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A trace-based approach to identifying users' engagement and qualifying their engaged-behaviours in interactive systems

Application to a social game

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Abstract Analysing and monitoring users' engaged-behaviours continuously and under ecologically valid conditions can reveal valuable information for designers and practitioners, allowing them to analyse, design and monitor the interactive mediated activity, and then to adapt and personalise it. An interactive mediated activity is a human activity supported by digital interactive technologies. While classical metric methods fall within quantitative approaches, this paper proposes a qualitative approach to identifying users' engagement and qualifying their engaged-behaviours from their traces of interaction. Traces of interaction represent the users' activities with an interactive environment. The basis of our approach is to transform low-level traces of interaction into meaningful information represented in higher-level traces. For this, our approach combines three theoretical frameworks : the Self-Determination Theory, the Activity Theory and the Trace Theory. Our approach has been implemented and tested in the context of the QUEJANT Projet. QUEJANT targets the development of a system allowing the actors of Social Gaming to analyse players' engagement from an analysis of their activity traces. In order to demonstrate the feasibility of our approach, we implemented the whole pro-

A preliminary version of the approach described in the present article has been presented at the CSEDU 2013 conference (Bouvier et al, 2013a) and has received the Best Paper Award of the conference. A preliminary and shorter version of the implementation section was published at the ICALT 2013 conference (Bouvier et al, 2013b).

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cess in a prototype and applied it to 12 players' interaction data collected over four months. Based on these interaction data, we were able to identify engaged and non-engaged users and to qualify their types of engaged-behaviours. We also conducted a user study based on a validation of our results by experts. The high prediction rate obtained confirms the performance of our approach. We finally discuss the limitations of our approach, the potential fields of application and the implications for digital behavioural interventions.

Keywords Engagement Assessment · Engaged Behaviours · Qualitative Approach · User Behaviour Analysis · Self-Determination Theory · Activity Theory · Interaction Traces · Social Game

1 Introduction

User's engagement is considered as an important dimension (O'Brien and Toms, 2008) of the user experience¹ (Hassenzahl and Tractinsky, 2006; Law et al, 2009) during an interactive mediated activity. An interactive mediated activity is a human activity supported by digital interactive technologies such as mobile platforms, Internet, computer applications or virtual reality system.

Indeed, several works highlight the significance of the user's engagement in different scientific fields such as digital gaming (Brockmyer et al, 2009), Web applications (Attfield et al, 2011), human-robot interaction (Rich et al, 2010), virtual reality (Schubert et al, 2001) or education (Garris et al, 2002).

Further to their systematic review of engagement in entertainment digital gaming, Boyle et al (2012) acknowledge that the nature of engagement is still not fully understood and there is a lack of a widely accepted definition of engagement. Many definitions of engagement have been proposed in the literature (see for instance (Chen et al, 2011) in digital gaming, (Sidner et al, 2004) in human-robot interaction or (Fredricks et al, 2004) in education). While this discussion about the nature of engagement goes beyond the scope of this paper, we still consider it necessary to clarify the object of the present study. In this work we consider engagement as the willingness to have emotions, affect and thoughts directed towards and aroused by the mediated activity in order to achieve a specific objective (Bouvier et al, 2013a). In our view, engagement may continue beyond the duration of the mediated activity. For instance, even when the activity is finished, engaged-users may think back to the previous session of the mediated activity or may anticipate the following one.

The objective of our research is to propose a generic approach to identifying users' engagement and qualifying their engaged-behaviours from their traces of interactions. By trace, we mean the history of users' actions collected in real time from their interactions with a computer system. Through our approach

¹ According to ISO 9241-210, user experience refers to "a person's perceptions and responses that result from the use or anticipated use of a product, system or service."

we can analyse engagement continuously (i.e. session after session) and under ecologically valid conditions. We consider that the conditions are ecologically valid since the activity is performed in its natural environment and in authentic conditions (the process underlying our approach does not interfere with the normal course of the activity and so is fully transparent for the user).

This paper proposes a theory-driven and qualitative approach. Our proposal is theory-driven as it relies on a theoretical work on engagement and engaged-behaviours, the Self-Determination Theory, the Activity Theory and the Trace Theory combined through a three-stage process. Our proposal is also qualitative as it can qualify the users' engaged-behaviours according to four categories : environmental-directed, social-directed, self-directed and action-directed. In our model, a behaviour corresponds to a chain of actions (i.e. an aggregation of actions) actually performed by the user in the interactive system. Considering some chains of actions rather than single actions provides comprehensive contextual information on behaviours and thus, facilitates their understanding.

This work has been conducted in the context of the QUEJANT Project. This project targets the development of a system allowing the actors of Social Gaming to analyse players' engagement based on an analysis of their activity traces. This project is undertaken in partnership with the LIRIS laboratory and video games companies.

The proposed approach has been implemented in a prototype that supports the whole process of analysis within the context of the QUEJANT project. We analysed the interaction traces of twelve players selected by experts as representative of user's engaged and non-engaged behaviours. We were able to identify four high-level activities that reflect several types of engaged-behaviours. This implementation shows the feasibility of our approach. We also present the results of a user study that involved three experts. The objective of this study, based on a comparative method, was to validate the performance of our approach with real data. The principle of this evaluation consisted in comparing, for the same traces, the results generated by our prototype with those of three experts. The high prediction rates obtained suggest that our models and prototype are valid in this context. This evaluation also highlights some limitations of our proposal regarding its implementation and the question of scalability.

The assessment of users' engagement during an interactive mediated activity can provide some relevant information for designers, practitioners and facilitators to analyse, design or modify the activity. Indeed, the information on users' engagement given by our tool may be different from their intuitions and may help them to gain a better understanding of the users. These information may also be used to adapt and personalise the form and the content of the application. For instance, the analysis may inform about users' specific interests or about design problems of the activity (like a wrong balance between the different types of engagement). Thus the activity may be modified or adapted accordingly in order to maintain engagement.

The article is organized as follows. Section 2 outlines the background and motivation of our work on engagement for behavioural interventions. Section 3

presents the state of the art regarding the existing methods to identifying user's engagement in interactive activities. Section 4 details the three theories (Self-Determination Theory, Activity Theory and Trace Theory) on which we rely in order to define our approach. Section 5 describes the three stages of our approach to identifying and qualifying engaged-behaviours from the users' interaction traces. Section 6 presents the architecture of the system we have developed and the implementation of our approach in the context of the QUEJANT project. We also give some examples in order to illustrate the process. Section 7 is devoted to the user study we conducted in order to validate our approach. The principle consists of comparing, for the same traces, the results generated by our system with those of three experts. Section 8 summarizes our contribution and highlights some limitations and implications of our works. Section 9 is devoted to our future works.

2 Background and motivation

Our contribution may be particularly relevant in the digital behaviour intervention field. A behaviour change is desirable since the change may be beneficial for instance to the person, to the environment or to society. Thus, behaviour change may be applied in various fields such as health (for instance to promote a good diet (Baranowski et al, 2003) or exercise (Consolvo et al, 2006) or to manage chronic diseases (Camerini et al, 2011)), sustainable development (Jackson, 2005) or education (Mintz and Aagaard, 2012).

The role of interactive technologies such as mobile platforms (Kjeldskov et al, 2012), Internet (Barak et al, 2008), social networking (Maitland and Chalmers, 2011), computer games (Baranowski et al, 2008) or virtual reality (Chittaro and Zangrando, 2010) in supporting behaviour change in a desirable way is a growing area of research.

But, to change or influence users' behaviour, technology-based behavioural interventions must be attractive and motivating (Vassileva, 2012). User's motivation is known as one of the users' key determinants of behaviour change (Michie et al, 2008). Vassileva (2012) notes that "motivation is always personal". And so, what a user can judge attractive and motivating may be experienced in a very different manner by another user. Therefore, personalising the mediated activity according to gamer types (Orji et al, 2014) or to users' specific needs and motivations is a relevant solution to support the effectiveness of the digital intervention (Ritterband et al, 2009; Vassileva, 2012). But detecting users' needs and motivations to adapt the intervention accordingly, is particularly challenging.

To achieve better results, some adaptation or personalisation techniques using persuasive technology (Fogg, 2002) or affective computing (Picard, 2000) strategies may be implemented (Mintz and Aagaard, 2012). Persuasive technology deals with interactive technologies intentionally designed to support behaviour change (Fogg, 2009). Affective computing aims to understand and modelling emotions and related affective phenomena in order to design inter-

active systems that can recognize, interpret and simulate them (Honka et al, 2011). The objective of these strategies is to personalise the digital intervention (its form and/or content) according to users' motivations.

In the health intervention field, users' adherence is considered as the key determinant in the effectiveness of treatment or in promoting a healthy lifestyle (Ritterband et al, 2009). Adherence corresponds to the intensity of the use and the variety of intervention program usage by the user (Donkin et al, 2011). Then adherence can be measured through the time spent online or the number of completed tasks (Donkin et al, 2011). The connection between adherence and engagement is quite obvious and often highlighted (Christensen et al, 2009; Doherty et al, 2012). Beyond the health sphere, users' engagement is also considered as a key factor in supporting behaviour change in the environmental (Froehlich et al, 2009) or educational (Linehan et al, 2011) fields. The information about users' engaged-behaviours obtained with our approach can be used to adapt and personalise the form and the content of the interactive system and so improve the digital intervention.

3 Related research works

As Chen et al (2011) acknowledge, measuring engagement is not straightforward. In this section, we present and discuss some subjective and objective methods for the assessment of users' engagement.

3.1 Subjective methods

Subjective measures mostly rely on self-report methods like Likert scale questionnaires (Jennett et al, 2008; Brockmyer et al, 2009). These measures seek to assess the engagement and some associated states like the allocation of attention or immersion. Questionnaires present a number of advantages. They are not expensive, they are easy to administer and to analyse. When they are proposed after the activity, questionnaires have the advantage of not disrupting the activity. However, they suffer from numerous biases and limitations, such as the wording of the questions that can lead to ambiguities. This is particularly true when the object of the study is an abstract quantity like engagement.

There are other post-activity and subjective methods, such as interviews (Brown and Cairns, 2004), discussions with a small group of participants or asking them to write and describe their experience. This type of study may provide comprehensive results. So it may enable the analysis of engagement in a more accurate and subtle way than with a questionnaire. But, the amount of data collected make the results more difficult to administer and to interpret.

While most self-report methods are performed after the activity, D'Mello et al (2006) and Arroyo et al (2009) propose two different methods that can be used during the activity. But this kind of continual self-report may disrupt

the activity and so the user experience. Measurement by self-report may also suffer from a lack of introspection on the user's part. When these measures are conducted after the activity, there is no guarantee that the remembered experience is identical to the actual experience. Furthermore, apart from the few methods that can be completed during the activity, self-report methods do not make it possible to reflect the changes in engagement that may occurred during the activity.

So these subjective measures can provide complementary information when conducted in parallel with objective measures of engagement. For example, it may be interesting to know when and why a user is more or less engaged during the activity. But it is necessary to evaluate engagement in an objective way if we want the results to be interpretable and usable by the interactive system to adapt and personalize the mediated activity.

3.2 Objective methods

Objective measures assess users' unconscious or spontaneous manifestations or responses that result from their engagement. The latter may be physiological, emotional or behavioural. For example, Mandryk et al (2006) use some psychophysiological techniques (recently reviewed by Kivikangas et al (2011)) to measure users' physiological responses. As engaging tasks lead to a shorter duration estimation, Hägni et al (2007) evaluate users' altered perception of time. Other behavioural manifestations such as gaze tracking (Jennett et al, 2008) or body movements (Bianchi-Berthouze, 2013) may be assessed. The assumption underlying these kinds of methods is that the physiological, emotional or behavioural responses reflecting engagement are sufficiently pronounced to be detected. We consider that physiological, emotional or behavioural methods show great promise. But currently, the technology to be implemented may be complex and intrusive and so disrupt the user's experience. Another significant difficulty with these methods is determining which manifestations or responses are objective and really inherent to user engagement. A final limit to these objective methods is that the physiological, emotional or behavioural responses reflecting users' engagement that these methods seek to recognise, depend on the content of the activity.

