NEES

Núcleo de Excelência em Tecnologias Sociais

Gamification and Intelligent Learning Environments

From Theories to Evidences

Ig Ibert Bittencourt

ig.ibert@ic.ufal.br

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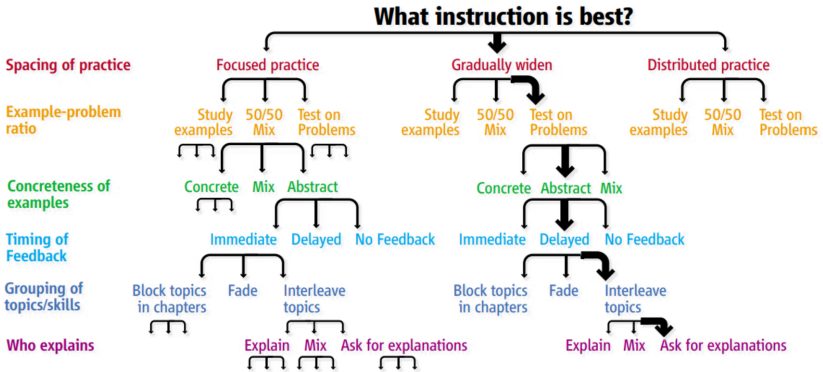
Agenda

Instructional Complexity

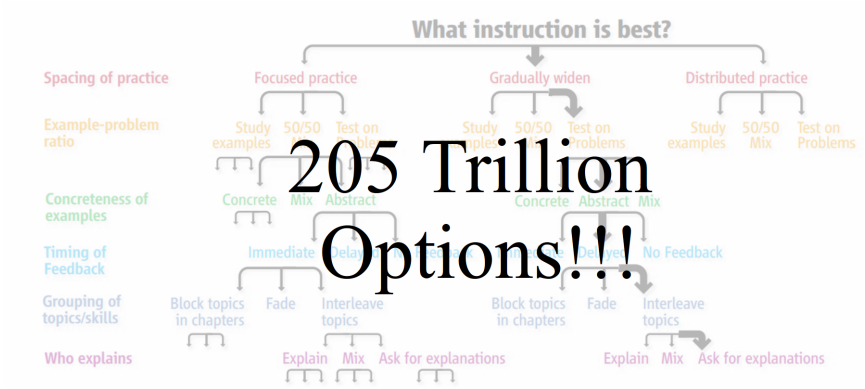
Different choices along different instructional dimensions can be combined to produce a vast set of instructional options



Koedinger, K. R., et. al (2013). Instructional complexity and the science to constrain it. Science, 342(6161), 935-937

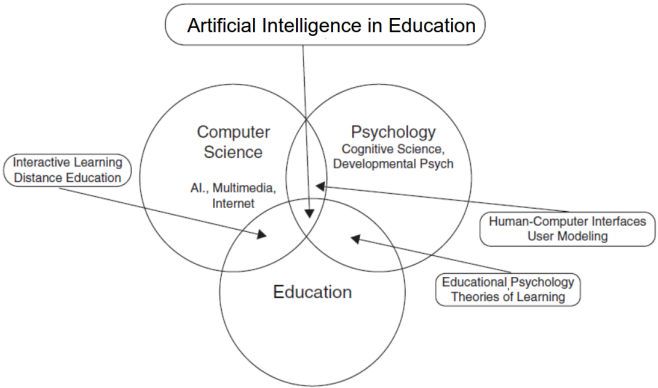
Instructional Complexity

The path with thicker arrows illustrates one set of choices within a space of trillions of such options



Koedinger, K. R., et. al (2013). Instructional complexity and the science to constrain it. Science, 342(6161), 935-937

Artificial Intelligence in Education



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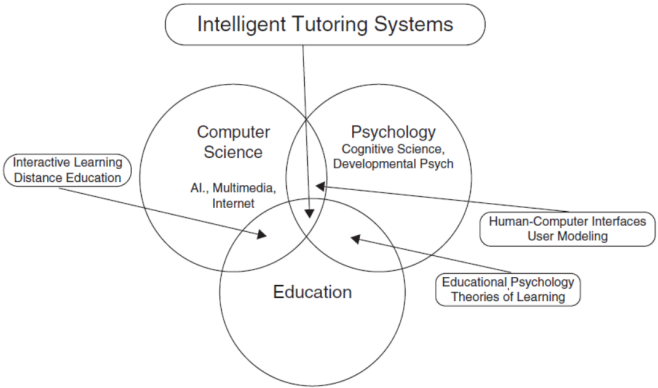
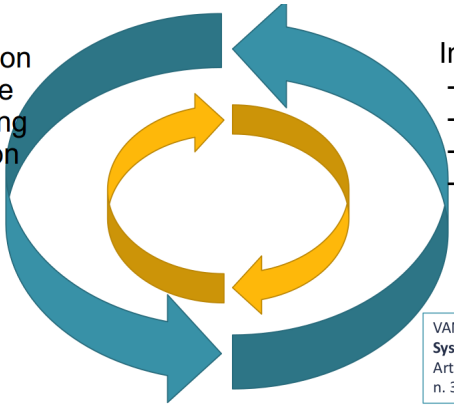


- *Woolf, B. P. (2010). Building intelligent interactive tutors: Student-centered strategies for revolutionizing e-learning. Morgan Kaufmann.*

Intelligent Tutoring Systems

What you mean by inner loop and outer loop ?

Outer Loop
- Student Selection
- Fixed Sequence
- Mastery Learning
- Macroadaptation



Inner Loop
- Minimal Feedback
- Error Flaging
- Hint
- Student Diagnosis

VANLEHN, K. **The Behavior of Tutoring Systems**. International Journal of Artificial Intelligence in Education, v. 16, n. 3, p. 227–265, 2006.

