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# Simulating serious games: a discrete-time computational model based on cognitive flow theory

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## ABSTRACT

This paper presents a computational model for simulating how people learn from serious games. While avoiding the combinatorial explosion of a games micro-states, the model offers a meso-level pathfinding approach, which is guided by cognitive flow theory and various concepts from learning sciences. It extends a basic, existing model by exposing discrete-time evolution, allowing for failure, drop-out, and revisiting of activities, and accounting for efforts made and time spent on tasks, all of which are indispensable elements of gaming. Three extensive simulation studies are presented involving over 10,000 iterations across a wide range of game instances and player profiles for demonstrating model stability and empirical admissibility. The model can be used for investigating quantitative dependences between relevant game variables, gain deeper understanding of how people learn from games, and develop approaches to improving serious game design.

## ARTICLE HISTORY

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## KEYWORDS

Serious game; learning; simulation; computational model; flow theory

## Introduction

Games for teaching and learning have been around for over four decades (Abt, 1970). In recent years renewed interest in these so-called “serious games” arose because of greatly improved conditions for game development and distribution: better end-user connectivity, deep market penetrations of PCs, handheld devices and game consoles, and reduced production costs because of low cost middleware tools for graphics design, media production and game creation (Saveski et al., 2015). As serious games are among the most complex and diverse learning environments (Björk & Holopainen, 2005), the relationship between the designed structural properties of a game and its pedagogical capabilities is not well understood. Ideally, serious game design should be paired with instructional design, requiring the cautious balancing of “playful” game mechanics and “serious” instructional principles (De Gloria, Bellotti, & Berta, 2014). But unfortunately both game design and instructional design are ill-structured domains that are often considered an art rather than an established profession, thereby lacking appropriate scientifically-grounded knowledge and evidence (Björk & Holopainen, 2005; CERJ, 2000).

In accordance with a wider debate between methodological camps in the social sciences (De Marchi, 2005; Reeves, 2006), this paper proposes to extend the scientific study of serious games by complementing both the empirical hypothesis-testing framework and the game-theoretical deductive-modelling framework with an approach of computational systems modelling. The computational approach aims to capture the individuals’ behaviours in behavioural rules along with a set of contextual parameters and constraints, and produce dynamic models that recreate observed phenomena. This

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paper extends a preliminary event-based computational model to a discrete-time computational model that simulates how people learn while playing serious games (Westera, 2017). The proposed model combines gaming concepts (decision strategies, flow theory, challenges) and concepts from learning sciences and cognitive psychology (experiential learning, motivation, knowledge states, learning curves). It would allow game researchers and developers to deeply investigate quantitative dependences between relevant game variables and player characteristics, gain deeper understanding of how people learn from games, and eventually develop methods and tools to improving serious game design. As a preparatory step in this line of research, the model will be tested for stability and empirical admissibility. Research questions are formulated as follows:

- How to express a discrete-time simulation model for serious gaming that avoids inherent complexity?
- To what extent does the model produce stable and plausible outcomes across different game models?
- To what extent does the model produce stable and plausible outcomes across different player models?
- To what extent does model evaluation allow for investigating how people learn during the game?

The paper is setup as follows. First, we will summarise related work in computational game models. Second, we will present and explain the discrete-time model. Third, we will report on a wide range of simulation experiments. Finally, we will discuss our findings.

## Related work

In game research computational models of games are used for three different purposes: (1) understanding a particular strategy game (e.g. chess), (2) playtesting, and (3) automated game level generation.

Over half a century of research in the domain of strategic turn-based board games has procured a variety of intelligent algorithms and computer programmes that simulate game play (Van den Herik, Uiterwijk, & Van Rijswijck, 2002). Its successes are in outperforming the world chess champion in 1997, and recently the defeat of the reigning world champion Go. Apart from the specific game-theoretical insights this research produces about the game in question, e.g. its winning strategies, it is strongly motivated by the advancement of artificial intelligence (AI).

Quite some research has been directed to machine-driven play testing and game balancing. For understanding how a game would work, game developers usually arrange a playtest of a game prototype by test players. Data thus collected can be used for identifying dominant patterns (for instance a heat map indicating where players frequently are), characterisation of play styles, or analysis of player experiences. However, such testing is expensive and laborious, and can only be done at the end of a design cycle, when a complete and playable version of the game is available. As an alternative to using test players as the exclusive source of information, simulation models can be used. In recent years, various AI-driven methods and tools have been proposed to simulate game play for automated game testing, be it largely as proofs of concept tailored to one particular game (Salge, Lipski, Mahlmann, & Mathiak, 2008; Zook, Fruchter, & Riedl, 2014; Volz, Rudolph, & Naujoks, 2016; Dolmans, 2011; Jaffe, 2013).

Automated generation of new game levels requires smart algorithms that take into account the game mechanics and object types that underlie the game. New levels should extend existing ones and offer challenges that take into account accumulated skills of the player. Generally evolutionary methods or other AI methods are used to design and generate new levels (Sorenson & Pasquier, 2010; Neufeld, Mostaghim, & Perez, 2015). Automated video game playing agents are then used to evaluate the levels, and to tweak parameter values to player skills and optimal player enjoyment. An important part of level generation is the automated creation of content objects, e.g. 3D buildings,

furniture, maps, mazes, etc. These procedural generative techniques help to substantially reduce the costs needed for game content creation and personalised game play (Togelius, Justinussen, & Hartzen, 2012).

