	Socialiser	Free Spirit	Disruptor	Philanthropist
IMVar	-.407	-.029	.366	.145	.478	-.372	-.049	.006	.183
EMVar	.431	-.390	.100	-.056	.296	-.363	-.018	-.028	-.091
AMOTVar	.029	.168	-.426	-.111	.064	.041	.305	-.154	-.059
Mot. Beha.	.345	.055	.179	-.041	-.186	-.089	-.008	.139	.316

(c) Results for the Badges game element

	IM	EM	AMOT	Achiever	Player	Socialiser	Free Spirit	Disruptor	Philanthropist
IMVar	-.337	-.099	.085	-.007	.308	-.056	-.308	-.016	.091
EMVar	.292	-.408	-.095	-.160	.095	-.206	-.198	-.181	.149
AMOTVar	.497	-.111	-.361	-.419	-.117	.036	.199	-.013	-.036
Mot. Beha.	-.544	-.039	-.302	.097	-.053	.014	.136	.505	.322

(d) Results for the Progress game element

	IM	EM	AMOT	Achiever	Player	Socialiser	Free Spirit	Disruptor	Philanthropist
IMVar	-.680	.229	-.108	-.048	.178	-.015	-.115	.374	-.028
EMVar	.092	-.574	-.108	.234	.295	.068	.112	-.014	-.207
AMOTVar	.122	-.092	-.853	-.231	.128	-.001	.043	-.071	-.026
Mot. Beha.	.018	-.165	-.076	.425	-.018	-.124	.022	-.063	.132

(e) Results for the Ranking game element

	IM	EM	AMOT	Achiever	Player	Socialiser	Free Spirit	Disruptor	Philanthropist
IMVar	-.466	-.143	.248	.150	.018	-.001	.055	-.039	-.140
EMVar	.319	-.609	.108	.122	.116	.120	.323	-.396	-.172
AMOTVar	.477	-.052	-.328	-.447	.163	.088	.018	.326	-.091
Mot. Beha.	-.016	-.125	.006	.225	-.326	-.199	.114	.263	-.036

(f) Results for the Score game element

	IM	EM	AMOT	Achiever	Player	Socialiser	Free Spirit	Disruptor	Philanthropist
IMVar	-.909	-.098	-.615	.261	-.202	.208	-.032	.120	-.183
EMVar	.304	-1.032	-.302	.250	.040	.465	-.030	-.289	-.202
AMOTVar	-.342	.156	-.752	.041	.208	-.005	-.058	.490	.015
Mot. Beha.	.786	-.721	-.423	.071	-.127	.131	.168	.204	-.631

(g) Results for the Timer game element

	IM	EM	AMOT	Achiever	Player	Socialiser	Free Spirit	Disruptor	Philanthropist
IMVar	-.571	-.101	.325	.639	.104	.180	-.170	-.228	-.366
EMVar	-.421	-.111	.288	.689	-.015	.065	.318	-.013	-.407
AMOTVar	-.325	-.140	-1.112	.097	.056	.124	.073	.011	-.226
Mot. Beha.	.120	.130	.287	.749	.313	.011	-.332	-.222	-.435

- **Ranking** Results show many significant influences for the ranking element (see Table 19e). The initial **intrinsic** motivation influenced negatively the variation of intrinsic motivation, and positively the variation of amotivation. The initial **extrinsic** motivation negatively influenced the variation of extrinsic motivation. For the **Achiever** profile, score negatively influenced the variation of amotivation. The **free spirit** dimension positively influenced the variation of extrinsic motivation, whereas the **Disruptor** dimension negatively influenced it. The latter dimension also positively influenced the variation of amotivation.
- **Score** Score is the game element that showed the most statistically significant influences (see table 19f). The initial **intrinsic** motivation influenced negatively the variation of intrinsic motivation, and positively the motivated behaviours performed. The initial **extrinsic** motivation negatively influenced both the variation of extrinsic motivation and the motivated behaviours. The initial **amotivation** negatively influenced the variations of intrinsic motivation and of amotivation, as well as the motivated behaviours performed. For the Player profile, the **Socialiser** dimension positively influenced the variation of extrinsic motivation, the **Disruptor** the variation of amotivation, whereas the **Philanthropist** dimension negatively influenced the motivated behaviours observed.
- **Timer** We found eight significant influences for this game element (see table 19g). The initial **intrinsic** motivation negatively influenced the variation in intrinsic motivation, and initial **amotivation** negatively influenced the variation in amotivation. For the Player profile, the **Achiever** dimension positively influenced the variation of intrinsic, and extrinsic motivation, as well as the motivated behaviours generated. The **free spirit** dimension positively influenced the variation of extrinsic motivation. Finally, the **Philanthropist** score negatively influenced both the variations in both intrinsic and extrinsic motivations.

5.6.3 Discussion - contrasting effects depending on individual learner characteristics

As shown in sections 5.6.2.2 and 5.6.2.3 the effects of gamification on learner motivation vary greatly depending on initial motivation and player profile of the learners.

5.6.3.1 The influence of initial motivation

The negative influence between each type of motivation on the variation of this motivation (e.g. *initial intrinsic motivation* influences negatively the *variation of intrinsic motivation*) highlighted that gamification motivated learners who were less motivated initially, i.e. learners who had low initial motivation levels gained more motivation than learners with higher motivation levels. This result has great implications for a gamification approach not adapted to

learners. Such an approach should be used with extreme caution depending on learner initial motivation for the discipline.

The analysis performed per game element (see section 5.6.2.4) allowed us to further investigate these results and to show that game elements affect learners differently.

Among the positive influences, we noted that the **Avatar** game element increased the *intrinsic motivation* and decreased the *amotivation* of the more *amotivated* learners. This result could be explained by an increase in the satisfaction of their need for social relatedness [129], as shown by Sailer et al. [131]. The **Progress** game element also decreases the *amotivation* of the most *amotivated* learners. This could be explained by an increase in the feeling of competence from this game element [125, 129]. The **Score** game element has a positive influence on the variation in *motivated behaviours* of *intrinsically motivated* learners, which could also be explained by a desire to do better and to feel more competent. The fact that the **Score** game element is, in this study, a non-controlling reward (learners have the choice of restarting the exercise or not), contributes to this increase in their *intrinsic motivation* [23]. Lastly, the more *amotivated* learners, who received the **Timer** game element, saw their *amotivation* decrease, suggesting once again that this performance incentive was perceived more as an affirmation of their need for competence [23, 131].

However, we found that certain game elements degraded the motivation of some learners, as also observed when considering the learners as an entire group. Learners with a high level of *intrinsic motivation* who used the **Badges** game element, experienced a decrease in their *motivated behaviours*. This could be explained by the controlling nature of this game element [62]. The **Progress** and the **Ranking** game elements degraded the levels of *intrinsic* and *extrinsic* motivation of learners that had high initial levels of these motivations. These results suggest that game elements that foster social comparison [43, 123] could be detrimental to learner motivation. The **Score** game element also decreased the *motivated behaviours* of the most *amotivated* learners as well as their *intrinsic motivation*. Learners may perceived this game element more as a negative feedback [142], confronting them with their own difficulties in mathematics. Finally, learners initially *intrinsically motivated* to do mathematics, who received the **Timer**, experienced a decrease in their *intrinsic motivation*. This game element may have caused stress among the most motivated learners, something that was also reported by the teachers following the experiment. This result is common with many gamification studies that show Timers as stressful for learners [59, 70].

In conclusion, all types of initial motivation have an influence on the variation of motivation whatever the game element, mostly negative. Only *amotivation* and *motivated behaviours* are positively impacted by **Progress**, **Timer** and **Score**. Based on these findings, we can conclude that game elements do not have the same potential to increase learners' motivation according to their level of initial motivation, and thus that it must be taken into account if we do not want it to be detrimental to learners.

5.6.3.2 *The influence of the player types*

When looking at learners' player profile, the most impactful game elements vary considerably. The **Timer** had the greatest impact, involving an increase both in the intrinsic and extrinsic motivations for *achiever* and *free spirit* learners. However, for *philanthropists*, this game element had the opposite effect, generally demotivating them. These findings nuance the results presented in Chapter 3 by providing results from a contextualised setting.

Next is the **Ranking** game element came next and showed four influences. Learners with high *free spirit* scores gained in *extrinsic* motivation and *achievers* became less amotivated. As *achievers* are motivated by competence [101], it is not surprising that the virtual challenge of the ranking system motivated them. *Free Spirit* learners possibly looked for a way to "stand out from the crowd" [101] and therefore tried to come first. However, learners with high *disruptor* scores lost *extrinsic* motivation and gained in *amotivation*. This game element could have made them feel demotivated since such players are looking to go against the rules and will not be challenged by the ranking system that mainly highlights learners who follow the rules.

For **Score**, we observe positive effects only on *socialisers* with an increase in extrinsic motivation. Both *disruptors* and *philanthropists* had, respectively, an increase in their amotivation and a decrease in their motivated behaviours. This is not surprising as scoring systems are generally not recommended for motivated learners [4, 59]. This finding for *socialisers* is coherent with the results obtained in [150] that noted that learners like to compare their scores with others.

With the **Avatar** game element, we noted an increase in motivation for those with a high *player* score, as well as a decrease for those with a high *socialisers* score. Being able to develop their **Avatar** based on their correct answers was probably perceived by *players* as a way to satisfy their personal success [131]. As there were no possibilities to show their avatars to others, it is not surprising to observe a negative effect for *socialisers*.

We also found that **Badges** game elements encouraged *motivated behaviours* only for learners with a high *disruptor* score. This is surprising as **Badges** are one of the most widely used game elements for gamification [59, 83, 86], and are generally accepted as motivating.

Finally, no influences were observed for the **Progress** game element depending on the player dimensions. These result is contradictory with other studies, like the one conducted in [59] that shows influences depending on the *socialisers* and *disruptor* player types. These differences may be due to the design of the game element itself.

These findings show that five player types have an influence on the impact of game elements on learner motivation, and that all types of motivation and motivated behaviours are impacted, but in very different ways depending on the game elements involved. The *achiever* and *disruptor* player types have the most impact. These results allow us to provide some recommendations for learners based on either their Hexad profile or initial motivation for mathematics (see table 20 for a summary of the recommendations).

Table 20: Game elements that can be recommended to some learners, and that should be avoided by others.

Game Element	Recommended for learners with high	Avoid for learners with high
Avatar	Amotivation, Player	Socialiser
Badges	Disruptor	Intrinsic Motivation
Progress	Amotivation	Intrinsic Motivation, Extrinsic Motivation
Ranking	Free Spirit	Intrinsic Motivation, Extrinsic Motivation, Achiever, Disruptor
Score	Socialiser	Extrinsic Motivation, Amotivation, Disruptor, Philanthropist
Timer	Amotivation, Achiever, Free Spirit	Intrinsic Motivation, Philanthropist

5.7 HOW THE CHOICE OF USER MODEL AFFECTS ADAPTATION

The results of the first two research questions showed us that both of the models used to classify learners (Hexad and initial motivation) can have an impact on learner motivation and behaviour depending on which game element the learner used. However, when taken individually, these different profiles can offer different, sometimes contradictory game element recommendations. When taken together, we cannot ensure that the recommendations from both profiles are taken into account. Thus, we asked **RQ3** and simulated different adaptation approaches, based either solely on a learner's Hexad Profile, their Initial motivation, and a compromise between both. We then used the variation of learner motivation, and engagement metrics to evaluate the effectiveness of these approaches.

5.7.1 Data sets

To answer **RQ3** we first needed to create three sets of adaptation rules. One for each of the single user models (Hexad profile and initial motivation) and one for the dual profile adaptation (considering the two profiles). The learners were then split into one of two groups for each adaptation simulation, based on whether they used an adapted game element or not. Finally we compared the variations of motivation for each subset, as well as the three engagement metrics using a Wilcoxon rank sum test. A summary of the three data sets is presented in figure 23.

5.7.1.1 Single profile adaptation rules

To create the adaptation rules for the two single user models, we ran two PLS-PM models between the profile values and the variations of motivations for each subset of learners that used a particular game element (Fig. 24). Similar to the ones used for the previous analyses, except that we treated both

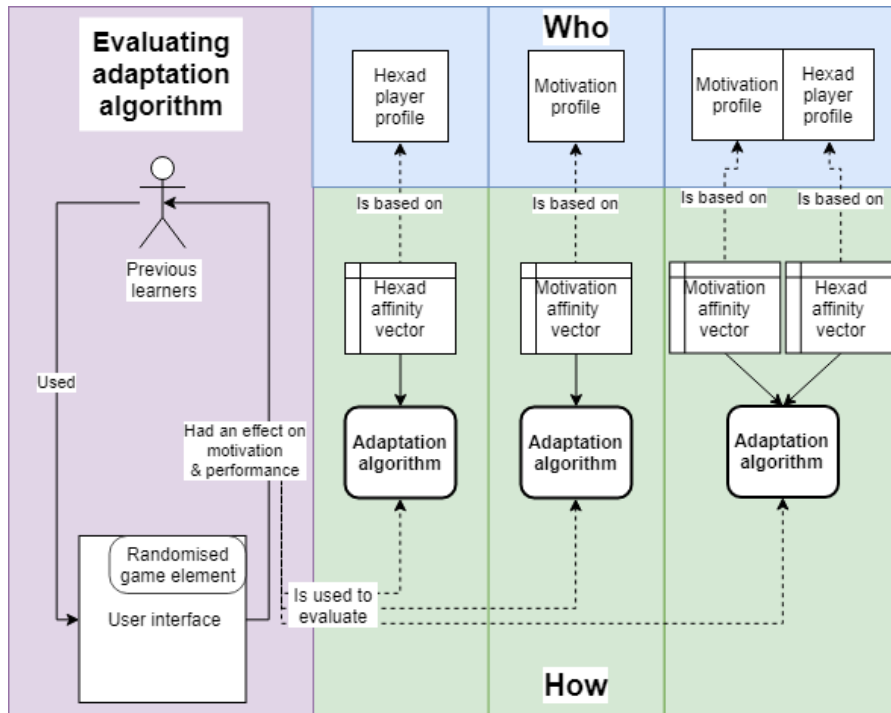


Figure 23: The three adaptation simulations tested. Each of the adaptation simulations were evaluated by comparing learners who used adapted game elements to those who did not.

the Hexad player profile and the initial motivation profile independently. This gave us a set of 6 matrices of influences for each profile (one per game element, an example for the Avatar game element is given in table 21).

By combining all six of these matrices, we obtained a final affinity matrix, that showed for each game element, how important a given profile metric is in their influences (the full affinity matrix for the Hexad Profile is given in table 22). By combining these matrices with learner profiles, we generated a recommendation of game element based on the Hexad profile and one based on the initial motivation. For example, a learner with the Hexad profile (Pl:0; Ac:-8; So:2; FS:0; Di:6; Ph:7), would have the following affinity vector ('Avatar': .385, 'Badges': .0364, 'Progress': -.241, 'Leaderboards': -.920, 'Points': -.577, 'Timer': .225) and would therefore be recommended the Avatar game element.

5.7.1.2 Dual profile adaptation rules – compromise algorithm

For the dual profile user model, we developed an algorithm that recommended a game element based on both Hexad and initial motivation profiles. In our original dataset, out of the 258 learners, 87 of them used a game element that was either adapted to their Hexad profile, or adapted to their initial motivation scores (no learners had a game element adapted to both their Hexad profile and initial motivation). The algorithm proposes a compromise between both recommendations: we evaluate if there is a positive overlap between the two

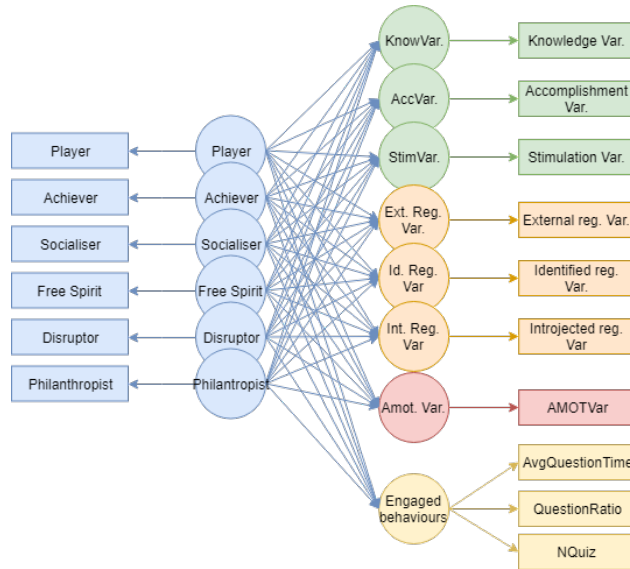


Figure 24: PLS PM Model for creating the Hexad influence matrices.

Table 21: Influence matrix for the Hexad profile on the Avatar game element. Only the significant ($p < .05$) influences are shown here.

	Pl.	Ac.	So.	FS.	Di.	Ph.
Know.Var.	0.329	-0.356				
Acc.Var.	0.541		-0.521			
Stim.Var.						
Ext.Reg.Var.						
Id.Reg.Var.						
Int.Reg.Var.						
Amot.Var.						
Behaviours						0.396

Table 22: Final affinity matrix for the Hexad profile

	Pl.	Ac.	So.	FS.	Di.	Ph.
Avatar	0.870	-0.356	-0.521			0.396
Badges			-0.548	-1.233		1.229
Progress		-0.011	-0.331		-0.061	
Leaderboards			-0.459		-0.870	
Points	0.490		-0.467			-0.694
Timer		1.772	0.439	0.530	0.398	-1.125

affinity vectors, and we take the game element that minimises the ranks in the positive overlap. If there is none, we take the game element that minimises the ranks from both affinity vectors (or maximises the affinities if tied). The full algorithm is presented in algorithm 1.

Algorithm 1 : Compromise algorithm

Initialisation – Sort both affinity vectors in decreasing order of affinity

affVecHex ← sorted Hexad affinity vector

affVecMot ← sorted initial Motivation affinity vector

These vectors are structured using the following format: [(gameElement,affinity), (gameElement,affinity)...]

overlap ← positive overlap between *affVecHex* & *affVecMot*

This contains a list of all game elements that have a positive affinity in both affVecHex and affVecMot

if *overlap* is not empty **then**

if *overlap* contains exactly one element **then**

 └ Suggest element in *overlap*[0]

else

 Combine the rankings and affinities for game elements in *overlap* from *affVecHex* & *affVecMot*;

if one game element has smallest combined ranking **then**

 └ Suggest that element

else

 └ Suggest game element that has highest combined affinity

else

 Combine the rankings and affinities for all game elements from *affVecHex* & *affVecMot*;

if one game element has smallest combined ranking **then**

 └ Suggest that element

else

 └ Suggest game element that has highest combined affinity

5.7.2 Analysis

As with **RQ1** and **RQ2** we used the variation of learner motivation (calculated from the differences in their responses to the AMS questionnaires) between the start and the end of the experiment to estimate the effect of the different adaptation simulations on learner motivation. As for engagement metrics we decided to expand on the previously used metrics (mainly because there were little differences between learners for the Restarted Quiz count, therefore comparing this metric between subsets of learners would not show any differences):

- **Average Question Time:** The average time spent to answer a question (computed over all questions)
- **Quiz Ratio:** The number of correctly answered quizzes divided by the total number of attempted quizzes (this was an evolution of the question ratio metric used for RQ2).
- **Number of quizzes attempted:** The total number of quizzes attempted.

5.7.3 Results

From our set of 258 learners, we built the following data subsets using the three approaches presented:

- Hexad data subset: 42 learners used game elements adapted to their Hexad player profile (216 did not).
- Initial motivation data subset: 45 learners used game elements adapted to their initial motivation (213 did not).
- Dual profile data subset: 42 learners used a game element recommended by the dual profile algorithm (216 did not).

5.7.3.1 Hexad adaptation results

Comparing metrics for the two subsets, we found that learners using an adapted game element spent significantly less average time per question and had a significantly lower correct question ratio (i.e. they got more questions wrong) than learners who had a non adapted game element (see Table 23a). The adaptation process had no significant impact on learners' motivation.

5.7.3.2 Initial motivation adaptation results

Adaptation based on the initial motivation profile had significant positive impacts on the variation of intrinsic motivation (see Table 23b). Learners with adapted game elements lost significantly less Intrinsic Motivation for Knowledge (Know.Var.), i.e. their satisfaction to learn new things decreased less than for learners with non adapted game elements. They also gained significantly more Intrinsic Motivation for Accomplishment (Acc.Var.), i.e. their pleasure for overcoming a challenge increased, whereas it decreased for learners with non adapted game elements. The adaptation process had no significant effects on learner engaged behaviours.