Intelligent Tutoring Systems
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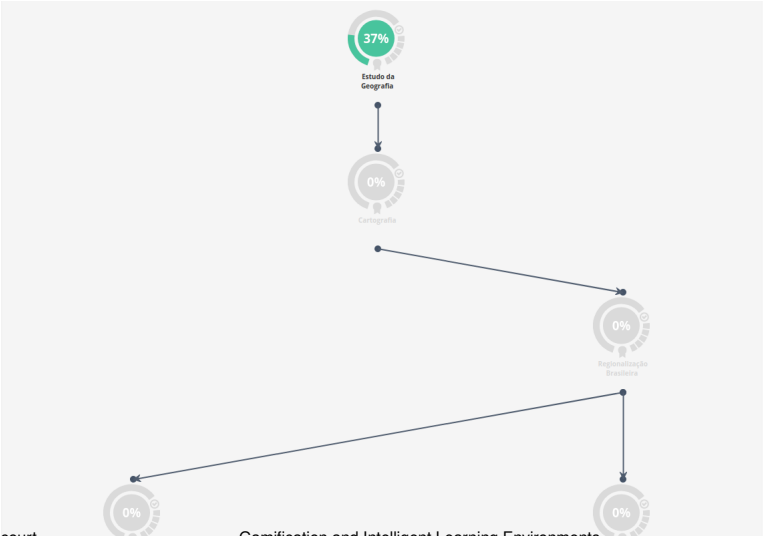

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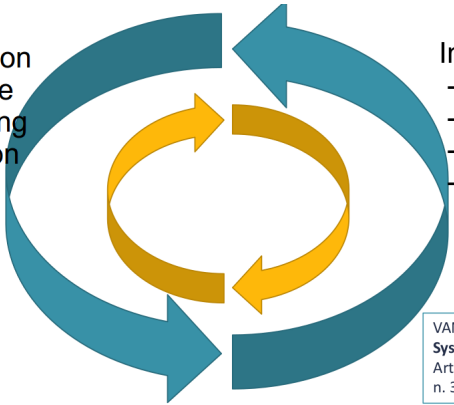

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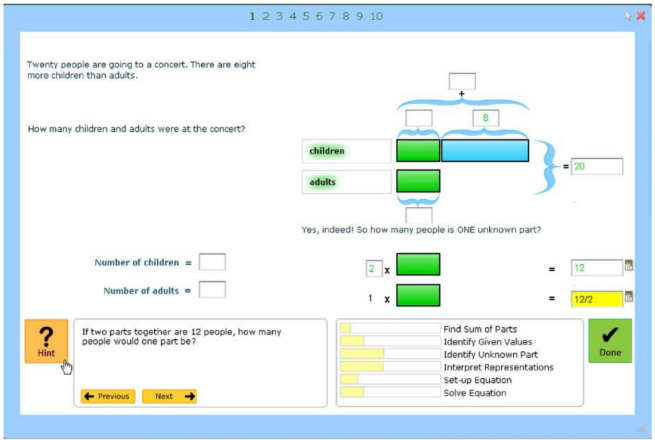
Intelligent Tutoring Systems
What you mean by inner loop and outer loop ?

ALEVEN, Vincent et al. Example-Tracing tutors: Intelligent tutor development for non-programmers. International Journal of Artificial Intelligence in Education, v. 26, n. 1, p. 224-269, 2016.

Mathtutor



Intelligent Tutoring Systems
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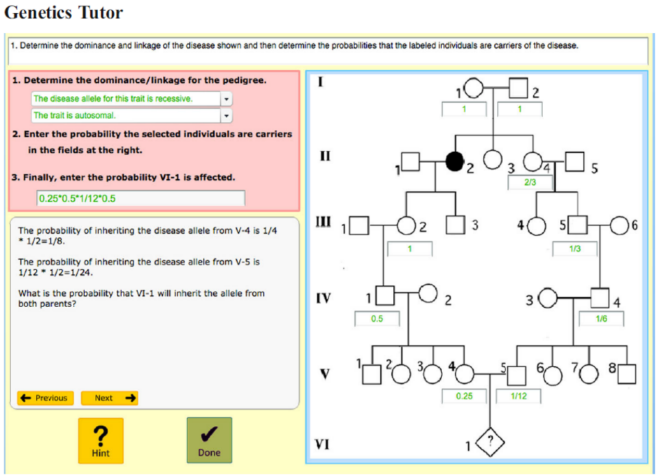
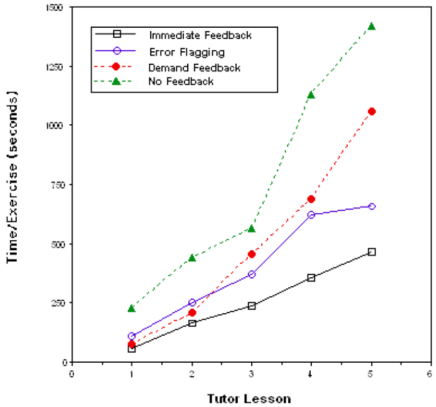


Feedback Studies in LISP Tutor (Corbett & Anderson, 1991)



Time to Complete Programming Problems in LISP Tutor

Immediate Feedback Vs Student-Controlled Feedback

Intelligent Tutoring Systems effectiveness

Improved teaching:

2 Sigma for human one-to-one tutoring

.50 Sigma for interactive multimedia, (raises the median score from 50% to 69%)

1.05 Sigma for intelligent tutors (raises the median score from 50% to 85%).

Reduced Cost:

~63% less less expense to provide instruction with technology.

Improved cost-efficiency:

Bring instruction to learners rather than bringing learners to the schoolhouse.

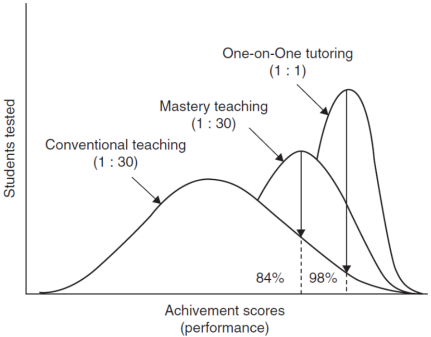


FIGURE 1.1

Advantages of one-to-one tutoring. (Adapted from Bloom, 1984.)