Metrics, another objective measure, is used in industry and by academics in order to fulfil the constraints mentioned above. It consists in automatically collecting and storing any users' actions performed, through input devices toward the system, such as users' choices, interactions with agents or time spent connected. It is possible to record the complete users' activity. In the gaming domain, this user-centred analysis, mainly based on statistical processing, may be used during the game development (Kim et al, 2008; Tychsen and Canossa, 2008) or after the game launch (Gagné et al, 2011). The purpose is to inform designers about users' behaviour. Without interfering with the activity, metrics enable one to analyse user's behaviour during the activity and not a posteriori. It also makes it possible to conduct research on the whole popula-

tion and not only on a selected sample and, over a long time interval. Metrics data are directly and automatically collected and sent by the system. In addition, the process does not require any intervention from the user nor does it disrupt the process underlying the activity. So this process is transparent for the user performing the activity. Regarding the assessment of engagement, Canossa and Drachen (2009) restrain the use of metrics for monitoring users' actions as they consider that metrics cannot give information about abstract or psychological quantities. Yet, Bauckhage et al (2012) note that since engagement influences the behaviour, some measurable quantities can be considered in identifying engaged-behaviours. However, the main difficulty with metric methods is to select the relevant telemetry data to convert to metrics in order to extract some valuable (i.e. interesting, interpretable and useful) information about engaged-behaviours.

Several data mining or analysis techniques can be applied on user-generated data to analyse the engagement. To assess the impact of tutorials on players' engagement in digital entertainment games, Andersen et al (2012) collect some raw data such as the number of unique levels completed, the total playing time and the number of times players have loaded the game. Expecting to predict when players will stop playing, Bauckhage et al (2012) study how engagement evolves over time. They apply techniques from lifetime analysis on players' playing time information (when they play and for how long) collected from five AAA-games like Tomb Raider or Crysis. Dealing with learners' disengagement detection in web-based e-learning system, Cocea and Weibelzahl (2009) compare eight machine learning techniques on several raw data. The latter are mainly related to reading pages (number of pages read, time spent reading pages) and quiz events. By conducting quantitative measure on isolated (i.e. unlinked) utilitarian metrics, these methods remain on a basic level that only give information about what the user is actually doing during the activity but cannot reach the experiential level where engagement is situated. Indeed, Pagulayan et al (2003) discuss the differences between hedonic applications such as video games and utility applications such as tax management systems or spreadsheets. One difference is that utilitarian metrics such as the time required to perform a task or the number of tasks successfully completed do not enable the analysis of the experiential level of a mediated activity and thus engagement.

While the methods presented in the previous paragraph only consider some isolated users' actions, sequence-mining methods consider user's engaged-behaviour as sequences of actions. Beal et al (2006) propose a classification approach to user engagement within an ITS to learn mathematics. For that purpose, they defined five student's time-dependent patterns of actions based on time traces of actions within the ITS: 1. The problem is displayed for at least 10 seconds + selection of the correct answer; 2. The problem is displayed for at least 10 seconds + selection of an incorrect answer + the problem is displayed for at least 10 seconds + selection of the correct answer; 3. Student selected one or more answers within 10 seconds of the problem presentation and no help was viewed; 4. The student clicked on help with inter-click in-

tervals of less than 10 seconds; 5. The problem is displayed for at least 10 seconds + help was requested and presented for at least 10 seconds before an answer was selected or another hint was requested. More recently, Köck and Paramythis (2011) adopt a clustering approach to detect sequences of learner's actions in the Andes ITS. These studies only occur in high-constraint environments like ITS. In such environments, the variety of actions is limited and fully determined by the interactive activity (attempts, request for hint, results etc.) and so the number of items is limited. Thus, sequence-mining may constitute an efficient method for discovering some statistically relevant sequences of actions. But, in low-constrained interactive systems like digital games, a wide range of actions may be possible. For instance in entertainment digital games, players have more freedom to explore the environment or to interact with agents than in an Intelligent Tutoring System. Then, sequence-mining may return a high number of sequences that are difficult to interpret. Also, the sequences of user's actions discovered by the sequence-mining algorithm are not necessarily directly valuable and still need to be interpreted by the analyst. Finally, machine learning for sequential data mining suffers from several issues such as long-distance interactions (Dietterich, 2002). Indeed, if the elements that compose a significant sequence are not adjacent or in the near neighbourhood, the sequence-mining algorithm may not be able to discover this sequence.

To sum up, subjective methods may provide some accurate and subtle information on engagement. But as these methods require the active and voluntary participation of the users, their implementation tends to restrain them to laboratory experimentations. Physiological or behavioural measures show great promise but they are hard to implement in ecologically valid conditions and they require the users to possess some specific devices. Metrics methods are transparent to the users but the strategies currently implemented do not allow for the assessment of users' engagement during low-constraint interactive mediated activities. In section 5 we present our approach to identifying engagement in low-constraint interactive mediated activities, directly, continuously and under ecologically valid conditions and over a long period of time. But first, in section 4 we detail the theories on which we rely in order to define this approach.

4 Theoretical background

The approach proposed in section 5 relies on three theories: the Self-Determination Theory to identify users' motives, the Activity Theory to deconstruct high-level engaged-behaviours in *activity*, *actions* and *operations* and the Trace Theory to extract meaningful information from low-level interaction traces.

4.1 Self-Determination Theory (SDT)

The Self-Determination Theory (SDT) is a theory of human motivation initiated by Ryan and Deci (2000). The two psychologists developed this theory in order to understand Human personality development and well-being. This theory postulates A) that individuals have three basic psychological needs: competence (sense of efficacy), autonomy (volition and personal agency) and relatedness (social interaction) and B) that Humans strive to fulfill these three needs in order to enhance wellbeing. Then Humans engage in tasks that enable them to satisfy these needs and so their behaviour is determined by this need fulfillment. SDT has been applied in many fields such as education, health or digital gaming ².

4.2 Activity Theory (AT)

The Activity Theory (AT) initiated by Vygotsky (1978) and Leontiev (1978) aims to understand Human development through an analysis of the genesis, structure and processes of activities. AT has been used for more than a few years in the Human-Computer Interactions field (Kaptelinin and Nardi, 2006). Activity Theory proposes to deconstruct human' activities according to the three different levels of analysis it distinguishes:

- An *activity* is performed by a subject, through a tool, in response to a specific need or motive in order to achieve an object (i.e. an objective). The need generates the motive, the motive elicits the *activity*, the object structures and directs (Kaptelinin, 2005) the *activity* towards a desired and anticipated (Bardram, 1997) outcome. The object is what characterizes an *activity* and differentiates one *activity* from another (Leontiev, 1978). The object has to be of high significance to the subject i.e. be self-sufficient.
- An *action* (or chains of *actions*) can be seen as the actual transcription of the *activity*. An *action* can be used by different *activities* in order to reach a goal. Thus, the goal of the *action* (and so of the chain of *actions*) depends on the *activity* to which it is subordinated. The difference between objects (*activity* level) and goals (*action* level) is the significance regarding the motive of the *activity*. The object directly depends on the motive that elicits the *activity*. The goals can be seen as sub-object or steps that have to be reached in order to complete the object. *Actions* are performed consciously and with effort through *operations*.
- An *operation* enables the actual realization of the actions. *Operations* are automatized, that means performed without conscious thoughts or efforts. They are determined by the environmental and contextual conditions of the *activity* and can be used by different *actions*.

² see <http://www.selfdeterminationtheory.org> for a list of practical applications of the SDT.

4.3 Trace Theory (TT)

The Trace Theory (TT) is a framework for collecting, analyzing and representing users' interaction traces (Clauzel et al, 2011). At the lowest level of the framework are the observed elements (labeled *obsels*). Typically, an *obsel* corresponds to a user's raw action collected in the interactive system (like a mouse click or a key pressed on the keyboard). An *obsel* contains a type of event, a timestamp and a set of contextual information useful for characterizing the event and deriving meaning. A primary trace is a set of temporally situated *obsels* that may be connected. A primary trace may contain a very large number of *obsels* whose informational level may be very low. So, it may be difficult to extract valuable knowledge from a primary trace. The formalization proposed by Settouti et al (2009) aims to facilitate the transition from primary traces to meaningful information represented in high-level traces. It consists in transforming a primary trace into a trace of a higher level based on a rule-based system. A rule consists in temporal constraints or in operations on the contextual attributes performed between *obsels*. The transformation process can aggregate several *obsels* according to the rules. The *obsels* generated constitute the new transformed trace. The experts' knowledge that has been injected during the construction of the rules leads to the extraction of a more complex or abstract knowledge than the one that can be initially extracted from the primary trace.

5 A qualitative approach to identifying and qualifying engaged-behaviours from users' interaction traces

We consider engagement as the willingness to have emotions, affects and thoughts directed towards and aroused by the mediated activity, in order to achieve a specific objective (Bouvier et al, 2013a). This means that emotions such as enjoyment, pride or accomplishment are provoked by the game or that players' thoughts are focused on the game during, but also between, gaming sessions. In this view, engagement is considered as a connection maintained between players and the gaming sessions. From an operational point of view, we qualify in this study a player as being engaged since s/he manifests at least one engaged-behaviour (i.e. at least one *obsel* from the *activity* level is generated).

In this section, we propose an approach to identifying engaged-behaviours from the users' interaction traces. Two main questions have to be addressed:

1. How can engaged-behaviours be distinguished from non-engaged-behaviours?
2. How can these engaged-behaviours be detected among all the collected data?

To address the two questions above, we propose an approach that combines the three theories mentioned in section 4. Our approach is composed of three stages explained in the following three subsections. In part 5.1, we answer the

first question mentioned above by identifying four types of high-level engaged-behaviours. Parts 5.2 and 5.3 allow us to address the second question. First, in part 5.2 we explain how we deconstruct these high-level engaged-behaviours into *activities*, chains of *actions* and chains of *operations* actually performed within the interactive system. Then, in part 5.3 we explain how, among all the collected data, we detect all these elements (identified in part 5.2) that constitute an engaged-behaviour.

5.1 Determining engaged-behaviours with the SDT

The aim of this stage is to distinguish engaged-behaviours (i.e. behaviours reflecting an engagement) from non-engaged behaviours. To structure the analysis of engaged-behaviours, we first consider that most of the mediated interactive activities consist in performing actions (decision-making process), directly or through a character (by adopting a specific role), within an environment (or at least on a frame) which may involve social interaction with human or virtual agents. The role adopted during the mediated activity may be the one intended by the mediated activity or another one independently chosen by the participant. This categorization enables us to identify four types of high-level behaviours.

Then, in agreement with the SDT (introduced in part 4.1) we consider that users engage in behaviours that enable them to fulfil their basic needs. This leads to the identification of the four following types of engaged-behaviours:

- environmental, in relation to the need for autonomy and directed towards the environment or frame that support the activity;
- social, in relation to the relatedness need and directed towards the social connections that may occur during the activity;
- self, in relation to the autonomy need and directed towards the character or role adopted during the activity;
- action, in relation to the competence and autonomy needs and directed towards the actions to perform during the activity.

This categorization of engaged-behaviours (environment-directed, social-directed, self-directed and action-directed) aims to define some hypotheses about the high-level engaged-behaviours that we seek to detect within the recorded users' actions. By relying on these basic psychological needs perspective rather than on empirical observation of users' behaviours in interactive systems, our approach aims to determine a wide and non-stereotyped range of behaviours.

5.2 Characterizing engaged-behaviours with Activity Theory

The work conducted during the first stage of our approach (section 5.1) enables us to establish the relationships between users' needs and the corresponding high-level engaged-behaviours. These high-level engaged-behaviours

remain distant from the users' actions actually performed during the activity. Thus, it is necessary to extend these relationships to the actions actually performed. To this end we combine the SDT with the Activity Theory (described in part 4.2). We use the Activity Theory to deconstruct an engaged-behaviour (determined during the previous stage using the SDT) in *activity*, chains of *actions* and chains of *operations* actually performed in the interactive system by the users.

According to the Activity Theory the need generates the motive and the motive elicits the *activity* (see section 4.2 page 9). We consider that the emotions felt by the users when one of their needs is fulfilled constitute the motive of the engagement. So the emotions sought determine users' engaged-behaviours within the interactive system. The support and the orientation of the emotions are specific to each of the four types of engaged-behaviours and so can differentiate the four types of engaged-behaviours (environmental-oriented vs. social-oriented vs. self-oriented vs. action-oriented). For instance the emotions that motivate the social-engagement *activities* are oriented towards the other users, while the emotions that motivate the action-engagement *activities* are oriented towards the action to perform. But within each type of engaged-behaviours, while the emotions felt may be different, the emotions share the same orientation. For instance the emotions related to collaboration or to social recognition are different but share the same orientation towards the other users.