5.7.3.3 Dual profile adaptation results

When compared to learners who used a non adapted game element (see table 23c), we found that learners with adapted game elements gained significantly less amotivation (Amot.Var.), meaning that they were less reluctant

Table 23: Results for different simulations. The values given are the averages for each group. In light grey: no significant differences, in bold and highlighted in grey: significant at $p < .05$, and highlighted in light grey: almost significant $p \approx .05$

Metric	(a) Hexad			(b) Motivation		
	p	Adapted	Non	p	Adapted	Non
Know.Var.	.233	-1.489	-2.099	.022	-1.156	-2.169
Acc.Var.	.289	0.422	-0.352	.008	0.756	-0.423
Stim.Var.	.458	0.289	-0.263	.335	0.267	-0.258
Id.Reg.Var	.447	0.289	-0.117	.383	-0.400	0.0282
Int.Reg.Var	.492	0.222	-0.282	.233	0.378	-0.315
Ext.Reg.Var	.482	-1.089	-1.235	.141	-0.667	-1.324
Amot.Var.	.619	2.267	2.953	.867	2.956	2.808
AvgQTime	.016	60.73	67.78	.066	71.42	65.51
QRatio	.010	0.608	0.665	.224	0.637	0.659
NQuiz	0.792	34.56	35.33	.189	34.18	35.41

(c) Dual profile			
Metric	p	Adapted	Non
Know.Var.	.052	-1.326	-2.137
Acc.Var.	.056	0.739	-0.425
Stim.Var.	.045	0.848	-0.387
Id.Reg.Var	.691	-0.283	0.005
Int.Reg.Var	.445	0.326	-0.307
Ext.Reg.Var	.476	-1.043	-1.245
Amot.Var.	.012	1.391	3.146
AvgQTime	.812	68.07	66.21
QRatio	.137	0.630	0.661
NQuiz	.923	36.17	34.98

to learn mathematics. They also gained significantly more Intrinsic Motivation for Stimulation (Stim.Var.), meaning that they had more fun and excitement performing the maths activities. As with the initial motivation adaptation, we also found that these learners lost less intrinsic motivation to knowledge (Know.Var.) and gained more intrinsic motivation for accomplishment (Acc.Var.) (although these differences were only slightly significant $p \approx .05$).

5.7.4 Discussion - different possible adaptation effects on learners based on the model used to categorise learners

Tailoring gamification based only on the Hexad profile led learners to be more engaged in the learning task (answering questions faster) than learners who used untailored (randomly assigned) game elements, which confirms the results obtained by [108] in a computer network design course regarding learner engagement. However, our study highlights that this engagement is associated with lower performances (lower quiz ratio), which is contradictory with the study reported in [79], where they found that personalised badges and feedback had a positive effect on maths performance. We also show that an adaptation based only on player types has no effect on learner motivation for the learning task, as also observed in [106] when learning French spelling. We can conclude that game elements could be beneficial to engage learners in the learning activity, but only if these elements give direct feedback on their performance. Regarding the results found for RQ1, whilst tailoring to a Hexad profile does not affect motivation (meaning that learners still lost motivation), learners will be **more engaged** with the learning task.

Providing learners with game elements adapted to their initial motivation led to a positive effect on two kinds of intrinsic motivation to learn Mathematics compared to no tailoring. This finding is consistent with other studies on the impact of a tailored gamification based on learner motivation in a technical English course [128], and a database management course [64]. More precisely, this adaptation reduced the decrease in intrinsic motivation for knowledge that was generally observed (as compared to the untailored approach studied in to answer RQ1.) and made learners more intrinsically motivated to overcome maths challenges. The increase of intrinsic motivation to Accomplishment is the opposite of what was observed for RQ1., meaning that this tailoring approach actually had a positive effect, reversing the general loss in motivation observed.

It therefore seems promising to use learner motivation for the learning subject as a basis to tailor gamification in education, although it was rarely considered in previous studies. This echoes the findings discussed in Chapter 2 where we showed that, especially in the education field, profiles composed of more specific learner data are somewhat rare. The findings in this chapter also show the importance of taking the context into account (through the usage of a context specific profile: motivation for the learning task). This idea is introduced in Chapter 3, and confirmed here. Combining both profiles with the dual adaptation reinforced the observed results with initial motivation, but also led learners to be more motivated to learn Mathematics for fun or excitement. This finding is in line with previous studies on the impact of tailored gamification that show an increase in perceived fun [106] or flow induced by some game elements depending on the player types [36]. Dual adaptation also reduced learner amotivation to learn Mathematics.

5.8 STUDY LIMITATIONS

We identified some limitations to our study related to the context-dependency and generalisability of our results. We employed 6 game elements designed especially for young learners (around 13 years old), for a specific learning environment (secondary school mathematics). First, the influences measured for each game element could be different for other learners. Younger learners may be more receptive to the playfulness induced by our game elements whereas older, or less technology fluent learners, might have been less receptive. In short the final results obtained here are highly contextual, and re-applying them directly in another context may not work as intended. However our methodology (comparing different gamification approaches, combining both contextual and uncontextual user information) is a lot more generalisable, and could be adapted to a different context. Second, we may obtain different results when considering other game elements implementing other game mechanics (such as collaboration or competition). Then, as pointed out by Lessel et al. [94], the effect of gamification widely varies for willing participants (i.e. participants performed better when they had a choice in using the game elements). As the learners in our study did not choose their gamification, this could have affected their motivation, or behaviour.

5.9 CONCLUSION

This chapter presents the results from the first large-scale study in the LudiMoodle project, on how gamification affects learner motivation, and behaviour. This study ran for about six weeks in four different secondary schools in France involved 258 students from twelve different classes. Learners interacted with 10 specifically designed mathematics lessons, gamified using six different game elements. The results show that, in general, gamification through randomly assigned game elements works better for less motivated or amotivated learners (i.e. those who do not perceive mathematics as interesting), with other learners being generally demotivated. A more thorough analysis revealed that the impact of game elements on learners' motivation varies greatly depending on their initial motivation for mathematics and their Hexad player profile. These results highlight the necessity to adapt gamification not only based on a learners' player profile as commonly acknowledged in the literature, but also based on their initial motivation (for mathematics in our case). Both of these factors are important for determining how a game element will affect learners' motivation, behaviour and engagement. Furthermore, the results obtained considering each game element separately highlight that they affect learners' motivation differently. Care must be taken when proposing game elements to learners, as these may have contradictory effects depending on their profile, as observed through our second analysis.

Using these results we took a step further and created adaptation rules using three different profile sources (Hexad, initial motivation for mathematics or both). We then simulated three different adaptation techniques based on these

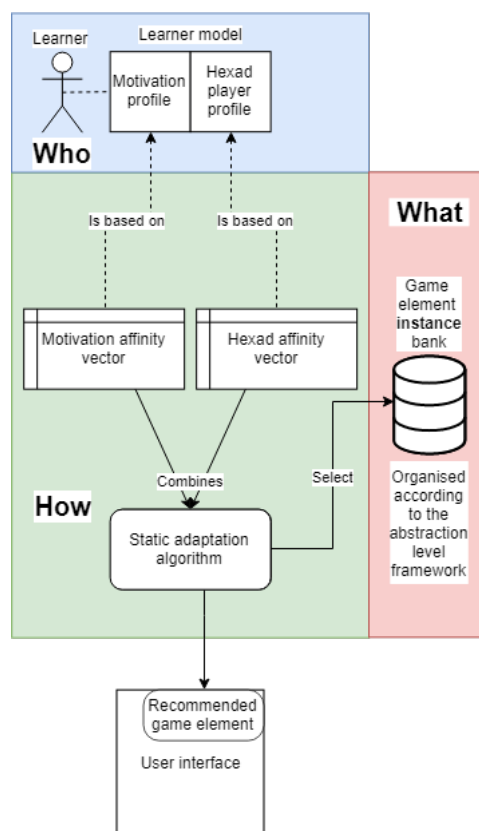


Figure 25: The updated version of the adaptation engine architecture containing the new learner model (composed of both the Hexad Player profile, and the initial motivation for mathematics) as well as the updated static adaptation algorithm which finds a compromise between both affinity vectors.

rules. Finally compared the effects of our gamified platform on learners based on whether they had used an adapted game element following these simulations, to compare the three different adaptation techniques. This second analysis showed three important findings. First, the user model chosen to tailor game elements has different significant effects on learners. Second, when choosing only a single profile for tailoring game elements, initial motivation performed better than the Hexad profile, meaning that the learners motivations for learning mathematics trumped their motivations for playing games. Finally, when combining both player profile and initial motivation, adapted learners not only retained the positive effects of the initial motivation adaptation, but also reflected other different positive effects. The combination of both adaptations results in something that is greater than the sum of its parts.

From these results we can recommend to take greater care when choosing the tool to model learners. It seems that uncontextualised profiles (such as Hexad) may be useful for engaging learners, whereas more contextual ones (such as motivation for the learning task) could be useful for motivating learners. Finally combining both types can also help motivate learners, whilst also making sure they are not as bored by the learning task.

In any case, for the purposes of the LudiMoodle project, using both the Hexad, and the initial motivation profiles appeared to be sufficient for tailoring game elements to learners, especially when used with the proposed compromise algorithm. By using the real world data generated from previous versions of the main experiment we were able to create domain and context appropriate adaptation rules. Going back to the proposed adaptation engine architecture, we can update figure 13 by adding the initial motivation profile to the learner model, and the new compromise algorithm (see figure 25).

Up until now, the proposed adaptation model uses a "static" adaptation, where the gamified system is adapted to learners once, before using the learning environment. Following the definition provided in chapter 2, I propose to extend the current model to allow for a dynamic adaptation based on learner behaviour, using the trace data gathered from the LudiMoodle experiment presented in the previous chapter (see chapter 5) to create dynamic adaptation rules. As a reminder dynamic adaptation can occur at multiple times during the usage of a gamified system if required. In the LudiMoodle context the dynamic adaptation system should be able to monitor learner engagement and motivation, and when detecting an abnormal drop, propose a different game element to re-motivate and/or reengage the learner. For this we needed a way to evaluate how log traces represent motivation and or engagement. We first derived a set of metrics to represent learner engagement with the learning platform from these log traces. Then using a factor analysis approach, we grouped these metrics into overarching engagement factors, thus creating a learner engagement model based on learner interaction with the platform. This engagement model was implemented in a new version of the Adaptation engine, which would have been tested in the final LudiMoodle experiment, that due to the current COVID19 pandemic could not take place.

6.1 INTRODUCTION

As presented in Chapter 2 we define dynamic adaptation as an adaptation that *can* occur multiple times during the usage of a gamified system if needed, and that is based on dynamically observed learner characteristics (i.e. behaviour or performance). This is opposed to the static adaptation approach we have used up until now that *always* occurs, only *once*, before using the gamified system, and is based on static learner profiles (i.e. the profiles are gathered once before using the gamified system). In the context of the LudiMoodle project we needed our dynamic adaptation system to be able to propose a game element recommendation for each learner after *each* lesson *if required*. In short we needed a method for estimating learner motivation or engagement based on their behaviour during a lesson. Existing tools such as the User Engagement Scale proposed by O'Brien et al. [116] are not well suited for this task, as they state that "in general participants should be able to complete the UES in less than 15 minutes". It would therefore not be feasible to require learners to fill our surveys after each lesson in the LudiMoodle project con-

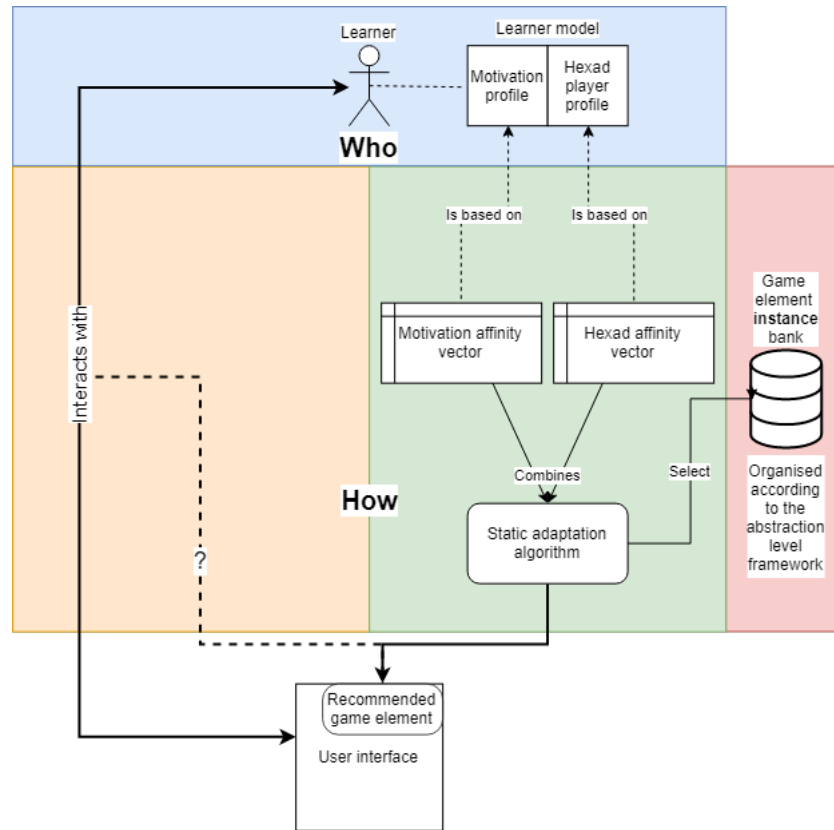


Figure 26: How the dynamic adaptation module will fit into the general adaptation engine architecture. The full specifications of this module are presented in this chapter.

straints (even the short form of the UES requires between 5-10 minutes would still be too long).

To understand how we designed and implemented our dynamic adaptation system, I propose to explain these ideas in the following sections of this chapter: 1. How our dynamic adaptation system works 2. How we determined learner engagement through log traces 3. When our dynamic adaptation system intervenes 4. Who controls the dynamic adaptation

Regarding the general adaptation engine architecture, the dynamic adaptation takes on the form of a module that provides dynamic adaptation without modifying the previously presented static adaptation (see figure 26).

6.2 DYNAMIC ADAPTATION APPROACH

To better explain how our dynamic adaptation system functions I will use the PDA-LPA design space proposed by Bouzit et al. [15] for describing and understanding interface adaptation. The design space is split over two usage loops (one for the end user, and one for the system) that follow two successive cycles: PDA (Perception Decision Action) and LPA (Learning Prediction, Adaptation). In short users **perceive** an adaptation change, make a **decision** about this change, and **perform** an action (PDA). They then **learn** from this

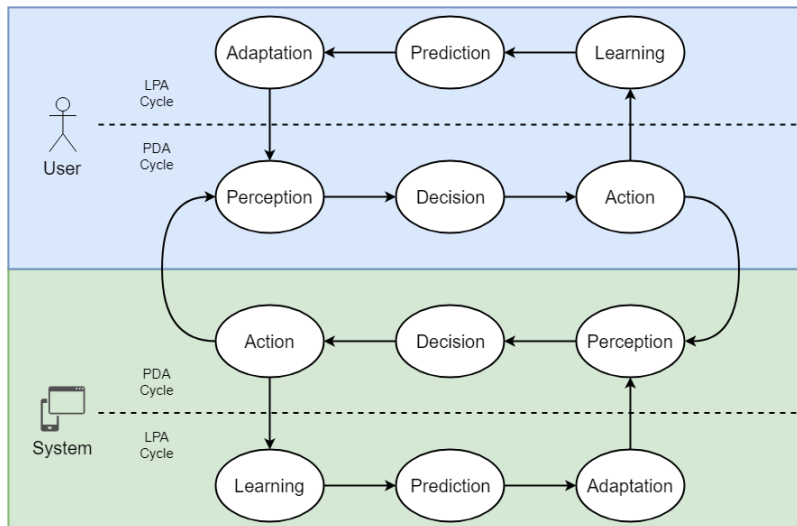


Figure 27: The PDA-LPA cycles as described by Bouzit et al. [14]

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 anew. 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 impact the user, and **adapts** its adaptation system (LPA) (see figure 27). Not all of the steps in the LPA-PDA cycles have to be fulfilled to create a dynamically adaptive system, but they serve as guidelines as to how it can be designed.

The dynamic adaptation system used in the LudiMoodle prototype generally functioned in the following manner: Learners interact with the gamified platform as usual during a lesson. After finishing a lesson, the system analyses their interaction logs, generates an estimation of their engagement during this lesson, and computes the variation of engagement from the last lesson. These variations are then compared to the other learners in the same class, and if a learner is in the lower third of their class, the system signals to the teacher that this learner might need an adaptation (i.e. game element change) is signalled to the teacher. The teacher can then use this information, along with their knowledge of the learner, and their behaviour to decide whether the proposed change is appropriate or not. In the LudiMoodle context, teachers were involved in the design of the game elements, and understood the design rationale behind them, we therefore judged that they were capable to estimate if the proposed changes would be appropriate. In any case, when an adaptation is proposed, the system uses the learners affinity vector (see chapter 5) and selects the next highest game element that isn't blacklisted (a learners blacklist contains all game elements they have already used, and those that the system proposes). The blacklist was put into to place to avoid the system constantly proposing the same game element for a learner. The full algorithm is presented at the end of this chapter in Algorithm 2. Through the lens of the PDA-LPA design space: (see figure 28). We added the teacher's role between

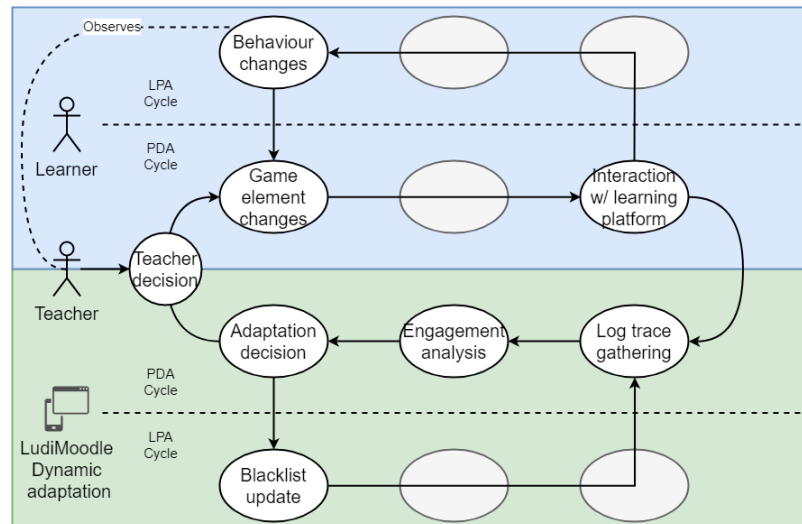


Figure 28: The LudiMoodle dynamic adaptation engine as described in the PDA LPA design space. In the LudiMoodle context, the teacher is an essential actor in the dynamic adaptation process, as they have the final decision on whether an game element change is operated for a learner. They make this decision after the system signals that a change might be needed. Teachers use their knowledge of both the learner, and their behaviour to inform their acceptance or refusal of the game element change.

the action state of the system and the perception state of the learner so that the teacher could have the final say on the proposed adaptation, based on their observation and understanding of learner behaviour changes (see section 6.4).

- Learner (user)
 - Action: Interacting with the learning environment, answering questions, completing quizzes etc.
 - Adaptation: Changing behaviour / re-engaging with the learning content influenced by the game element assigned.
 - Perception: Noticing a game element change
 - Decision, Prediction, Learning – Not used
- System
 - Perception: Learner log trace analysis
 - Decision: Engagement comparison with other learners
 - Action: Game element proposal
 - Learning: Blacklist updating
 - Prediction, Adaptation – Not used

6.2.1 *Determining learner engagement through learner behaviour*

The first step of understanding how the dynamic adaptation engine functions is understanding how we determine learner engagement from log data. Engagement is a complex process. O'Brien & Toms [117] define it as "*a quality of user experience characterised by attributes of challenge, positive affect, endurance, aesthetic and sensory appeal, attention, feedback, variety/novelty, interactivity, and perceived user control*". Generally user engagement is evaluated using one of two kinds of methods : subjective, or objective methods.

As stated previously, subjective methods using questionnaires & scales are not suited for our situation, we therefore decided to estimate engagement via learner behaviour following the method proposed by Bouvier et al. [13]. They present a study on the engaged behaviours of players in a online sport game. They present a trace model that categorises user trace actions into four different categories of engagement that are then linked back to the different SDT (Self Determination Theory [129]) categories. 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 (i.e. education) in [87].

We therefore followed a procedure inspired by Bouvier et al. [13] for our log trace analysis (i.e. creating a trace based model for analysing and aggregating the log trace data), and Fincham et al. [46] for identifying learner engagement factors. Fincham et al. present a study where they analysed metrics from three university MOOCs (online learning), using Exploratory Factor Analysis (EFA) to identify and Confirmatory Factor Analysis (CFA) to validate a latent variable data model to estimate learner engagement.

Our analysis proceeded in three steps, first we reviewed and collated the data available from the previous Ludimoodle study using a log trace approach (following Bouvier et al. [13]). Second we ran two factor analyses to create and verify an overarching engagement model, that identified the three engagement factors (following Fincham et al. [46]). We then used these factors to track the variation of learner motivation and engagement, and propose an adaptation when necessary.