Woolf, B. P. (2010). Building intelligent interactive tutors: Student-centered strategies for revolutionizing e-learning

Intelligent Tutoring Systems

AIED

Gamification

Gamification and ILE

Grand Challenges


Int J Artif Intell Educ (2016) 26:536–537
DOI 10.1007/s40593-015-0060-1

LETTER TO THE EDITOR

Recent Meta-reviews and Meta–analyses of AIED Systems

Benedict du Boulay[1]

Published online: 6 August 2015

It is pleasing to see that the 25th Anniversary of IJAIED also brings a certain maturity to the field. In the last 5 years there have been a number useful and positive analyses of the effectiveness of AIED systems designed to tutor one-to-one. For example, VanLehn (2011) found that the effectiveness of the "step-based" intelligent tutoring systems he surveyed were nearly as effective as average human tutors, and that neither of these were as effective as expert human tutors, but certainly both better than providing the domain content without tutoring. "Step-based" means that the tutor evaluates and reacts to each step that the learner makes in a problem-solving session as opposed to evaluating only the final answer given by the learner.

In a meta-analysis, Ma et al. (2014) found similar positive results for step-based ITSs both when compared to a no tutoring condition and when compared to large group human teacher led-instruction, but no differences when compared to small group human tutoring or to one-to-one tutoring. The same authors analysed systems for teaching programming and also found a "a significant advantage of ITSs over teacher-led classroom instruction and non-ITS computer-based instruction" (Nesbit et al. 2014). Likewise Kulik and Fletcher (2015) found similar sized improvements but distinguished between studies that used standardised tests and those where the tests were more specifically tuned to the system providing tuition. Smaller effect sizes were found by Steenbergen-Hu and Cooper (2013) in their meta-analysis of pupils using ITSs in a School setting. They also noted that lower-achievers seemed to do worse with ITSs than did the broad spectrum of school pupils. In a parallel study of university students, Steenbergen-Hu and Cooper (2014) found more positive effects for ITSs as compared to conventional instruction.

Finally in a large-scale study in the USA of the Cognitive Tutors, (Pane et al. 2014) found only limited evidence of the relative effectiveness of these tutors over conventional teaching, though we note that how the tutors were actually used in the classrooms

✉ Benedict du Boulay
B.du-Boulay@sussex.ac.uk

[1] Human Centred Technology Group, Department of Informatics, University of Sussex, Brighton BNI 9QJ, UK

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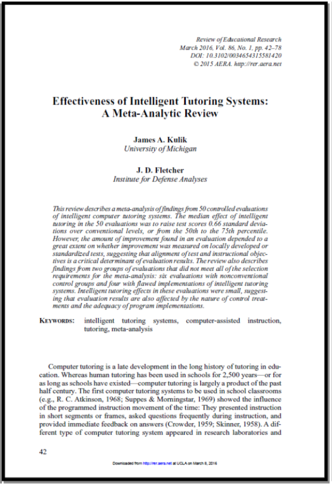
Review of Educational Research
March 2016, Vol. 86, No. 1, pp. 42–78
DOI: 10.3102/0034654315581420
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Effectiveness of Intelligent Tutoring Systems: A Meta-Analytic Review

James A. Kulik
University of Michigan

J. D. Fletcher
Institute for Defense Analyses

This review describes a meta-analysis of findings from 50 controlled evaluations of intelligent computer tutoring systems. The median effect of intelligent tutoring in the 50 evaluations was to raise test scores 0.66 standard deviations over conventional levels, or from the 50th to the 75th percentile. However, the amount of improvement found in an evaluation depended to a great extent on whether improvement was measured on locally developed or standardized tests, suggesting that alignment of test and instructional objectives is a critical determinant of evaluation results. The review also describes findings from two groups of evaluations that did not meet all of the selection requirements for the meta-analysis: six evaluations with nonconventional control groups and four with flawed implementations of intelligent tutoring systems. Intelligent tutoring effects in these evaluations were small, suggesting that evaluation results are also affected by the nature of control treatments and the adequacy of program implementations.

KEYWORDS: intelligent tutoring systems, computer-assisted instruction, tutoring, meta-analysis

Computer tutoring is a late development in the long history of tutoring in education. Whereas human tutoring has been used in schools for 2,500 years—or for as long as schools have existed—computer tutoring is largely a product of the past half century. The first computer tutoring systems to be used in school classrooms (e.g., R. C. Atkinson, 1968; Suppes & Morningstar, 1969) showed the influence of the programmed instruction movement of the time: They presented instruction in short segments or frames, asked questions frequently during instruction, and provided immediate feedback on answers (Crowder, 1959; Skinner, 1958). A different type of computer tutoring system appeared in research laboratories and

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0022-0663/14/$12.00 http://dx.doi.org/10.1037/a0037123

Intelligent Tutoring Systems and Learning Outcomes: A Meta-Analysis

Wenting Ma
Simon Fraser University

Olusola O. Adesope
Washington State University

John C. Nesbit and Qing Liu
Simon Fraser University

Intelligent Tutoring Systems (ITS) are computer programs that model learners' psychological states to provide individualized instruction. They have been developed for diverse subject areas (e.g., algebra, medicine, law, reading) to help learners acquire domain-specific, cognitive and metacognitive knowledge. A meta-analysis was conducted on research that compared the outcomes from students learning from ITS to those learning from non-ITS learning environments. The meta-analysis examined how effect sizes varied with type of ITS, type of comparison treatment received by learners, type of learning outcome, whether knowledge to be learned was procedural or declarative, and other factors. After a search of major bibliographic databases, 107 effect sizes involving 14,321 participants were extracted and analyzed. The use of ITS was associated with greater achievement in comparison with teacher-led, large-group instruction ($g = .42$), non-ITS computer-based instruction ($g = .57$), and textbooks or workbooks ($g = .35$). There was no significant difference between learning from ITS and learning from individualized human tutoring ($g = -.11$) or small-group instruction ($g = .05$). Significant, positive mean effect sizes were found regardless of whether the ITS was used as the principal means of instruction, a supplement to teacher-led instruction, an integral component of teacher-led instruction, or an aid to homework. Significant, positive effect sizes were found at all levels of education, in almost all subject domains evaluated, and whether or not the ITS provided feedback or modeled student misconceptions. The claim that ITS are relatively effective tools for learning is consistent with our analysis of potential publication bias.