However, all these simulation studies essentially focus on leisure games and do not take into account learning processes. A provisional version of a computational model for serious gaming was proposed and successfully tested by Westera (2017). The model relies on flow theory, decision theory and experiential learning theory. In the model, game play is considered a pathfinding process across a set of game activities that enhance the player's knowledge states. The current paper will extend the original model, while removing some of its manifest weaknesses. First, the model will expose discrete-time evolution rather than discrete events (game activities). Second, as opposed to the previous work the model will allow for failure, drop-out, and the revisiting of activities, all of which are relevant factors in learning from games. Third, the model would account for efforts made and time spent on tasks, both of which are relevant for guarding the efficacy of learning.

## Model description

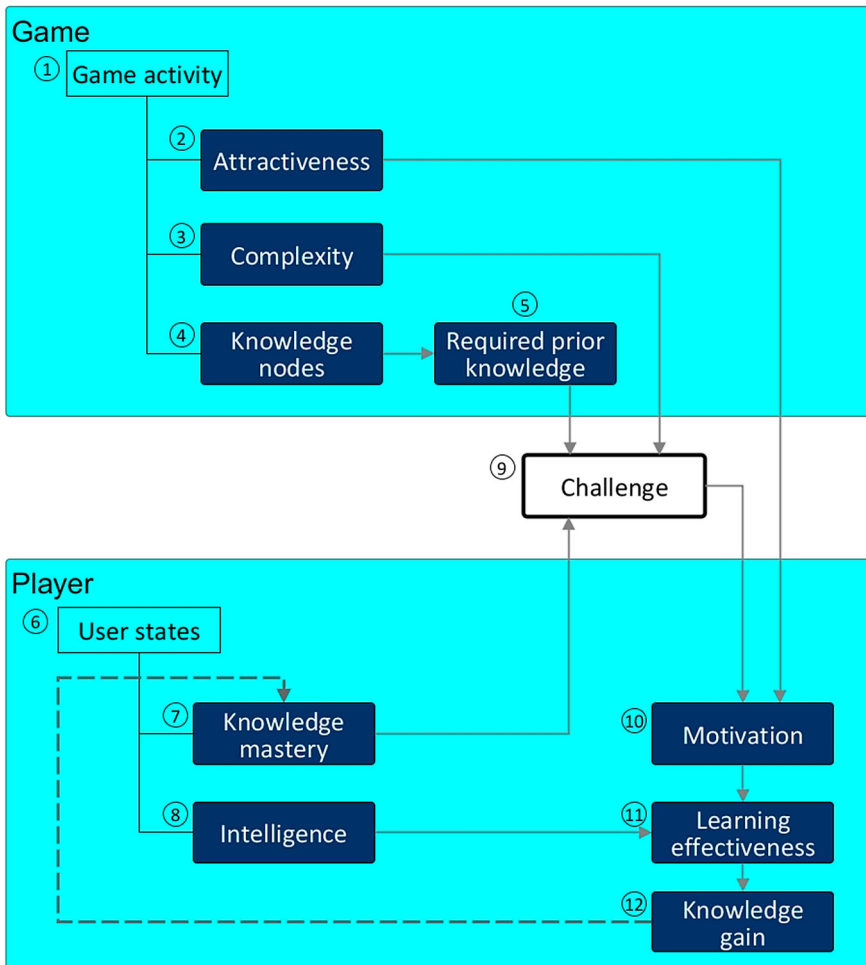
### *Summary of starting points*

The proposed model extends a preliminary model published elsewhere, which is summarised below (Westera, 2017). To reduce overall complexity and to avoid model overfitting and the combinatorial explosion of game states and player states, the model focuses on meso-level aggregates that constitute meaningful activities, typically learning activities, directly originating from the game scenario, e.g. write a note, interview a person, track a hidden object, buy supplies, navigate. The game is thus described by a pathfinding process across such meso-level game activities, while elementary cognitive flow theory is used for evaluating the match between player skills and the challenges posed (Csikszentmihalyi, 1991). Also, Vygotsky's theory of social development (Vygotsky, 1933–1987) is incorporated in the model: one may want to challenge players slightly beyond the boundaries of their abilities in order to preserve the curiosity and engagement that are needed for learning new things. By replacing the event-based model description with a discrete-time description, a finer grainsize level description is achieved that covers the evolution of parameters across time. Every game activity will be described in a series of discrete time steps, in order to do justice to the detailed dynamics of play. This is a necessary extension for the detailed investigation of knowledge growth, efforts made, intermediate failures, mood changes, emergent phenomena and the occurrence of critical events.

Basic ingredients of the model are the knowledge model, the player model and the game model, all of which are bound together in the pathfinding algorithm. The productive outcomes of a serious game need to be expressed as knowledge gains. The knowledge model is generally expressed as a knowledge tree of operationalised learning goals or learning outcomes, e.g. skills, facts, competences, while child nodes in the tree have a precedence relationship with their parent nodes. While the game is represented as a network of meso-level activity nodes, each activity in the game is allowed to address one or more nodes from the knowledge tree. Each activity in the game is characterised by prior knowledge requirements and by an inherent complexity. The player model accounts for the player's mental states, preferences and behaviours. In accordance with the initial model only few, primary player factors will be taken into account: overall intelligence, knowledge state, and motivation. While both intelligence and prior knowledge refer to the player's learning capability, motivation is linked to personal attitudes, emotions and ambitions. These are exactly the key dimensions that reflect the potential of serious games: learning new knowledge from serious games, while benefitting from their motivational power.

### *Conceptual outline*

The relationships between the main model variables are depicted in [Figure 1](#).