6.2.2 *Determining engagement metrics*

By studying the data that was available to us from the LudiMoodle experiment, we extracted a set of engagement metrics and traces that we believed would allow us to follow the evolution of learner engagement and motivation throughout the usage of the system. These metrics were all calculated through aggregation and transformation of the log traces automatically collected by the LudiMoodle system. We applied a similar process for aggregating our low level log traces into higher level operations as described by Bouvier et al. [13]. These metrics were designed to be calculated for each lesson (as

opposed to those used in the previous chapter, that were calculated for the whole experiment). The evolution of these metrics over the course of the lessons allow us to track learner engagement. The final engagement metrics that emerged from the log trace analysis are as follows:

- **AvgQuestionTime** : The average time taken for a learner to answer a question (computed for all correctly answered questions).
- **NPassedQuiz**: The number of quizzes successfully completed. A quiz was counted as successfully completed is at least 70% of all questions in the quiz were answered correctly.
- **QuestionRatio** : The average correct question ratio for all quizzes. This ratio was calculated only for the first quiz attempt, as learners could see their answers on subsequent attempts, and therefore change their answers based on this information. (bonus quizzes included).
- **StreakRatio** : The streak ratio for the lesson. A streak ratio is the number of successively completed quizzes in a lesson, without restarting any of the completed quizzes divided by the number of quizzes attempted during this lesson. For example Learner001 completed Quiz1-Quiz2-Quiz3 in succession before restarting Quiz2. They then completed Quiz4 and attempted (but did not complete) Quiz5. Their Streak-Ratio for this lesson would therefore be $3/5=0.6$ (they completed 3 quizzes before restarting a completed quiz, and attempted 5 total quizzes).
- **LessonRatio**: The ratio of completed quizzes for the lesson. If a learner attempted ten quizzes in a lesson, and completed seven of them, they would have a lesson ratio of 70%.
- **NQuizDistinct**: The number of distinct passed quizzes. Here each completed quiz is counted only once.
- **NbBonusQuiz** : The number of bonus quizzes completed. Teachers had previously designated a set of bonus quizzes that were harder and only available at the end of lessons (learners were not expected to complete these bonus quizzes). Each bonus quiz was only counted once (completing a bonus quiz multiple times would not increase this number).
- **NLoop**: The number of times a passed quiz (i.e. completed at least at 70%) was restarted.
- **NPassedFirstQuiz** : The number of quizzes successfully completed for during the first attempt (bonus quizzes included).

Figure 29 presents an overview of how the different log levels are structured, as well as which operations are used to calculate the different engagement metrics.

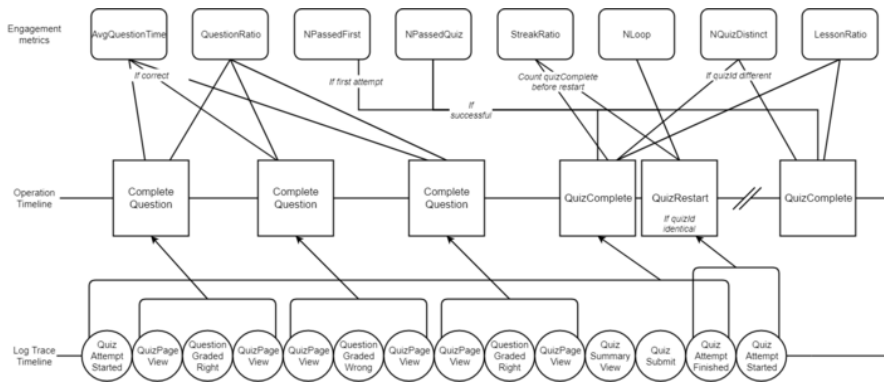


Figure 29: The three levels of log data in our model. The lowest level is the log trace data extracted from the LudiMoodle platform. Above this is the operation level that aggregates and contextualises the log traces. Each of the identified engagement metrics uses one of multiple of the operations.

6.2.3 Log trace transformation

Each log trace was represented by a single line in a csv file that was extracted from the MySQL database. Each log trace used the following format `timestamp, learnerID, GameElementUsed, Log, Info`. A few examples of raw log traces are given with the other examples of log traces at the end of this chapter, in table 27. These log traces were then aggregated into higher level operations. For example, the `quiz_attempt_finished` log did not provide the results for each of the questions in said quiz attempt. However these results were given in each of the `question_gradedX` logs that were present between the `quiz_attempt_started` and `quiz_attempt_finished` (see table 28). We therefore transformed these logs into one operation **CompleteQuiz**. For the analyses in this chapter we mainly used three higher level operations: **CompleteQuiz**, **QuestionComplete**, and **RestartQuiz**.

6.2.3.1 CompleteQuiz

As shown previously the **CompleteQuiz** operation was created after a quiz attempt. For the example presented in table 28, the final operation was : `CompleteQuiz, elevekf10, progress, 2019-03-14 16:39:30, 2019-03-14 16:40:45, QuizId:quiz : Exercice 1.1 : QCM, Attempt: attempt : 3 , Interruption : False, Success: True, Ratio: 0.8`

6.2.3.2 QuestionComplete

Other than **QuizComplete**, we also used the **QuestionComplete** operation. This was created using the following pattern `quiz_pageview, question_gradedX, quiz_pageview`. For example the log trace presented table 29 would be transformed into the **QuestionComplete** operation with `success = True`.

Table 24: The computation rules for each of the different engagement metrics

Metric	Operations used
AvgQuestionTime	Average of duration of all correct QuestionComplete
NPassedQuiz	Count of successful QuizComplete
QuestionRatio	Average of QuizComplete ratio
StreakRatio	Count of QuizComplete before RestartQuiz
LessonRatio	Count of successful QuizComplete divided by total number of quizzes in lesson
NDistinctQuizzes	Count of different QuizComplete
NbBonusQuiz	Count of QuizComplete with bonus ID
NLoop	Count of RestartQuiz after a successful CompleteQuiz
NPassedFirstQuiz	Count of successful CompleteQuiz with attempt number at 1

6.2.3.3 *RestartQuiz*

Finally we also used the **RestartQuiz** operation. This was created when a learner restarted a quiz that they had previously attempted. The log trace presented in table 30 shows an example of a log trace that would lead to the creation of this operation. The **RestartQuiz** operation also used the previous **CompleteQuiz** operation's success variable to create the afterSuccess variable stored in **RestartQuiz**.

6.2.4 *Computing engagement metrics from log trace transformations*

These higher level operations were then used to calculate the different engagement metrics. Table 24 shows how each metric was calculated.

6.2.4.1 *Creating and validating an engagement factor model*

To better understand how these metrics were linked we ran an exploratory factor analysis (EFA), inspired by the approach presented by Fincham et al. [46]. EFA is a statistical technique whose overarching goal is to identify the underlying relationships between measured variables. After we performed a further analysis, a Confirmatory Factor Analysis (CFA) through which we validated the model proposed by the first analysis. In order to increase the models reliability, we ran the first analysis (EFA) on half of the previous data, and the second analysis (CFA) on the other half. For the EFA model the number of factors was chosen using a parallel analysis, as it has been shown to be the most effective way to determine the number of factors to retain in a factor analysis [152]. A parallel analysis involves the generation of

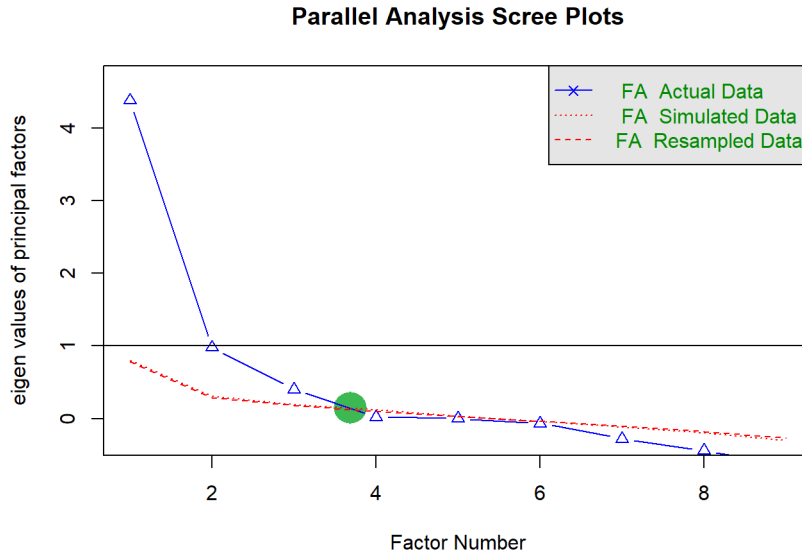


Figure 30: Scree plot for the EFA analysis. In blue, the actual data, in red, the simulated data. The point in which they start to somewhat overlap (highlighted in green) indicates the suggested number of factors (three in this case).

a random data set of the same dimensions as the data being analysed. Factor analysis is then performed on the random data to extract eigenvalues. These random eigenvalues are then compared with the eigenvalues of the real data, and factors in the real data are only retained if their eigenvalues are greater than the eigenvalues from the random data[2]. It is important to note that it is generally recommended to test values either side of the value recommended by the parallel analysis. In this case we used a scree plot [95] to visualise the correct number of factors.

Our scree plot analysis 30 revealed that three factors should best represent our model. As previously stated we also tried creating data models with both four and five factors, but as these provided less satisfactory results than the three factor model, we ended up keeping this suggestion.

After establishing the appropriate number of factors, we ran the EFA. The results are presented in table 25. The loadings were filtered using a cutoff of 0.65 to keep only those metrics that adequately contributed to the corresponding factor. From this analysis we noted that one metric (*NbBonusQuizzes*) did not load into any of the three factors, and were therefore discarded for the following model construction. Using this model with the CFA yielded the final loadings presented in table 26.

As both of these analysis yielded significant factors we then proceeded to the final step, interpreting and making sense of these factors. Using the loadings calculated with the EFA method, we had three factors composed thus:

- $F1 = 0.991 * NQuizDistinct + 0.855 * NPassedQuiz + 0.744 * NPassedFirst - 0.595 * AvgQuestionTime$ - This relates to a 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. Therefore we chose to call this factor **Wide learning engagement**.

- $F2 = 0.883 * \text{QuestionRatio} + 0.718 * \text{LessonRatio}$ - This directly links to a learners performance, how well they answered each question and completed each quiz. Therefore we named this factor **Performance engagement**.
- $F3 = 0.973 * \text{NLoop} - 0.704 * \text{StreakRatio}$ - This relates to how much a learner tried to achieve a complete (100%) score for each quiz, or how much they strived to improve a quiz score. Therefore we chose to call this factor **Deep learning engagement**.

Table 25: EFA results. The loadings for each factor are presented with a lower bound cutoff of 0.5. The metric BonusQuizzes did not load with any of the factors, and therefore was not included in the subsequent analyses.

	Factor1	Factor2	Factor3
AvgQuestionTime	-0.595		
NPassedQuiz	0.855		
QuestionRatio		0.883	
StreakRatio			-0.704
LessonRatio		0.718	
NQuizDistinct	0.991		
NLoop			0.973
NPassedFirst	0.744		
BonusQuizzes			

6.3 DYNAMIC ADAPTATION TRIGGER

As presented in the general Dynamic adaptation algorithm (see Alg. 2), briefly explained in section 6.2, we propose to adapt when we detect an abnormal decrease in learner engagement. For each lesson completed, we calculate the three engagement factors (**Wide learning**, **Performance**, and **Deep Learning**) for each learner, and the variation of these engagements with 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 learner displays a decrease in any of the engagement it is difficult to tell if it is "normal" or "expected". For example, in the Ludimoodle experiment the later quizzes were harder and more complicated

Table 26: CFA results. The loadings indicated are all significant a $p < .05$; except for StreakRatio that had a $p > 0.05$. However it was ≈ 0.1 so we decided to keep it in our final engagement metric model.

Factor	Metric	Estimate	Std.Err	z-value
1	NQuizDistinct	0.744	0.067	11.129
	NPassedQuiz	0.906	0.043	21.017
	NPassedFirst	0.764	0.072	10.666
	AvgQuestionTim	-0.067	0.014	-4.927
2	QuestionRatio	0.661	0.063	10.542
	LessonRatio	1.125	0.066	17.098
3	NLoop	1.216	0.351	3.466
	StreakRatio	-0.112	0.081	-1.386

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 taken as exceptional, and therefore should not trigger a change. This is why we decided to compare a learners' variations to those of their classmates.

It is important to note that when a game element is changed, we impose a three lesson cool-off period, where a learner will not be subjected to another adaptation. This is put in place 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. The teachers in the LudiMoodle experiment planned to use the platform during ten lessons, we decided to use three lesson cool-off period between adaptations as this would results with a maximum of 2-3 game element changes for the least engaged learners. Too short a cool-off period could result in an unstable learning environment (frequent changes) and cause learners to be too distracted, and too few changes might reduce the systems capacity to react to learner behaviour.

An example of this timing is presented in figure 31. 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*. 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 between session one and two (noted Var_{12x}) between session two and three (noted Var_{23x}). 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 *green* game element. Their blacklist is therefore updated to contain *blue* and *green* meaning that these game elements will not be proposed in the future. In the first timeline, the teacher ac-

cepts 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. Between session four and five the system uses analyses Var_{23x} and Var_{34x} to determine whether an adaptation is required. In this example the system also detects a decrease in engagement, and proposes the *red* game element. The teacher accepts this new proposal, and the learner is assigned a new game element for the next session.

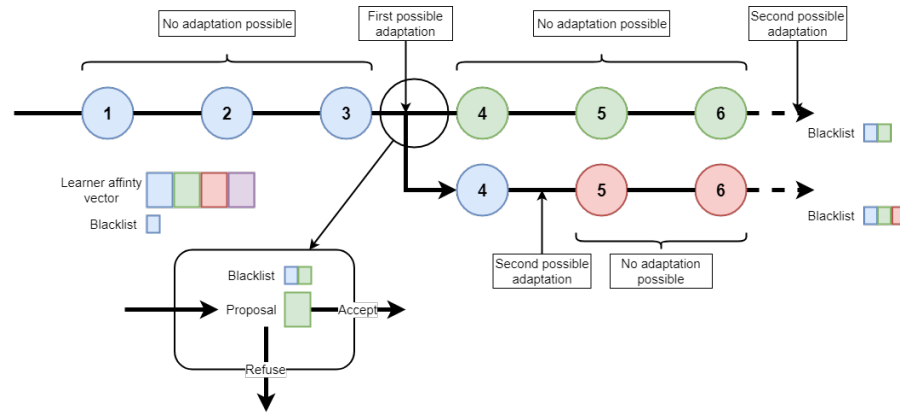


Figure 31: An example of a learners' progression through the learning sessions. Two possible timelines are displayed based on whether the teacher accepts or refuses the proposed game element (each game element is represented by a different colour). The learner's affinity vector, as well as the blacklisted game elements are shown for the different steps.

6.4 DYNAMIC ADAPTATION CONTROL

Finally when the system has detected and proposed a new game element, the change is not automatic, it falls to the teacher to decide whether to adapt or not. As there are many events that happen outside of the observation of the learning platform, the teachers can provide insights that our log traces can miss. They can observe learner behaviour and when a change is proposed by the system, they can judge whether this change is appropriate or not. This also provides a way for further taking the context into account. Teachers were provided with a simple dashboard (figure 32) that showed them the game elements used for each learner during each lesson, as well as any suggestions, and decisions made by the teacher.

6.5 CONCLUSION AND FUTURE DIRECTIONS

In this chapter I have presented this first approach into dynamic adaptation, by integrating questions of when the adaptation can occur, and tracking learner engagement through their behaviour into the adaptation engine. The original plan for this approach was to be tested in a second experiment of the Ludim-

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 32: The proposed decision teacher interface. Here a class with two learners is shown. The first learner was assigned the Timer game element based on their profile. After using it for three lessons, the system proposed they change to the Ranking game element. The teacher accepted this change providing the reason "The learner seems to lack challenge from the timer". For the second learner, they were initially assigned the Avatar game element. After three lessons, the system recommended they change to the Badges game element. However the teacher refused this change citing that the learner "really liked the avatar game element".

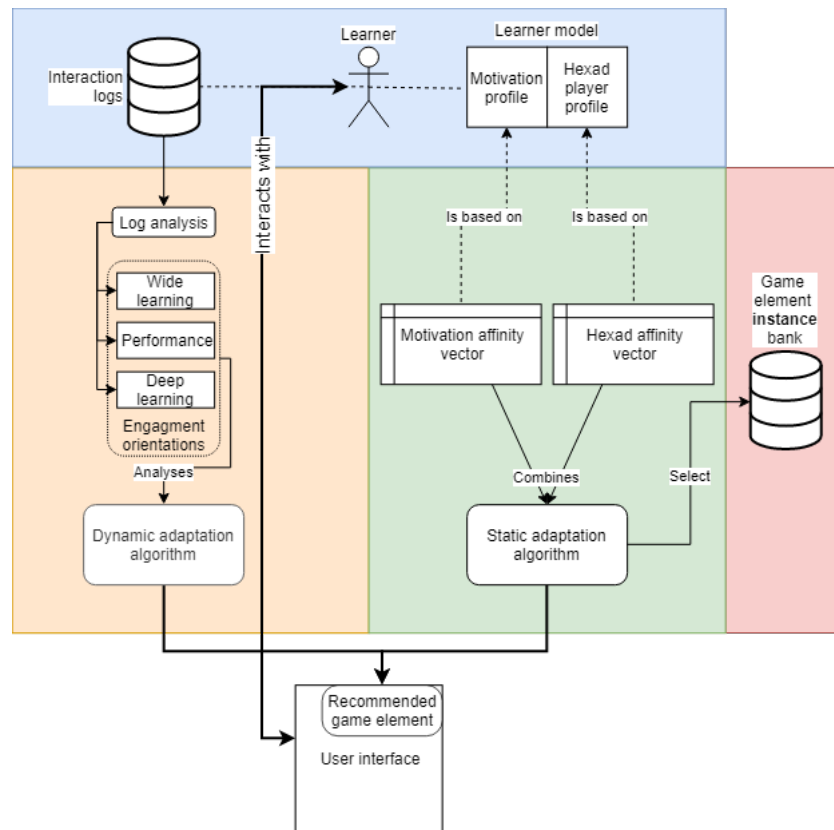


Figure 33: The final step of the adaptation engine architecture

oodle environment that was to be tested during the spring of 2020. Unfortunately due to the COVID19 crisis, and the closing of French schools this experiment was cancelled. The proposed dynamic adaptation could therefore be evaluated using a few different metrics, such as: the number of game element changes proposed, number of refusals/acceptations decided by teachers, general learner and teacher satisfaction with changes (obtained via questionnaire).

First of all, we can update the proposed adaptation engine architecture. Figure 33 shows the new version of the adaptation architecture. On the left is when the learner initially uses the system, in this case, only the static adaptation module is active. On the right, is after the learner has used the system for a while, their traces are collected, split into the three identified engagement factors, and the dynamic adaptation algorithm can run and check if an adaptation intervention is required.

6.5.1 Including different forms of engagement, and data

As observed in the literature on engagement, this model only relies on what can be called Behavioural engagement as we are currently limited to deriving engagement through observable behaviours. Other forms of engagement, such as cognitive and emotional engagement would be highly interesting to

add to this dynamic adaptation approach. However we would need to build a more complex model for estimating these types of engagement.

It is also important to note that in our proposition for dynamic adaptation we focus mainly on *engagement* metrics, and that a dynamic adaptation is triggered when we detect a decrease in engagement. However we could argue that a *decrease* in engagement is not *necessarily* an increase in disengagement. We could therefore think about implementing different metrics more related to disengagement (for example frequent long pauses, not re-attempting failed quizzes) however the log traces we had access to did not allow for this. For example in their current state we cannot tell the difference between a learner that is working on an exercise using a pen and paper, and one that is daydreaming (both would appear as a gap in log traces). We could envisage a system that couples a video analysis with the log analysis to provide context, however such a system would be expensive (if automatic) or time consuming (if manual). Another possibility would be to provide teachers with real-time information about possible confusing log traces, and ask them directly to help clarify. This would however increase the number of things teachers have to control in the classroom.

6.5.2 *Improving the dynamic adaptation system*

Going back to the PDA-LPA design space proposed by Bouzit et al. [15] we could improve on our dynamic adaptation system by exploring the other PDA-LPA system cycle steps. Currently our dynamic adaptation does not make use of the *Prediction* or *Adaptation* steps. One way we could improve our system is by making it *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. For example if a learner loses more **Wide Learning** engagement than the other two, the dynamic adaptation could weight it higher, providing the learner with a more personalised adaptation.