Keywords: Intelligent Tutoring System, student model, effect size, meta-analysis

Supplemental materials: http://dx.doi.org/10.1037/a0037123.supp

In 1970, computer scientist Jaime Carbonell published a report on SCHOLAR, a program he designed to conduct limited, mixed-initiative, instructional dialogues with a student about South American geography (Carbonell, 1970). SCHOLAR used natural language to answer a learner's question or pose a question and give feedback about the correctness of the learner's response. Although the term Intelligent Tutoring System (ITS) was not used in Carbonell's article, SCHOLAR is often regarded as the first ITS (Corbett, Koedinger, & Anderson, 1997). Beyond the mixed-initiative dialogue, what was remarkable about SCHOLAR was the way its architecture represented domain knowledge separately from the natural language interface. The separate, explicit domain representation allowed the program, in theory, to generate a diverse and combinatorally large set of questions and answer a similarly large and diverse set of questions posed by the learner. Framing his work as an extension and application of research in artificial intelligence, Carbonell emphasized the fundamental differences between SCHOLAR and the other types of computer-assisted instruction being designed at the time. In particular, he discussed how a domain representation can serve as the basis for modeling student knowledge.

BIP, another early example of an ITS (Barr, Beard, & Atkinson, 1976) assigned programming tasks to students that matched their individual learning needs and competencies. The BIP researchers constructed a domain representation that mapped goal skills (e.g., printing variables) to the programming tasks that exercised them. Students' performances on a task supported inferences about their acquisition of skills linked to that task. In this early ITS, like many that have been designed since, the student model was an overlay or subset of the domain model. By the time a special issue on Intelligent Tutoring Systems appeared in the *International Journal of Man-Machine Studies* (Sleeman & Brown, 1979) it was clear that a new type of instructional system and a new field of research

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Wenting Ma, Faculty of Education, Simon Fraser University; Olusola O. Adesope, Educational Psychology Program, Department of Educational Leadership, Sport Studies, and Educational/Counseling Psychology, College of Education, Washington State University; John C. Nesbit and Qing Liu, Faculty of Education, Simon Fraser University.
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Correspondence concerning this article should be addressed to Olusola O. Adesope, Department of Educational Leadership, Sport Studies, and Educational/Counseling Psychology, College of Education, Washington State University, Cleveland Hall 356, Pullman, WA 99164-2114. E-mail: olusola.adesope@wsu.edu

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Intelligent Tutoring Systems

Table 2
Weighted Mean Effect Sizes for Characteristics of Intelligent Tutoring Systems (ITS)

			Random-effects model						Fixed-effect model					
			Effect size		95% CI				Effect size		95% CI			
Moderator variables	*N*	*k*	*g*+	*SE*	Lower	Upper	Q_B	*p*	*g*+	*SE*	Lower	Upper	Q_B	*p*
Type of ITS							4.18	.52					36.37	<.001
Model tracing	5,970	21	0.35*	0.07	0.22	0.47			0.25*	0.03	0.20	0.31		
Constraint-based modeling	569	7	0.24	0.16	−0.08	0.56			0.20*	0.09	0.03	0.37		
Bayesian network modeling	1,417	10	0.54*	0.10	0.35	0.73			0.52*	0.06	0.41	0.63		
Expectation and misconception tailoring	142	3	0.34	0.35	−0.35	1.02			0.24	0.18	−0.12	0.59		
Other	4,425	53	0.44*	0.06	0.32	0.56			0.44*	0.03	0.38	0.50		
Not reported	1,798	13	0.40*	0.10	0.20	0.59			0.43*	0.05	0.32	0.54		
ITS intervention							2.41	.79					32.38	<.001
Principal instruction	4,505	35	0.37*	0.07	0.23	0.51			0.32*	0.03	0.26	0.38		
Integrated class instruction	4,045	15	0.33*	0.08	0.17	0.49			0.25*	0.03	0.18	0.31		
Separate in-class activities	1,939	24	0.47*	0.10	0.27	0.67			0.53*	0.05	0.43	0.62		
Supplementary after-class instruction	933	8	0.43*	0.11	0.22	0.64			0.36*	0.07	0.23	0.48		
Homework	2,480	15	0.45*	0.07	0.32	0.59			0.46*	0.04	0.38	0.54		
Not reported	419	10	0.48*	0.13	0.23	0.74			0.47*	0.10	0.27	0.66		
Feedback provided?							4.55	.10					13.53	<.001
No	1,411	10	0.54*	0.15	0.25	0.83			0.40*	0.05	0.30	0.51		
Yes	11,728	86	0.42*	0.04	0.34	0.50			0.37*	0.02	0.33	0.41		
Not reported	1,182	11	0.21*	0.10	0.02	0.41			0.15*	0.06	0.04	0.27		
Model misconception?							0.02	.99					5.14	.08
No	1,508	21	0.40*	0.07	0.27	0.54			0.39*	0.05	0.29	0.49		
Yes	9,911	58	0.40*	0.05	0.31	0.49			0.33*	0.02	0.29	0.37		
Not reported	2,902	28	0.42*	0.10	0.23	0.61			0.43*	0.04	0.35	0.51		

Note. CI = confidence interval.
* $p < .05$.