**Figure 1.** Causal model of learning from a game activity.

The proposed model reflects the interplay between the game and the player. The game is assumed to be made up of game activities (1) each of which is characterised by an attractiveness value (2) and a complexity value (3). Each activity addresses one or more knowledge nodes (4), which may require some prior knowledge (5). The player in turn is characterised by a set of user states (6), in particular the player's actual knowledge state (7), which may gradually increase during the game, and player intelligence (8), which is likely to be constant. The perceived challenge (9) that is posed by the game activity at a certain moment in time is determined by any gaps between the required prior knowledge (5) and the player's actual knowledge mastery level (7) in the respective knowledge nodes. Also, the inherent complexity (3) of the activity influences the severity of the challenge. According to flow theory, the challenge will influence the player's motivation (10), either leading to high levels of cognitive flow when the challenge is sufficiently doable, or to reduced interest and engagement in case of a mismatch (too hard, or too easy). In addition, also the attractiveness (2) of the game activity would directly influence the player's motivation. Finally, both the player's motivation level (10) and the player's intelligence (8) determine the effectiveness of learning (11) and eventually the knowledge gained (12). Then, after updating the player's knowledge states (7), the whole cycle is repeated for the next time step, while the player progresses in the game.

## Model extensions

### Discrete time model

For extending the original model to a discrete-time model, all original equations constituting the model have been converted to incorporate time dependency. Whilst the reader be referred to Westera (2017) for mathematical details of the model, we confine ourselves here to the Equation (1) below that holds for the learning effectiveness  $L(p,j,t)$  of player  $p$  at time  $t$ , in game activity  $j$ :

$$L(p, j, t) = A(j) \cdot I(p) \cdot e^{\left( - \frac{(\bar{C}_H(p, t) - F_V)^2}{2\sigma_F^2} \right)}. \quad (1)$$

Here  $A(j)$  is a metric of the attractiveness of game activity  $j$  that the player is carrying out at time  $t$ ;  $I(p)$  is the overall intelligence of player  $p$ ;  $\bar{C}_H(p, t)$  is the challenge posed to the player, which is determined by the (average) knowledge deficits or knowledge surpluses that hold for respective knowledge nodes in game activity  $j$ , and the game activity's inherent complexity;  $\sigma_F$  is the flow factor, which indicates the sensitivity of the player's motivation to a challenge mismatch;  $F_V$  is the Vygotsky factor, which establishes that optimal learning occurs at a slightly positive challenge (Westera, 2017). The exponential factor in Equation (1) reflects the mechanism of optimisation.

### System updates

In each time step  $\Delta t$  the player's knowledge state has to be updated to account for the knowledge gained. The process of updating the mastery  $P(p,n,t)$  of player  $p$  for knowledge node  $n$  (which is covered by activity  $j$ ) is described by the differential expression of Equation (2):

$$P(p, n, t + \Delta t) = P(p, n, t) + L(p, j, t) \cdot (1 - P(p, n, t)) \cdot \Delta t \quad (2)$$

Since a node in the knowledge tree, as a parent, combines, integrates and extends all child nodes, the process of mastering a parent node inherently contributes to the further mastery of all subordinate nodes in the parent tree. Hence, in the updating process Equation (2) should also be applied for updating the respective child node states and deeper subordinate levels. As a consequence, mastering a parent node in the game, be it partially, will directly contribute to knowledge gains in all conditional nodes in the knowledge tree.

### Success and failure

A system that allows for successes and failures requires a rule set for these. First, it should be clear when an activity (and in the end the full game) is successfully completed. Secondly, players should be allowed to prematurely quit an activity and (potentially) revert to it later on. Hence it should be clear in what conditions a player will abandon an activity early. To avoid endless swapping between dropping out and retrying the same activity, additional restrictions are needed. Also it should be clear when a failure becomes a definitive failure, which cannot be undone. All these conditions are greatly dependent on the game under question. For being able to test the model a generic set of conditions for success and failure are defined below. These are only used for testing purposes and do not necessarily imply constraints to the core of the computational model.

For successful completion of an activity the player's mastery of all its associated knowledge nodes should have passed a predefined cutting score level  $S_c$ . The cutting score is the performance assessment benchmark, which is likely to be the same for all nodes. Equation (3) presents the activity completion criterion in case of  $q$  knowledge nodes with player  $p$ 's mastery level  $P_q(p,n,t)$ :

$$\frac{1}{q} \cdot \sum_{n=1}^q P_q(p, n, t) \geq S_c \quad (3)$$

(Alternatively, one may require that this threshold holds for each separate knowledge node).

Premature drop-out would be triggered by low learning progress (or likewise, unfavourable challenge or low motivation). By dropping out early, players can engage in alternative, more productive activities before revisiting the activity at a later stage, when prior knowledge or motivation is brushed up. A few rules are needed for this. First, players should not be allowed to drop out an activity during the first few time steps, as it may lead to unwanted repetitive cycles of quitting and re-entering in activities. Players should be allowed to get acquainted with a new challenge. Therefore, a dead-time interval  $T_D$  should apply: during the first  $T_D$  after having entered the activity, drop-out is inhibited (except in case of successful completion). Second, also a quality criterion should be applied. A rationally motivated stop criterion could be based on actual learning gains. By using Equation (2) and introducing a lower limit  $\epsilon$  ( $\epsilon \ll 1$ ) for the knowledge gained during time step  $\Delta t$ , a player drop-out rule can now be expressed as (see Equation (4)):

$$L(p, t) \cdot \Delta t \cdot \frac{1}{q} \sum_{i=1}^q (1 - P(p, n, t)) < \epsilon, \text{ for } P(p, n, t) < S_c \quad (4)$$

Third, when an activity is quit, it should be excluded from the next options. Fourth, to prevent players from endlessly revisiting the same activity with a challenge too hard, an upper limit  $U_t$  for the number of trials is needed. After  $U_t$  unsuccessful trials to complete the activity, it is registered as a persistent failure and removed from the activity options. The overall game has ended when the game's activities are either successfully completed or, in case of persistent failure, are no longer accessible.

