

# Using Traces to Qualify Learner’s Engagement in Game-Based Learning

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**Abstract**—Analysing learners’ behaviour continuously and under ecological conditions can help designers, trainers and teachers to analyse, design, validate, and also to adapt and personalize the learning game. Metrics methods propose to collect any interactions between a user and the game. While classical metrics methods fall within quantitative approaches, we aim to extract some qualitative information on high-level behaviours. This paper is focused on learners’ engaged-behaviours. Thus, to identify and to qualify learners’ engagement from their traces of interaction, we combine a theoretical work on engagement and engaged-behaviours, the Self-Determination Theory, the Activity Theory and a trace framework. We implemented this approach on 12 players’ interaction data collected during four months. As a result, we identified and qualified four activities that refer to different types of engaged-behaviours. Thus, this user study show the feasibility and the validity of the proposed approach.

**Keywords**- Game-Based Learning; Learner’s Behaviour; Engagement Measurement; Qualitative Approach; Digital Gaming; Activity Theory; Trace Theory.

## I. INTRODUCTION

Analysing learners’ behaviour continuously and under ecological conditions is crucial in game-based learning. This can help to maintain the effectiveness of the digital game as educational tool. Metrics methods, which have been developed for that purpose, automatically collect and store any users’ actions performed through input devices. The extracted knowledge can be used by designers, trainers and teachers both during the development phase (to analyse, design and validate the learning game (LG)) and after its release (to adapt and personalize the LG).

Current metrics methods stay at a basic level by only considering quantitative information. Thus, they only reveal what learners are doing. We want to go beyond these results in order to extract high-level knowledge from learners’ interactions. Thus, the challenge is to qualitatively analyse some quantitative learner-generated raw data. For that purpose we combine the Self-Determination Theory, the Activity Theory and the Trace Theory to establish a relationship between needs, motives, high-level behaviours and the actions actually performed.

Engagement is an effective indicator of learners’ motivation, acceptance and attachment to the LG. In entertainment

digital gaming, engagement is also considered as an important dimension of the player experience. Thus, we chose to focus on engagement to apply our qualitative approach. Through a user study conducted on 12 users, we present how our approach can identify and qualify learners’ engagement from their traces of interaction.

In section 2 we present some relevant works regarding the qualitative approach that we describe in section 3. The user study and the results are described and discussed, in comparison with other related works, in section 4. Finally, we conclude by presenting our future works.

## II. BACKGROUND

Several works are relevant to our objective: those regarding the nature of engagement but also several theories on which our qualitative approach relies.

### A. Defining Engagement in Digital Gaming

Qualifying engagement in game-based learning requires, in the first place, to have a clear vision of engagement. In [1], the authors consider engagement in digital games ”as a generic indicator of game involvement”. In the educational field, engagement can be viewed as the ”behavioral intensity and emotional quality of a person’s active involvement during a task” [2]. The similarity between these two definitions supports the idea of a definition of engagement that is relevant in both entertainment and learning games. As the nature of engagement in digital games is still not well understood [3], defining a subjective experience like engagement is not straightforward. A common issue with existing definitions of engagement is the reference to ambiguous and overlapping concepts such as immersion or involvement [4]. To avoid this issue [5] propose a conceptual definition that focuses on the state on engagement rather than to its factors or outcomes. Then, engagement is defined as ”the willingness to have emotions, affect and thoughts directed towards and determined by the mediated activity” [5]. In this vision, that we adopt, players and learners accept that, during a given time, their emotions, affect and thoughts are mainly elicited by the mediated activity. Also, they get engaged in order to live more intensely the mediated activity.

## B. Relevant theories

1) *Self-Determination Theory (SDT)*: Like [6], we adopt the SDT [7] for explaining digital game engagement. The SDT identifies three universal Human psychological needs: *competence* (sense of efficacy), *autonomy* (volition and personal agency) and *relatedness* (social interaction). It seems quite obvious that digital games have the ability to fulfil these needs and this may explain why people play games.

2) *Activity Theory (AT)*: This theory initiated by [8] and [9] aims to understand Human development through a structured analysis of the genesis, structure and processes of their activities. AT is also used in the Computer-Human Interactions field for several years now [10]. AT distinguishes three different levels of analysis:

- An *activity* is performed by a subject, through a tool, in response to a specific need or motive in order to achieve an object (objective) [11].
- 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.
- An *operation* enables the realisation of the *actions*. *Operations* are determined by the environmental and contextual *conditions* of the *activity* and can be used by different *actions*.