Table 1 illustrates the categorization of the four types of engaged-behaviours according to the basic needs these engaged-behaviours can fulfill and the elicited associated emotions. We also list some examples of *activities* that the users may conduct according to the entertainment digital game context of the QUEJANT project. Regarding the elicited (or at least sought) emotions, we use the term pleasure as a blanket term that can cover several basic emotions such as joy, surprise, fear, stress and non-basic emotions such as curiosity or enjoyment (Calvo and D'Mello, 2010). The frequency and the intensity of these engaged-behaviours depend on the nature of the mediated activity.

The decomposition of an engaged-behaviour into *activities*, chains of *actions* and chains of *operations* is illustrated in Figure 1. Within the social-engagement type, Motive A and Motive B share the same orientation towards the other users and generate *Activity A* and *Activity B* respectively. Object A and Object B are the object of Activity A and Activity B respectively. As the object structures and directs the *activity*, the object determines the underlying chain of *actions*. For instance *Activity A* is supported by the chain *Action 1* - *Action 2* - *Action 4* while *Activity B* is supported by the chain *Action 2* - *Action 3* - *Action 5*.

The example above highlights that an *action* (in this case *Action 2*) may belong to several chains of *actions* which have different goals. Indeed, as an *activity* is realised through a specific (i.e. unique) chain of *actions*, the goal of the chain depends on the *activity* to which the chain is subordinated. For instance *Action 2* whose goal (entitled Goal 2) remains stable may belong to two different chains of *actions*. But these two chains have their own goals

Table 1 Categorization of the four types of engaged-behaviours according to the universal and basic needs these engaged-behaviours can fulfill and some emotions associated with need fulfillment. Example of *activities* users may conduct in an entertainment digital game.

	Environmental engagement	Social engagement	Self engagement	Action engagement
SDT basic psychological needs	Autonomy towards the environment	Relatedness	Autonomy towards the character or role	Competence Autonomy towards the actions
Elicited emotions	Escapism, Curiosity, Surprise, Imagination, Relaxation, Aestheticism	Pleasure in social connectivity, Pleasure in collaboration or competition, Pleasure in social recognition	Pleasure in possessing, Pleasure in managing an avatar, Pleasure in disguising themselves or adopting a role	Accomplishment, Self-esteem, Arousal
Activities	Virtual trip Trying to reach the limit of the game Discovering extra-content	Expanding social network Livening up the group of actual friends Enjoyment with others	Customizing the character Developing a story around the character	Mastering the game Completing challenges Elaborating a strategy

(Goal A and Goal B) according to which *activity* (*Activity A* and *Activity B* respectively) the chain belongs to. Finally each *action* is realized through its own chain of *operations* actually performed with the input devices provided. Similarly, an *operation* may belong to several chains of *operations* in order to enable the realization of different *actions*.

5.3 Detecting engaged-behaviours with Trace Theory

To detect the engaged-behaviours among all the actions recorded, we combine the Activity Theory and the Trace Theory (see part 4.3) by establishing the following correspondences:

- An *operation* corresponds to an *obsel* from the primary trace.
- An *action* corresponds to an *obsel* from the transformed trace.
- An *activity* corresponds to an *obsel* from the highest-level transformed trace.

The Trace Theory can detect the relevant *operations* among all the collected and stored *obsels* and then reify (through the transformation process) the relationship between a chain of *operations* and an *action* and between a chain of *actions* and an *activity*. These relationships have been identified during the second stage of our approach using the Activity Theory. The *obsels* which compose the highest-level trace correspond to the *activities* that belong to a specific engaged-behaviour. The highest-level transformed trace may have been generated after several transformation processes. For instance in

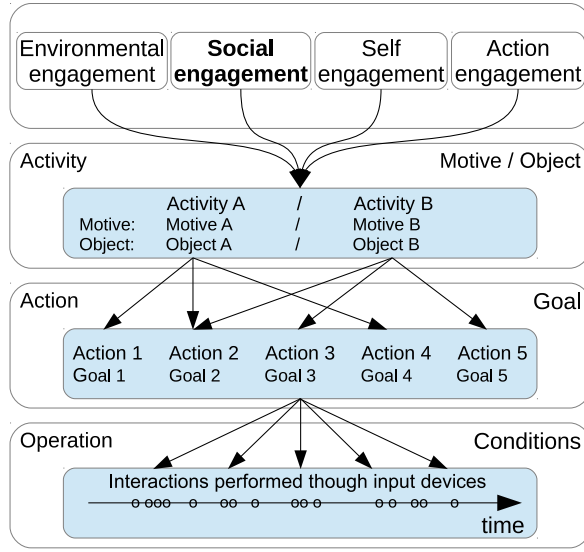


Fig. 1 Our approach combines the Self-Determination Theory and Activity Theory in order to decompose an engaged-behaviour into *activity*, chain of *actions* and chain of *operations*.

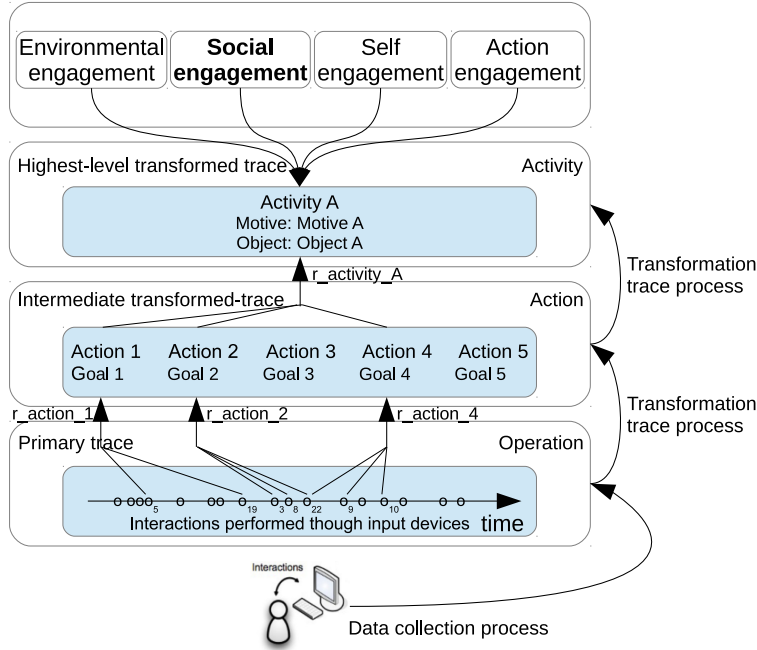


Fig. 2 To detect user's engaged-behaviours among the collected and recorded data, our approach uses the Trace Theory to reify through the transformation process, the relationship between a chain of *operations* and an *action* and a chain of *actions* and an *activity*.

Figure 2, the highest-transformed trace that corresponds to the *activity* level has been computed after two transformations. The first transformation has enabled the generation of the intermediate transformed trace (of *action* level).

Let us consider an example illustrated in Figure 2. During a session we collect numerous *obsels* from different types (i.e. which may correspond to different specific events that occurred during the activity). In relation to the work conducted during the second stage of our approach, a transformation rule labelled *r_action_1* is defined in order to aggregate some specific *obsels* from the primary trace (see section 6.4 for an example of rule). This rule enables us to detect, in the primary trace, the presence of the targeted specific chains of *operations* according to some temporal constraints determined during the second stage. For instance, if *operation 5* and *operation 19* occurred within the right time interval then the transformation rule generates a new *obsel* with higher-level labelled *Action 1* in the transformed trace of level *Action*. The time intervals are defined during a step of analysis of the game that belongs to this third stage. This step involves analysing the traces in order to determine the suitable time interval for each rule. The input data (i.e. the lower-level *obsels*) and the constraints constitute the signature of a rule. Since this signature is unique, the higher-level *obsels* generated are from a single type and so with a single purpose.

The transformation process has also a rule labelled *r_action_2* that enables us to aggregate another targeted chain of *operations* (for instance *operation 3*, *operation 8* and *operation 22*). This transformation rule may generate an *obsel* labelled *Action 2* in the transformed trace of level *Action*. A third rule labelled *r_action_4* is defined in order to generate the *obsel Action 4* from its own chain of *operations* (for instance *operation 22*, *operation 9* and *operation 10*). This example highlights that an *operation* (in this case *operation 22*) may belong to several chains of *operations* in order to enable the realization of different actions (*Action 2* and *Action 4*).

Then in a second transformation process of higher level, a rule labelled *r_activity_A* is defined in order to aggregate the three *obsels* of level *Action* labelled *Action 1*, *Action 2* and *Action 4*, according to a specific temporal constraint. If this chain of actions occurred during the right interval time then the *obsel Activity A* is generated. This *obsel* belongs to the trace of highest-level i.e. the *activity* level. The same process is reiterated in order to define and instantiate the set of rules that enable us to identify each *action* and each *activity* identified during the second step.

5.4 Summary of the proposed approach

Figure 2 illustrates the three stages of our approach. The first stage (see section 5.1) combines a theoretical work on engagement, engaged-behaviours and the Self-Determination Theory. By determining some high-level engaged-behaviours, this stage allows us to address the first question mentioned at the top of the section 5 (*How can engaged-behaviours be distinguished from non-*

engaged-behaviours?). The second and third stages (see sections 5.2 and 5.3 respectively) allow us to address the second question identified at the top of the section 5 (*How can these engaged-behaviours be detected among all the collected data?*). Indeed, the high-level engaged-behaviours identified during the first stage may be very distant from the users' actions actually performed in the system. So, to identify the relationship between these high-level engaged-behaviours and the actions actually performed we adopt an Activity Theory perspective in the second stage. The latter enables us to deconstruct these high-level engaged-behaviours into *activities*, chains of *actions* and chains of *operations* actually performed by the users. Then, in the last stage, we rely on the Trace Theory to detect and extract the relevant chains of *operations* among all the collected and recorded actions and also to reify (through the transformation process) the relationship between a chain of *operations* and an *action* and between a chain of *actions* and an *activity*. So, a chain of *actions* is an aggregation of several user's actions according to the temporal constraints or to the characteristics of the actions. Considering some chains of *actions* rather than single *actions* provides comprehensive contextual information on behaviours and thus, facilitates their understanding. Each *activity* belongs to a specific type of engaged-behaviour.

6 Implementation

We implemented all the processes underlying our approach: collecting the system- or user-generated events, storing and organising the data, characterising the engaged-behaviours and detecting the engaged-behaviours within the interaction traces. This implementation is based on an actual commercial game rather than on a laboratory product. This enables us to analyse actual players' engaged-behaviours in low-constraint interactive systems, directly, continuously, under ecologically valid conditions and over a long period of time.

6.1 Context

For this implementation, we used the BodyBoarding game developed by the company IntellySurf³. The game consists in travelling from spot to spot on the five continents in order to perform some bodyboarding maneuvers, to complete some challenges or to play against other players. The game has a strong social dimension in that it encourages competition between players. It also promotes game events sharing on social networks. In addition, by offering a realistic rendering of the bodyboarding activity (performing maneuvers, the weather and wave conditions depend on actual meteorological and topographical reports)

³ YouRiding: <http://www.youriding.com>

the game highlights a strong action dimension. Thus, this game provides a variety of engaged-behaviours that can cover the four types of engaged-behaviours identified in section 5.1.

YouRiding BodyBoarding game already collects information about the players' actions. The objective is twofold. The first one, technological, aims to track bugs, to check the effectiveness of the game (response time etc.) or to ensure the relevance of the gameplay⁴ (level of difficulty of the tutorial, use of the help information etc.). The second objective is to compute some marketing metrics such as retention rate⁵, DAU (Daily Active Users), MAU (Monthly Active Users) or ARPU (Average Revenue Per User).

6.2 Architecture

Figure 3 illustrates the architecture underlying our approach. The BodyBoarding game developed by our partners is instrumented to automatically collect players' interactions. This collection uses a classic client-server architecture with JavaScript and PHP scripts in order to trigger the collection of the data and then, their storage in a MySQL database (see Figure 3 - step 1). Each collected *obsel* contains two timestamps, a name that identifies its type and at most three attributes that provide some contextual information such as the name of the button that triggered the collection or the ID number of an object (spot, equipment etc.). The first and second timestamps refer to the beginning and the end of the event respectively. Thus, most of the time the two timestamps of an *obsel* of the primary trace are the same.