Algorithm 2 : General dynamic adaptation algorithm

*Initialisation – Static adaptation***for** *Learner* in *allLearners* **do**

Learner fills out profile questionnaires;

Learner.generateAffinityVector(questionnaireResponses);

*This gives us a list of game elements for each learner, sorted by decreasing order of predicted affinity.***while** *Main usage loop* **do**

allLearners use platform for one lesson;

allLearners.lastChange + 1;

lessonCount + 1;

System generates engagement factors based on traces;

if *previous lesson factors exist* **then** **for** *Learner* in *allLearners* **do**

Learner.calculateVariationWithPrevious(factors);

if *lessonCount* < 3 **then**

restart Loop;

for *Learner* in *allLearners* **do** **for** *factors variation in range(currentLesson, currentLesson-2)* **do** **if** *Learner.variation in lowestThird(allLearners)* **then**

Learner.lowCount + 1;

if *Learner.lowCount* >= 4 & *Learner.lastChange* > 3 **then**

proposal = generateProposal(Learner);

Teacher.proposeChange(Learner, proposal);

if *Teacher.acceptChange(Learner)* **then**

Learner.changeGameElement(proposal);

Learner.lastChange = 0;

Learner.blacklist.add(proposal);

Algorithm 3 : generateProposal method. This method uses the affinity vector generated from the static adaptation module sorted from highest to lowest affinity.

input : A Learner that needs a new game element proposal
output : The proposed game element for the learner

```

for Game Element in Learner.affinityVector do
  | if Game Element not in Learner.blacklist then
    | | return Game Element;

```

Algorithm 4 : Streak counting algorithm

input : A Learner, a lesson number
output : The streak ratio for the given lesson

```

count = 0;
total = 0;
keepCounting = True;

for operation in Learner[lesson].operations do
  | if operation is AttemptQuiz then
    | | if keepCounting then
      | | | count + 1;
      | | | total + 1;
    | else
      | | if operation is RestartQuiz then
        | | | if operation.afterSuccess then
          | | | | keepCounting = False;

if total == 0 then
  | Learner.lessonRatio[lesson]=0
else
  | Learner.lessonRatio[lesson] = count/total ;

```

Table 27: Three examples of log traces before transformation

Timestamp	LearnerID	GEUsed	Log	Info
1554478862	elevelg04	progress	progression_update	course : calcul-litteral-2019; property : progress; section : 8; value : 46
1554478915	elevelf03	timer	question_gradedright	attempt : 2; course : calcul-litteral-2019; question : 2; quiz : Exercice 10.3; section : 12; sequence : 1; state : gradedright
1554478932	elevelf10	progress	quiz_attempt_finished	attempt : 1; course : calcul-litteral-2019; quiz : Exercice 10.3; section : 12

Table 28: A quiz attempt example made by Learner "evekf10". In this example, the learner answered four questions correctly out of a possible five. The "info" columns have been omitted for simplicity.

Timestamp	LearnerID	GameElementUsed	Log
1552581570	evekf10	progress	quiz_attempt_started
1552581571	evekf10	progress	quiz_pageview
1552581574	evekf10	progress	quiz_pageview
1552581574	evekf10	progress	question_gradedwrong
1552581590	evekf10	progress	quiz_pageview
1552581600	evekf10	progress	quiz_pageview
1552581600	evekf10	progress	question_gradedright
1552581604	evekf10	progress	quiz_pageview
1552581608	evekf10	progress	quiz_pageview
1552581608	evekf10	progress	question_gradedright
1552581613	evekf10	progress	quiz_pageview
1552581617	evekf10	progress	quiz_pageview
1552581617	evekf10	progress	question_gradedright
1552581624	evekf10	progress	quiz_pageview
1552581631	evekf10	progress	quiz_pageview
1552581631	evekf10	progress	progression_update
1552581631	evekf10	progress	question_gradedright
1552581637	evekf10	progress	quiz_summaryview
1552581645	evekf10	progress	quiz_review
1552581645	evekf10	progress	quiz_submit
1552581645	evekf10	progress	quiz_attempt_finished

Table 29: A question attempt made by Learner "evekf10". In this example they failed to answer the question correctly. This log trace would be transformed into the **QuestionComplete** operation with `success = True`.

Timestamp	LearnerID	GameElementUsed	Log
1552581486	evekf10	progress	quiz_pageview
1552581486	evekf10	progress	question_gradedwrong
1552581491	evekf10	progress	quiz_pageview

Table 30: An example of a log trace that would lead to the creation of a **RestartQuiz** operation.

Timestamp	LearnerID	GEUsed	Log	Info
1552581528	elevekf10	progress	quiz_attempt_finished	attempt : 2; course : calcul-litteral-2019; quiz : Exercice 1.1 : QCM; section : 2
1552581540	elevekf10	progress	quiz_moduleview	course : calcul-litteral-2019; quiz : 138
1552581546	elevekf10	progress	quiz_review	course : calcul-litteral-2019; quiz : Exercice 1.1 : QCM ; quiz_attempts : 204 ; section : 2
1552581562	elevekf10	progress	quiz_moduleview	course : calcul-litteral-2019; quiz : 138 ; ;
1552581570	elevekf10	progress	quiz_start	course : calcul-litteral-2019; quiz_attempts : 247 ; ;
1552581570	elevekf10	progress	quiz_attempt_started	attempt : 3 ; course : calcul-litteral-2019; quiz : Exercice 1.1 : QCM ; section : 2

DISCUSSION OF THE MANUSCRIPT AND CONCLUSION

This chapter summarises the contributions presented in this manuscript, and offers future research directions that can be followed to deepen the work presented here.

7.1 THESIS OVERVIEW

Gamification is used more and more in educational settings to foster learner engagement and motivation in otherwise tedious or repetitive tasks. As learners have different expectations and preferences towards game elements, it is important to be able to provide them with appropriate game elements. This is essential for making sure that gamification works for every learner.

The work presented in this manuscript was all aimed at proposing new methods of tailoring and adapting game elements to learner profiles, as well as methods for evaluating the efficacy of different adaptation approaches. Furthermore, as learner expectations and preferences can vary overtime, we also investigated how adaptive systems can monitor learner engagement through behaviour and how we can leverage this to propose better adaptations when required. The manuscript presented here shows that by adapting game elements statically to learner profiles, and dynamically to learner behaviour we can better foster engagement and motivation in learners. Through such systems, we consider each learner as an individual, crafting a meaningful gameful experience for each of them. In chapter 1 (section 1.3) I proposed three research questions grounded in the "second wave" of gamification research that motivated the rest of the work. Most notably it served as an initial structure for the adaptation engine architecture, the final version of which is presented in figure 34. Whilst this final version is context specific in its nature, the different modules and the research that severed to build them can be extended and adapted to different contexts.

7.2 SUMMARY AND DISCUSSION OF THE CONTRIBUTIONS

This thesis serves to deepen the knowledge in the adaptive gamification for education field.

In this manuscript I have presented four major contributions summarised here. All of my contributions plug into a generalised adaption engine architecture that serves as a general framing device.

Chapter 2 presents a study of the related work in the adaptive gamification in education field that identifies four research gaps. These gaps are somewhat filled by the other contributions. As a reminder the four research gaps are:

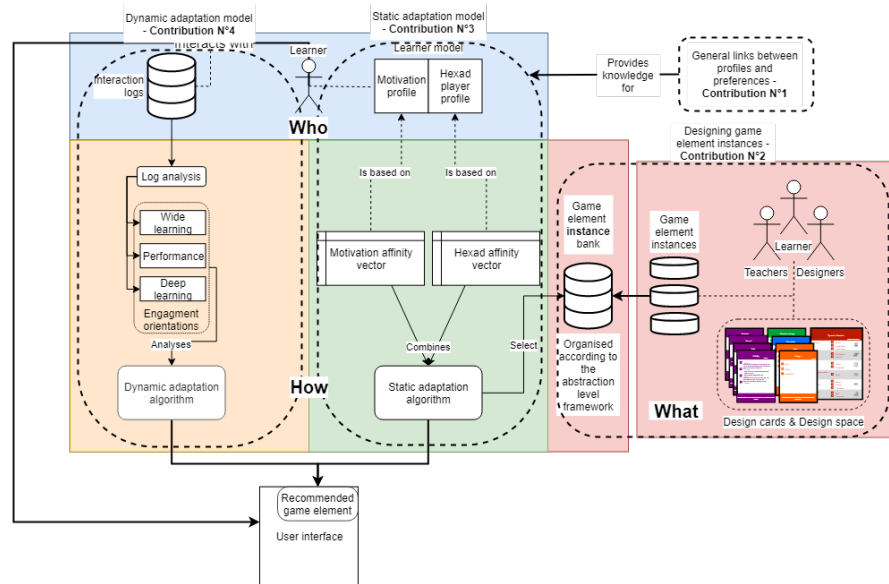


Figure 34: The full adaptation engine architecture. My contributions are highlighted and numbered here.

1. a gap in game element nomenclature and design
2. a gap in comprehensive learner models
3. a gap in the evaluation of adaptation methods
4. a gap in dynamic adaptation methods.

7.2.1 Contribution 1: A study on the importance of context and implementation of game elements.

The work presented in chapter 3 shows the importance of the gamified context and the implementation of the different game elements. We showed that three major factors influence user motivation in tailored gamification: the implementation of a given motivational strategy, the choice of the user typology, and the gamified context. We provided some general game element recommendations for different Hexad profiles (considering the entirety of the user profile, and not just the dominant type) independently from the context of the gamified system. However, it is important to note that the context plays an important role in the effect of game elements on user motivation and engagement. Using these recommendations directly is therefore ill-advised, and should be seen as a fall-back when no other context relevant recommendations are available (some game elements such as Badges seem to work no matter the context, and therefore could be used). The approach we used to generate these recommendations (the partial least squares analysis) however can directly be reused to generate recommendations for other specific contexts. This inspired our approach for creating domain appropriate rules in chapter 5.

The work presented in this chapter is a first step in filling **gap 1** (by providing insights in creating user profiles using non-contextual information) and **gap 2** (by providing a structured game element classification based on abstraction levels, and motivational strategies).

7.2.2 *Contribution 2: A game element design space and design tools to explore it*

Chapter 4 addresses the gap in "*game element design and nomenclature*". We demonstrated that by integrating all the actors of the gamification process via a comprehensive design process, and design tools, we could design game elements that were suited to learners needs and expectations. The design space and tools were designed to be as simple to use as possible and to guide designers to consider many different possibilities for game element design. Through the use of these tools, we found that designers were able to consider many different ways to implement the various motivational strategies and game elements used in the LudiMoodle project. The design space also allows us to consider the context and gamified activity when designing game elements, which was shown to be important by the previous contribution. Although we did not extensively test our design space, we believe that it could be an extremely useful tool for creating meaningful game elements that consider both the users and the usage context.

7.2.3 *Contribution 3: Domain specific static adaptation rules - A contextualisation of contribution 1*

Following the recommendations made by contribution 2, we used the results from the LudiMoodle study presented in Chapter 5 to create domain appropriate adaptation rules. Comparing the effects on learners based on adaptation from contextual (initial motivation for learning) and de-contextualised (Hexad player profile) information, we created a learner model based that combined both, as the combination of both provided better effects on learner motivation and engagement than either of the single profile approaches. Using a compromise algorithm to combine the recommendations from both learner profiles we able to generate an appropriate game element recommendation based on this dual learner model. This learner model is therefore a combination of both context dependant and context independent information about the learner and serves to fill the gap in *comprehensive learner models*. This contribution also provides an insight into the gap in the *evaluation of adaptation methods* by proposing an approach that evaluates and compares different adaptation methods.

7.2.4 *Contribution 4: A dynamic adaptation based on learner behaviour*

In chapter 6 we explored a new adaptation method: a dynamic adaptation approach. This adaptation is based on observed learner engagement through an

analysis of their behaviour using a trace based approach. The evolution of learner engagement is tracked during the usage of the gamified tool and compared to those of the other learners in the same class. If the system detects an abnormal decrease in engagement (when compared to other learners), it proposes a new game element for this learner. The teacher then has the final say on whether the adaptation takes place or not, allowing them to provide their expertise, and avoid unnecessary changes to the learner's environment. This contribution serves as a first step in exploring the gap in *dynamic adaptation methods*, by proposing a method for analysing learner behaviour using a trace based approach, and by showing how this behaviour can be linked to learner engagement.

7.3 LIMITATIONS

7.3.1 *Specificity of our approach*

A first major limitation is the specificity of the the approach presented in this manuscript. Even though I have tried throughout this manuscript to present the most generalisable results possible, I cannot ignore the highly specific nature of these findings. As stated first in chapter 3 and throughout the rest of this current work, game element recommendations to users are highly context dependant. The work presented here cannot be taken as is and reused in a different context. Even if we stay in an educational context, changing even the learners (age, cultural background etc.) may have a significant impact on the effects of gamification on their motivation and engagement. The future research perspective presented in 7.4.1 attempts to provide an idea of how the general adaptation engine approach can be adapted to different contexts. In summary, the final adaptation engine is highly context dependant, but the approach, and ideas that were used to create it are not.

7.3.2 *Game element design limitations*

Currently the design space presented in chapter 4 was only tested with teachers, designers, and engineers. Due to constraints in the LudiMoodle project we were unable to directly include the learners in the design process. Although their feedback was obtained during interviews held after they used an initial prototype of the LudiMoodle platform, and taken into account during the design process, we were unable to have them participate in design sessions directly. Participatory design has been shown to be quite effective in the field of game design [76, 78], however can designing with young children can present some interesting challenges [144].

7.3.3 *Shortsightedness of the dynamic adaptation log trace analysis*

The goal of the dynamic adaptation approach is to track and analyse learner behaviour and propose an adaptation when learner behaviour shows a loss

of engagement with the learning platform. However many of the learner behaviours happen outside of the learning platform. For example, during the experiment ran in the context of the LudiMoodle project, teachers noted out of platform behaviours generally related to interactions with other learners. One of the factors that motivated us to give teachers the final say on game element adaptations is that they would be able to observe these out of platform behaviours and make informed decisions about game element recommendations provided by the system. However the fact that our system cannot directly observe out of platform behaviours is a limitation. Furthermore as specified in chapter 6 the current model does not estimate learner *disengagement* which could be different than a loss engagement. Therefore we could expand by investigating more measures of *disengagement*, for example: long pauses (whilst being careful to take out of platform behaviours) and repeated mistakes (especially when the same mistakes) could be considered.

7.4 FUTURE RESEARCH PERSPECTIVES

The contributions presented in this manuscript offer a substantial advancement in the field of adaptive gamification. I believe that they could be extended following these lines.

7.4.1 *Re-purposing the adaptation engine for other contexts*

Our adaptation engine is tailored for use in a specific context: secondary school level mathematics. However we believe that it can be easily extended to other contexts. For the educational context, re-using the academic motivation scale, albeit transposed for the different subject (i.e. the initial question "Why do you go to maths class?" becomes "Why do you go to french class?" for example). However as stated many times throughout this manuscript, the context is extremely important in determining the impact of game elements on learners. We cannot be sure that appropriate static adaptation rules for secondary school learners in mathematics class will also be appropriate for learning French for example. We therefore recommend to generate new adaptation rules by running a pre-study where learners will be able to interact with the game elements over a short period of time and evaluating their motivational variations and behaviours. From this trial period, new affinity matrices for each of the profile models and individual learner affinity vectors should be generated. Once these have been recreated the rest of the adaptation engine functions in a similar manner as in our current context. For the static adaptation approach we could simply re-use the compromise algorithm to select the appropriate game elements for learners. However we cannot ensure that in a different context the dual profile approach would result in the best game element recommendation for learners. We would therefore need to re-compare the three profile models (both single and dual) to be sure. Furthermore for our dynamic adaptation approach, a new set of metrics and engagement factors would need to be created based on behaviour observations in the new context.

In short, for re-use in other contexts (different learning subject / other gamified context) our general adaptation engine approach can be re-used, even if the individual modules need to be recreated with context specific information. This makes our approach somewhat robust to re-use in other contexts, even if the actual prototype is rather context specific. Changing contexts does not have to be limited to educational contexts neither, we could easily adapt this adaptation engine to other contexts such as sport or healthy living using a similar approach.

7.4.2 *Different approaches to game elements*

7.4.2.1 *Finer grained adaptation*

In this manuscript, the different adaptation approaches presented are operated only by *changing* the game element proposed to learners (for example by swapping points for badges, or timer). However, as shown in chapter 2 for instance, we could adapt by *modifying* the rules of the game element. For example, we could increase the number of points provided by a score game element, or hide badge conditions meaning that learners have to explore the platform more. An interesting idea could be to use the dimensions presented in the game element design space (presented in Chapter 4) as possible modifications to the game elements. This would essentially create a new set of game element instances, with only slight modifications to their functionalities or presentations. This would, however, still run into the problem of having to manually design all of the instances from which the adaptation engine selects relevant game elements. Furthermore new adaptation rules would need to be established to propose links between the learner model and the design dimensions or game element properties. In their current state, the rules associate game elements (points, badges, timers etc.) with the learner model, but do not offer insight into how the different game element properties can affect these preferences. An experiment similar to the one presented in chapter 3 could be ran, with storyboards presenting different game element instances derived from the same game element, which would provide us with generalised findings. Figure 35 shows an example of different storyboards for the points game element.

The results and links observed from such a study could help improve the design space and design tools by indicating which of the different design choices actually have an impact on learner motivation or behaviour. If this study was ran in a de-contextualised setting (like in chapter 3) we would only gain information about whether these lower level decision affect the effect of game elements. These findings would also need to be contextualised for the specific context. As it stands we have a general idea (based on related literature) of how each design dimension can affect learners, but we still lack validation of how the lower-level choices affect learners. A recent study by Hicks et al. [66] shows a first investigation into this idea. They explored the concept of "Juiciness" in gamification design (i.e. adding animations, particle effects, dynamic soundtrack and sound effects). They compared four versions

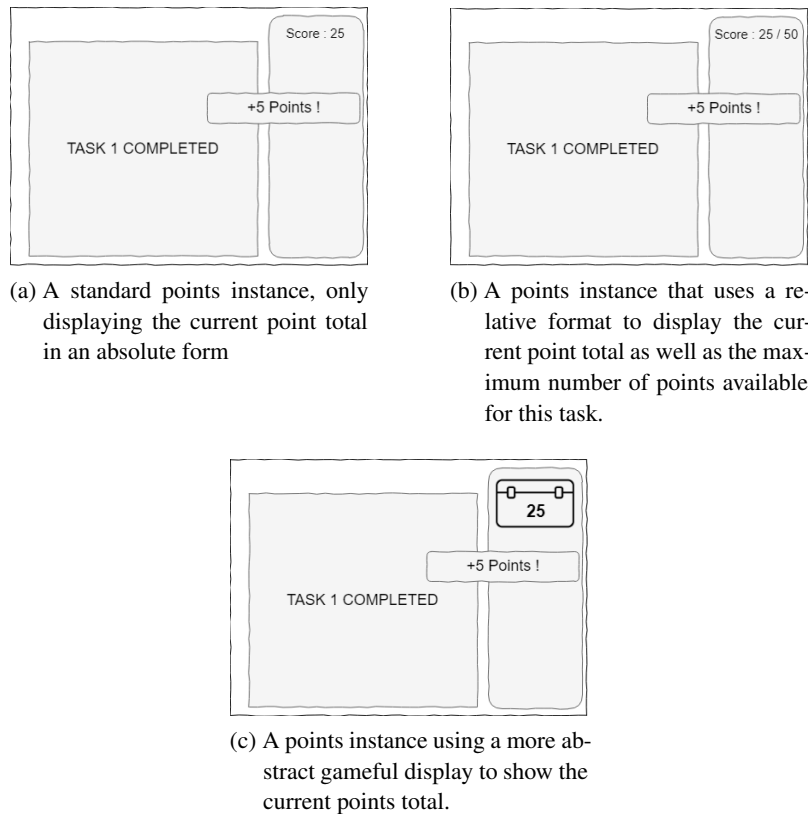


Figure 35: An example of three different points instances that could be compared in a study to investigate the links between learner profiles and the game element design dimension choices.

of their game (basic, gamified, juicy, and combined juicy gamified) and found that only the juicy conditions improved the three self determination theory needs. This points to the effect of game elements being a result of their design rather than their functionality, and warrants further investigation into what exactly affects learners in each game element.

7.4.2.2 Combining game elements

At the moment, our results and analysis are based on the central idea of one learner, using one game element. In fact, all of our analyses are based on the observations of the effects of single game elements on individual learners. However, in most commercial gamification approaches game elements are used in combination with each other. Points based systems serve to fuel leaderboards, timers are used to judge how many points, or what kinds of badges are given out, etc. Currently little is known about how multiple game elements interacting with each other can affect learners (or users in a general gamification context). A study to investigate this could be somewhat long and complex as even by restricting the scope to pairs of game elements would result in a large number of experimental conditions.

7.4.3 *Understanding learners better*

7.4.3.1 *Expanding the learner profile*

Another perspective could be to further expand the learner profile taking more context related information into account. As shown in Chapter 2 section 2.2.4.1, only one of the reviewed papers uses learner domain expertise to adapt [11] (they used learner roles, tutor or tutee, i.e. expert or non expert to adapt). I believe that we could expand further on this by looking into ways to include learner domain knowledge as a profile for adapting gamification. For example learners with a higher level of domain expertise could be expected to respond positively to more challenging game elements than those with lower expertise (it is possible however that there is an overlap between intrinsically motivated and expert learners, meaning that this distinction might be redundant). During the feedback session held with the learners who participated in the LudiMoodle experiment, many learners stated that they found the *Timer* game element was too difficult and stressing. However a few stated that they found it challenging and fun. I believe that this difference in perception could be linked to learner expertise. It is worth noting that Monterrat et al. [105] showed a difference in how learners perceived game elements and how they were affected by them, so we should be wary about basing adaptation rules solely on subjective measures.