Intelligent Tutoring Systems

Table 3
Weighted Mean Effect Sizes for Student and Study Characteristics

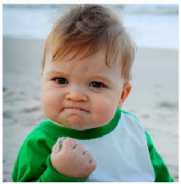
			Random-effects model						Fixed-effect model					
			Effect size		95% CI				Effect size		95% CI			
Moderator variables	*N*	*k*	*g*+	*SE*	Lower	Upper	Q_B	*p*	*g*+	*SE*	Lower	Upper	Q_B	*p*
Grade levels							2.2	.82					25.74	<.001
Elementary school	1,496	19	0.31*	0.08	0.16	0.47			0.26*	0.05	0.16	0.37		
Middle school	810	10	0.41*	0.13	0.15	0.66			0.45*	0.07	0.31	0.59		
High school	4,355	14	0.40*	0.10	0.21	0.59			0.25*	0.03	0.18	0.31		
Postsecondary	6,767	60	0.43*	0.05	0.33	0.53			0.43*	0.03	0.38	0.48		
Mixed grades	771	3	0.61	0.32	−0.02	1.25			0.42*	0.07	0.28	0.57		
Not reported	122	1	0.33	0.18	−0.02	0.69			0.33	0.18	−0.02	0.69		
Subject domains							6.53	.48					50.67	<.001
Mathematics and Accounting	8,038	35	0.35*	0.05	0.24	0.45			0.29*	0.02	0.25	0.34		
Physics	2,890	24	0.38*	0.07	0.26	0.51			0.41*	0.04	0.33	0.49		
Computer Science	1,152	19	0.51*	0.11	0.30	0.72			0.46*	0.06	0.34	0.58		
Language and Literacy	1,075	14	0.34*	0.11	0.12	0.56			0.27*	0.06	0.15	0.39		
Chemistry	141	2	0.16	0.17	−0.17	0.48			0.16	0.17	−0.17	0.48		
Biology and Physiology	210	3	0.59*	0.27	0.07	1.11			0.51*	0.14	0.23	0.78		
Humanities and Social Science	671	8	0.63*	0.22	0.20	1.06			0.84*	0.08	0.68	1.01		
Others and Not Reported	144	2	1.23	0.96	−0.65	3.10			0.53	0.17	0.20	0.87		
Prior domain knowledge							3.45	.49					11.87	.02
Low	5,265	32	0.38*	0.06	0.27	0.49			0.37*	0.03	0.31	0.43		
Medium	1,356	17	0.28*	0.08	0.12	0.45			0.27*	0.06	0.16	0.38		
High	77	2	0.51	0.29	−0.06	1.07			0.53*	0.23	0.07	0.98		
Varied	2,699	22	0.48*	0.12	0.25	0.71			0.27*	0.04	0.19	0.34		
Not reported	4,924	34	0.46*	0.06	0.34	0.58			0.41*	0.03	0.35	0.47		

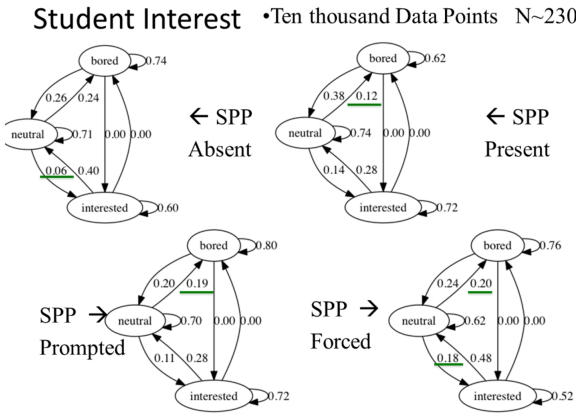
Note. CI = confidence interval.
* $p < .05$.

Intelligent Tutoring Systems
Motivation and Engagement in ITS!!!

- Students can sometimes become **disengaged** and **bored** while using ITS (particularly, in a long-term interaction). **(Arroyo et al., 2007) (Bell & McNamara, 2007) (Baker et al., 2010) (Jackson & McNamara, 2013)**

- **Motivated**, **challenged** and **intrigued** students may have better learning performance. **(VanLehn, 2011)**





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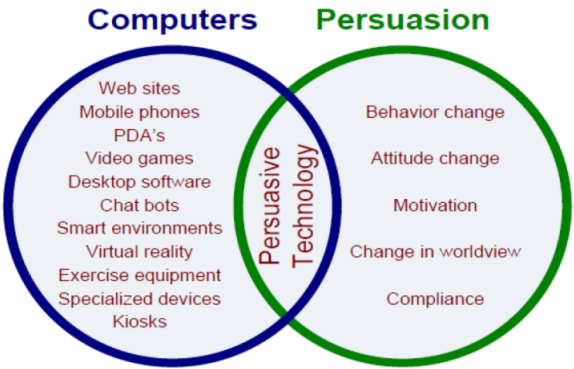
Persuasive Technology



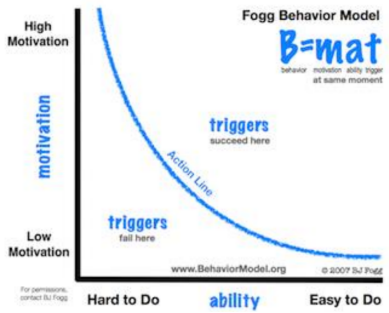
- Brian J Fogg. Persuasive technologies. Communications of the ACM, 42(5):26–29, 1999.

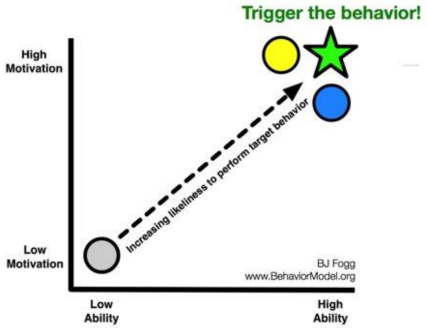
Persuasive Technology
Why ?

1. To help the individual achieve their personal goals, e.g. quit smoking or fight alcoholism, lose weight, eat healthier, exercise more
2. To encourage contribution to group / society goals, e.g. save energy, reduce waste, reduce noise, vote, volunteer, etc;
3. To achieve a third party's goals, e.g. increase sales, optimize system load, improve service, e.g. advertisement, P2P file-sharing systems
4. Areas: Health, Environment/Society, Personal Improvement, **Education**, and so on

Brian J Fogg. Persuasive technologies. Communications of the ACM, 42(5):26–29, 1999.

Persuasive Technology
Fogg's Model





- captology.stanford.edu

Gamification

Gamification is the use of game design elements in non-game contexts

Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011, September). From game design elements to gamefulness: defining gamification. In Proceedings of the 15th international academic MindTrek conference: Envisioning future media environments (pp. 9-15). ACM

Gamification is the use of game design elements in non-game contexts

Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011, September). From game design elements to gamefulness: defining gamification. In Proceedings of the 15th international academic MindTrek conference: Envisioning future media environments (pp. 9-15). ACM

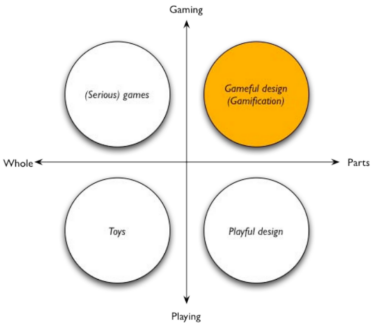
Gamification is the use of game elements and game design techniques in non-game contexts.

Werbach, K., & Hunter, D. (2012). For the win: How game thinking can revolutionize your business. Wharton Digital Press.