The interaction data are then exported from the MySQL database in a CVS (Comma-Separated Values) file (Figure 3 - step 2). The following example is extracted from the CVS file of a collected trace.

```
08/01/2012 00:42:10;08/01/2012 00:42:10;open_profile_skills;skillsBtn
08/01/2012 00:42:42;08/01/2012 00:42:42;open_profile_improvements;improvementBtn
08/01/2012 00:43:14;08/01/2012 00:43:14;open_shop;placeZone_spotSurfShop
08/01/2012 00:43:46;08/01/2012 00:43:46;item_equip;24
08/01/2012 00:44:02;08/01/2012 00:44:02;goto_spot;placeZone_spot_button_1;66
08/01/2012 00:44:16;08/01/2012 00:44:16;play_start_on_spot;66
```

The primary traces are recorded in a trace based management system called kTBS⁶ (Champin et al, 2011). The kTBS can store and execute the transformation rules in order to compute the transformed traces. The kTBS records the primary and transformed traces in RDF⁷ format. The transformation rules are written in SPARQL⁸ query language in the kTBS. To interact with the kTBS, we use the graphical software D3KODE⁹ (Champalle et al, 2012). D3KODE

⁴ In digital gaming, gameplay is a blanket term which refers to the structure, the dynamics or the interactive aspects of a game.

⁵ Retention rate is the percentage of the people who used a service in month 1 and are still using it in month 2.

⁶ kernel for Trace-Based Systems.

⁷ <http://www.w3.org/RDF/>

⁸ <http://www.w3.org/TR/rdf-sparql-query/>

⁹ Define, Discover, and Disseminate Knowledge from Observation to Develop Expertise.

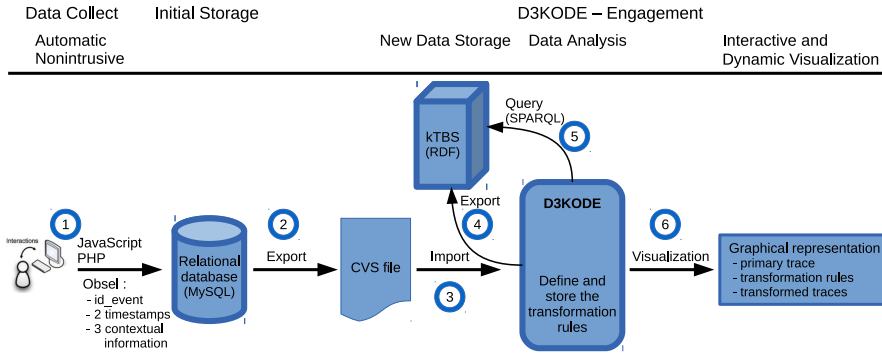


Fig. 3 The process underlying our approach. The main steps are: collecting the system-or-user generated events, storing and organising the data and qualifying users' behaviours.

implements the Trace Theory (presented in section 4.3) by providing the following features: loading the CVS data as a primary trace, creating the transformation rules and visualising the primary and transformed traces. The CVS file is loaded (Figure 3 - step 3) into the tool D3KODE. The primary trace is converted (Figure 3 - step 4) into RDF format by D3KODE in order to be stored in the ktBS. D3KODE can graphically create the transformation rules and convert them into SPARQL language so that they can be recorded in the ktBS (Figure 3 - step 5). The ktBS executes the transformation rules to compute the transformed traces. The transformed traces are also stored under RDF format in the ktBS. Finally D3KODE proposes a graphical representation of the primary and transformed traces and of the transformations that link them (Figure 3 - step 6). See Figure 5 for a screenshot of this last step.

6.3 Identification of high-level activities

Considering the features of the game studied within the QUEJANT project, we identify four *activities* from three of the four types of engaged-behaviours identified in section 5.1. Indeed, the self-engagement dimension is not sufficiently promoted to be detected in the user traces. We characterized the following four *activities*:

- Social-engagement dimension:
 - the *activity* 'Develop new social relationship' is supported by the *actions*: 'Propose confrontation', 'Find players', 'Be interested in other player', 'Ask to be friend' and 'Accept to be friend';
 - the *activity* 'Share moment with real friends' is supported by the *actions*: 'Share game events on social networks', 'Import real friends into the game' and 'Propose confrontation with friends';
- Action-engagement dimension:

- the *activity* 'Achieve challenges' is supported by the *actions*: 'Seek information about challenges', 'Improve character equipment', 'Improve player' and 'Improve character';
- Environment-engagement dimension:
 - the *activity* 'Increase knowledge about the game' is supported by the *actions*: 'Seek information about the game', 'Practice the tutorial' and 'Configure the game options'.

We also decomposed each *action* in the chain of *operations* that enables the actual realisation of the *actions*. These *operations* are performed with the input devices (which in our case are the mouse and the keyboard).

6.4 Transformation rules

Transformation rules allow us to reify the relationships between the chains of *operations* (belonging to the primary trace) and the *actions* (belonging to the intermediate transformed trace) and between the chains of *actions* and the *activities* (belonging to the highest-level transformed trace). In this part, we first give an example of the transformation process that we implemented in D3KODE. Then we present an example of transformation rule.

During sessions, we collect many *obsels* from 89 types. Each type of *obsel* corresponds to a specific type of action that the player can undertake in the game. Among the 89 types of collected actions, i.e. types of *obsels* in the primary trace, one can find for instance 'Proposing a challenge to another player', 'Buying new equipment for the character', 'Changing the configuration of the keyboard', etc.

For instance in the social-engagement dimension (see Figure 4 for an illustration), we identified the *activity* 'Develop new social relationship' whose motive is 'Feeling emotions related to social interactions' and object is 'Increasing the number of Friends'. We defined a transformation rule labelled 'Find players' in order to aggregate some specific *obsels* from the primary trace. This rule makes it possible according to some temporal constraints to detect the presence of the pair of *obsels* 'game_social_open' and 'game_social_search' in the primary trace. The presence of these *obsels* in the primary trace indicates that the player has opened the social panel of the game and has looked for other players according to several attributes such as the name and/or the town or the country. If these *obsels* occurred within a certain time interval, then the transformation rule generates a new *obsel* with higher-level labelled 'Find players' in the transformed trace of *action* level. The transformation rule labelled 'Propose confrontation' enables to aggregate some specific *obsels* regarding the phase of play where several players challenge one another on the same wave. This rule may generate an *obsel* labelled 'Propose confrontation' in the transformed trace of the *action* level. This process was reiterated for the three other *actions* ('Be interested in other players', 'Ask to be friend' and 'Accept to be friend'). Then a second transformation process of higher level contains some rules to aggregate the previously generated *obsels* of *action* level.

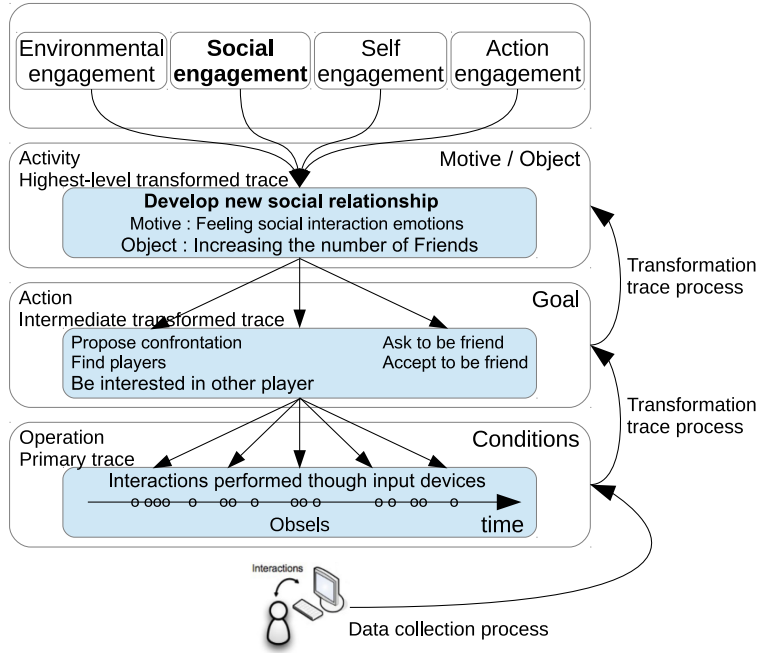


Fig. 4 Example of the deconstruction of a social engaged-behaviour in *activity*, chain of *actions* and chain of *operations* performed during the QUEJANT project. To identify, qualify and detect engaged-behaviours within users' traces of interaction, our qualitative approach combines a theoretical work on engagement and engaged-behaviours, Self-Determination Theory, Activity Theory and Trace Theory.

The highest-level transformed trace may contain the *obsel* of highest-level that corresponds to the *activity* 'Develop new social relationship'.

A rule can rely on temporal constraints or on the contextual attributes. Lets consider an example illustrated in Figure 5. Figure 5 is a screenshot extracted from D3KODE that graphically represents the transformation process. For a better readability, this example representing the identification process of the *activity* 'Develop new social relationship' has been simplified by considering only two underlying *actions*: 'Propose confrontation' and 'Be interested in other players'. Regarding this graphical representation, D3KODE allows one to zoom and translate within the traces (and so the transformation process). The *obsels* 'Propose confrontation' and 'Be interested in other players' indicate that the player proposes a challenge to other players and that the player opens the players' profile page respectively.

According to our characterisation, the *obsels* 'challenge_wait', 'challenge_start' and 'challenge_end' may be aggregated if they match the temporal constraint. If the condition is validated then the *obsel* of *action* level 'Propose confrontation' is generated. The following rule detects when these three *obsels* occurred in the primary trace in the interval of 10 minutes (the temporal constraint is defined in seconds).

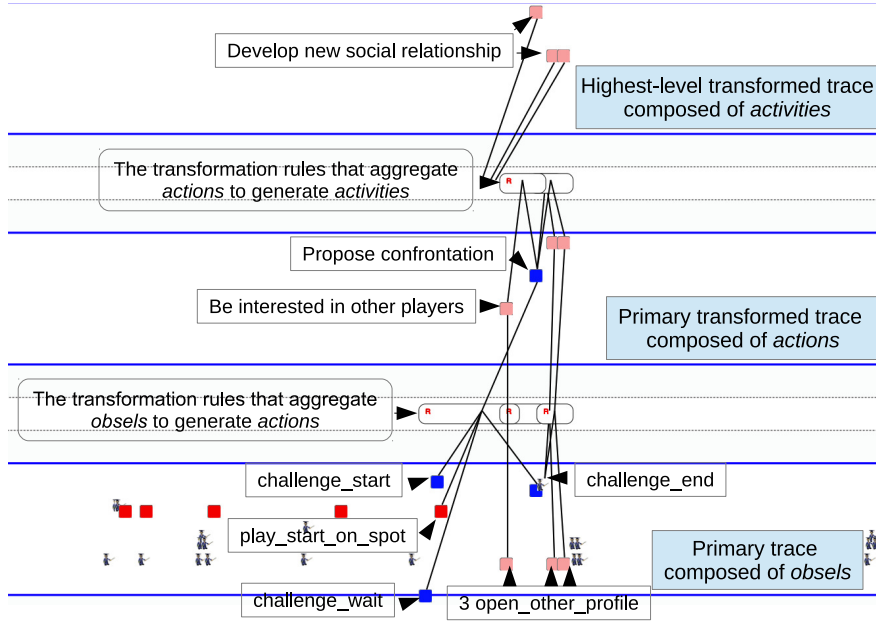


Fig. 5 Graphical representation in D3KODE of the transformation process from a primary trace to the highest-level transformed trace. In the primary trace the red, blue and pink squares are representing `play_start_on_spot`, challenge (`_wait`, `_start` and `_stop`) and `open_other_profile` operations respectively. In the primary transformed trace, the blue and pink squares are representing `Propose confrontation` and `Be interested in other players` actions respectively. In the highest level transformed trace the pink squares are representing the activity `Develop new social relationship`.

```
{
  (game_challenge_wait.hasEnd < game_challenge_start.hasBegin) AND
  (game_challenge_start.hasEnd < game_challenge_end.hasBegin) AND
  (game_challenge_end.hasBegin - game_challenge_wait.hasEnd) <=600
}
```

The generated 'Propose confrontation' *obsel* incorporates the information from the underlying *obsels*. So, its begin and end timestamps take the 'game_challenge_wait.hasEnd' and 'game_challenge_end.hasBegin' timestamps respectively. In Figure 5, the temporal dimension of the *obsel* 'Propose confrontation' is loosely represented by a blue square. Indeed it would be more relevant to represent this *obsel* by a blue rectangle to reflect the duration of this *action*. Also, the *obsel* 'open_other_profile' is simply selected and transformed in the *obsel* of *action* level 'Be interested in other players'.