3) *Trace Theory (TT)*: Among the different possibilities for managing learner's actions, TT provides a framework for collecting, representing and visualising user's activity traces (i.e. any user's actions performed toward the system) [12]. At the lowest level, there is the observed elements (labelled *obsels*). Typically, an *obsel* corresponds to a raw action collected by the system (a mouse click or a key pressed on the keyboard).

A primary trace is a set of *obsels* temporally situated that may be connected. A primary trace may contain a very large number of *obsels* whose informational level may be too low. So, it may be difficult to derive knowledge from a primary trace. The formalization proposed by [13] aims to facilitate the transition from primary traces to information that makes sense. It consists in transforming a primary trace in a trace of a higher level based on rule-based system. A rule consists in temporal constraints or in operations on the contextual attributes performed between *obsels*. The transformed traces help to derive a more complex or abstract knowledge.

## III. QUALIFYING ENGAGED-BEHAVIOURS

As collecting user's actions only inform on what they are doing but not why, [14] acknowledge that it is not possible to derive information about abstract quantity (like engagement). But, as engagement affects learners' behaviour, some measurable quantities can be considered for identifying engaged-behaviours [15]. As we aim to identify and qualify learner's engaged-behaviours from the actions performed in the learning game, two main issues have to be overcome.

How to distinguish engaged-behaviours from nonengaged-behaviours? How to detect engaged-behaviours among all the actions collected?

### A. Nature of Engaged-Behaviour

We consider that learners' behaviours in the learning game are determined either by the motives of the learner or by the gameplay<sup>1</sup> of the game. Thus, the significance of the motives behind the behaviour is what distinguishes engaged-behaviours from nonengaged-behaviours. We consider that the Human universal psychological needs identified by the SDT (see section II-B1) are in fact, the needs for feeling the corresponding emotions. We assume also that in a process similar to the suspension of disbelief [16], players or learners may willing to get engaged in order to feel more intensely these emotions. Thus, as the definition of engagement highlights it, players' and learners' behaviours are determined by the emotions they seek and the emotions felt during the activity are the motives for playing.

We consider a behaviour as a chain of actions actually performed in the game. Thus, to establish that a chain of actions reflects an engagement we need to identify a link between learners' motives and the chains of actions. For that purpose we combine the SDT and the Activity Theory (see section II-B2). So, the universal needs identified by the SDT generate the *motives* to get engaged (to feel the corresponding emotions), these *motives* elicit the *activities* and these *activities* are performed through a chain of *actions* that are realised through a chain of *operations* (see Figure 1).

For conducting a comprehensive and structured analysis of engaged-behaviours, [5] consider that digital gaming consists in performing some *actions* (decision-making process), *directly or through a character*, within an *environment* (or at least on a frame), which may involve *social interaction* with human or virtual agents. Thus, the gaming activity may encompass four types of engaged-behaviours: *environmental* (generated by the *autonomy* need), *social* (*relatedness* need), *self* (*autonomy* need) and *action* (*competence* and *autonomy* needs). The frequency and the intensity of these engaged-behaviours depend on the nature of the learning game. So, within each type of engaged-behaviour, several *activities* can share the same *motive* but have different *objects*. For example, in the user study presented in section IV the *activities* *Develop new social relationship* and *Share moment with real friends* share the same social *motive* but have different *objects* (respectively Increasing the number of friends and Maintaining social relationship within the group). Then, according to the *object* of the *activity*, the *activity* is supported by several *actions* that are realised through many *operations* performed with the input devices. This approach enables to determine a wide and non-stereotyped range of engaged-

<sup>1</sup>In digital gaming, gameplay is a blanket term which refers to the structure, the dynamics or the interactive aspects of a game.

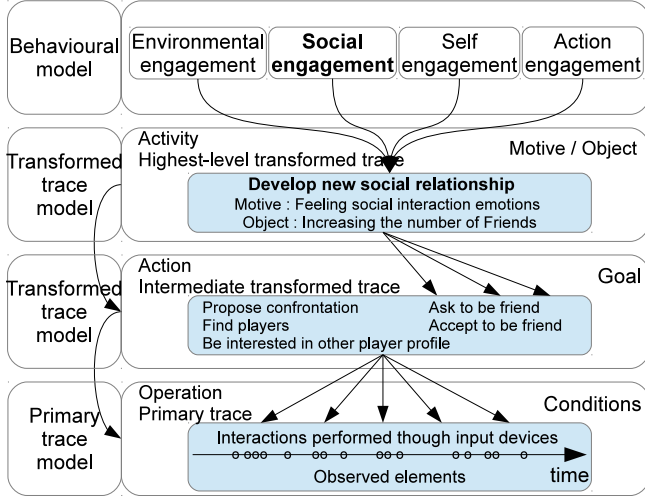


Figure 1. To identify and qualify engaged-behaviours, our qualitative approach combines a theoretical work on engagement and engaged-behaviours, SDT, Activity Theory and Trace Theory. The data are extracted from the user study presented in section IV.

behaviours (i.e. that does not depend on the gameplay of the game). See section IV for an example.