7.4.3.2 *Automatically detecting learner profiles*

In our current adaptation model, learner profiles are established using questionnaires, the academic motivation scale for initial motivation [143], and the Hexad survey for the player profile [141]. This can be a problem as these questionnaires are somewhat long and use sometimes confusing language, meaning that some learners may not fully understand the statements or responses, which can lead to imprecise profiles. It is important to note that we did try to ensure that the questionnaires were adapted to learners during the LudiMoodle project, by simplifying the statements and instructions, however some learners still stated that they were confused by some of the more complex statements. Furthermore, these questionnaires are filled out before learners can start using the platform, requiring a long startup period where learners have to complete this unrelated (to the learning) task before they can interact with the gamified experience.

Investigating automatic ways to assign profiles could be interesting as a way to skip a lengthy questionnaire phase when starting to use a gamified platform. Learners would be able to jump right into the system, using a more generic version, or experimenting with the different game elements. We could use their behaviours towards the different game elements and the gamified system in general to establish a profile and recommend game elements. For example by categorising users based on their behaviours, then checking if these behaviour based categories present similar Hexad or initial motivation profiles. The literature review by Klock et al. [80] also identifies the auto-

mation of gamification tailoring as a future research agenda, however they talk mainly about the attribution of game elements to learners rather than the creation of profiles. Monkarezi et al. [102] proposed an automatic method to estimate learner engagement during a structured writing activity using facial expressions and heart rate. Their results showed detecting of engagement with "moderate" accuracy, and an improvement over current facial detection methods.

7.4.3.3 *Learner controlled adaptation*

As it stands, it is the teacher who has final say on any adaptation recommendations. This was mainly decided due to the age of learners in the LudiMoodle project. However, recent research by Tondello & Nacke shows that when given the choice to select which game elements they wished to activate in a gamified image tagging app [139], user choice partly corresponded to their Hexad player types. We could therefore investigate if learners would be able to appropriately respond to game element recommendations by the system (i.e. select game elements that will motivate them, and avoid those that will demotivate them). For example instead of providing the teacher with the game element recommendations, we could show them directly to the learners. To test whether they would be able to select the most appropriate game elements, we could offer two choices when recommending a game element: the one recommended by the system, and the one that our system would detect as "counter-adapted" (i.e. scoring the lowest affinity). Such an experiment could provide useful insights into how well learners understand the different propositions made by the system, and if they are capable of understanding how the different game elements affect them.

7.4.4 *Testing the final version of the adaptation engine - comparing the effectiveness of a static versus dynamic adaptation approach*

This final version of the adaptation engine (combining both static and dynamic adaptation) is still to be tested in real world learning conditions (due to the COVID19 crisis). To evaluate the different adaptation (static and dynamic) approaches, we could follow a similar experimental procedure as presented in chapter 5, but with three different gamified conditions, and one non gamified control condition :

1. Learners would be randomly assigned game element (gamified control condition)
2. Learners would be assigned game elements based on their Hexad and Motivation profile (static adaptation condition)
3. Learners would initially be assigned game elements based on their Hexad and Motivation profile. Their behaviour would then be tracked, and they would be proposed different game elements during the experiment based on this (dynamic adaptation condition).

4. Learners receive no game elements. They use a version of the learning platform without any gamification (non gamified control condition).

This study would therefore allow us to compare the effectiveness of adaptation versus no adaptation (conditions 2 & 3 vs 1) and the effectiveness of static versus dynamic adaptation (condition 2 vs 3). We could also compare each of the gamified conditions to the non gamified control to understand on whole if these gamified conditions are more or less effective than no gamification at all. The results of this would help to assess one of the research gaps identified in my first contribution: the gap in the evaluation of different adaptation methods.

8

GOING FURTHER, DYNAMIC ADAPTATION IDEAS AND PREVISIONS

Studying the interaction traces (as discussed in the previous chapter), to analyse behaviour to see motivation, engagement etc in learners. Then using this data in real-time (with the intervention of teachers) to refine and perfect the proposed adaptation.

8.1 A STUDY OF BEHAVIOURS IN AN IMAGE TAGGING SETTING.

APPENDIX TO CHAPTER 3 - ADDITIONAL
INFORMATION FOR THE CROWDSOURCED STUDY

A.1 PARTICIPANT INSTRUCTIONS

Participants were presented with the instructions shown in figure 36. The link provided redirected participants to the profile questionnaire which was hosted on the *google forms* platform. The participants were shown pairs of storyboards and asked **Which situation would motivate you more to use the system?** (as shown in figure 37).

Game Element Preference Survey

Instructions -

Presentation:

The aim of our work is to motivate users to complete tasks in a system. This survey will help us to understand what types of motivators different types of users prefer.

In the following survey, you will be presented with a set of storyboards that show a system that uses various types of motivators.

The system could be for example an app that helps you learn a new language where the tasks are different vocabulary exercises. The motivators could be a badge that is given to the user for completing tasks, or a timer that incites users to complete each task faster than the last. Each storyboard presents a situation where a given motivator is proposed.

Example:

1 2 3

In this situation, after completing a task, the user is rewarded with the "Key" badge (motivator).

Instructions:

You will be presented with pairs of storyboards. For each pair of storyboards, we ask you to choose the one that you would personally find motivating.

Before completing the survey please fill out the other questionnaire [here](#) and provide your Figure Eight contributor ID at the end to receive the full payment. This step should take between 4 and 5 minutes to complete.

If the link provided doesn't work, please paste the following into a new browser page: <https://goo.gl/forms/K0HGrsW4sV5syj813>.

You can find your Contributor ID by clicking on the "help" button in the upper tool bar.

Figure 36: Participant instructions

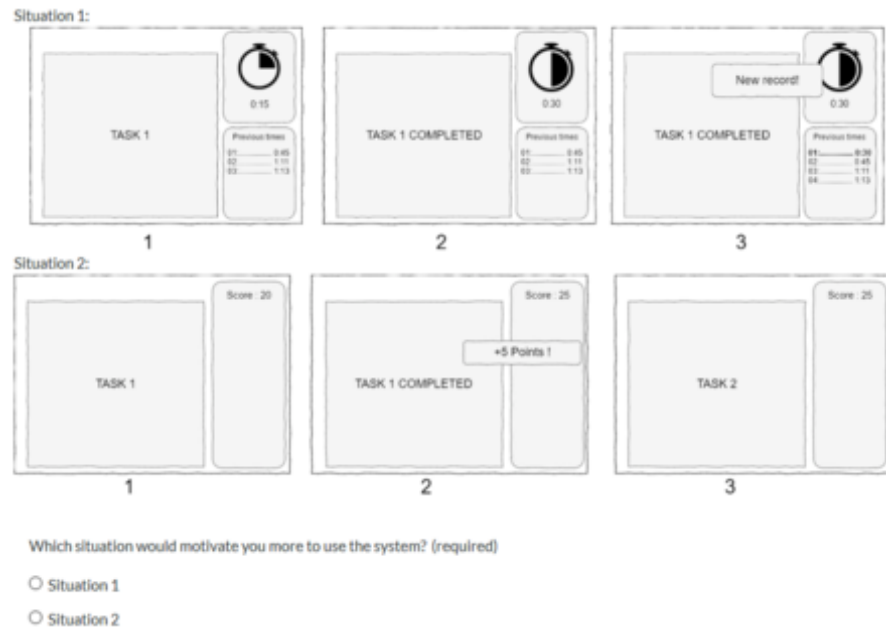


Figure 37: An example of one of the pairs shown to participants, in this case the Timer and Points game elements were compared.

A.2 STORYBOARDS USED TO PRESENT EACH GAME ELEMENT.

The following figures show the storyboards used to represent our game elements. Each storyboard illustrates a user completing various generic tasks.

A.2.1 Rewards

These storyboards represent the three game elements that implement the Rewards motivational strategy. In the Points storyboard (fig. 38), the user receives points each time he/she completes a task. The panel on the right shows how many points the user has accumulated. In the Badges storyboard (fig. 39), the user gains a badge for completing the task. The panel on the right shows the user which badges he/she has unlocked (in black) and which badges he/she has not unlocked yet (in grey). The Useful Rewards storyboard (fig. 40) shows the user completing a task and receiving a "Give example" item. This can be used to show the user an example to help him/her complete tasks.

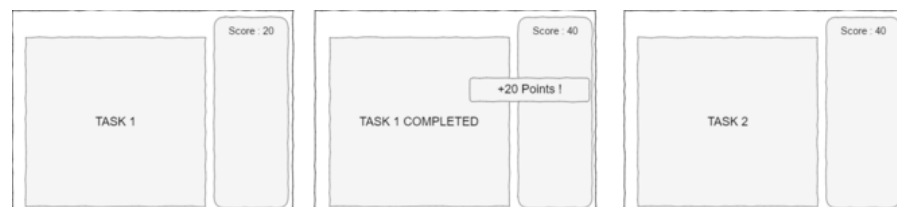


Figure 38: The Points storyboard.

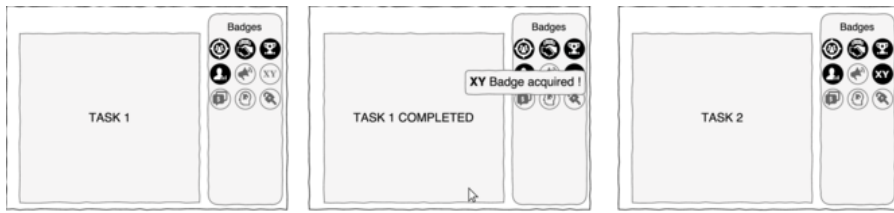


Figure 39: The Badges storyboard.

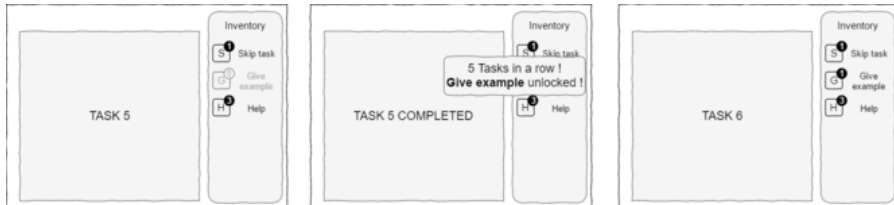


Figure 40: The Useful Rewards storyboard.

A.2.2 Goals

These storyboards show the two game elements corresponding to the Goals motivational strategy. In the External Goals storyboard (fig. 41) the user completes a task, and is given a new goal by the system. On the right the user can see what goals he/she currently has, and can track which are completed. For the Self Goals storyboard (fig. 42), the user can click on a button in the right panel to open an interface that lets them add a new goal. The panel on the right shows completed goals.

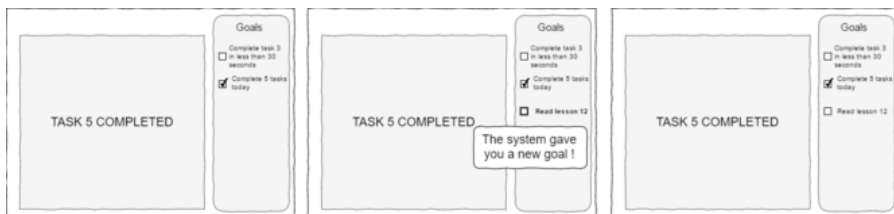


Figure 41: The External Goals storyboard.

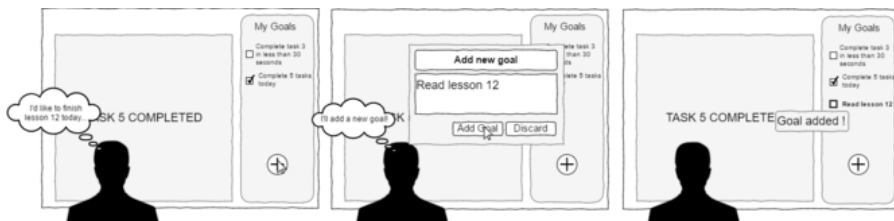


Figure 42: The Self Goals storyboard.

A.2.3 Time

For the Time motivational strategy we used two game elements. The Schedule storyboard (fig. 43) shows a user over the course of five days. The user needs to complete a task everyday. The user successfully completes a task each day and on the final day unlocks a bonus. The Time storyboard (fig. 44) shows a stopwatch that shows the user how long it took to complete the task. On the bottom right, the user can see a table of previous times.

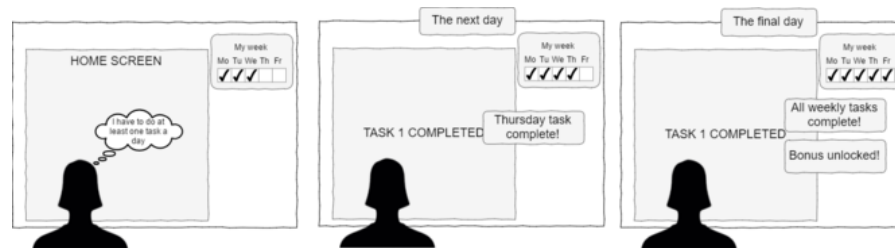


Figure 43: The Schedule storyboard.



Figure 44: The Timer storyboard.

A.2.4 Social Interaction

These storyboards represent the 3 game elements that implement the Social Interaction strategy. The Trading storyboard (fig. 45) shows a user that cannot advance without a "key" item. The user then uses the chat on the right to ask if someone can trade a key. Another user (Fred) accepts and proposes to trade a key for three "gems".

The Teams storyboard (fig. 46) shows a user completing a task. On the right the user can see the other members of his/her team as well as an overview of his/her teammates progress. Each time a user in the team completes a task, the team receives points.

In the Discussion storyboard (fig. 47) a user is stuck on a task. He/she uses the chat on the right to ask other users for advice. Another user offers an answer, that the user tries and is able to complete the task. The user also leaves a "like" on the other users' message to let them know that he/she helped.

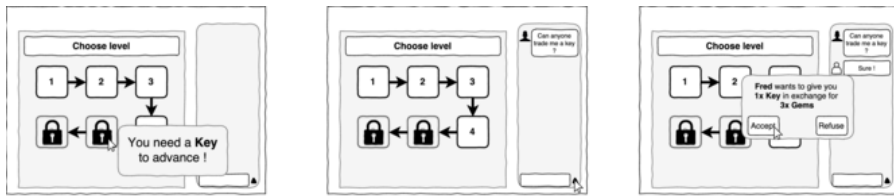


Figure 45: The Trading storyboard.

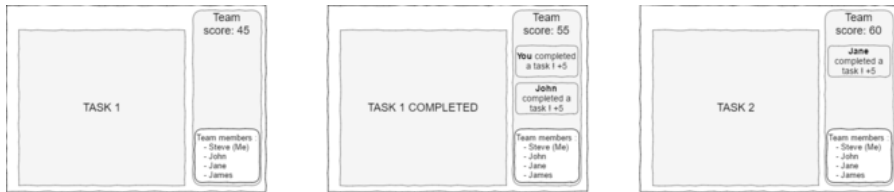


Figure 46: The Teams storyboard.



Figure 47: The Discussion storyboard.

A.2.5 Progress

These storyboards show the two Progress game elements. In the Progress Compared storyboard (fig. 48) the user can see a progress bar on the right. To the left of this progress bar, the user can see how the 25% 50% and 75% of their class is doing. When the user completes more tasks than 50% of the class, he/she is shown a popup that notifies him/her of this. The Progress Task storyboard (fig. 49) shows a simple progress bar on the right. When the user completes a task the bar fills up.

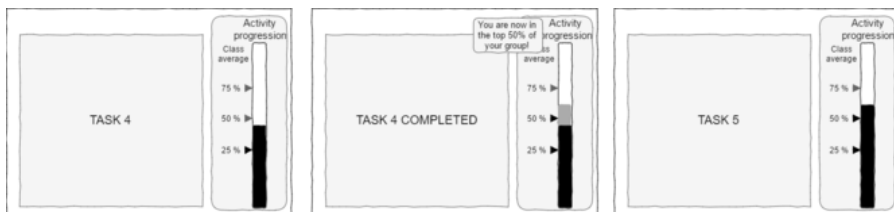


Figure 48: The Progress Compared storyboard.



Figure 49: The Progress Task storyboard.

A.2.6 Test storyboards

As described in section 3.4.5, these are the storyboards used for the "test" questions. Each of these storyboards was presented in a pair with their non test counterpart. Participants that selected more than one wrong answer in these test questions were rejected from our study. The principle is the same for each storyboard, the user receives a penalty for completing the task. For example in the Test situation for Task Progress (fig. 50) the participant had to decide between a storyboard where the gain progression for a task completed, and one where they lose progression for the same task. For the Test situation Badges, the user loses badges (fig. 51), and for both Test situations for Points (fig. 52 & fig. 53) the user loses points.

The order of the test situations was randomised and they were not presented together.

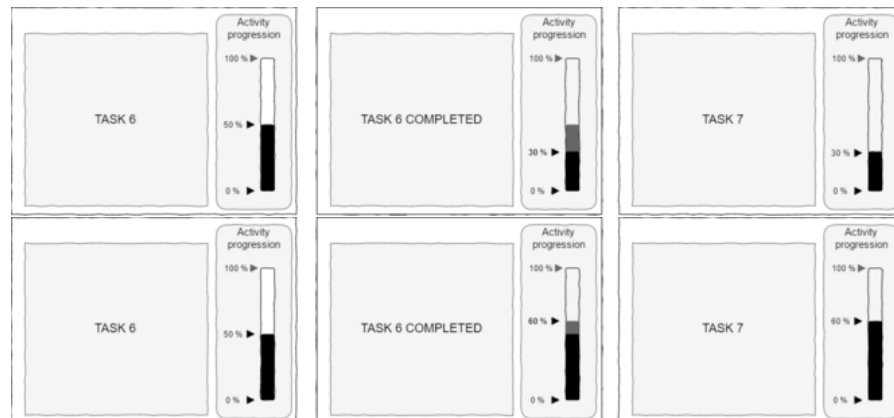


Figure 50: Test situation for Task Progress.

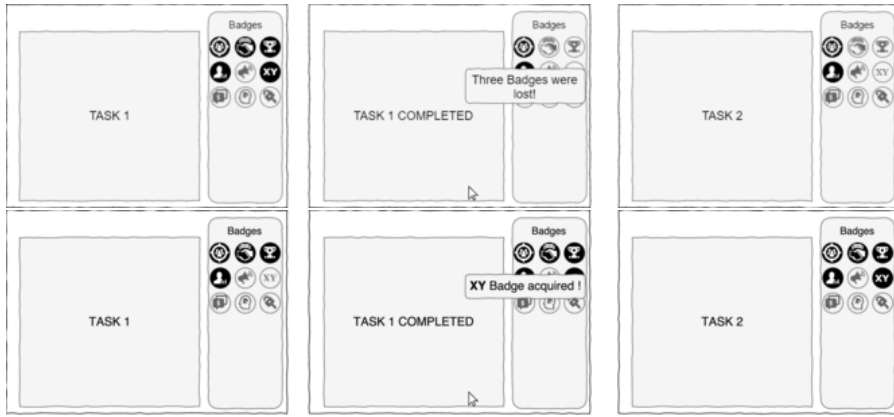


Figure 51: Test situation for Badges.

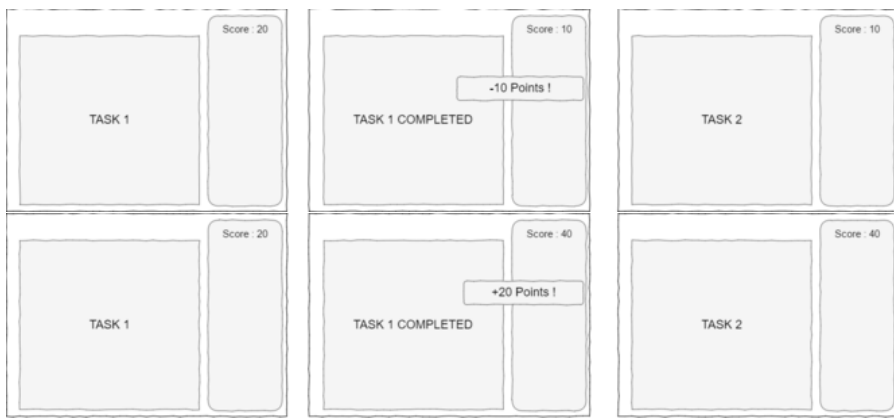


Figure 52: One of the Test situations for Points.

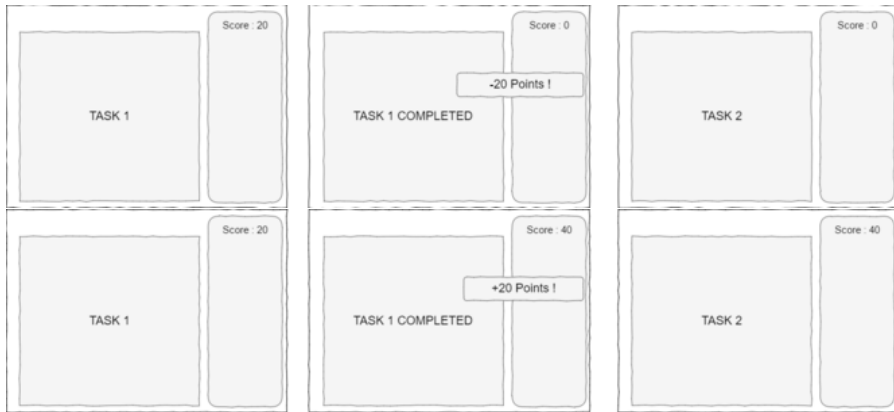


Figure 53: One of the Test situations for Points.