In a second step, the *obsels* 'Propose confrontation' and 'Be interested in other players' are aggregated, if they match the temporal constraint, in order to generate the *obsel* of *activity* level 'Develop new social relationship'. We consider the following three cases:

- the player opens the profile of another player and then proposes a confrontation to this player

- the player opens the profile of another player during the confrontation
- the player opens the profile of the other player just after the confrontation

The following rule enables to address these three cases respectively:

```
{
  (be_interested_in_other_players.hasEnd < propose_confrontation.hasBegin) AND
  ((propose_confrontation.hasBegin - be_interested_in_other_players.hasEnd) <= 120)
}
OR
{
  (propose_confrontation.hasBegin < be_interested_in_other_players.hasBegin) AND
  (be_interested_in_other_players.hasEnd < propose_confrontation.hasEnd)
}
OR
{
  (propose_confrontation.hasEnd < be_interested_in_other_players.hasBegin) AND
  ((be_interested_in_other_players.hasBegin - propose_confrontation.hasEnd) <= 120)
}
```

In the actual implementation, we defined in D3KODE the whole set of rules that make it possible to generate all the *actions* underlying the *activity* 'Develop new social relationship'. We iterated the transformation process to generate all the *obsels* of highest-level that indicate the presence of the *activities* reflecting the four engaged-behaviours identified in section 6.3.

6.5 Summary of the implementation

This implementation shows the feasibility of our approach. The implementation required several steps. We first set up an architecture that can collect and store the data and to implement our approach. We collected and integrated in our system 12 users' interaction traces (see section 7.2.1 for details on these data). Then we analysed the game in order to characterize four *activities* reflecting three of the four types of engaged-behaviours identified in section 5.1. The fourth step consisted in determining and implementing in D3KODE the whole set of transformation rules that can reify the relationship between the chain of *operations* and an *action*, and between the chain of *actions* and an *activity*. Then we applied these transformation rules to the 12 interaction traces that we collected. This implementation shows the feasibility of our approach and its relevance to identifying and qualifying engaged-behaviours in interactive mediated activities. This implementation also highlights some limitations that we discuss in section 8.2.1.

7 User study

We performed a user study to validate the performance of our approach 1) to distinguish engaged-users from non-engaged ones, and 2) to identify the types of engaged-behaviours for the engaged users. The evaluation of this performance is based on an agreement rate between the results returned by our prototype and the results given by experts on the interaction traces of engaged and non-engaged users.

7.1 Experts involved in the validation

This study involved three experts in social gaming. Two experts are Chief Executive Officer (CEO) and one expert is Chief Technology Officer (CTO) in digital game companies since more than five years. They were selected for several reasons:

- They are CEO and CTO of the companies involved in the QUEJANT project but they were not involved in the theoretical and implementation parts of our approach, presented in the previous sections. This ensures that there is no bias in this study.
- They have a high level of expertise in social gaming and more precisely in the analysis of players' engagement. So they know how to identify engagement and types of engagement based on the interaction traces of the players.
- They are all currently working on the BodyBoarding game we used for the user study and thus have in-depth knowledge of this game (mechanics, gameplay, data collected) and of the players.

7.2 Materials

The experts were provided with two types of materials: interaction traces of players and documents.

7.2.1 Interaction traces of players

We collected the traces of a representative sample of players, according to a selection made by game designers of the BodyBoarding game. These designers are in charge of following the daily activities of hundred of thousands of players and adjust the game based on these observations. They selected traces of players considered as being representative, based on information from their profiles and their activities in the game.

12 raw traces of 12 different players¹⁰ were transmitted by game designers according to two groups: Users Group 1 is composed of six players considered as engaged and Users Group 2 of six non-engaged players. These twelve traces were communicated with these engaged or non-engaged labels and without any other information. Table 2 and Table 3 summarize the descriptive information on the traces for the two groups.

The interaction traces were collected in the period from January to April 2012. A trace may contain up to 89 types of *obsels* and can be composed of several thousands of *obsels* (10718 *obsels* for the most active player). These *obsels* may give information about the players' routes (which zone, which spot, which specific panel is opened etc.) but also about the players' strategy (visits

¹⁰ When players register for the game, it is stipulated that their activity can be anonymously collected for the purpose of improving the service or the gaming experience.

Table 2 Statistics of the traces of the Users Group 1 composed of the 6 engaged-players.

	Trace_1	Trace_2	Trace_3	Trace_4	Trace_5	Trace_6
Period of activity	01/03 04/29	01/08 04/29	01/04 04/24	01/08 04/22	01/06 04/18	01/08 04/27
Number of <i>obsels</i>	10718	4075	3137	4658	4874	4846
Variety of <i>obsels</i> (/89)	62	51	53	56	50	58

Table 3 Statistics of the traces of the Users Group 2 composed of the 6 non-engaged players.

	Trace_7	Trace_8	Trace_9	Trace_10	Trace_11	Trace_12
Period of activity	01/01 04/29	01/02 02/03	01/03 04/10	01/09 04/22	01/30 04/03	01/31 04/03
Number of <i>obsels</i>	1757	313	608	103	323	250
Variety of <i>obsels</i> (/89)	48	27	42	25	32	36

to the surf school, changes in the equipment etc.). Although these traces are potentially composed of 89 types of *obsels* (according to the player's actions), 50% to 60% of the primary traces are composed of the four *obsels goto_map*, *goto_zone*, *goto_spot* and *play_start*, which reflect the path followed by the player in the game.

7.2.2 Documents

We communicated to the experts a document stating our position regarding the nature of engagement and describing, through simple examples, the four types of engagement that we have identified (see Appendix A). It was important to give them examples for each type of engaged behaviours so that they understand the distinction we make between each type. However the definition of engagement given to the experts was of secondary importance because the experts were selected according to their expertise in this area.

The experts were also provided with an online questionnaire. The experts had three options (Yes, No, Without opinion) in answer to the five following questions (the questions were originally in French so we provide an English translation here):

1. Would you say that the Trace_X corresponds to an engaged-player?
2. Would you say that the Trace_X corresponds to a social-directed engagement?
3. Would you say that the Trace_X corresponds to an action-directed engagement?
4. Would you say that the Trace_X corresponds to an environment-directed engagement?

5. Would you say that the Trace_X corresponds to a self-directed engagement?

The questionnaire was composed of 12 pages (1 page per trace/player) containing the same five questions.

7.3 Procedure

The three experts evaluated the engagement and the type of engagement of players from these interaction traces. We note that the experts felt qualified to make this evaluation from the raw traces. The evaluation followed the following procedure:

- The experts were gathered in one room so that we can answer questions if needed.
- The twelve users' traces were mixed before being communicated to the experts. The experts had no information about the players or the traces.
- They read the definition and examples of different types of engagement presented a document (see Appendix A). We asked them to keep this information on hand while completing the questionnaire.
- The 12 log files (referred to Trace_A to Trace_L) were sent to the three experts by email so that they can read them while they answer the questionnaire.
- We asked them to fill in the five repeated questions of the questionnaire for the 12 log files (i.e. 12 x 5 answers to give). They so indicated via the online questionnaire if, after reading the log file, they thought that the player is engaged and, if so, to precise the type(s) of engagement.
- They completed the questionnaire in one time.

The participants asked no questions, neither on the definitions and examples given on engagement, nor on the interaction traces.

We gave the experts simple rules to respect:

- There is no right or wrong answer. Thank you for giving your first opinion simply by selecting your answer.
- Answer the questions independently of each other (for example, a player may have several types of engagement).
- Do not skip a question and do not come back on a question to change your answer.
- Do not discuss this evaluation before having communicated the results.

To extract a meta-expertise from each triplet of experts' answers, we applied the following rules to each question:

1. If the three experts give the same answer (three Yes or three No) then their opinion is retained.
2. If two experts give the same answer (two Yes or two No) and the third expert gives an opposite answer or Without opinion, then the opinion of the majority is retained.

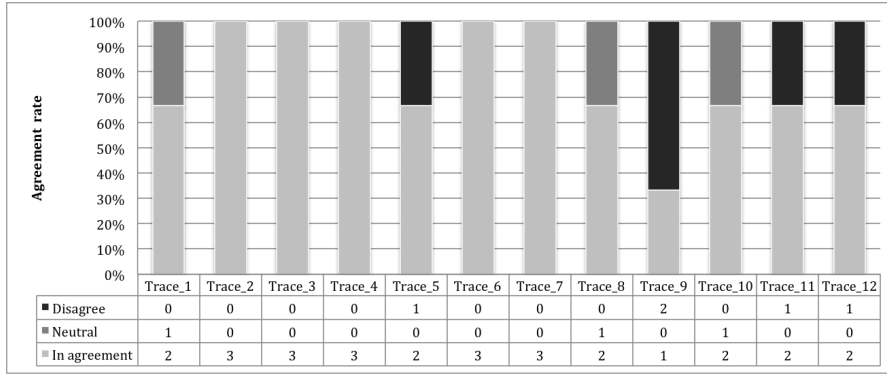


Fig. 6 Agreement rate between our results and the experts' analysis regarding the players' engagement. We consider that our results are validated since at least two experts are in agreement with them. The experts corroborated 11 of our results from 12 players. Thus, the agreement prediction rate of our approach is 91,67%

3. If two experts give a Without opinion answer and the third answers by a Yes or a No, then the significant (the Yes or the no) answer is retained (this case did not occur in this study).
4. If the three experts disagree (one Yes, one No and one Without opinion), then the answers are omitted.

7.4 Results

We introduced the user traces into D3KODE in order to analyse them automatically. In order to do this, D3KODE was configured with all the transformation rules (see section 6.4) that enable to detect the four *activities* mentioned in section 6.3. We considered a player as being engaged if this player expressed at least one engaged-behaviour (i.e. at least one *obsel* from the *activity* level occurred in any implemented *activity*). As explained in section 6.3, we implemented two social-directed *activities*, one action-directed *activity* and one environment-directed *activity*.

We conducted a comparative evaluation based on the data collected. It consisted in measuring engagement, and the engaged-behaviour types, of our representative sample of players from their traces, and then comparing the results obtained with the experts' analysis.

7.4.1 Engagement prediction

Figure 6 presents the agreement between our results and the analysis of the experts regarding player's engagement (experts' answers to question 1). Note that we consider that there is agreement, on a specific trace, since at least two experts are in agreement with our result. In these histograms Neutral means that the expert chooses the "Without opinion" answer. We can observe

that the experts' analysis corroborates our results for 11 of the 12 interaction traces. Therefore the engagement prediction rate of our approach is 91,67%.

Regarding Trace_9, this player was identified as non-engaged by the game designers who collected the traces, by our results and by one expert. But 2 experts identified her/him as engaged. We conducted a deeper analysis of this trace in order to understand this disagreement. During the four months of the collection phase, we observe that Trace_9 played during 11 sessions spread from the 3rd January to the 10th April. Compared to the activity of the engaged-players, Trace_9 is quite low (see Table 2 and Table 3). Indeed this player can stay several weeks without playing. More interestingly, while no *obsels* from the activity level has arisen, some *obsels* of the action level (belonging to the *activity* 'Achieve challenges') were generated during our analysis. This indicates that this player has expressed an interest for this *activity* but not an engagement (according to our definition). So maybe this relative activity misleads the 2 experts.

Another result is worth discussing. We identified one player of the Users Group 2 (Trace_7) as being engaged while this player belongs to the group of players judged as non-engaged by the game designers who collected the traces. As indicated in Figure 6, the three experts agreed with our analysis. By comparing Table 2 and Table 3 we can observe that Trace_7 has quite a low number of *obsels* from a low variety compared to the engaged-players of the Users Group 1. This difference may mislead the game designers regarding his/her engagement. We notice that Trace_7 has less number of *obsels* from the *activity* level than the other engaged-players. This observation gives rise to a question regarding the level of engagement of the players. We address this question of the level of engagement in the section 9 relative to our future work.

7.4.2 Types of engagement prediction

In this part, we validate our approach regarding the identification of the types of engaged-behaviours (i.e the qualitative dimension of our approach). Based on the engaged players' interaction traces, we identified their types of engaged-behaviours and compared our results with the analysis of the experts. We consider that there is consistency between our prediction and experts' analysis since at least two experts are in agreement with our results.