## Simulation experiments

### Preparations

The proposed model of serious gaming was technically implemented using Scilab 5.5.2 ([www.scilab.org](http://www.scilab.org)). A baseline game skeleton and a baseline player were defined as a starting point for experimental adjustments. The baseline game skeleton was defined to be composed of 40 game activities. Learning goals were represented as a 4-level knowledge tree with degree 3, resulting in 40 interdependent knowledge nodes. The knowledge nodes were randomly distributed across the game activities, whereby each game activity addresses 3 knowledge nodes, and (evidently) each knowledge node has 3 occurrences in the game. For the time being each game activity was assigned a constant, moderate attractiveness of 0.5 in the interval [0,1], as well as a constant, moderate complexity ratio of 0.5. The activity with lowest overall rank in the knowledge tree was assigned the start activity and, conversely, the activity with highest overall rank in the knowledge tree was assigned the end activity. The process of playing the game would in principle allow any trajectory from the start activity across the remaining activities toward the end activity. The cutting score for each game activity was set to  $S_c = 0.6$ . The lower threshold for prematurely leaving an activity was set to  $\epsilon = 0.002$ , based on an empirically tested estimate. Activity dead-time  $T_D = 20$  and the maximum number of trials  $U_t = 5$ .

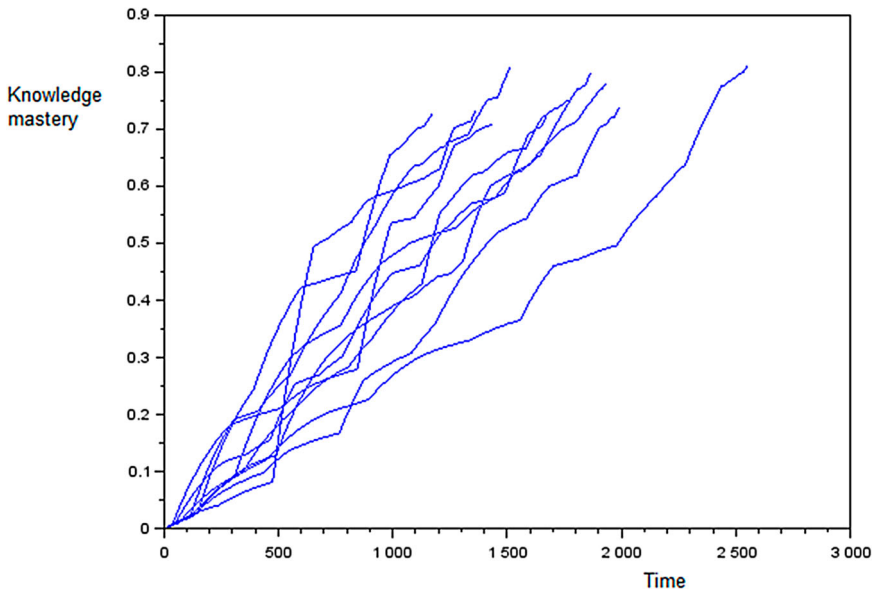
Provisionally the baseline player was equipped with a moderate intelligence ratio of 0.5 and without any prior knowledge with regard to the nodes in the knowledge tree. The player's strategy of selecting the next activity after completing or quitting the one before is based on maximum expected learning effectiveness. Cognitive flow influence was initially excluded by setting a default value of  $\sigma_F$  as large as 100. Likewise, Vygotsky's effect was initially disabled by setting the Vygotsky factor of the baseline player to a default value of  $F_V = 0$ . The time scaling factor of  $\Delta t = 0.01$  was found to provide sufficient detail.

### Model stability and plausibility across different game profiles

#### Learning curves

Using the baseline player profile as a fixed reference, different instances of the baseline game were generated by randomly redistributing the knowledge nodes across the set of game activities. **Figure 2**





**Figure 2.** Learning curves of the baseline player in 10 random instances of the baseline game.

shows the learning curves of the baseline player for 10 different (random) instances of the baseline game. In total the simulation comprised 1500 game iterations.

The player's knowledge mastery (vertical scale) is expressed as the average mastery level of all nodes in the knowledge tree at the end of the game. In all cases a pattern of gradual knowledge gain can be observed, demonstrating convergence and stability.

### **Variability of learning curves**

Variability of the 1500 learning curves in the experiment is substantial, both horizontally (time spent) and vertically (knowledge mastery). Time spent averages at 1762 time steps, with a standard deviation of  $SD = 473$  (27%). The final knowledge mastery levels attained in the games show some variation around an average of 0.75 (standard deviation  $SD = 0.03$ ; 4%).

Vertical variability of the learning curves was calculated by first transforming the time scales to a uniform scale, and then calculating the vertical variance across the different game sessions (vertical scale) for each time step. By averaging these over the full time scale (horizontal scale) a weighted value of the curves' vertical spread can be obtained. **Figure 3** shows how the vertical variability of the learning curves depends on the number of game iterations.

The figure shows that the learning curve variability saturates at a level of 0.0600 (standard deviation  $SD = 0.0003$ ; 0.5%), measured in the interval [500,1500].