Gamification
What is and What is not Gamification!!!

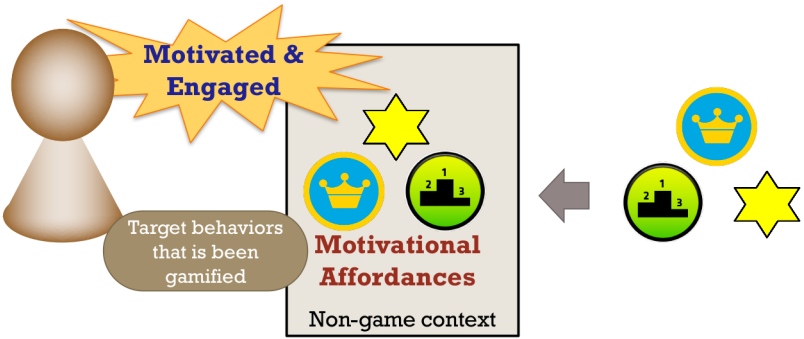
In gamification:

- The users **are motivated and engaged by the game elements and rules**
- The game design elements are **applied for part of non-game context**.



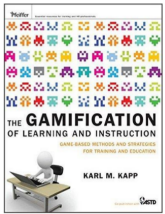
Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011, September). From game design elements to gamefulness: defining gamification. In Proceedings of the 15th international academic MindTrek conference: Envisioning future media environments (pp. 9-15). ACM

Gamification
Triggering the behavior!!!



Challco, G.; Isotani, S. Gamification of Collaborative Learning Scenarios: An Ontological Engineering Approach to Deal with Motivational Problems caused by CSCL Scripts. PhD Thesis. University of São Paulo, 2018

Gamification
Does Gamification Work ?



(Kapp, 2012)

2014 47th Hawaii International Conference on System Science

Does Gamification Work? — A Literature Review of Empirical Studies on Gamification

Juho Hamari
School of Information Sciences,
University of Tampere
juho.hamari@uta.fi

Jonna Koivisto
School of Information Sciences,
University of Tampere
jonna.koivisto@uta.fi

Harri Sarsa
School of Science,
Aalto University
harri.sarsa@aalto.fi

(Hamari et al., 2014b)

A Systematic Mapping on Gamification Applied to Education

Simone de Sousa Borges
University of São Paulo (ICMC) – USP
São Carlos, SP - Brazil
sborges@icmc.usp.br

Vinicius H. S. Durelli
University of São Paulo (ICMC) – USP
São Carlos, SP - Brazil
durelli@icmc.usp.br

Helena Macedo Reis
University of São Paulo (ICMC) – USP
São Carlos, SP - Brazil
helenamcd@icmc.usp.br

Seiji Isotani
University of São Paulo (ICMC) – USP
São Carlos, SP - Brazil
sisotani@icmc.usp.br

(Borges et al., 2014)

Int. J. Human-Computer Studies 74 (2015) 14–31

Contents lists available at ScienceDirect

Int. J. Human-Computer Studies

journal homepage: www.elsevier.com/locate/ijhcs

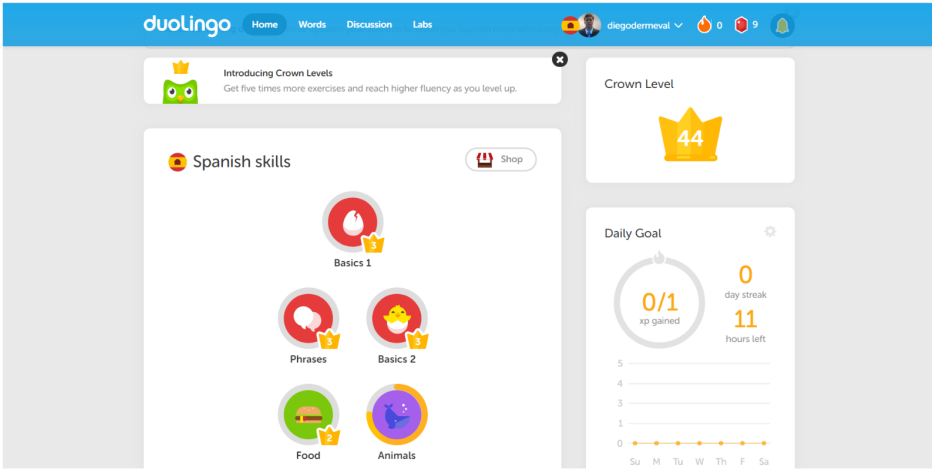
Gamification in theory and action: A survey☆

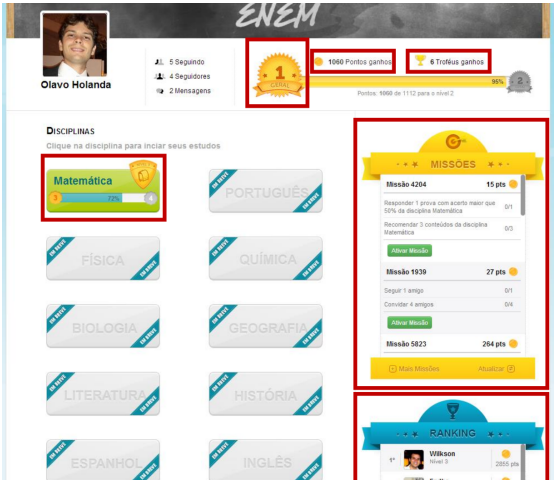
Katie Seaborn [a,*], Deborah I. Fels [b]

[a] University of Toronto, 5 King's College Road, Toronto, Ontario, Canada M5S 3G8
[b] Ryerson University, 350 Victoria Street, Toronto, Ontario, Canada M5B 2K3

(Seaborn et al., 2015)