Figure 7 presents the agreement rate between our results and the analysis of the experts regarding players' social-engagement (experts' answers to question 2). As we implemented two social-directed *activities*, we consider that a trace reflects a social-engagement if at least one *obsel* from the level *activity* occurred in any of these two *activities*. The cases of Trace_4 and Trace_5 are omitted since the three experts disagreed (rule 4 of the meta-expertise). The experts' analysis corroborate the results obtained with our approach for 4 of the 5 traces of interaction (since Trace_4 and Trace_5 are omitted). Therefore the social-engagement prediction rate of our approach is 80%.

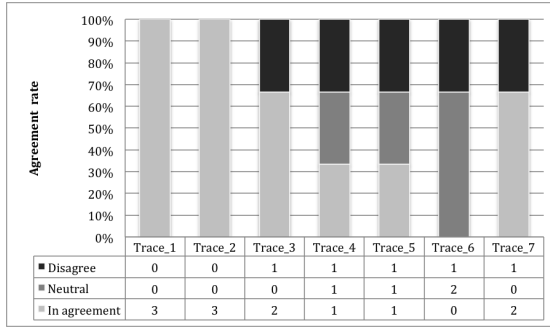


Fig. 7 Agreement rate between our results and the experts' analysis regarding the social-engagement. We consider that our results are validated since at least two experts are in agreement with them. Thus, the social-engagement prediction rate of our approach is of 80%

To go deeper into the analysis of this prediction rate we identified three profiles of players:

1. the players engaged in both of the implemented social-activities: Trace_1, Trace_3;
2. the players engaged in only one activity: Trace_4, Trace_5, Trace_6, Trace_7;
3. the players who have manifested no social-engagement: Trace_2.

We can observe that the agreement rate is very high when the players adopt a contrasted behaviour (cases 1 and 3). But in case 2 the judgement of the experts is more difficult (and so this validation step). Among the two implemented social-activities, 'Develop new social relationship' is oriented towards the unknown players while 'Share moments with real friends' is oriented towards the social network of the players. It may be possible that some experts had some preconceptions about the type of social-engagement they were looking for in players' traces (social-engagement oriented towards unknown players vs. towards the players' social network). This may explain the disputed cases of this step.

Figure 8 and Figure 9 present the agreement rate between our results and the analysis of the experts regarding players' action-engagement (experts' answers to question 3) and environment-engagement (experts' answers to question 4) respectively. Regarding the action and environment engagement identified in section 5.1, the experts' analysis in both cases corroborates our results obtained with our approach for the 7 interaction traces. Therefore the action and environment engagement prediction rate is 100%. As for each types of engaged-behaviours we analysed only one *activity*, the ambiguity that might occur with the social-engagement agreement rate could not occur here.

In summary, considering the three types of engaged behaviours, 21 judgements have been performed (three types of engagement applied to 7 traces of interaction). In accordance with the rule 4 of the meta-expertise presented in section 7.3, the judgements for the traces Trace_4 and Trace_5 were omitted in the analysis of social engagement. Thus the experts corroborate the results

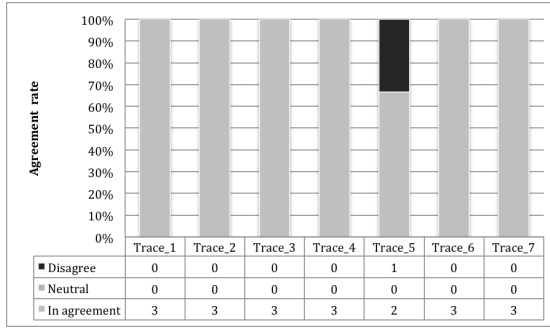


Fig. 8 Agreement rate between our results and the experts' analysis regarding the action-engagement. We consider that our results are validated since at least two experts are in agreement with them. Thus, the action-engagement prediction rate of our approach is 100%

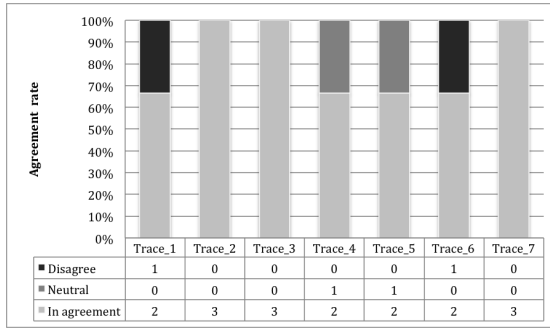


Fig. 9 Agreement rate between our results and the experts' analysis regarding the environmental-engagement. We consider that our results are validated since at least two experts are in agreement with them. Thus, the environmental-engagement prediction rate of our approach is 100%

of our approach for 18 of the 19 retained cases. Regarding the prediction of the type of engaged-behaviours, we obtain the rates of 80% for the social-engagement and 100% for both the action-engagement and the environment engagement.

7.5 Discussion and limitations of the study

As the Bodyboarding game was played online with anonymous players from all over the world, we could not contact them to ask them to participate in a study on a large scale. So we decided to set up a validation protocol based on the expertise of experts in this game. As this validation by several experts is long and complex, the number of traces of players analysed was limited. However, we set up a longitudinal study over a long period (4 months), and an evaluation protocol based on the intervention of experts, that ensure the quality of the data analysed (extraction of representative traces) and a qualified expertise to evaluate the results of our approach. It should be noted that this kind

of study collects data from a small number of participants because of the labour intensive nature of the data collection and analysis (e.g., analysis of data, identification of low-level transformation rules, analysis of traces by the experts).

This study showed the performance of our approach in the context of a social game, applied to a set of heterogeneous traces that gather engaged and non-engaged players and also several types of engaged-behaviours. In fact, we observed that some engaged-players may express both social and action types of engaged-behaviours (like Trace_1 and Trace_7) while other engaged-players express a social or an action engaged-behaviour. For example, despite the game used in our study being considered as a social game, Trace_2 shows absolutely no interest in other players (neither confrontation nor consultation of other players' profiles). This last observation highlights the fact that the results may be different from designers' intuitions.

We also demonstrated that our approach can identify two clearly differentiated types of *social* engagement : one directed toward players' existed friends (Trace_1), the other directed toward unknown players (Trace_5). Furthermore, 50% to 60% of the primary traces studied are composed of the four *obsels* *goto_map*, *goto_zone*, *goto_spot* and *play_start*, which reflect the path followed by the player in the game. Notice that these *obsels* are fully determined by the gameplay and do not reflect a behaviour. Thus, most of the sequences returned by sequence-mining would derive from these 4 *obsels*. These results show the relevance of a tool that allows for a qualitative analysis of users' engagement.

8 Summary and discussion

8.1 Summary of the contribution

This paper presents a qualitative approach and its implementation with the D3KODE prototype in order to identifying users' engagement and qualifying their engaged-behaviours from their interaction traces in interactive systems. Our approach enables us to detect engaged-behaviours in low-constraint interactive systems, directly, continuously and under ecologically valid conditions and over a long period of time.

To extract valuable and qualitative, rather than quantitative, information from users or system-generated raw data, we adopt a theory-driven approach. This approach establishes a relationship between users' needs, motives, high-level engaged-behaviours and the actions actually performed during the interactive mediated activity. To this end, it relies on three theories combined through a three-stage process:

1. The Self-Determination Theory to determine high-level engaged-behaviours.
2. The Activity Theory to characterize engaged-behaviours.
3. The Trace Theory to detect and extract engaged-behaviours from the raw data collected and recorded.

We implemented this approach with the D3KODE prototype by providing the following features: loading the data as a primary trace, creating the rules of transformation and visualising the primary and transformed traces. This prototype can detect the *operations* between the recorded users' interactions and establish the relationship between users' *operations*, *actions* and *activities*. We implemented 4 *activities* reflecting different types of engaged-behaviours. This implementation thus demonstrates the feasibility of the process underlying our approach (collecting the events, storing and organising the data and qualifying users' behaviours).

In order to ensure the validity of the engagement and engaged-behaviours identified with our approach, we conducted a user study on a social game. According to a precise protocol, we validated the results obtained with our approach with the results of the three experts' analysis. Regarding the players' engagement prediction, the prediction rate of our approach is 91,67%. Regarding the prediction of the type of engaged-behaviours, we obtain the rates of 80% for the social-engagement and 100% for both the action-engagement and the environment-engagement. These results demonstrate that our approach can be used to identify users' engagement and their type of engaged-behaviours from their interaction traces, with a high prediction rate.

The following examples illustrate how the qualitative analysis provided by our approach may be used by designers within the QUEJANT project. Our results may support the designers in gaining a better understanding of their players. For instance, quantitative methods may simply compute statistics on the waves surfed with the interaction data collected. So, while quantitative methods may only inform about the activity of the players (i.e. the number of waves surfed), our approach allows us to know if a wave was surfed in order to achieve a challenge, to play with friends or to meet other players. This informs about the specific interests of each players. In the present example we can know if a wave is surfed from an action or social perspective. The information returned through our approach may also help designers to implement a strategy of personalisation in order to maintain users' engagement. For instance during our study we observed that Trace_2 is indifferent to the social mechanics implemented in the game. This indicates that, in this game, Trace_2 did not express a social engagement. In order to maintain his/her engagement, the designers should focus on the other dimensions of the game (action, environment or self) to fulfill the other needs that this player may have expressed. Also the identification of the type of users' social-engaged behaviours (oriented towards unknown players or towards their social network) may be used by designers and facilitators to adapt and personalise the interactive system regarding the community engagement.

8.2 Discussion

8.2.1 Genericity and applicability of our approach

We adopt the Self-Determination Theory to distinguish some engaged-behaviours. Relying on this perspective rather than on empirical observation of users' behaviours, enables one to determine a wide and non-stereotyped range of behaviours. Indeed, since the basic psychological needs are considered as being universal, the behaviours reflecting engagement are not constrained by the "observed" features of the interactive system. For instance, as the game used in our implementation is a social game, we should have only considered some social engaged-behaviours. But through the SDT perspective we have also considered some action and environmental engaged-behaviours. This approach allows one to deal with more varied and particular engaged-behaviours in different contexts.

Our approach was applied to a social online game in the QUEJANT project. This application context allowed us to compare our proposals with the reality on the ground through experts and real data. But the decomposition of engaged-behaviours into *activities* and *actions* can be transferred to other games or interactive systems. Indeed, the *activities* and *actions* levels, and the rules that can infer *activities* from *actions* are broadly shared by different types of systems.

The specific part of the approach, which depends on the interactive system used, is the construction of transformation rules to infer the generic *actions* from the *operation* level (the *obsels* of the primary trace dependent on the interactive system). This specific part of the approach requires good knowledge of the actions that users can perform with the interactive system, so as to be able to identify among all the events collected in the primary trace those that make it possible to identify these actions. The construction of the transformation rules may require definition of some time intervals between the input *obsels* of the rules. This step involves carefully analysing the traces in order to determine the suitable time interval for each rules. This step may appear laborious but is quite straightforward for the designers or the facilitators of the interactive mediated activity as they know their system and how the users use it well.

To identify high-level activities, our approach requires an analysis of the mediated activity from an Activity Theory perspective. Then the Trace Theory can reify the relations previously identified between a chain of *operations* and an *action*, and a chain of *actions* and an *activity*. The application of the proposed process on interactions traces makes it possible to observe the potential generation of intended high-level *obsels*. We specify that our approach does not make it possible to discover unexpected high-level *obsels*. It is focused on the identification of qualitative information that cannot be discovered by classical data mining methods.

From a methodological point of view, the use of our approach involves three steps:

1. Collection of traces: it consists in collecting events generated by user actions and representing them in generic *obsels* in the primary trace. The adaptability to various interactive systems is fairly simple as a few lines in JavaScript are needed in order to collect an event.
2. Execution of transformation rules: the execution of transformation rules can extract high-level information reflecting the engagement of the user from the primary trace.
3. Visualisation of different trace levels: it consists in visualizing the three trace levels and the relationships between them. This visualization allows the expert to better understand the origin of the users' engagement or non-engagement.