### B. Identification of Engaged-Behaviours

For detecting the engaged-behaviours among all the actions recorded, we combine Activity Theory and Trace Theory (see section II-B3) by establishing the following correspondences:

- *operation*  $\Leftrightarrow$  primary trace composed of *obsels*
- *action*  $\Leftrightarrow$  primary transformed trace
- *activity*  $\Leftrightarrow$  highest-level transformed trace

Figure 1 illustrates our approach. We combine a theoretical work on engagement, the SDT and the Activity Theory to distinguish and to deconstruct engaged-behaviours. Then, we rely on the Trace Theory to discover and extract the relevant *operations* among all the collected and recorded actions and also to reify (through the transformation process) the relationship between *operation*, *action* and the *activity* that belongs to a specific type of engaged-behaviour.

## IV. IMPLEMENTATION AND USER STUDY

Through this user study we aim to ensure the feasibility of our approach (collecting, organising and qualifying the learner-generated data) and to check its validity (the detected behaviours reflect an actual engagement).

### A. Context

For this study, we use the BodyBoarding game developed by the company IntellySurf<sup>2</sup>. Although this game is not a typical learning game, we chose it for the following

<sup>2</sup>YouRiding: <http://www.youriding.com>

reasons. It enables to analyse engaged-behaviours in low-constraint interactive systems, directly, continuously and under ecological conditions and over a long time period. This game consists in travelling from spot to spot all over the world in order to select the most effective waves to perform some maneuvers of surfing (like tube ride), to complete a challenge or to challenge other players. Thus, regarding the four types of engaged-behaviours identify in section III-A, the *social* and *action* dimensions are significant enough to provide a wide variety of engaged-behaviours.

### B. Implementation

We collected twelve player's traces 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).

Learners' interactions are collected, session after session, with a classic client-server architecture with JavaScript and PHP scripts and stored in a MySQL database. Then, learners' interaction data are exported from the MySQL database in a CVS (Comma-Separated Values) file to be loaded into the tool D3KODE<sup>3</sup> [17]. D3KODE implements the Trace Theory by providing the following features: loading the data as a primary trace, creating the models of transformation and the associated rules and visualising the primary and transformed traces. D3KODE enables to detect the *operations* among the recorded learner's interactions and to reify the relationship between *operations*, *actions* and *activities*.

Each *obsel* composing the primary trace contains two timestamps, a name and at most three attributes in order to provide some contextual information such as the name of the button pressed or the identification number of an object. We use D3KODE for defining the transformation rules. A rule can rely on temporal constraints or on the contextual attributes. For example the *obsels* *open\_profile\_improvements* and *open\_profile\_skills* are aggregated in order to generate the *action seek information about challenges*. The following rule detects when the two pages *Improvements* and *Skills* are opened during an interval of 2 minutes.

```

1 { open_profile_skills.hasEnd < open_profile_
2   improvements.hasBegin
3   (open_profile_improvements.hasBegin - open_profile_
4     _skills.hasEnd) <=120 }
5 OR
6 { open_profile_improvements.hasEnd < open_profile_
7   skills.hasBegin
8   (open_profile_skills.hasBegin - open_profile_
9     improvements.hasEnd) <= 120 }

```

We proceed in a similar way to create the rules that generate the *actions* level. Then, we iterate the transformation process to aggregate the *actions* and thus to generate the *obsels* of highest-level that indicates the presence of an *activity* reflecting an engaged-behaviour.

<sup>3</sup>Define, Discover, and Disseminate Knowledge from Observation to Develop Expertise

### C. Results of the User Study

Regarding the four types of engaged-behaviours we identified in section III-A and according to the features of the game, we implemented the four following *activities* and characterized them through the Activity Theory:

- *Develop new social relationship* (social engagement dimension) is notably supported by the *actions: propose confrontation, find players, be interested in other player profile, ask to be friend and accept to be friend.*
- *Share moment with real friends* (social engagement dimension) is notably supported by the *actions: share game events on social networks, import real friends into the game and propose confrontation with friends.*
- *Achieve challenges* (action engagement dimension) is notably supported by the *actions: seek information about challenges, improve character equipment, improve player and improve character.*
- *Increase knowledge about the game* (environmental engagement dimension) is notably supported by the *actions: seek information about the game, practice the tutorial and configure the game options.*

We also deconstructed every *actions* in many *operations* performed by the learner with the input devices (mouse and keyboard).