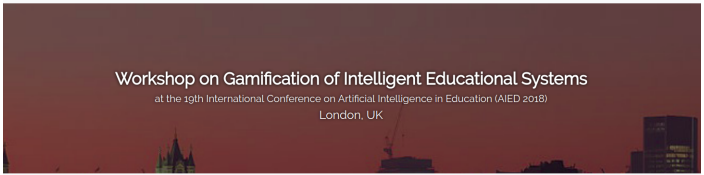
Gamification
Duolingo





Gamification and AIED

Gamification and AIED
First Workshop



Goals

Artificial Intelligence in Education is an interdisciplinary field that integrates researchers with different backgrounds (Computer Science, Engineering, Education, Psychology, instructional design and others) but has one common goal: to use Artificial Intelligence techniques to support new learning experiences where students can work mediated by technology and learn more effectively. The support of robust learning is a complex issue due to many factors (e.g., psychological, technological, personal, instructional, etc.) that affect learning processes and hence, the learning outcome.To tackle this problem, researchers in the field have always been innovative. Through the analysis of different learning settings, researchers have found ways to integrate major advances in Artificial Intelligence, Learning Science, Experimental Psychology, Human-Computer Interaction and other areas to leverage the development of Intelligent Educational Systems. For teachers, an intelligent educational system offers better ways to create/reuse/share content, new methodologies and instruments to deploy effective learning activities and accurate tools to analyze students' progress throughout the learning process. For students, it allows for the presenting the content in an intelligent and adaptive fashion, which enables the restructuring of learning content according to students' needs and stimulates the occurrence of deep and long-term understanding.

However, it is still very common that students become disengaged or bored during the learning process by using intelligent educational systems. On the 1 other hand, there is a growing interest in gamification as well as its applications and implications in the field of Artificial Intelligence in Education since it provides an alternative to engage and motivate students during the process of learning. The term Gamification originated in the digital media industry, however, such a term only gained widespread acceptance after late 2010. Gamification refers to the use of game-based elements such as mechanics, aesthetics, and game thinking in non-game contexts aimed at engaging people, motivating action, enhancing learning, and solving problems [1].

Indeed, gamification has risen to significance in the past six years and shows no sign of slowing growth. The first wave of gamification research has predominantly consisted of (1) definitions, frameworks and taxonomies for gamification and game design elements; (2) technical papers describing systems, designs, and architectures; and (3) effect and user studies of gamified systems [2]. Such phenomenon also occured in the context of education

gile.nees.com.br

Gamification and ILE
Ways of Approaching

Gamification-based Design

Gamifying an Intelligent Learning Environment

Gamification-based Design

Gamifying an Intelligent Learning Environment

Intelligent Gamification

Use Artificial Intelligence in a Gamified Educational Environment

Gamification-based Design

Gamifying an Intelligent Learning Environment

Intelligent Gamification

Use Artificial Intelligence in a Gamified Educational Environment

Amplified Gamification

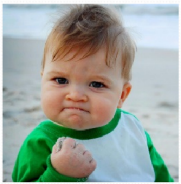
Combine Gamification with Artificial and Human Intelligence into an Educational Environment

Gamification-based Design

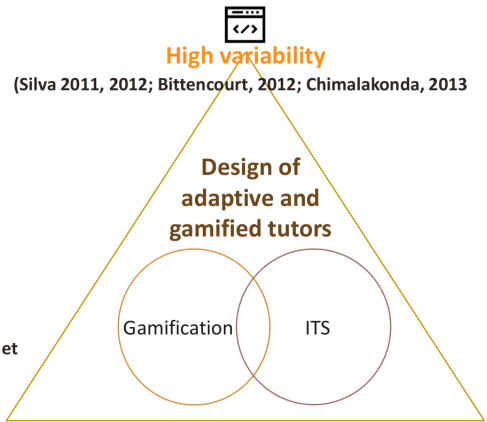
Gamifying an Intelligent Learning Environment

- Students can sometimes become **disengaged** and **bored** while using ITS (particularly, in a long-term interaction). **(Arroyo et al., 2007) (Bell & McNamara, 2007) (Baker et al., 2010) (Jackson & McNamara, 2013)**

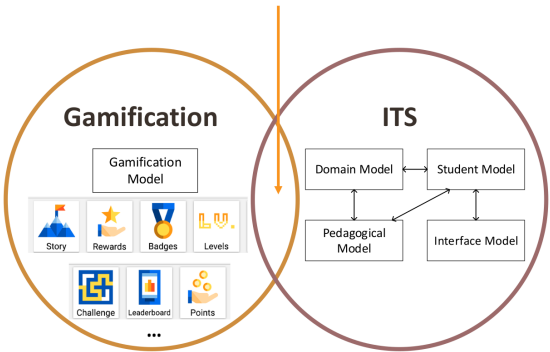
- **Motivated**, **challenged** and **intrigued** students may have better learning performance. **(VanLehn, 2011)**



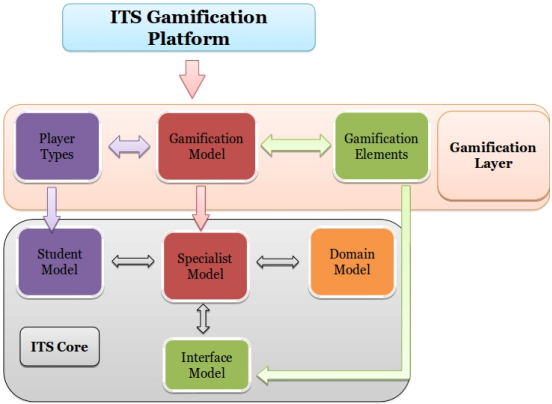
Gamification-based Design
Gamification and Intelligent Tutoring Systems



Gamified and Adaptive Tutoring Systems

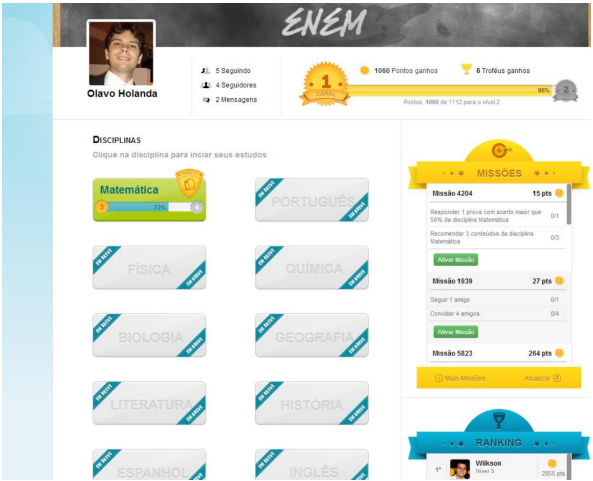


Dermeval, D.; Bittencourt, I. I. Authoring Gamified Intelligent Tutoring Systems. PhD Thesis. Federal University of Alagoas, 2017