This methodology has of course some technical limits associated with the collection of traces and scalability. Indeed, our approach based on users' traces requires a collection system for recording users' actions in the system. Thus, in certain applications, this collection could reduce the system performance. In addition, data collection requires a modelling effort and additional development since the designer must a priori define the events to trace, develop tools to record and process the data collected in order to represent them in generic *obsels*. For instance in a massively multiplayer online game, the storage and processing of the recorded data can pose problems, especially when scaling, such as: the server capacity to support a very large storage capacity and data cleaning. Thus, scaling requires additional processing that we have not discussed in this paper, but that could be the subject of future work. This is part of all the current issues related to big data.

8.2.2 Implications for behaviour change

We discussed in Section 2 the importance of detecting users' specific needs and motivations to being able to personalise the digital intervention accordingly. In this section, we present more specifically the implications of the identification and qualification of the users' engagement for the behaviour change.

We consider users' engagement as a pre-requisite for ensuring the effectiveness of the behaviour change process. The approach proposed in this paper and its implementation are a contribution for this process, as it makes it possible to identifying users' engagement directly and continuously. As our approach can identify the type(s) of users' engaged-behaviour, it is thus possible to personalise the digital intervention according to this information for each user or each type of engaged-behaviour. Furthermore, as this approach is based on the universal Self-Determination Theory, it can also establish a link between users' needs and motivations and users' engagement. So we argue that our approach can be part of the process of digital intervention for behaviour change. Also, since users' needs, expectations and motivations, and thus their engagement and type of engaged-behaviours, may evolve during the activity; our approach may be relevant to conducting longitudinal studies and thus addressing the alternative phases of engagement and disengagement.

According to our contribution, the digital intervention for behaviour change will be based on the information returned by our system: the engaged and non-engaged users, and the type(s) of engaged-behaviours. This information can be communicated to the designer or to the facilitator of the activity in order to personalise its form and its content, or to adapt the persuasive or affective strategies. Let us take an example where the activity uses a social engagement strategy to support behaviour change. If our system indicates that no social activity *obsels* can be generated from the participants' traces, this may lead to several interpretations. Either the participants show no need or motivation for social interactions, or the activity proposed is lacking in social interaction support or strategy. The designer can so modify the system to add more social interaction possibilities or the facilitator can propose more social interactions between users with the proposed interactive technology.

The information about users' engagement could also be communicated to the users themselves to provoke and support reflexive processes (Clauzel et al, 2009). Reflexivity is defined as the ability to interact with the situation in order to meet its own cognitive and socio-cognitive limitations (Schön, 1984). Through reflexivity, individuals can exercise control over their cognitive activity and actions, which allows individual and collective self-assessment and constructive criticism on oneself. This is particularly interesting in project-based learning, which aims to help learners acquire various linked skills or develop their behaviours (Michel et al, 2012). In this context, learners can regulate their learning by monitoring their own behaviours (Zimmerman, 2000; Scheffel et al, 2010).

In a collaborative mediated activity, this information could be part of the information presented on group awareness tools. Group awareness has been well defined by Buder and Bodemer (2011) as knowledge about the social and collaborative environment in which the person is working (e.g., knowledge about the activities, presence or participation of group members). Group awareness tools supply information to students to facilitate coordination and regulation of activities in the content space or the relational space (Janssen et al, 2011). They were developed in the Computer Supported Collaborative Learning (CSCL) area to foster the acquisition of group awareness, which is helpful for efficient group performance by presenting social comparison and guide for activities (Engelmann et al, 2009). Engagement with the mediated activity could be part of the information presented to the group to foster the social comparison and maybe discussions within the group to establish new goals and/or strategies.

Finally, we can imagine that the system itself could use the information about engagement for an automatic adaptation of the mediated activity. For this, the system should be parametrised so as to generate the relevant intervention according to the information about users' engagement. In addition, this requires the system to have information about its own processes, the mediated activity, and adaptation rules. So this could be the last step in an automatic digital intervention process based on our approach.

9 Future work

A challenging part of our future work will be to address the group dimension of engagement. At this stage of our works, we analyse individual users' engagement. The group dimension involves two different issues: 1) the detection of community engagement and 2) obtaining information about a group of users on a same interface. Concerning the first issue, analysing how users interact together during the interactive activity may enable us to identify and qualify community engagement. This analysis can be based on the interaction traces of the community. That first implies to define new high-level activities according to theoretical works on community engagement and then to identify the underlying actions, operations and transformation rules. These rules can then be implemented in the D3KODE system. The second issue concerns the visualization of the engagement and types of engaged-behaviours of several users at the same time. This information could be very useful for the designer or facilitator, so as to adapt the game to collective behaviours. In fact, for an interactive system used by many users, designers need information on all these users on a synthetic view so as to be able to adapt it to the users' behaviours. A synthetic view should present the behaviours of many users at a glance, for instance the number of engaged and non-engaged users or the number of users for each type of engaged-behaviour. These two issues give rise to a problem of scalability (number of users, volume of collected data) referring to the Big Data issue.

Another important part of our future work will be dedicated to the design of interfaces for both designers and users of the interactive system. The analysis of the interaction traces can currently be visualized and understood by analysts that are familiar with the D3KODE tool. As we plan to help designers to adapt the interactive system and to support reflexive processes for the users, we have to design adapted interfaces (i.e. dashboards) that present the engaged (vs non-engaged) users, and the type(s) of engaged-behaviour(s) in a relevant way. So we will have to automatically deduce this synthesis information on engagement from the actual information given by the D3KODE system. According to the functioning of dashboards, we will also have to offer the possibility to access analysis views to help designers and users to understand the synthesis information. For instance, they may be interested in visualizing the actions level so as to understand the process of engagement, for example the reasons why the users are identified as being engaged or not. Furthermore, the interfaces have to be different as the needs of designers and users are different. So their design will require their participation for a relevant analysis of their needs according to an iterative and participative design approach.

Looking further ahead, we plan to refine our approach to be able to analyse more precise information on users' engagement. On the one hand, we will address the complex issue of the alternative phases of engagement, disengagement and reengagement. For that, we will take into account the distribution (e.g. number, frequency) of the high-level *obsels* during over the time. On the other hand, we will address the issue of the identification of the level of

users' engagement. For example, can we consider that a user that generates ten high-level *obsels* (activities) and another one that generates only two high-level *obsels* have the same level of engagement? To answer this question, it will be necessary to conduct complex user studies by combining different analysis methods like questionnaires or interviews and experts analysis.

Appendix A Information regarding the nature of engagement communicated to the three experts involved in the user study

We communicated to the experts a document stating our position regarding the nature of engagement and describing, through simple examples, the four types of engagement that we have identified.

Note from the authors: the document was originally in French so we provide an English translation below.

DEFINITION 1: engagement

We consider the engagement of a player as the desire to have emotions, affect and thoughts directed to and determined by the mediated activity. This "engaged" state means in particular that:

- The game arouses emotions (such as joy, pride, accomplishment, enjoyment or frustration) for the player.
- The game occupies the thoughts of the player during the gaming sessions but also outside.
- The player wishes to continue playing.

Thus, the engagement requires an intellectual and emotional investment from the player which goes beyond the discovery phase of the game. Engagement can be considered as a link between gaming sessions and between the sessions and the player.

DEFINITION 2: environment-directed engagement

The player engagement can be directed to the game environment. Such engagement includes two types of behaviours:

- Contemplation: the player attaches importance to the aesthetic of the game (visual, sound), the scenario, the storytelling, the ability to 'walk' in the game, etc..
- Curiosity: the player has fun in the discovery phase of the game, s/he likes configuring the characteristics of the game, s/he wants to understand the game mechanisms, to explore the environment, to discover hidden content, to get further information on the game, etc..

DEFINITION 3: social-directed engagement

The player engagement can be directed to the other players of the game. In that case, the player plays for example to:

- Share moments with friends.

- Connect with others players.
- Feel the pleasure of social interactions (competition, cooperation) with other players.
- Establish a position in the group.

DEFINITION 4: self-directed engagement The player engagement can be directed to her/his character in the game. In that case, the player has fun in:

- Managing her/his character.
- Customizing and differentiating her/his character (name, gender, appearance, equipment).
- Giving life to her/his character, creating a story.

DEFINITION 5: action-directed engagement The player engagement can be directed to the action to carry out in the game. In that case, the player plays to:

- Take up a challenge (set by the game or by him/herself), or to break records.
- Feel a sense of accomplishment, skill or excitement.
- Confront the difficulties and challenges.
- Develop strategies, improve his/her technique.

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References

- Andersen E, O'Rourke E, Liu YE, Snider R, Lowdermilk J, Truong D, Cooper S, Popovic Z (2012) The impact of tutorials on games of varying complexity. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, ACM, Austin, Texas, USA, CHI 2012, pp 59–68
- Arroyo I, Cooper DG, Burleson W, Woolf BP, Muldner K, Christopherson R (2009) Emotion sensors go to school. In: Proceedings of the 2009 conference on Artificial Intelligence in Education: Building Learning Systems that Care: From Knowledge Representation to Affective Modelling, IOS Press, Brighton, UK, pp 17–24
- Attfield S, Kazai G, Lalmas M, Piwowarski B (2011) Towards a science of user engagement (position paper). In: WSDM Workshop on User Modelling for Web Applications, Hong Kong, China

- Barak A, Hen L, Boniel-Nissim M, Shapira N (2008) A comprehensive review and a meta-analysis of the effectiveness of internet-based psychotherapeutic interventions. *Journal of Technology in Human Services* 26(2-4):109–160
- Baranowski T, Baranowski J, Cullen KW, Marsh T, Islam N, Zakeri I, Honess-Morreale L, deMoor C (2003) Squire's quest!: Dietary outcome evaluation of a multimedia game. *American Journal of Preventive Medicine* 24(1):52 – 61
- Baranowski T, Buday R, Thompson DI, Baranowski J (2008) Playing for real: Video games and stories for health-related behavior change. *American Journal of Preventive Medicine* 34(1):74 – 82
- Bardram JE (1997) Plans as situated action: an activity theory approach to workflow systems. In: *Proceedings of the fifth conference on European Conference on Computer-Supported Cooperative Work*, Kluwer Academic Publishers, Lancaster, UK, ECSCW'97, pp 17–32
- Bauckhage C, Kersting K, Sifa R, Thureau C, Drachen A, Canossa A (2012) How players lose interest in playing a game: An empirical study based on distributions of total playing times. In: S Lucas MSE S-B Cho (ed) *Proceedings of the IEEE Conference on Computational Intelligence and Games*, Granada, Spain, CIG 2012, pp 139–146
- Beal CR, Qu L, Lee H (2006) Classifying learner engagement through integration of multiple data sources. In: *Proceedings of the 21st national conference on Artificial intelligence - Volume 1*, Boston, Massachusetts, AAAI'06, pp 151–156
- Bianchi-Berthouze N (2013) Understanding the role of body movement in player engagement. *Human Computer Interaction* 28(1):40–75
- Bouvier P, Lavoué E, Sehaba K, George S (2013a) Identifying learner's engagement in learning games - a qualitative approach based on learner's traces of interaction. In: Foley O, Restivo MT, Uhomoibhi JO, Helfert M (eds) *Proceedings of the 5th International Conference on Computer Supported Education*, SciTePress, Aachen, Germany, CSEDU 2013, pp 339–350
- Bouvier P, Sehaba K, Lavoué E, George S (2013b) Using traces to qualify learner's engagement in game-based learning. In: *Proceedings of The 13th IEEE International Conference on Advanced Learning Technologies*, IEEE Computer Society, Beijing, China, ICAALT 2013, pp 432–436
- Boyle EA, Connolly TM, Hainey T, Boyle JM (2012) Engagement in digital entertainment games: A systematic review. *Computers in Human Behavior* 28(3):771–780
- Brockmyer JH, Fox CM, Curtiss KA, McBroom E, Burkhart KM, Pidruzny JN (2009) The development of the game engagement questionnaire: A measure of engagement in video game-playing. *Journal of Experimental Social Psychology* 45(4):624–634
- Brown E, Cairns P (2004) A grounded investigation of game immersion. In: *CHI '04 extended abstracts on Human factors in computing systems*, Vienna, Austria, CHI EA 2004, pp 1297–1300
- Buder J, Bodemer D (2011) Group awareness tools for controversial cscl discussions: Dissociating rating effects and visualized feedback effects. In: 9th