As another result, we observed that the six players who played the most (the sessions of play were spread over the whole period of four months) showed either a unique engaged-behaviour (only one type of *activity*) or a mixed engaged-behaviour (several *activities* from several types of engaged-behaviours). For example, one player showed many occurrences of the *activity Achieve challenges* but demonstrated absolutely no interest in other players. We also identified two clearly differentiate types of *social* engagement: one directed toward the existing friends of the player, the other directed toward unknown players. On the contrary, players who stopped playing after only several sessions of play (typically spread on only one month) showed no *activities*, except one player who showed the *Increase knowledge about the game activity*. This confirms that the behaviours we detected reflect an engagement and thus, shows the feasibility and the validity of the whole process. Also this user study seems to indicate that the variety of the performed *activities* is a relevant information regarding the engagement.

### D. Discussion and related works

Dealing with learners' disengagement detection in web-based e-learning system, the authors compare in [18] 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 quizzes events. By conducting quantitative measure on isolated (i.e. unlinked) utilitarian metrics, this method stays at a basic level that cannot analyse the user experience (and so engagement) [19]. In our case,

quantitative methods may simply compute some statistics on the waves surfed. With our qualitative approach we are able to know if a wave is surfed in order to achieve a challenge, to play with friends or to meet some other players.

Some approaches consider user's engaged-behaviour as sequences of actions. [20] propose a classification approach of learner's 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. More recently, [21] adopt a clustering approach to detect sequences of learner's actions in the Andes ITS. These studies only occur in high-constraint environment like ITS. In such environments, the variety of actions is tight and fully determined by the interactive system (attempts, request for hint, results etc.) and so the number of items is limited. Thus, sequence-mining may constitute an efficient method to discover some statistically relevant sequences of actions. But, in low-constrained interactive systems like digital game, a wide range of actions may be possible. Then, sequence-mining may return a high number of sequences difficult to interpret. Moreover, although our traces are potentially composed of 89 types of *obsels* (according to 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 follows by the player in the game. These *obsels* are fully determined by the gameplay and do not reflect a behaviour. Thus, most of the sequences returned by sequence-mining will derive from these 4 *obsels*. Also, as the temporal succession of actions does not imply that there is a coherence between them, the sequences computed may not be useful to derive valuable information about high-level behaviours. Machine learning for sequential data mining suffers from several issues like long-distance interactions [22]. This is problematic in our case as a long period may occur between actions within an engaged-behaviour. For example the *action improve character equipment* occurs less often than the *action seek information about challenges*.

### V. CONCLUSION AND FUTURE WORK

In this paper, we propose an approach that enables to extract high-level knowledge (like engaged-behaviours) from learners' traces of interaction. This approach identifies engaged-behaviours in low-constraint interactive systems, directly and continuously. To qualitatively analyse learners' raw data, we combine a theoretical work on engagement, engaged-behaviours, SDT and Activity Theory. This enables to establish a relationship between needs, motives, behaviours and the actions actually performed. Then, we rely on the Trace Theory to discover and to extract engaged-behaviours.

The results of the user study conducted on twelve traces of interaction composed of several thousands of data demonstrate the feasibility and the validity of our approach. Also, as engaged-behaviours are rooted in the satisfaction of the

universal needs identified by the SDT, these behaviours are broadly present in all gameplays. Thus the deconstruction of engaged-behaviours in *activities* and *actions* performed during the user study can be transferred in other games. Indeed, the *activities* and *actions* levels, and the rules allowing to infer *activities* from *actions* are broadly shared by different types of games. Therefore, only the *operations* and the rules allowing to infer *actions* from *operation* depend on the game. Moreover, the adaptability to various game engines would be fairly simple as few lines in JavaScript are needed in order to collect an event.

Our approach is not limited to engaged-behaviours and can be applied for analysing any evolution of any behaviour (since there is some chains of actions to analyse). Also, it would be interesting to address the dimension of group like analysing how learners are interacting together within the learning game. This will probably give rise to a problem of scalability (number of users, volume of collected data) that refers to the Big Data issue.

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