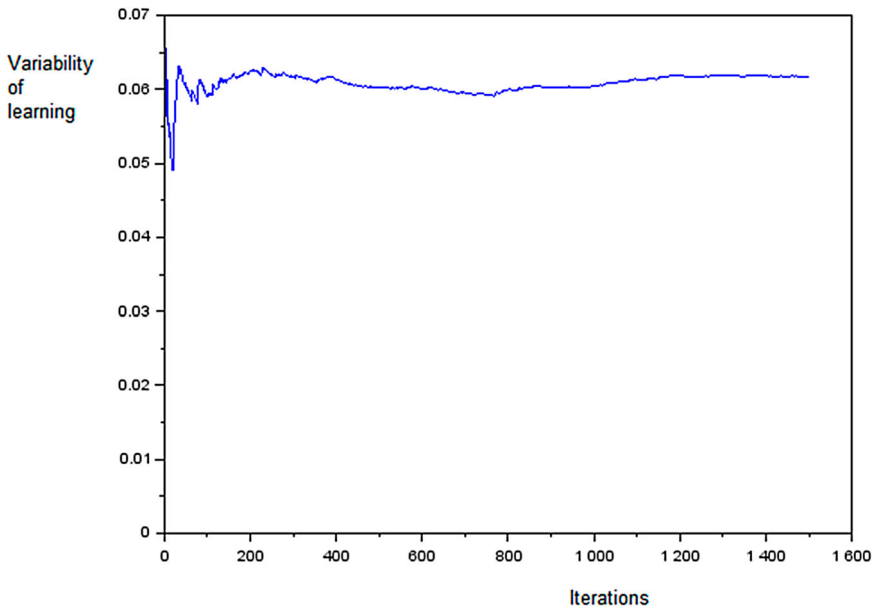
### **Drop-out and failure**

Early activity drop-out is correctly accommodated by the stop rules for failure. Within the given set-up of the games, on average 34 out of 40 activities were successfully completed, while 6 activities showed a failure. The average number of early drop-outs was 50 ( $SD = 16$ ; 32%), largely predetermined by the drop-out rules. It demonstrates that early drop-out of an activity does not necessarily block successful completion of the activity at a later stage.

### **Regression of learning outcomes against time spent**

Generally learning outcomes increase with time spent. In the sample a positive correlation was found between the time spent in the game and the knowledge gained:  $r = 0.725$ . This suggests that about





**Figure 3.** Vertical variability of learning curves as a function of the number of iterations.

half of the variance of learning outcomes can be explained by time spent. Figure 4 shows a scatter-plot of the 1500 data points and the least-squares regression line with intercept 0.6599 and slope 0.0000515.

### **Model stability and plausibility across different player profiles**

#### **Learning curves**

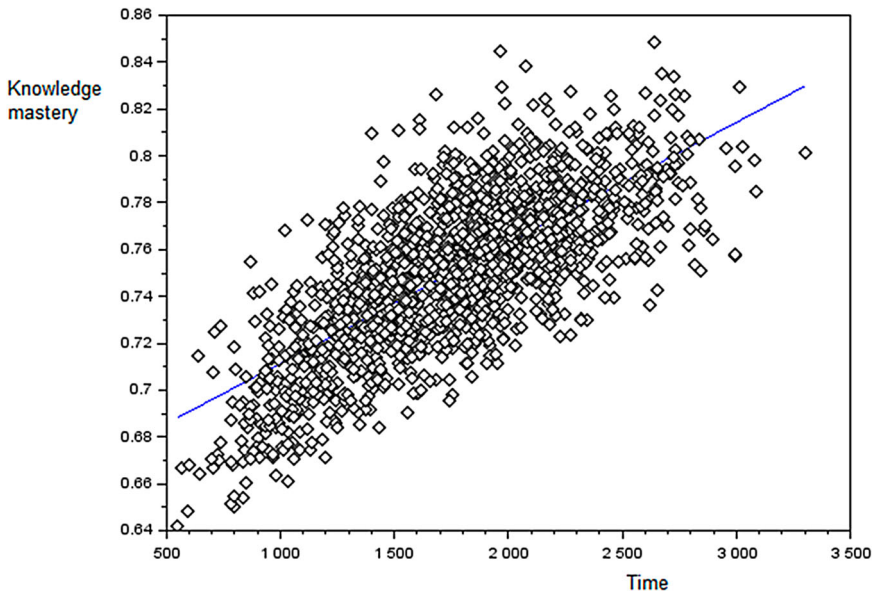
Using a single baseline game instance as a fixed environment, a large set of player profiles were generated to test the model. Player variables include the player's prior knowledge, the player's intelligence, and the player's susceptibility to flow, respectively. The latter, which is expressed by the flow factor  $\sigma_F$ , is potentially the most critical factor, because of its nonlinear occurrence in the model: for small values  $\sigma_F$  Equation (6) may readily lead to breakdown of learning. In contrast, player intelligence is more likely to act as a scaling factor for the speed of learning. Likewise, the player's prior knowledge will speed up the learning because of reduced knowledge gaps. Figure 5 shows the learning curves for the baseline player in the baseline game for different values of  $\sigma_F$ .

As  $\sigma_F$  decreases, the total knowledge gained decreases, while the learning takes more time. When  $\sigma_F < 0.1$  a critical region is entered, where the learning collapses. As opposed to this: when  $\sigma_F$  is larger than 0.15, which covers the range where the player is less sensitive to flow, the knowledge mastery gets more or less stable. This is consistent with the results shown in Figure 6 below.