B

APPENDIX TO CHAPTER 4 - EXAMPLES OF DESIGN BOARDS

Presented here are some of the design boards completed during the co-design sessions presented in [Chapter 4](#).

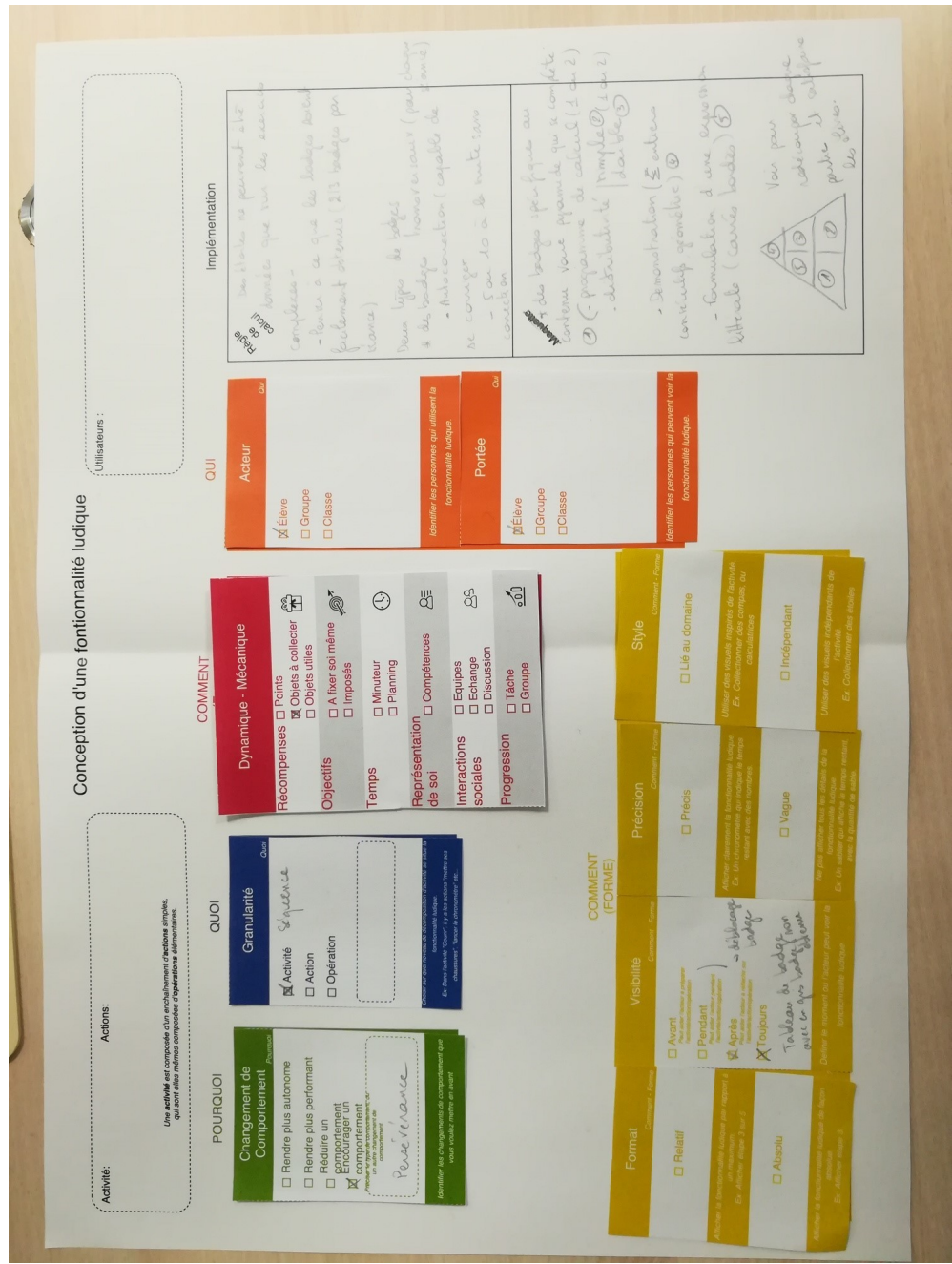


Figure 54: This design board shows the "Badges" game element designed during the co-design sessions. This game element was designed to "encourage learner perseverance", and concerned the whole gamified activity (a lesson). It was designed to be used by and be visible by single learners. Teachers did not use all the visual design dimensions, only specifying that the badges be visible after a quiz (learners would be informed after a quiz if they obtained any badges). They would also be able to access a badge page to check objectives. Teachers designed a few of the different types of badges that would be available as well as the general look of the badge page.

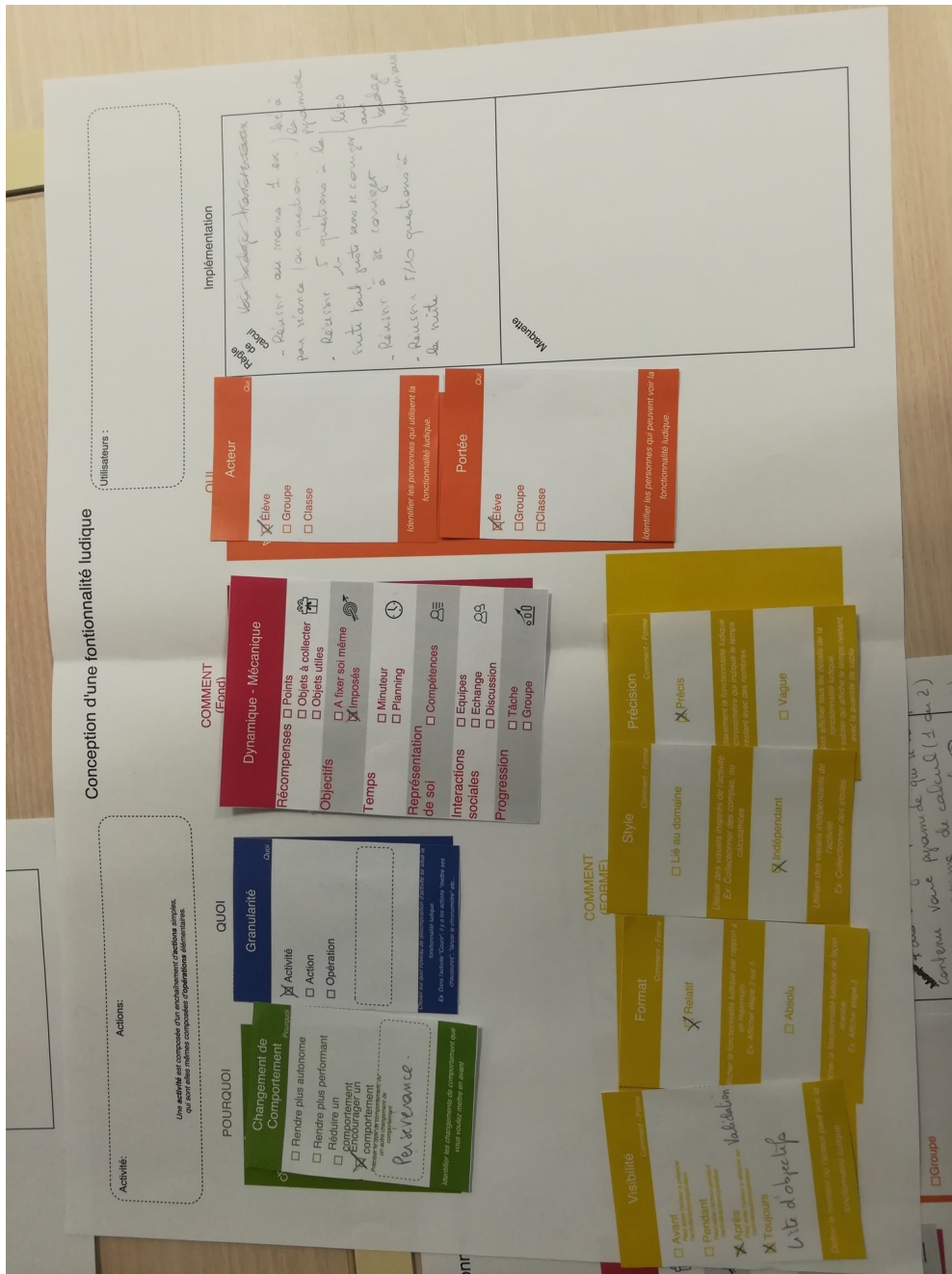


Figure 55: This design board shows the external goals game element designed during the co-design sessions. Teachers chose to implement a straight-forward design for this game element, with a simple list of objectives, and check boxes to help learner track which objectives they have already completed. Teachers also used the space on the left to specify the different objectives that would be provided to learners. This game element was ultimately not used in the LudiMoodle experiment, as it was decided that the proposed goals would be too repetitive and would not offer a diversity of interest to learners.

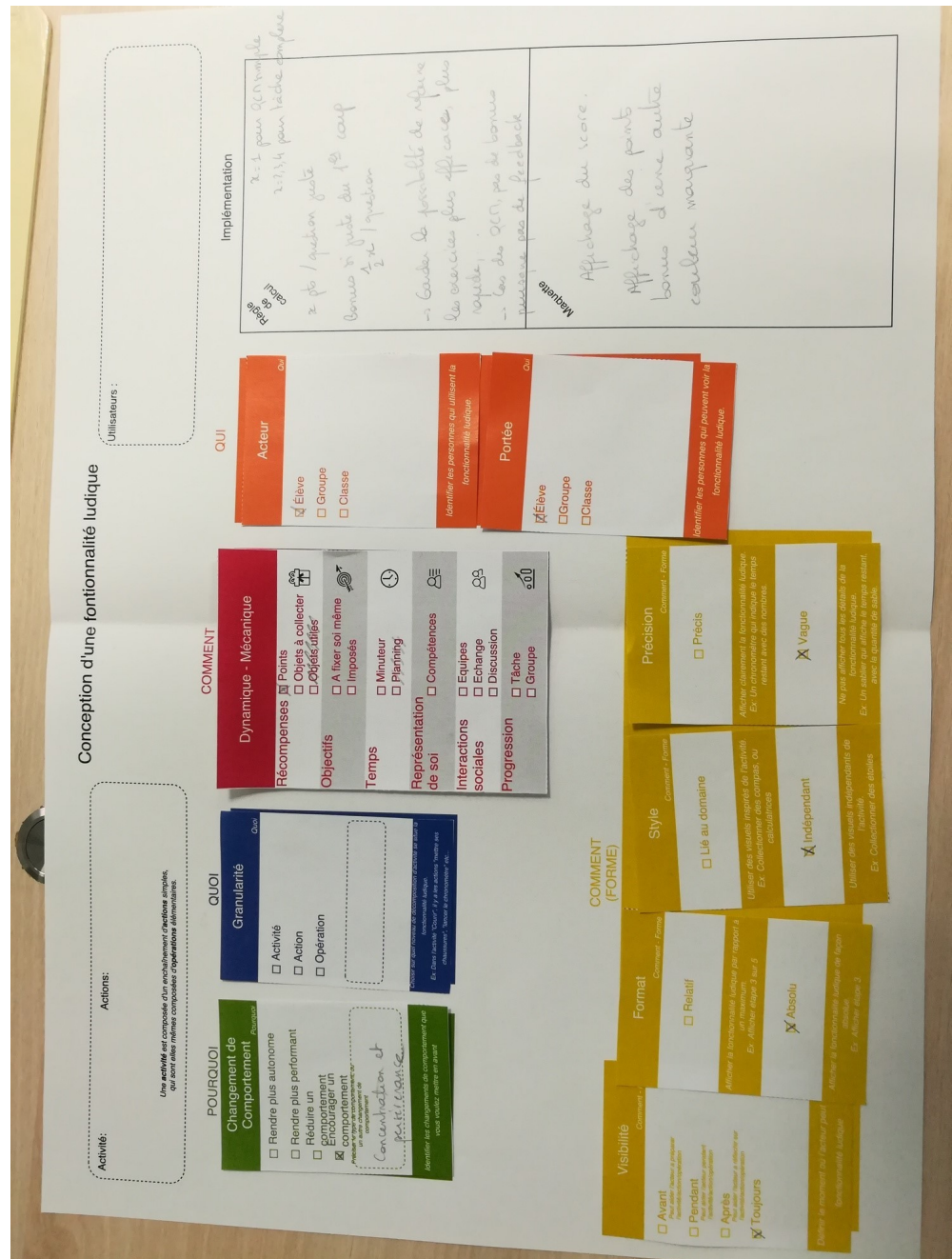


Figure 56: This design board shows the score game element designed during the co-design sessions. Teachers designed this game element to aid learner concentration, with a simple independent design. An important point is that they wanted to make it clear to learners that this score was in no way related to possible grades, so they decided that it should be displayed in an absolute format (i.e. without a maximum). Teachers mainly focused on the different point values that would be given for each of the different quizzes.

USER PROFILE DEFINITIONS AND QUESTIONNAIRES USED

c.1 BRAINHEX PLAYER TYPOLOGY

This player typology was used in the crowdsourced study presented in Chapter 3.

c.1.1 *Types*

The Brainhex[110] player typology describes 7 types of players:

- Seeker: people who like finding strange and wonderful things, or finding familiar things.
- Survivor: people who like escaping from hideous and scary threats, pulse-pounding risks.
- Daredevil: people who like negotiating dizzying platforms or rushing around at high speed while you are still in control.
- Mastermind: who like solving puzzles and devising strategies.
- Conqueror: people who like defeating impossibly difficult foes, struggling until you eventually achieve victory, and beating other players.
- Socialiser: people who like hanging around with people you trust, and helping people.
- Achiever: who like collecting anything you can collect, and doing everything you possibly can.

c.1.2 *Questionnaire*

Participants were first asked to rate each of the following statements from 1 (I hate it) to 5 (I love it):

- Exploring to see what you can find.
- Frantically escaping from a terrifying foe.
- Working out how to crack a challenging puzzle.
- The struggle to defeat a difficult boss.
- Responding quickly to an exciting situation

- Picking up every single collectable in an area
- Looking around just to enjoy the scenery.
- Being in control at high speed.
- Devising a promising strategy when deciding what to try next.
- Feeling relief when you escape to a safe area.
- Taking on a strong opponent when playing against a human player in a versus match
- Talking with other players, online or in the same room.
- Finding what you need to complete a collection.
- Hanging from a high ledge.
- Wondering what's behind a locked door.
- Feeling scared, terrified or disturbed.
- Working out what to do on your own.
- Completing a punishing challenge after failing many times.
- Co-operating with strangers.
- Getting 100% (completing everything in a game)
- Playing in a group, online or in the same room

Participants were finally asked to order the following game related experiences into a sequence from 0 (worst) to 6 (best):

- A moment of jaw-dropping wonder or beauty.
- An experience of primeval terror that blows your mind.
- A moment of breathtaking speed or vertigo.
- The moment when the solution to a difficult puzzle clicks in your mind.
- A moment of hard-fought victory.
- A moment when you feel an intense sense of unity with another player.
- A moment of completeness that you have strived for

c.2 BIG FIVE TRAITS

This personality model was used in the crowdsourced study presented in Chapter 3.

c.2.1 *Traits*

The Big Five[49] personality trait system describes five types of personality traits.

- Agreeableness: people who are generally considerate, kind, generous, trusting and trustworthy, helpful, and willing to compromise their interests with others.
- Conscientiousness: a tendency to display self-discipline, and strive for achievement.
- Emotional Stability: the tendency to not experience negative emotions, such as anger, anxiety, or depression.
- Extraversion: a pronounced engagement with the external world and enjoyment from interacting with people.
- Openness to experiences: a general appreciation for art, new ideas, imagination, curiosity, and variety of experience

c.2.2 *Questionnaire*

Participants were asked to score between 1 (Disagree Strongly) and 7 (Agree Strongly) for each of the following statements. They were also told that they should rate the extent to which the pair of traits applies to them, even if one characteristic applies more strongly than the other.

- I see myself as: Extraverted, enthusiastic.
- I see myself as: Critical, quarrelsome.
- I see myself as: Dependable, self-disciplined.
- I see myself as: Anxious, easily upset.
- I see myself as: Open to new experiences, complex.
- I see myself as: Reserved, quiet.
- I see myself as: Sympathetic, warm.
- I see myself as: Disorganized, careless.
- I see myself as: Calm, emotionally stable.
- I see myself as: Conventional, uncreative.

c.3 HEXAD TYPOLOGY

This player type model was used both in the crowdsourced study presented in Chapter 3 (the original version), and in the LudiMoodle study presented in Chapter 5 (the translated version).

c.3.1 *Types*

The player types Hexad [101] describes six types of players:

- Philanthropist: people who are motivated by purpose. They are altruistic and willing to give without expecting a reward.
- Socialiser: people who are motivated by relatedness. They want to interact with others and create social connections.
- Free Spirit: people who are motivated by autonomy, meaning freedom to express themselves and act without external control. They like to create and explore within a system.
- Achiever: people who are motivated by competence. They seek to progress within a system by completing tasks, or prove themselves by tackling difficult challenges.
- Disruptor: people who are motivated by the triggering of change. They tend to disrupt the system either directly or through others to force negative or positive changes. They like to test the system's boundaries and try to push further.
- Player: people who are motivated by extrinsic rewards. They will do whatever to earn a reward within a system, independently of the type of the activity.

c.3.2 *Questionnaire*

For the study presented in Chapter 3 (the crowdsourced study) participants were asked to rate each of the following statements from -3 (strongly disagree) to 3 (strongly agree):

- If the reward is enough I will put in the effort.
- I like mastering difficult tasks.
- I like to provoke.
- It is important to me to always carry out my tasks completely.
- Interacting with others is important to me.
- It makes me happy if I am able to help others.
- Rewards are a great way to motivate me.
- The wellbeing of others is important to me.
- I like to question the status quo.
- It is important to me to follow my own path.

- Return of investement is important to me.
- It is important to me to feel like I am a part of a community.
- I like being part of a team.
- I dislike following rules.
- I see myself as a rebel.
- I like helping others to orient themselves in new situations.
- I like overcoming obstacles.
- I enjoy group activites.
- I like competitions where a prize can be won.
- I like sharing my knowledge
- It is difficult for me to let go of a problem before I have found a solution
- I often let my curiosity guide me.
- Being independent is important.
- I like to try new things.

For the LudiMoodle study presented in Chapter 5, participants were presented with this translation of the Hexad statements:

- Je suis content.e quand les autres le sont
- J'aime aider les gens dans des nouvelles situations
- J'aime partager mon savoir avec les autres
- J'aime aider les autres
- J'aime faire partie d'une équipe
- J'aime les activités de groupe
- J'aime interagir avec les autres
- J'ai besoin d'appartenir à un groupe
- Je laisse souvent ma curiosité me guider
- J'aime être indépendant
- J'aime faire mes propres choix
- J'aime essayer de nouvelles choses
- J'aime surmonter des obstacles

- J'ai du mal à abandonner un problème sans avoir trouvé la solution
- J'aime les tâches difficiles
- J'ai besoin de finir ce que j'ai commencé
- Je n'aime pas suivre les règles
- Je me perçois comme étant rebelle
- J'aime remettre en question les consignes
- J'aime provoquer
- J'aime être récompensé pour mes efforts
- Je suis prêt à faire des efforts pour une récompense
- Je suis motivé par les récompenses
- J'aime les compétitions où je peux gagner des prix

C.4 ACADEMIC MOTIVATIONAL SCALE

This scale was used in the LudiMoodle study presented in Chapter 5. Participants were presented with translation of the Academic motivational scale [143] (the English version here is presented as reference, participants were only shown the French version). Participants were asked "*Pourquoi vas-tu en cours de mathématiques ? (Indique entre Pas du tout d'accord, pas d'accord, Neutre, Un peu d'accord, Totalelement d'accord)*" "Why do you go to maths class? (For each answer select how well it relates to you, between, Strong disagree, Disagree, Neutral, Agree, Strong Agree)":

- J'adore apprendre de nouvelles choses – I like to learn new things
- J'aime me sentir capable – I like feeling capable
- J'aime vraiment faire des mathématiques – I really like maths
- Je pourrai avoir le choix pour mes études futures grâce aux mathématiques. – I will be able to chose my future course thanks to maths.
- Je veux me prouver que je suis capable de réussir en mathématiques. – I want to prove that I am capable to succeed in maths
- Je veux avoir de bonnes notes et une bonne moyenne générale – I want to get good grades.
- Je ne sais pas pourquoi j'y vais, j'ai l'impression de perdre mon temps – I don't know why I go, I think it is a waste of my time.
- J'aime découvrir de nouvelles choses – I like discovering new things.
- J'aime maîtriser les leçons abordées – I like mastering the lessons.