- International Conference on Computer Supported Collaborative Learning, Hong Kong, CSCCL 2011, pp 358–365
- Calvo R, D’Mello S (2010) Affect detection: An interdisciplinary review of models, methods, and their applications. *Affective Computing, IEEE Transactions on* 1(1):18–37
- Camerini L, Giacobazzi M, Boneschi M, Schulz PJ, Rubinelli S (2011) Design and implementation of a web-based tailored gymnasium to enhance self-management of fibromyalgia. *User Modeling and User-Adapted Interaction* 21(4-5):485–511
- Canossa A, Drachen A (2009) Patterns of play: Play-personas in user-centred game development. In: Barry A, Helen K, Tanya K (eds) *Breaking New Ground: Innovation in Games, Play, Practice and Theory: Proceedings of the 2009 Digital Games Research Association Conference*, Brunel University, London, UK
- Champalle O, Sehaba K, Cosmas D, Mille A, Prié Y (2012) Assistance to trainers for the observation and analysis activities of operators trainees on nuclear power plant full-scope simulator. In: *International Conference on Intelligent Networking and Collaborative Systems (INCoS 2012)*, IEEE Computer Society, Bucharest, Romania, pp 33–40
- Champion PA, Prié Y, Aubert O, Conil F, Cram D (2011) ktbs: Kernel for trace-based systems. URL <http://kernel-for-trace-based-systems.readthedocs.org/en/latest/>, a reference implementation of the notion of Trace Based Management System. Allows to store and compute modeled traces, and access them through a RESTful interface.
- Chen M, Kolko BE, Cuddihy E, Medina E (2011) Modeling but not measuring engagement in computer games. In: *Proceedings of the 7th International Conference on Games Learning Society*, ETC Press, Madison, Wisconsin, USA, GLS’11, pp 55–61
- Chittaro L, Zangrando N (2010) The persuasive power of virtual reality: effects of simulated human distress on attitudes towards fire safety. In: *Proceedings of the 5th international conference on Persuasive Technology*, Springer-Verlag, Copenhagen, Denmark, PERSUASIVE 2010, pp 58–69
- Christensen H, Griffiths MK, Farrer L (2009) Adherence in internet interventions for anxiety and depression: Systematic review. *Journal of Medical Internet Research* 11(2):e13
- Clauzel D, Sehaba K, Prié Y (2009) Modelling and visualising traces for reflexivity in synchronous collaborative systems. In: *Proceedings of the 2009 International Conference on Intelligent Networking and Collaborative Systems*, IEEE Computer Society, Barcelona, Spain, INCoS 2009, pp 16–23
- Clauzel D, Sehaba K, Prié Y (2011) Enhancing synchronous collaboration by using interactive visualisation of modelled traces. *Simulation Modelling Practice and Theory* 19(1):84–97
- Cocca M, Weibelzahl S (2009) Log file analysis for disengagement detection in e-learning environments. *User Modeling and User-Adapted Interaction* 19(4):341–385

- Consolvo S, Everitt K, Smith I, Landay JA (2006) Design requirements for technologies that encourage physical activity. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, ACM, Montréal, Québec, Canada, CHI 2006, pp 457–466
- Dietterich TG (2002) Machine learning for sequential data: A review. In: Proceedings of the Joint IAPR International Workshop on Structural, Syntactic, and Statistical Pattern Recognition, Springer-Verlag, Windsor, Ontario, Canada, pp 15–30
- D’Mello SK, Craig SD, Sullins J, Graesser AC (2006) Predicting affective states expressed through an emote-aloud procedure from autotutor’s mixed-initiative dialogue. *International Journal of Artificial Intelligence in Education* 16(1):3–28
- Doherty G, Coyle D, Sharry J (2012) Engagement with online mental health interventions: an exploratory clinical study of a treatment for depression. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, ACM, Austin, Texas, USA, CHI 2012, pp 1421–1430
- Donkin L, Christensen H, Naismith LS, Neal B, Hickie BI, Glozier N (2011) A systematic review of the impact of adherence on the effectiveness of e-therapies. *Journal of Medical Internet Research* 13(3):e52
- Engelmann T, Dehler J, Bodemer D, Buder J (2009) Knowledge awareness in cscl: A psychological perspective. *Computers in Human Behavior* 25(4):949–960
- Fogg B (2009) A behavior model for persuasive design. In: Proceedings of the 4th International Conference on Persuasive Technology, ACM, Claremont, California, USA, Persuasive 2009, pp 40:1–40:7
- Fogg BJ (2002) Persuasive technology: using computers to change what we think and do. December, Morgan Kaufmann, Amsterdam
- Fredricks JA, Blumenfeld PC, Paris AH (2004) School Engagement: Potential of the Concept, State of the Evidence. *Review of Educational Research* 74:59–109
- Froehlich J, Dillahunt T, Klasnja P, Mankoff J, Consolvo S, Harrison B, Landay JA (2009) Ubigreen: investigating a mobile tool for tracking and supporting green transportation habits. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, ACM, Boston, Massachusetts, USA, CHI 2009, pp 1043–1052
- Gagné AR, El-Nasr MS, Shaw CD (2011) A deeper look at the use of telemetry for analysis of player behavior in rts games. In: Proceedings of the 10th international conference on Entertainment Computing, Springer-Verlag, Vancouver, Canada, ICEC’11, pp 247–257
- Garris R, Ahlers R, Driskell JE (2002) Games, motivation, and learning: A research and practice model. *Simulation & Gaming* 33(4):441–467
- Hägni K, Eng K, Hepp-Reymond MC, Holper L, Keisker B, Siekierka E, Kiper DC (2007) The Effect of Task and Ownership on Time Estimation in Virtual Environments. In: Presence 2007: The 10th Annual International Workshop on Presence, Barcelona, Spain, pp 145–150

- Hassenzahl M, Tractinsky N (2006) User experience - a research agenda. *Behaviour & Information Technology* 25(2):91–97
- Honka A, Kaipainen K, Hietala H, Saranummi N (2011) Rethinking health: Ict-enabled services to empower people to manage their health. *Biomedical Engineering, IEEE Reviews in* 4:119–139
- Jackson T (2005) Motivating sustainable consumption. a review of evidence on consumer behaviour and behavioural change. Tech. rep., University of Surrey, URL http://hiveideas.com/attachments/044_motivatingfinal_000.pdf, a report to the Sustainable Development Research Network
- Janssen J, Erkens G, Kirschner PA (2011) Group awareness tools: It's what you do with it that matters. *Computers in Human Behavior* 27(3):1046 – 1058
- Jennett C, Cox AL, Cairns P, Dhoparee S, Epps A, Tijs T, Walton A (2008) Measuring and defining the experience of immersion in games. *International Journal of Human-Computer Studies* 66(9):641–661
- Kaptelinin V (2005) The object of activity: Making sense of the sense-maker. *Mind, Culture, and Activity* 12(1):4–18
- Kaptelinin V, Nardi BA (2006) *Acting with Technology: Activity Theory and Interaction Design*. The MIT Press
- Kim JH, Gunn DV, Schuh E, Phillips B, Pagulayan RJ, Wixon D (2008) Tracking real-time user experience (true): a comprehensive instrumentation solution for complex systems. In: *Proceedings of the twenty-sixth annual SIGCHI conference on Human factors in computing systems*, ACM, Florence, Italy, CHI 2008, pp 443–452
- Kivikangas JM, Chanel G, Cowley B, Ekman I, Salminen M, Järvelä S, Ravaja N (2011) A review of the use of psychophysiological methods in game research. *Journal of Gaming and Virtual Worlds* 3(3):181–199
- Kjeldskov J, Skov MB, Paay J, Pathmanathan R (2012) Using mobile phones to support sustainability: a field study of residential electricity consumption. In: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, ACM, Austin, Texas, USA, CHI 2012, pp 2347–2356
- Köck M, Paramythis A (2011) Activity sequence modelling and dynamic clustering for personalized e-learning. *User Modeling and User-Adapted Interaction* 21(1-2):51–97
- Law ELC, Roto V, Hassenzahl M, Vermeeren AP, Kort J (2009) Understanding, scoping and defining user experience: a survey approach. In: *Proceedings of the 27th international conference on Human factors in computing systems*, ACM, Boston, Massachusetts, USA, CHI 2009, pp 719–728
- Leontiev AN (1978) *Activity, consciousness and personality*. Prentice Hall, Englewood Cliffs, NJ
- Linehan C, Kirman B, Lawson S, Chan G (2011) Practical, appropriate, empirically-validated guidelines for designing educational games. In: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, ACM, Vancouver, BC, Canada, CHI 2011, pp 1979–1988

- Maitland J, Chalmers M (2011) Designing for peer involvement in weight management. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, ACM, Vancouver, BC, Canada, CHI 2011, pp 315–324
- Mandryk RL, Atkins MS, Inkpen KM (2006) A continuous and objective evaluation of emotional experience with interactive play environments. In: Proceedings of the SIGCHI conference on Human Factors in computing systems, ACM, Montré#233;al, Qu#233;bec, Canada, CHI 2006, pp 1027–1036
- Michel C, Lavoué E, Pietrac L (2012) A dashboard to regulate project-based learning. In: Proceedings of the 7th European conference on Technology Enhanced Learning, Springer-Verlag, Saarbr#252;cken, Germany, EC-TEL 2012, pp 250–263
- Michie S, Johnston M, Francis J, Hardeman W, Eccles M (2008) From theory to intervention: Mapping theoretically derived behavioural determinants to behaviour change techniques. *Applied Psychology* 57(4):660–680
- Mintz J, Aagaard M (2012) The application of persuasive technology to educational settings. *Educational Technology Research and Development* 60(3):483–499
- O’Brien HL, Toms EG (2008) What is user engagement ? a conceptual framework for defining user engagement with technology. *Journal of the American Society for Information Science* 59(6):938–955
- Orji R, Vassileva J, Mandryk RL (2014) Modeling the efficacy of persuasive strategies for different gamer types in serious games for health. *User Modeling and User-Adapted Interaction* this issue
- Pagulayan RJ, Keeker K, Wixon D, Romero RL, Fuller T (2003) User-centered design in games. In: Jacko JA, Sears A (eds) *The human-computer interaction handbook*, Lawrence Erlbaum Associates Inc., Hillsdale, NJ, USA, pp 883–906
- Picard RW (2000) *Affective computing*. MIT press, Cambridge, MA, USA
- Rich C, Ponsleur B, Holroyd A, Sidner CL (2010) Recognizing engagement in human-robot interaction. In: Proceedings of the 5th ACM/IEEE international conference on Human-robot interaction, IEEE Press, Osaka, Japan, HRI ’10, pp 375–382
- Ritterband L, Thorndike F, Cox D, Kovatchev B, Gonder-Frederick L (2009) A behavior change model for internet interventions. *Annals of Behavioral Medicine* 38(1):18–27
- Ryan RM, Deci EL (2000) Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *The American psychologist* 55:68–78
- Scheffel M, Wolpers M, Beer F (2010) Analyzing contextualized attention metadata with rough set methodologies to support self-regulated learning. In: *Advanced Learning Technologies (ICALT)*, 2010 IEEE 10th International Conference on, IEEE Computer Society, Sousse, Tunisia, ICALT 2010, pp 125–129
- Schön DA (1984) *The reflective practitioner: How professionals think in action*. Basic Books

- Schubert T, Friedmann F, Regenbrecht H (2001) The experience of presence: Factor analytic insights. *Presence: Teleoperators and Virtual Environments* 10(3):266–281
- Settouti LS, Prié Y, Marty JC, Mille A (2009) A trace-based system for technology-enhanced learning systems personalisation. In: *Proceedings of the 2009 Ninth IEEE International Conference on Advanced Learning Technologies*, IEEE Computer Society, Riga, Latvia, ICALT 2009, pp 93–97
- Sidner CL, Kidd CD, Lee C, Lesh N (2004) Where to look: a study of human-robot engagement. In: *Proceedings of the 9th international conference on Intelligent user interfaces*, ACM, Funchal, Madeira, Portugal, IUI '04, pp 78–84
- Tychsen A, Canossa A (2008) Defining personas in games using metrics. In: *Proceedings of the 2008 Conference on Future Play: Research, Play, Share*, ACM, Toronto, Ontario, Canada, Future Play 2008, pp 73–80
- Vassileva J (2012) Motivating participation in social computing applications: a user modeling perspective. *User Modeling and User-Adapted Interaction* 22(1-2):177–201
- Vygotsky L (1978) *Mind in Society: The Development of Higher Psychological Processes*. Harvard University Press, Cambridge, MA
- Zimmerman BJ (2000) Attaining self-regulation: A social cognitive perspective, pp 13–40

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