#### **Critical influence of flow factor $\sigma_F$ on learning**

In Figure 6 the knowledge gain is plotted for the whole range of the player's susceptibility to flow  $\sigma_F$ .

Each data point in Figure 6 reflects the average knowledge mastery of 20 players randomly assigned an intelligence ( $mean = 0.5$ ;  $SD = 0.1$ ) and uniform prior knowledge in all nodes (drawn from a normal distribution at  $mean = 0$ ,  $SD = 0.2$ , in the interval  $[0,1]$ ). The data likewise reveal a steep slope when  $\sigma_F < 0.1$ , indicating the collapse of learning. The vertical spread in the figure is typically 2%.

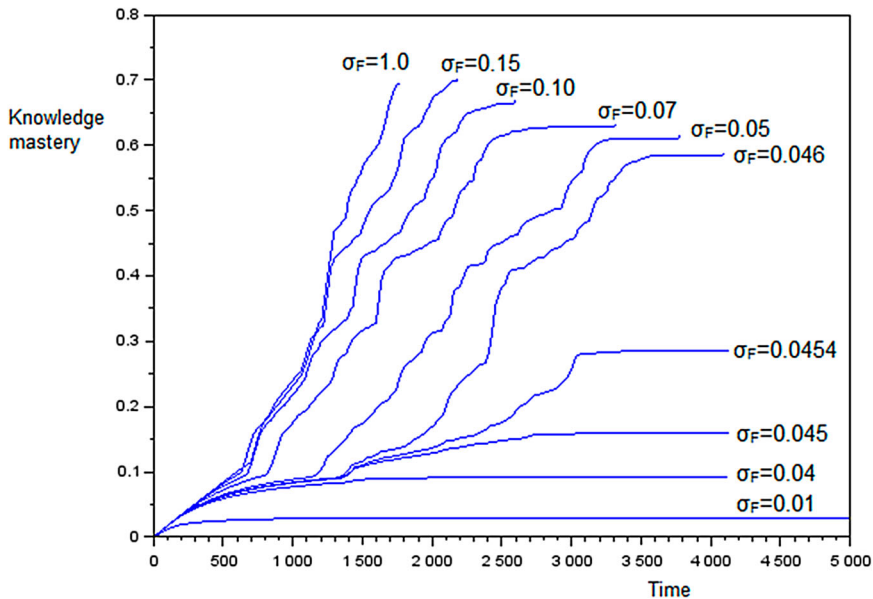


**Figure 4.** Linear regression of knowledge mastery versus time spent for 1500 data points.

### *Variability of learning curves*

For different values of  $\sigma_F$  the variability and stability of the model was extensively tested against 1500 iterations with randomly selected players (intelligence and prior knowledge sampled as before). **Figure 7** presents the average (vertical) variability of the learning curves against the number of iterations for  $\sigma_F = 0.07$ ,  $\sigma_F = 0.14$ , and  $\sigma_F = 0.20$ , respectively.

The curves are quite steady and do not show extreme variations or singularities. After some hundred iterations the variability tends to saturate. **Table 1** summarises the saturation levels in the



**Figure 5.** Learning curves for different values of flow factor  $\sigma_F$ .

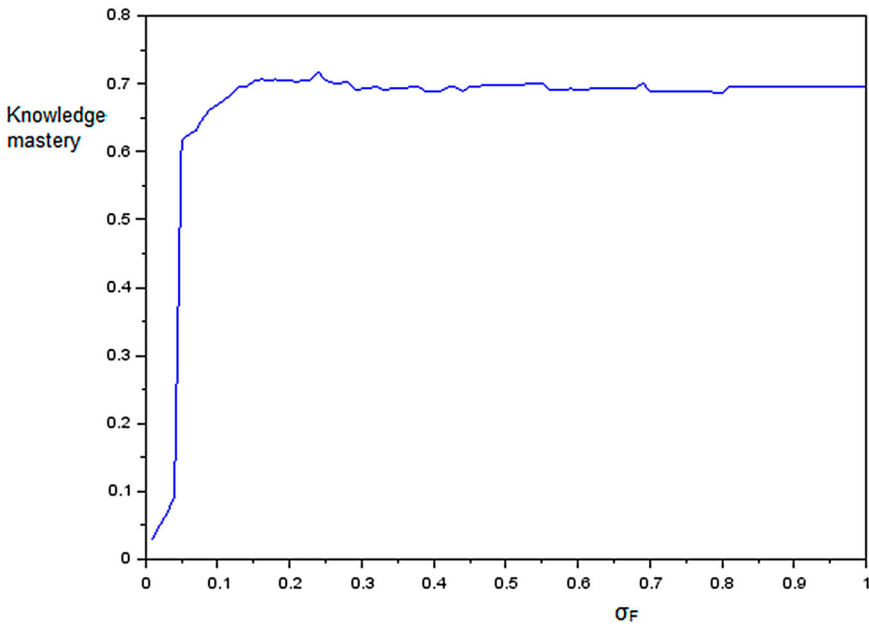


Figure 6. Knowledge mastery as a function of the player's susceptibility to flow  $\sigma_F$ .