- Je ne vois pas le temps passer en cours de mathématiques – The time flies when I'm in maths class.
- Je vais pouvoir travailler dans un domaine que j'aime grâce aux mathématiques. – I will be able to get a good job with maths.
- Pour me prouver que je suis capable. – I want to prove that I am capable
- Pour pouvoir passer en 3^e – To pass on to the next year
- J'avais de bonnes raisons d'y aller, mais aujourd'hui je n'en ai plus – I had good reasons to go, but I don't anymore
- J'aime en savoir toujours un peu plus en mathématiques – I like learning new things in maths
- Je suis content.e quand je réussis des activités mathématiques difficiles – I am happy when I solve difficult maths activities.
- Ça m'amuse de résoudre des problèmes en mathématiques – I find it fun to solve maths problems.
- Les mathématiques sont importantes dans la vie de tous les jours – Maths are important in everyday life.
- Pour me prouver que je suis intelligent.e – To prove that I am intelligent
- Parce que j'y suis obligé.e – Because I have to
- Je ne vois pas l'intérêt d'être bon.ne en mathématiques – I don't see the point to being good in maths.
- J'aime tout ce qui se rapporte aux mathématiques. – I like everything about maths.
- J'aime relever des défis – I like taking challenges
- J'adore faire des exercices difficiles – I like doing hard problems
- Je vais pouvoir trouver un travail plus tard grâce aux mathématiques. – I will be able to find a job later on thanks to maths.
- Si je ne vais pas en cours de mathématiques j'aurais des remords – If I don't go to maths class, I will feel remorse
- Si je ne vais pas en cours de mathématiques je serai sanctionné.e – If I don't go to maths class, I will get in trouble
- Je ne sais pas pourquoi je vais en cours de mathématiques – I don't know why I go to maths class.

LUDIMOODLE PLATFORM ADDITIONAL INFORMATION

Presented here are a few screenshots from the LudiMoodle platform described in Chapter 5. The platform is available for test here: <https://ludimoodle2020.edunao.com/> using the following test accounts (each account provides access for a different game element) - all of the test accounts use the same case sensitive password: "Ludi2020!".

- avatar.demo
- badges.demo
- progression.demo
- classement.demo
- score.demo
- timer.demo

The screenshot shows the Moodle course page for 'Calcul Littéral'. The page is titled 'Calcul Littéral' and features a grid of ten lessons, each with a unique illustration of a goblin character in a different setting. The lessons are:

- Leçon 1 : Découverte de la variable (Goblin in a boat)
- Leçon 2 : Simplification de produits (Goblin in a forest)
- Leçon 3 : Expression-type (Produit/Somme) (Goblin at a desk)
- Leçon 4 : Développements et factorisations faciles (Goblin on a beach)
- Leçon 5 : Développements et factorisations (réduire sans/avec relatifs) (Goblin in a desert)
- Leçon 6 : Suppression de parenthèses (Goblin on a boat)
- Leçon 7 : Distributivité double (Goblin at a desk)
- Leçon 8 : Application : géométrie dans le plan (Goblin in a castle)
- Leçon 9 : Application : géométrie dans l'espace (Goblin with a large green object)
- Leçon 10 : Conjecturer et démontrer (Goblin in a forest)

Figure 57: The course page for the Avatar game element. From this page learners could access the different quizzes in each of the lessons by clicking on the corresponding lesson. Each lesson showed the goblin character in a different universe.

The screenshot shows the 'Calcul Littéral' course page. At the top, there is a navigation bar with the 'LUDI moodle' logo and a user profile for 'Badges Stuart'. Below the navigation bar, there are icons for home, a grid, a square, and a checkmark. The main content area is titled 'Calcul Littéral' and contains ten lessons, each represented by a yellow shield icon with a percentage and a description. Lesson 1 is 5/16 completed, while lessons 2 through 10 are 0% completed. A pink circle highlights the progress indicator for Lesson 1.

Lesson	Description	Progress (Badges / Max)
Leçon 1	Découverte de la variable	5 / 16
Leçon 2	Simplification de produits	0 / 10
Leçon 3	Expression-type (Produit/Somme)	0 / 13
Leçon 4	Développements et factorisations faciles	0 / 10
Leçon 5	Développements et factorisations (réduire sans/avec relatifs)	0 / 13
Leçon 6	Suppression de parenthèses	0 / 16
Leçon 7	Distributivité double	0 / 22
Leçon 8	Application : géométrie dans le plan	0 / 10
Leçon 9	Application : géométrie dans l'espace	0 / 12
Leçon 10	Conjecturer et démontrer	0 / 9

Figure 58: The course page for the Badges game element. From this page learners could access the different quizzes in each of the lessons by clicking on the corresponding lesson. The number of badges obtained, and the max number of badges that they could obtain for each lesson is shown



Figure 59: The lesson view for the Badges game element. Learners were shown the number of badges unlocked for the current lesson, as well as the type of badges for each quiz. In this example the learner has obtained all four badges for the first quiz, and only the bronze badge for the second quiz. They have not unlocked the other quizzes (greyed out).



Figure 60: The course view for the Progress game element. Learners could access the different quizzes in each of the lessons by clicking on the corresponding lesson. Each lesson launched a different coloured rocket.

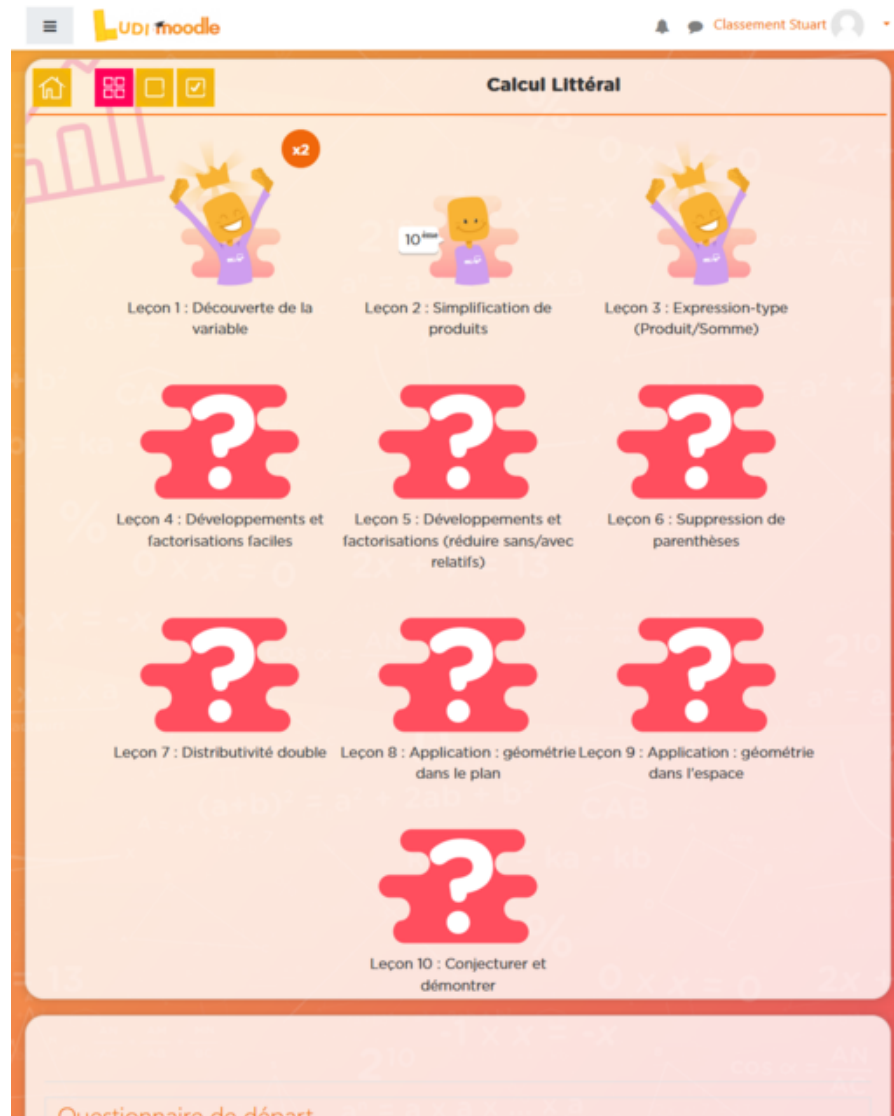


Figure 61: The course view for the Ranking game element. Learners could access the different quizzes in each of the lessons by clicking the corresponding lesson. The learner is shown the highest rank they have achieved for each of the lessons, as well as the number of times they have achieved this ranking. In this example, they have achieved first in two different quizzes in the first lesson, tenth in one of the quizzes in lesson two, and first in one of the quizzes in lesson three.

The screenshot displays the 'Calcul Littéral' course interface. At the top, the 'LUDIMOODLE' logo and user information 'Score Stuart' are visible. The course title 'Calcul Littéral' is centered. On the left, a treasure chest icon represents a total score of 22000 points. The main area shows 10 lessons, each with a bag of coins icon and a point value:

- Leçon 1 : Découverte de la variable (11000 Pts)
- Leçon 2 : Simplification de produits (11000 Pts)
- Leçon 3 : Expression-type (Produit/Somme) (0 Pts)
- Leçon 4 : Développements et factorisations faciles (0 Pts)
- Leçon 5 : Développements et factorisations (réduire sans/avec relatifs) (0 Pts)
- Leçon 6 : Suppression de parenthèses (0 Pts)
- Leçon 7 : Distributivité double (0 Pts)
- Leçon 8 : Application : géométrie dans le plan (0 Pts)
- Leçon 9 : Application : géométrie dans l'espace (0 Pts)
- Leçon 10 : Conjecturer et démontrer (0 Pts)

At the bottom, there are two sections: 'Questionnaire de départ' and 'Questionnaire de fin'. A 'Feedback: 1' indicator is visible in the bottom right corner of the course area.

Figure 62: The course view for the score game element. Learners could access the different quizzes in each of the lessons by clicking the corresponding lesson. Learners were shown the number of points scored for each lesson, as well as the total number of points scored.

The screenshot shows the Ludimoodle interface for a lesson titled "Leçon 1 : Découverte de la variable". At the top, there is a navigation bar with a home icon, a grid icon, a square icon, and a checkmark icon. The user's name "Score Stuart" is visible in the top right corner. The main content area is divided into two sections. The top section displays a large bag of gold coins with "12000 Pts" next to it. To the right, there are five exercise cards, each with a bag of gold coins and a score: "Exercice 1.1 : QCM" (5000 Pts), "Exercice 1.2 : QCM" (2000 Pts), "Exercice 1.3 : Etiquettes" (5000 Pts), "Exercice 1.4 : Etiquettes" (0 Pts), and "Exercice 1.5 : QCM Bonus" (0 Pts). The bottom section contains a checklist with two items: "Exercice 1.1 : QCM" and "Exercice 1.2 : QCM", both marked with a checkmark. The background of the bottom section is decorated with faint mathematical formulas and symbols.

Figure 63: The lesson view for the score game element. Learners were shown the number of points scored for each quiz in the lesson when they clicked on one of the lessons. In this example the learner has scored 5,000 points in the first and third quizzes, and 2,000 points in the second one. They are also shown their score total for the lesson.

The screenshot displays the course view for 'Calcul Littéral' on the Ludimoodle platform. The interface includes a navigation bar at the top with the Ludimoodle logo and a user profile for 'Minuterie Stuart'. Below the navigation bar, there are icons for home, a grid, a square, and a checkmark. The main content area is titled 'Calcul Littéral' and contains a grid of 10 lessons, each represented by a character icon and a title:

- Leçon 1 : Découverte de la variable (Yellow airplane character)
- Leçon 2 : Simplification de produits (Yellow car character)
- Leçon 3 : Expression-type (Produit/Somme) (Blue triangle character)
- Leçon 4 : Développements et factorisations faciles (Red question mark icon)
- Leçon 5 : Développements et factorisations (réduire sans/avec relatifs) (Red question mark icon)
- Leçon 6 : Suppression de parenthèses (Red question mark icon)
- Leçon 7 : Distributivité double (Red question mark icon)
- Leçon 8 : Application : géométrie dans le plan (Red question mark icon)
- Leçon 9 : Application : géométrie dans l'espace (Red question mark icon)
- Leçon 10 : Conjecturer et démontrer (Red question mark icon)

Below the grid, there are two questionnaires:

- Questionnaire de départ (Feedback: 1)
- Questionnaire de fin (Feedback: 1)

Figure 64: The course view for the Timer game element. The learners are shown the fastest they made their character go in any of the quizzes in the lesson (as with the ranking game element, a multiplier is shown if they achieved this speed in multiple quizzes).

The screenshot displays the Ludimoodle interface for a quiz titled "Exercice 3.1". At the top, there is a navigation bar with the Ludimoodle logo and a user profile for "Minuterie Stuart". Below the navigation bar, there are several icons representing different quiz elements. The main content area is divided into two sections. The top section features a large red puzzle piece with a blue character on it, a timer showing "00:00", and a "Temps de référence !" (Reference time!) of "00:14". The bottom section contains a question labeled "Question 2" with the text: "Voici un programme de calcul :". The instructions are: "Choisir un nombre" and "Multiplier par 4". Below this, it says: "L'expression correspondant à ce programme de calcul est un produit." The question asks to "Sélectionnez une réponse :" with two radio button options: "Vrai" and "Faux". A "Vérifier" button is located below the options. At the bottom of the screen, there are navigation links for "Exercice 2.2 : simplification de" and "Exercice 4.1".

Figure 65: The quiz view for the Timer game element. Learners were shown the current speed of their character in the quiz, their current time for the question, as well as a "reference time" that was calculated based off of their previous question times. Every time they would beat this reference time, their character would run faster, eventually driving a car or flying a plane as they moved faster.

RÉSUMÉ ÉTENDU EN FRANÇAIS

E.1 RÉSUMÉ GÉNÉRAL

La ludification, l'utilisation des éléments de jeux dans des contextes non-jeux, devient de plus en plus utilisé dans le domaine de l'éducation pour soutenir l'engagement, la motivation, et la performance des apprenants. Beaucoup d'approches actuelles proposent des systèmes où les apprenants utilisent les mêmes éléments de jeux. Cependant, d'études récentes montrent que les apprenants réagissent différemment aux éléments de jeux, et que leur motivation, engagement et performance peuvent varier grandement en fonction des caractéristiques individuelles tel que la personnalité, les préférences pour les jeux vidéo et la motivation pour l'activité d'apprentissage. Les résultats indiquent que dans certains cas les éléments non adaptés aux apprenants peuvent au mieux échouer dans leur tâche motivationnelle, et au pire démotiver les apprenants. Il est donc important d'adapter les éléments ludiques aux apprenants. Cette thèse s'est déroulée dans le cadre du projet LudiMoodle, qui a pour but la ludification de ressources pédagogiques afin d'améliorer l'engagement et la motivation apprenante. Dans cette thèse je propose un nouveau système qui adapte des éléments ludiques en utilisant des caractéristiques individuelles des apprenants, ainsi que leur engagement. Nos travaux se basent sur des résultats généraux du domaine de la ludification, ainsi que des résultats plus spécifiques dans le domaine de l'éducation. Notre but principal était de proposer un moteur d'adaptation générique, instancié avec des règles d'adaptation spécifiques à notre contexte. Ce manuscrit présente quatre contributions majeures: (1) Un moteur d'adaptation général qui peut être implémenté pour proposer des éléments de jeux appropriés aux apprenants, utilisant à la fois une approche d'adaptation statique et dynamique; (2) Un espace et des outils de conception qui permettent la création d'éléments de jeux pertinents, en collaboration avec les divers acteurs de la ludification (concepteurs, enseignants, apprenants etc.); (3) Une approche d'adaptation statique qui établit un compromis entre un le profil de joueur d'un apprenant et leur motivation initiale pour la tâche d'apprentissage; (4) Un modèle d'apprenant dynamique construit utilisant une approche basée sur les traces pour proposer des interventions d'adaptation quand des baisses d'engagement sont détectés. Ce moteur d'adaptation a été implémenté dans un prototype utilisé dans le contexte du projet LudiMoodle, qui a été utilisé par 258 apprenants dans 4 collèges Français différents pour l'apprentissage des mathématiques. Pour mettre en place ce prototype nous avons mené une étude dans des conditions réelles, où les apprenants l'ont utilisé pendant leur cours de mathématiques. Avec les résultats de cette étude nous avons fait plusieurs analyses pour mieux comprendre les facteurs qui ont influencé les variations motivationnelles des

apprenants, et comment leurs traces d'interaction peuvent prédire leur engagement avec la tâche d'apprentissage. Ces analyses ont servi à évaluer l'impact de l'adaptation des éléments de jeux sur la motivation et engagement des apprenants, et construire notre modèle de traces pour l'adaptation dynamique. Ce travail représente une avancée significative dans le domaine de la ludification adaptative, à travers un modèle générique pour l'adaptation statique et dynamique, le premier étant basé sur les caractéristiques individuelles des apprenants, et le second sur l'engagement observé des apprenants. Je fournis aussi des outils et recommandations pour les concepteurs, pour aider dans la conception d'éléments de jeux. Enfin, je discute ces résultats dans des perspectives de recherche futures, notamment au regard d'avancées possibles dans le domaine de l'adaptation dynamique.

E.2 RÉSUMÉ CHAPITRE 1

Ce premier chapitre introduit le contexte et les motivations pour ma recherche. Je présente d'abord les origines générales de la ludification, ainsi que les premières vagues de recherche dans ce domaine. A partir de cette vision générale, on se focalise rapidement sur le sujet principal, l'adaptation de la ludification aux utilisateurs individuels. Je présente ensuite le projet LudiMoodle qui a donné le cadre de mes travaux de thèse. Enfin je présente les trois questions qui ont guidé ma recherche, et la structure du manuscrit.

E.2.1 *Origines de la ludification*

Le terme de "Ludification" (*gamification* en anglais) est apparu pour la première fois au début des années 2000 ¹, mais ce n'est pas avant 2011 qu'une définition formelle est apparue, proposée par Deterding, Dixon, Khaled et Nacke [31]. Ces auteurs proposent que la ludification soit définie comme "*l'utilisation des éléments de jeux dans des contextes non jeux*". Une revue de la littérature sur la recherche en ludification récente [83] montre que les éléments de jeux les plus utilisés sont "*Points, score XP*", "*Challenges, quêtes, missions*", "*Badges, réussites*", et "*Leaderboards, classements*".

La ludification est déployée dans de nombreux domaines, du sport [1, 84] à la santé [10, 113, 120, 122] en passant par l'éducation [33, 73, 89, 90, 105], pour faciliter l'engagement, la motivation, et la performance des utilisateurs. Un exemple commercial bien connu de ludification est le programme d'apprentissage des langues Duolingo ². Cet outil en ligne propose un large panel d'éléments de jeux pour les encourager. Figure 66 montre une capture d'écran de l'application, on y voit quelques éléments de jeux proposés par l'application. Dans cet exemple on voit que les apprenants ont un objectif quotidien d'XP, montré sur une barre de progression. Ils ont aussi un classement où ils peuvent se com-

1 on dit souvent que c'est Nick Pelling qui a inventé le terme en 2003 <http://www.nanodome.com/conundra.co.uk/>

2 <https://www.duolingo.com>

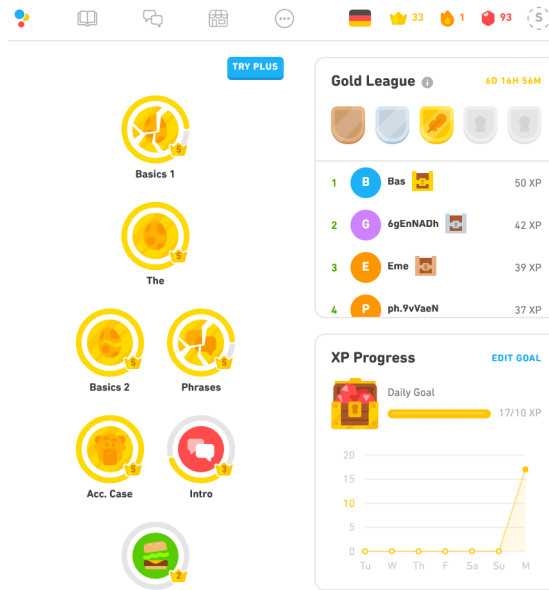


Figure 66: Une capture d'écran de l'application Duolingo. Ici les apprenants peuvent accéder à un leaderboard où ils peuvent comparer leur progrès avec celle des autres apprenants. On y voit aussi des barres de progression pour chaque leçon, un système de XP avec des objectifs quotidiens, et un planning hebdomadaire où ils sont encouragés à faire au moins une leçon chaque jour.

parer aux autres apprenants, et un système de badges où chaque leçon est représenté par un niveau et un badge différent.

Un autre exemple de ludification intéressante est celle des "Piano Stairs" présenté figure 67. En 2009 la compagnie Volkswagen a lancé une campagne de publicité en Suède qui visait à promouvoir comment le "Fun" pouvait changer le comportement pour le mieux. Une vidéo courte³ montre comment ces escaliers se comportent tel un piano, faisant des bruits quand on marchait dessus. L'objectif de ces escaliers piano était d'inciter les passants à prendre les escaliers au lieu de l'escalateur à côté, promouvant ainsi l'activité physique. La vidéo montre comment les passants ont privilégié les escaliers plus amusants. Dans cet exemple la ludification est appliquée comme une couche qui vient se poser par dessus de l'activité principale (ici prendre les escaliers). Cette couche de ludification n'a qu'un seul but: motiver les utilisateurs à réaliser l'activité sans la modifier.