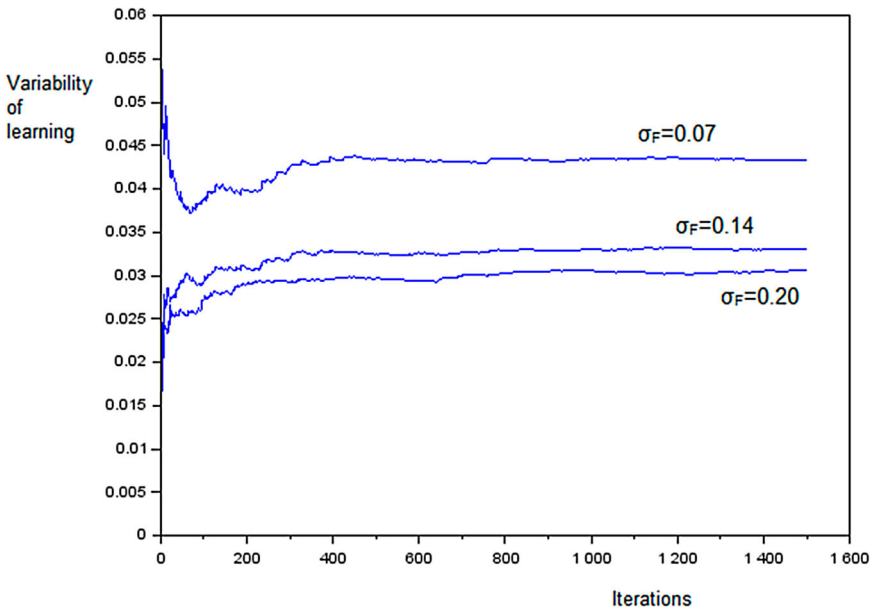


Figure 7. Vertical variability of learning curves versus the number of iterations, for different values of  $\sigma_F$ .

interval [500,1500], as well as the attained knowledge mastery levels and times spent. Also it lists the number of activities completed (out of all 40 activities) and the number of drop-out events.

At low values of  $\sigma_F$ , which means that players are more sensitive to unbalanced challenges, the vertical variability of the curves increases, as well as the time spent. The knowledge mastery level goes down, and less activities are successfully completed. At the same time players are dropping out of activities more often. This all fits in the frame of increased sensitivity to mismatches

**Table 1.** Variability of simulation data (and standard deviations) obtained from iterations in the interval [500,1500] for different flow parameters.

$\sigma_F$	Vertical variability	Level of mastery	Time spent	Completed out of 40	Drop-out events
0.20	0.030 (0.0003)	0.679 (0.15)	1393 (326)	36 (3)	58 (20)
0.14	0.033 (0.0002)	0.664 (0.016)	1575 (342)	34 (3)	68 (20)
0.07	0.043 (0.0001)	0.606 (0.015)	2642 (427)	19 (5)	123 (21)

between challenges offered and the players' capabilities, whereby the players' motivations and hence their learning effectiveness diminish.

### Playing strategies

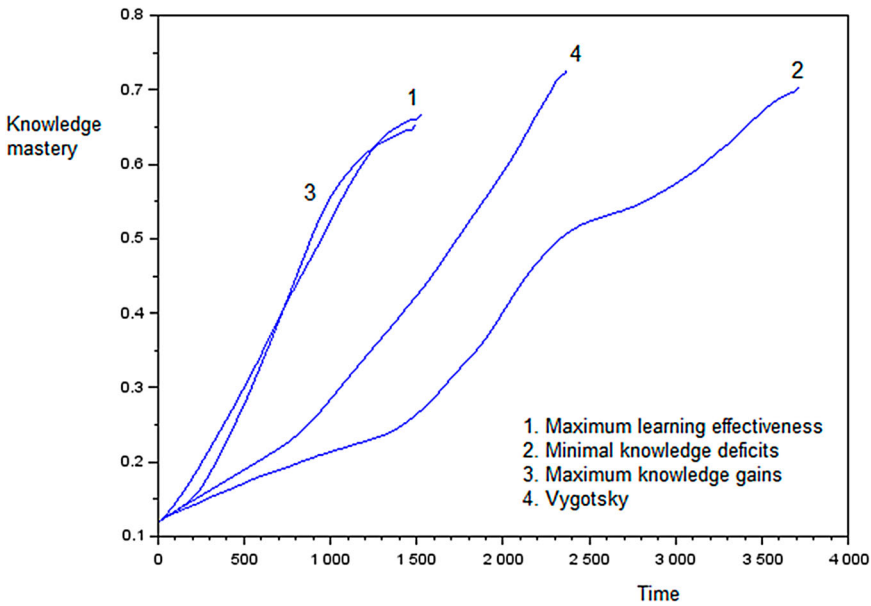
For studying how different playing strategies influence the attained knowledge mastery a set of 1000 players was generated by randomly assigning intelligence ( $mean = 0.5$ ;  $SD = 0.1$ ) and uniform prior knowledge in all nodes (drawn from a normal distribution at  $mean = 0$ ,  $SD = 0.2$ , in the interval [0,1]). The flow factor was fixed to  $\sigma_F = 0.15$ . Playing strategies refer to the pathfinding algorithms that apply for moving from one activity to the next, irrespective of the acting agent: either the player, teacher, the game or any other agent could control the strategy. The following decision strategies have been studied:

- (1) Highest learning effectiveness So far all studies have used this as the baseline strategy.
- (2) Minimal knowledge deficit With this strategy the selection of the next game activity is based on minimal knowledge deficit.
- (3) Maximum knowledge growth The strategy opts for activities that allow for maximum knowledge gains.
- (4) Vygotsky's challenge This strategy would select a small positive challenge, which is slightly beyond one's capabilities, as indicated by the Vygotsky factor  $F_V$ .

Alternative strategies of using optimal motivation or optimal challenge would duplicate the result of the strategy based on learning effectiveness (1), because for the same player they are proportional in the model. For the Vygotsky strategy (4), the Vygotsky factor was set to  $F_V = 0.1$ . For each of the 4 strategies 1000 learning curves were iterated. Thereafter the curves were subjected to a set of linear transformations to derive average data points both for the knowledge mastery scale and the time scale. [Figure 8](#) shows the 4 aggregate learning curves.

Not just the learning curves are different, but also their endpoints reflecting the knowledge mastery after game completion and the time spent. The curves, however, are deceptive, as they do not reflect the standard deviations and the numbers of successes and failures. [Table 2](#) summarises the statistics of the simulations for each of the strategies.

From the table it can be concluded that strategy 2 (minimal knowledge deficits) should be disqualified, because of the low completion rate and large number of drop-outs. Apparently, activities exposing minimal knowledge deficits do not necessarily produce optimal knowledge gains. Strategy 2 (Vygotsky) produces significantly highest learning outcomes, but this goes with long playing times. Most efficient are strategy 1 (highest learning effectiveness) and strategy 3 (highest knowledge growth), showing lower playing times and less drop-out events. It should be noted that all four strategies reflect one-sided, local optimisation by identifying the largest utility on the short-term. However, given the discrete nature of the model and the nonlinear dependencies of model variables, the pathways to long-term successes may not be based on local maximums. In principle, the model would allow to look ahead and do deep tree search for identifying winning strategies that maximise final learning outcomes against favourable conditions (time spent).



**Figure 8.** Average learning curves of a sample of 1000 random players for 4 strategies.

**Table 2.** Simulation outputs (and standard deviations) for 4 game strategies averaged over 1000 iterations each.

Strategy	Vertical variability	Level of mastery	Time spent	Completion out of 40	Drop-out events
1. Learning effectiveness	0.033 (0.014)	0.669 (0.016)	1528 (349)	34 (3)	66 (20)
2. Knowledge deficits	0.017 (0.007)	0.704 (0.017)	3715 (179)	6 (3)	172 (11)
3. Knowledge gains	0.028 (0.015)	0.654 (0.014)	1496 (333)	34 (3)	62 (21)
4. Vygotsky	0.023 (0.008)	0.725 (0.017)	2367 (506)	32 (7)	97 (33)

## Discussion and conclusion

The model presented in this paper provides a proof of principle of a computational modelling methodology for serious games. By avoiding the combinatorial explosion that would stem from using of detailed game states and player states, the proposed meso-level description has demonstrated to provide stable, reproducible and plausible results. In sum, the model requires a knowledge tree indicating the learning objectives, and a set of game activities, possibly annotated with complexity and attractiveness indices. Each activity is supposed to somehow contribute to the mastery of learning goals, which means that a mapping of knowledge nodes to game activities is needed. Although such mapping is not straightforward, various methodologies are available for defining the mapping, for instance Evidence-Based Design and Bayesian nets for stealth assessment (Shute, 2011). Players are characterised by intelligence, prior knowledge and susceptibility to flow, while their motivation and learning progress is evaluated and continually updated during their progression in the game.

Reverting to the research questions formulated in this paper it can be concluded that a discrete-time simulation model can be successfully built on meso-level concepts. The model has shown to provide stable and reproducible learning curves that are in agreement with empiricism and intuitions in serious gaming. Feasibility was demonstrated for a variety of different game instances and for a variety of different players. The model allows to describe and investigate a variety of game-internal variables and processes, including mismatches, time on task, failure and successes, motivation, game strategies and the progression of learning: it allows to open the black box and look into the

mechanisms that influence the quality of game-based learning. Thereby, the model as much as the methodology have the potential to establish a new line of research on serious gaming, in particular in using computational methods for obtaining a deeper understanding of the connection between learning and play.

Nevertheless, the model goes with several limitations. First, the model is only loosely based on concepts and theories of learning. It bypasses the complexities of instructional content and didactics by postulating that engagement in a game activity entails a productive learning experience. The productive influence of failure on learning is not (yet) accounted for (Mory, 2003; Mathan & Koedinger, 2005). Second, although “game activities” are a key concept in the model, the meso-level indication does not say much about their grainsize. In fact, the model is ignorant and indifferent about the grainsize. There are no limitations to the set of activities, which need not be a fixed, predefined set as used in this paper, but allows for emergent activities, which could in principle be added to the pool of alternatives to choose from, at any time during the game. Third, in some ill-defined domains such as soft-skills, well-elaborated knowledge trees as required by the model are rare. This, however, is a transcending problem that is not exclusive for the model. In some cases machine learning approaches can be applied for identifying knowledge patterns and their mapping on to game activities and behaviours (Shute & Ventura, 2013). Fourth, the model does not include cognitive models of human learning, but instead just relies on the phenomenology of the process of play. Connecting with existing models of human cognition, e.g. ACT-R (Anderson & Lebière, 1998), would allow for including a multitude of psychological constructs, be it at the expense of simpleness.

Now that a practicable model has become available, next research steps would cover empirical validation across a wide range of serious games, along with serious game theory development and ultimately the development of predictive systems and tools. So far, however, conditions for empirical validation with real players are only partially met, since some of the model’s variables are still hard to record, such as the real-time progression of motivation and flow. Hence, for the time being the link with real world experiments should be based on a discrete events approximation of the model (e.g. Westera, 2017) rather than the full discrete-time evolution version presented here. Existing instruments (e.g. questionnaire items) could then be used after each iteration step to capture the required data, be it not without practical or methodological difficulties. Still, advances in learner data analytics, stealth assessment, machine learning and physiological sensors for capturing such data are likely to offer new opportunities in the near future. Ultimately, the computational modelling approach would help to design serious games that are more effective for learning.

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