Ces deux exemples montrent la diversité des approches de ludification qui existent. Tous les utilisateurs utilisent les mêmes éléments ludiques. Ces systèmes ne s'adaptent pas aux différents utilisateurs. Cela peut poser un problème puisque la recherche montre que pour être efficace, la ludification doit être adaptée aux préférences et attentes individuelles des apprenants[41, 61, 108, 122]. Cette recherche récente montre que les éléments de jeux qui ne sont pas adaptés peuvent au mieux échouer dans leur rôle motivationnel, et au pire peuvent carrément démotiver les utilisateurs.

³ <https://www.youtube.com/watch?v=SByymar3bds>



Figure 67: Un escalier en piano conçu pour encourager les utilisateurs à prendre les escaliers au lieu de l'escalateur, et ainsi avoir une activité physique.

Les utilisateurs ne sont pas tous motivés par les mêmes éléments de jeux, puisqu'ils ne proposent pas tous les même affordances motivationnelles. Il est généralement accepté que la ludification fonctionne en élicitant les mêmes expériences motivationnelles et psychologiques des jeux vidéos [68]. Du coup, les éléments de jeux individuels devraient donc fournir des affordances motivationnelles spécifiques. D'autre travaux estiment que la ludification permet de combler les besoins de base décrit par la SDT (Self Determination Theory) [129] (SDT). La SDT propose trois besoins de base qui doivent être satisfait pour encourager le bien-être humain: l'autonomie, la compétence, et le besoin de liens sociaux.

Ryan et al. [130] ont décrit comment les jeux peuvent satisfaire ces besoins. Le jeu solitaire a tendance à satisfaire l'autonomie et le besoin de compétence, et les jeux multijoueurs le besoin de liens sociaux en plus. La ludification pourrait donc satisfaire ces trois besoins via les éléments atomiques des jeux.

E.2.2 Contexte de recherche le projet LudiMoodle

Le travail présenté dans ce manuscrit à été mené dans le cadre du projet LudiMoodle financé par le projet *e-FRAN Programme d'investissement d'avenir*⁴.

Le but principal de ce projet est la conception, évaluation et la validation d'une approche personnalisée de la ludification appliquée à l'enseignement numérique des mathématiques du collège, pour l'amélioration de la motivation des apprenants. Plus spécifiquement nous avons appliqué notre approche de ludification à une plateforme Moodle [107] pour l'apprentissage des mathématiques de 4ème. Cette plateforme a été développée en collaboration directe avec les partenaires du projet. Durant ce projet nous avons travaillé avec des chercheurs en sciences pédagogiques du laboratoire ECP⁵ (*Éducation,*

⁴ <https://www.gouvernement.fr/e-fran-1-ecole-change-avec-le-numerique>

⁵ <https://recherche.univ-lyon2.fr/ecp>

Cultures, Politiques) à l'université Lumière Lyon 2, des ingénieurs pédagogiques du PAPN (*Pole d'Accompagnement à la Pédagogie Numérique*) de l'université Jean Moulin Lyon 3, et Edunao, une entreprise spécialisée dans la conception et le déploiement des plateformes d'apprentissage numériques (tel Moodle). Dans le cadre du projet nous avons mené une expérimentation en conditions réelles, où des apprenants ont utilisé une plateforme ludifiée pendant leurs cours de mathématiques normaux. Cette expérimentation s'est déroulée dans quatre collèges dans la région Auvergne-Rhône-Alpes. Un total de cinq enseignants et 258 élèves ont participé à cette expérimentation. Les enseignants ont aussi contribué à la création des contenus pédagogiques et ludiques utilisés lors de cette expérimentation (voir chapitre 4 pour la description des séances de co-conception d'éléments ludiques).

E.2.3 *Questions de recherche*

Dans ce manuscrit je propose de répondre aux questions identifiées dans la seconde vague de recherche en ludification [112], en les adaptant à notre contexte éducatif:

- **Qui** sont les cibles de notre adaptation? Comment peut-on catégoriser les apprenants, et quelles sont les préférences liées à ces catégories?
- **Quels** éléments de jeux pouvons nous proposer à ces catégories d'apprenants? Comment pouvons-nous concevoir des éléments de jeux qui prennent en compte à la fois le contexte ludifié et les apprenants?
- **Comment** pouvons-nous adapter les éléments de jeux? Comment déterminer si les sélections d'éléments de jeux sont bel et bien appropriés?

Le travail présenté ici est centré autour d'une proposition d'un moteur d'adaptation des éléments ludiques utilisé dans le cadre du projet LudiMoodle. Ce moteur d'adaptation devrait servir comme outil qui propose des éléments de jeux appropriés pour les apprenants. L'architecture de ce moteur est présentée plus en détail dans la section suivante, et chaque chapitre de ce manuscrit permet d'analyser et approfondir chaque partie du moteur.

E.2.4 *Contributions de la thèse*

Dans ce manuscrit, je présente quatre contributions majeurs liées par l'architecture de moteur d'adaptation. Cette architecture sert comme cadre au reste du travail, puisque les autres modules qui le composent font l'objet des quatre contributions présentés ici. La figure 68 montre un schéma global de cette architecture.

Tout d'abord le travail présenté dans le chapitre 2 est une étude de la littérature sur la ludification adaptative en éducation, qui identifie quatre lacunes de recherche. Ces lacunes font l'objet du travail présenté dans les chapitres suivants de la thèse. Ces quatre lacunes, qui émergent d'une analyse approfondie de l'état de l'art, sont:

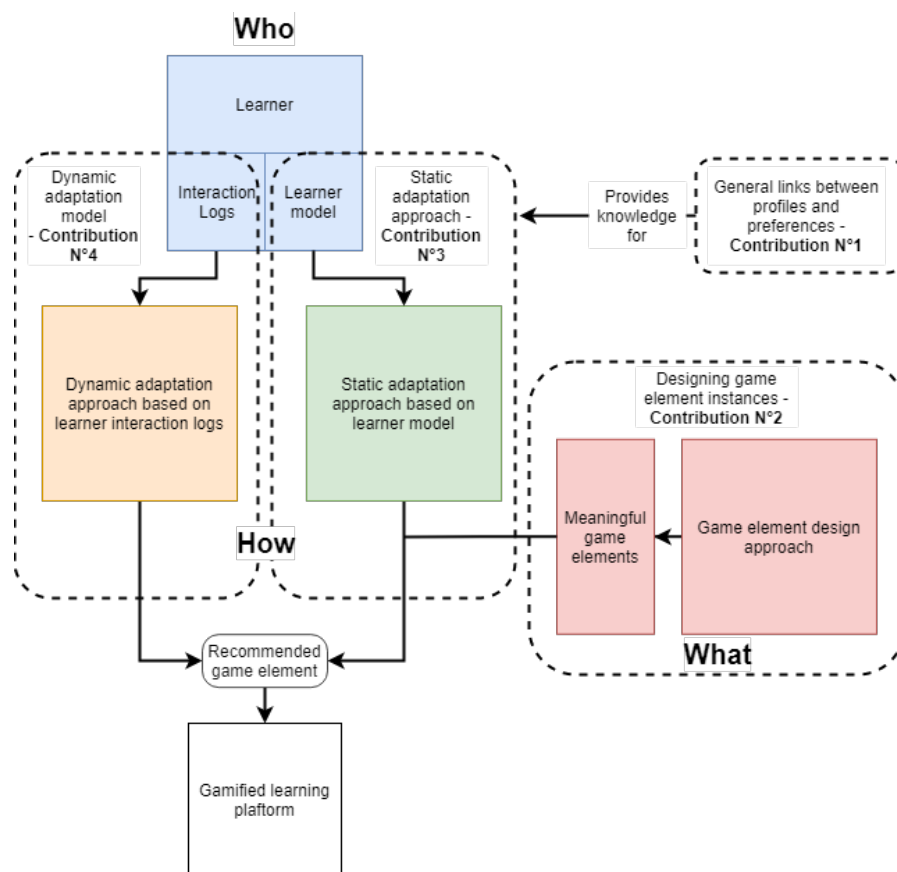


Figure 68: L'architecture du moteur d'adaptation, les contributions sont numérotées ici.

1. une lacune dans la nomenclature et conception des éléments de jeux
2. une lacune dans les modèles d'apprenants
3. une lacune dans l'évaluation des méthodes d'adaptation
4. une lacune dans les méthodes d'adaptation dynamique

Ma première contribution est une étude des liens entre modèles d'apprenants et éléments de jeux dans un contexte décontextualisé. Chapitre 3 présente une étude menée en recrutement participatif qui étudie les liens entre différents modèles utilisateurs et l'impact perçu des éléments de jeux sur la motivation. Notre objectif était d'obtenir des résultats applicables à n'importe quel domaine. Nous avons comparé trois modèles utilisateurs différents, liés aux préférences pour les jeux vidéos, ou au traits de personnalité. Nous avons aussi comparé l'impact de différents éléments de jeux implémentant les mêmes stratégies motivationnelles, utilisant une classification d'éléments de jeux conçu pour combler la **lacune 1**. Nos résultats montrent l'importance du choix d'éléments de jeux et de leur conception, et a aidé dans la sélection du modèle utilisateur à utiliser par la suite des travaux, et le moteur d'adaptation. Le travail présenté dans ce chapitre a permis une première réponse aux trois questions, en montrant comment on peut catégoriser les utilisateurs selon leur profil,

comment ces profils mettent en évidence des préférences et effets motivationnelles différentes, et comment l'instanciation des éléments de jeux influe ces effets. Cette contribution présente une première étape pour combler les **lacunes 1 & 2**.

Ma deuxième contribution est un espace de conception des éléments de jeux, ainsi qu'un ensemble d'outils (plateau & cartes) pour explorer cet espace. Ces outils visent la facilitation de la création des éléments de jeux appropriés aux contextes et aux apprenants lors des séances de co-conception unifiant les acteurs du processus de ludification de l'éducation. La recherche [115] montre que les éléments de jeux fonctionnent mieux si ils ont un sens pour les apprenants, si ils font des connections importantes et thématiques avec le contenu pédagogique. Chapitre 4 présente l'espace et outils de conception, et un scénario d'usage dans le cadre du projet LudiMoodle. Ces outils ont aidé les acteurs des séances de co-conception en fournissant un langage commun, et en les guidant vers des questions de conception aux quels ils n'avaient pas forcément pensé. Cette contribution sert à répondre entièrement à la deuxième question de recherche, en montrant une méthode pour créer des éléments de jeux appropriés au contexte et aux apprenants. Par ailleurs ces séances de co-conception ont servi de base pour créer la banque d'éléments ludiques utilisée dans le projet LudiMoodle. Cette contribution comble la **première lacune** en fournissant une approche simplifiée approfondie pour la conception des éléments ludiques.

Ma troisième contribution est l'ensemble des règles d'adaptation spécifique au domaine de l'éducation, basées sur un modèle de l'apprenant composé d'un profil contextualisé (motivation pour l'apprentissage) et d'un profil décontextualisé (préférences pour les jeux). Ces règles servent à créer une approche statique de l'adaptation. On propose un compromis par les recommandations d'éléments ludiques identifiés par les deux profils. Chapitre 5 présente l'étude menée dans le cadre du projet LudiMoodle. Au total 258 apprenants dans quatre collèges ont participé à l'étude, et ont utilisé notre plateforme ludifiée durant environ six semaines. De cette étude nous avons généré les premières règles d'adaptation basées sur les profils des apprenants, pour ensuite simuler trois approches d'adaptation différentes. Ces approches ont été évaluées, et les résultats ont fait émerger les règles finales pour l'adaptation statique. Cette contribution répond entièrement aux questions de "Qui" et "Comment" présentées au dessus. Elle sert aussi à combler la **deuxième et troisième lacune**.

Ma quatrième et finale contribution est une approche d'adaptation *dynamique* basée sur une étude des interactions apprenantes avec le système ludifié. Via cette étude nous avons pu identifier des facteurs d'engagement qui permettent de tracer l'engagement des apprenants au fil du temps, et proposer une intervention d'adaptation quand une baisse anormale est détectée. Le Chapitre 6 décrit notre approche pour construire et interpréter cette analyse des traces, ainsi qu'une possible implémentation d'un moteur d'adaptation dynamique et comment il serait utilisé en classe. Cette contribution sert à combler la **quatrième lacune**.

Les sections suivantes présentent la traduction en Français des résumés de chaque chapitre.

E.3 RÉSUMÉ CHAPITRE 2

La ludification, l'utilisation des éléments de jeux dans des situations non jeux, est utilisée de plus en plus dans l'éducation pour encourager la motivation, l'engagement et la performance des apprenants. Des travaux de recherche récents dans le domaine de la ludification suggèrent que pour être efficace, les éléments de jeux doivent être adaptés aux apprenants. Dans ce chapitre, je fournis une vision générale de la recherche menée dans la ludification en éducation pour mettre en évidence le besoin de ludification adaptative. Ensuite, je présente une étude approfondie de la littérature de la ludification adaptative spécifiquement en éducation, afin de fournir une synthèse des approches actuelles. Cette étude soulève 4 préoccupations de recherche principales: (1) Les différents types de contributions existantes, (2) la terminologie utilisée pour décrire les éléments de jeux utilisés, (3) Ce sur quoi les différentes adaptations se basent, et leur effet sur le système ludifié, (4) l'impact de la ludification adaptative sur les apprenants et comment cet impact est mesuré.

De cette étude de la littérature, j'identifie quatre lacunes, que je comble dans les chapitres suivants.

E.4 RÉSUMÉ CHAPITRE 3

Suite à l'étude de l'état de l'art, nous voyons qu'il est important de fournir des éléments de jeux adaptés et personnalisés aux apprenants. Une première approche, souvent observée dans la littérature est de catégoriser les apprenants selon leurs préférences pour les jeux vidéo (profils de joueurs). Cependant les résultats sont souvent très hétérogènes, et quelque peu difficiles à réutiliser à cause des contextes différents, des profils différents utilisés pour catégoriser les apprenants, et différentes implémentations d'éléments de jeux. Ce chapitre présente une première étude qui nous a permis d'investiguer les liens entre des différents modèles de profil, et différentes préférences pour éléments de jeux, comment des implémentations d'éléments de jeux similaires peuvent affecter les utilisateurs différemment, et comment le contexte de l'environnement ludifié peut affecter l'effet des éléments de jeux.

L'objectif de cette étude est de fournir des aperçus de comment on peut générer des recommandations pour des éléments de jeux appropriés, en se basant sur des caractéristiques utilisateurs individuels. Dans cet objectif nous avons mené une étude en recrutement participatif avec 300 participants pour identifier l'impact motivation d'éléments de jeux. Les participants devaient sélectionner quels éléments de jeux les aurait le plus motiver à réaliser une tâche non spécifiée. Ces choix ont été présentés en paire, afin de réduire la complexité de la décision. Cette étude est différente de travaux précédents de trois façons: d'abord, elle est indépendante de tout contexte, et activité utilisateur; ensuite, nous considérons trois typologies d'utilisateurs; et finalement on dis-

tingue clairement entre les stratégies motivationnelles et leurs implémentations à travers plusieurs éléments de jeux.

Nos résultats montrent que (1) les implémentations différentes d'une même stratégie motivationnelle ont des impacts différents sur la motivation, (2) le type d'utilisateur dominant n'est pas suffisant pour différencier entre les préférences des éléments de jeux, (3) la typologie Hexad semble plus appropriée pour la ludification personnalisée, et (4) l'impact motivationnel de certains éléments de jeux varie avec l'activité utilisateur, ou le domaine ludifié.

Cette étude a fait l'objet d'un article de recherche présenté à la conférence CHI Play en 2019, et à été récompensé d'une "Mention Honorable" [59]. Ce chapitre présente une première étape pour combler la lacune des modèles riches d'apprenants.

E.5 RÉSUMÉ CHAPITRE 4

D'après les résultats du chapitre précédent, nous constatons que les différentes implémentations des éléments jeux affectent les apprenants différemment. De plus, le contexte ludifié joue un rôle important sur l'effet motivationnel et engageant des éléments ludiques. Il est donc important que le contexte et les apprenants soient pris en compte lors de la conception des éléments de jeux. Pour cela, nous avons décidé d'unir tous les acteurs du processus de la ludification de l'éducation (concepteurs/ingénieurs pédagogiques, enseignants, apprenants) pour la création des éléments ludiques. Notamment les acteurs éducatifs (enseignants, et apprenants) puisqu'ils ont une meilleure compréhension de comment les éléments de jeux peuvent s'insérer dans les contenus pédagogiques. Cependant nous avons rencontré de nombreux soucis suite à l'unification de ces multiples acteurs. Principalement à cause du manque de langage commun, et des différents niveaux de connaissances de conception. Pour faire face à ce problème, et pour faciliter les sessions de co-conception, nous avons proposé un espace de conception pour encourager la créativité des acteurs. Pour explorer cet espace de conception et guider le processus, nous avons proposé un jeu de cartes et plateau de conception. Avec ces outils, nous avons pu observer que les enseignants et ingénieurs peuvent considérer de multiples différentes implémentations d'éléments de jeux communs, et ont été capable d'atteindre un consensus général sur les décisions de conception rapidement.

Le travail présenté dans ce chapitre, ainsi que la classification d'éléments de jeux présenté dans le chapitre précédent, servent à combler le besoin pour des éléments de jeux appropriés aux contexte présenté dans le chapitre 2.

E.6 RÉSUMÉ CHAPITRE 5

Comment pouvons nous générer des règles d'adaptation appropriées ? Comme montré dans le chapitre 3, les préférences liées aux différents types de joueur offrent une certaine idée de quels éléments pourraient être appropriés. De ces préférences nous pouvons donc établir une première base de règles d'adaptation.

Cependant comme montré dans le chapitre 3, ces préférences (et donc base de règles d'adaptation) varient fortement avec le contexte ludifié. Il est donc nécessaire d'investiguer les spécificités amené par notre contexte éducatif (les mathématiques en collège) pour identifier des règles d'adaptation appropriés. De plus, il est important d'avoir un moyen pour évaluer les suggestions d'adaptation proposées dans le cadre du projet LudiMoodle.

Dans ce chapitre nous proposons une base de règles d'adaptation issues des résultats d'une étude en conditions réelles (mené dans le cadre du projet LudiMoodle). Ces nouveaux résultats ont confirmé ceux observés dans la littérature qui montre qu'une ludification non adapté à tendance à démotiver les apprenants sur la durée. Une analyse plus poussée a montré que l'impact des éléments de jeux sur la motivation des apprenants varie énormément en fonction de leur motivation initiale à faire des mathématiques, et leur profil de joueur Hexad. Ceci soulève la nécessité d'adapter en fonction d'à la fois le profil de joueur **et** la motivation initiale.

Suivant ces résultats nous avons simulé différentes approches d'adaptation basé sur trois modèles d'apprenants différents (motivation initiale, profil de joueur, et une combinaison des deux), et nous avons analysé l'impact de ces trois adaptations sur l'engagement, la motivation et la performance des apprenants. Ces tests et simulations ont été effectués sur les données de l'expérimentation LudiMoodle qui s'est déroulé au printemps 2019. Les résultats de ces simulations nous ont permis de mettre en place les règles d'adaptation, déployés dans le prototype du moteur d'adaptation statique, qui a servi dans le projet LudiMoodle.

E.7 RÉSUMÉ CHAPITRE 6

Jusqu'à présent le modèle d'adaptation proposé utilise une approche "statique", où le système est adapté aux apprenants une fois, avant qu'ils utilisent l'environnement d'apprentissage. Suivant la définition posé au chapitre 2, je propose d'étendre le modèle actuel pour permettre une adaptation dynamique qui se base sur le comportement des apprenants, utilisant les traces d'interaction récoltées suite à l'expérimentation LudiMoodle (voir chapitre 5) pour créer des règles d'adaptation dynamique. Comme défini, l'adaptation dynamique peut se dé-clencher à plusieurs reprises durant l'utilisation du système ludifié si c'est nécessaire. Dans le cadre du projet LudiMoodle, le système d'adaptation dynamique doit pouvoir tracer l'engagement et la motivation des apprenants, et proposer une adaptation quand une baisse anormale est détectée. Cette adaptation prendra donc la forme d'un changement d'élément ludique, censée motiver, ou engager l'apprenant à nouveau.

Nous avons donc d'abord besoin d'un moyen d'évaluer comment les traces d'interactions témoignent de la motivation ou engagement des apprenants. Nous avons dans un premier temps déterminé un ensemble de métriques pour représenter l'engagement des apprenants avec la plateforme d'appren-tissage. Ensuite, grâce à une approche d'analyse factorielle nous avons mis en évidence trois facteurs d'engagement, formant ainsi un modèle de l'engagement

basé sur les traces d'interaction. Nous avons mis en place ce modèle d'engagement dans une nouvelle version du moteur d'adaptation qui comporte donc un module d'adaptation dynamique. Cette nouvelle version du moteur d'adaptation aurait été testée dans une finale vague d'expérimentations LudiMoodle, mais à cause de la crise COVID19 celle-ci n'a pas pu être mise en place.

E.8 RÉSUMÉ CHAPITRE 7

Ce chapitre résume les contributions présentées dans ce manuscrit, et propose des nouvelles futures directions de recherche qui peuvent être explorées pour poursuivre ce travail.

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