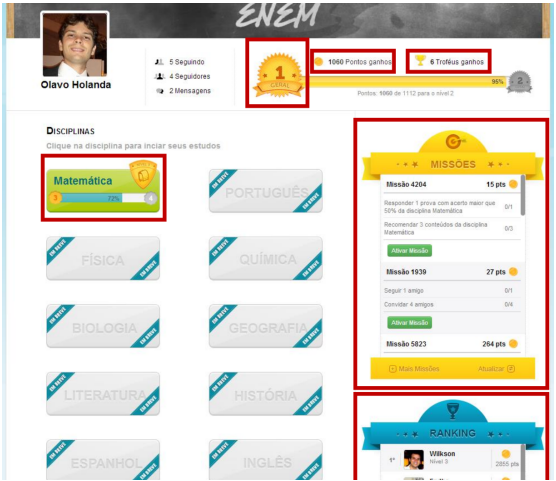


- Fernando, R.; Isotani, S. Personalized Gamification based on Gamer Types. PhD Thesis. University of São Paulo, 2018

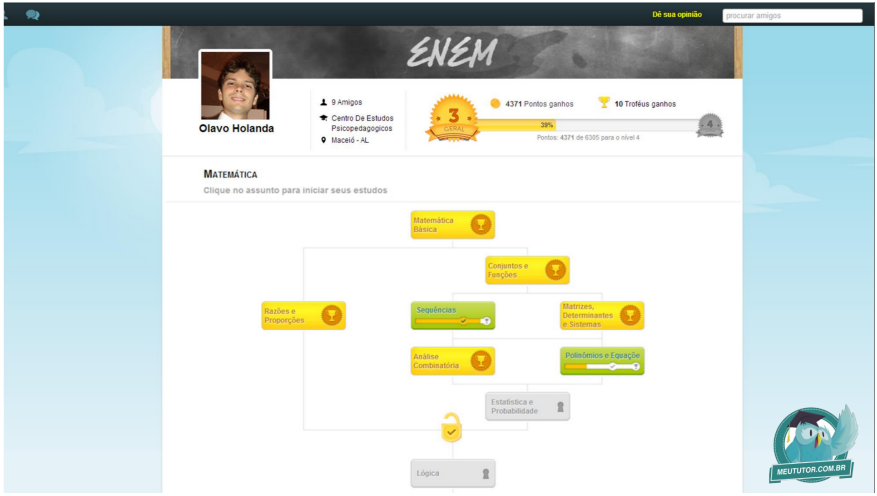
Gamification-based Design
Meu Tutor: A Brazilian ITS

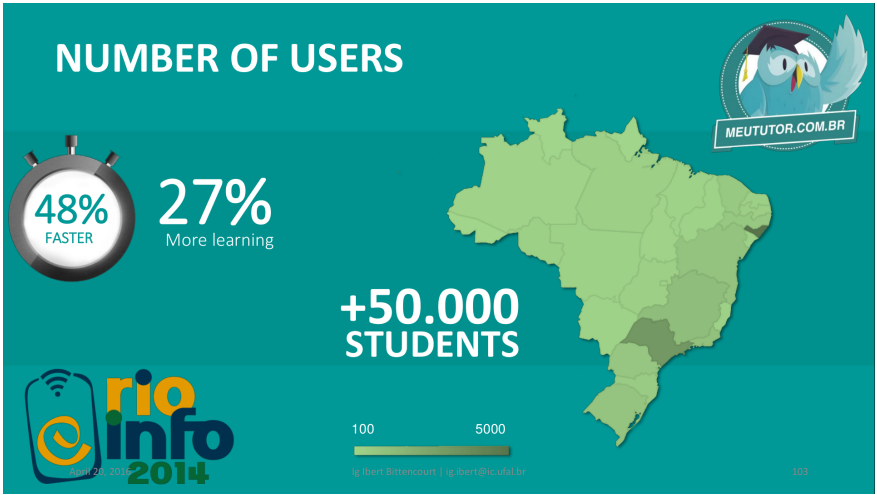


Gamification-based Design
Meu Tutor: A Brazilian ITS



Gamification-based Design
Meu Tutor: A Brazilian ITS





Intelligent Gamification

Use Artificial Intelligence in a Gamified Educational Environment

Cognitive Gamification
Player Types: BrainHex Model

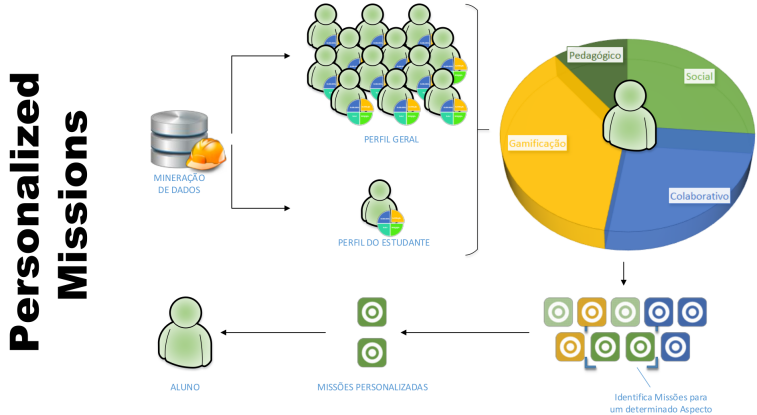
- NACKE, L. E., BATEMAN, C., & MANDRYK, R. L. (2014). BrainHex: A neurobiological gamer typology survey. Entertainment computing, 5(1), 55-62

Cognitive Gamification
Player Types: BrainHex Model

	Competition & Comparison	Cooperation	Customization	Personalization	Praise	Self-monitoring & Suggestion	Simulation	Reward
Achiever		.15				.10		.10
Conqueror	.25			12		.12	.14	
Daredevil	-.10					-.14	.11	
Mastermind	.12		.10	.12		.14	.12	
Seeker	.10		.19	.11	.10			
Socializer	.11	.17	-.12		-.12	-.13		
Survivor	.17	-.20	-.13			27		-.14

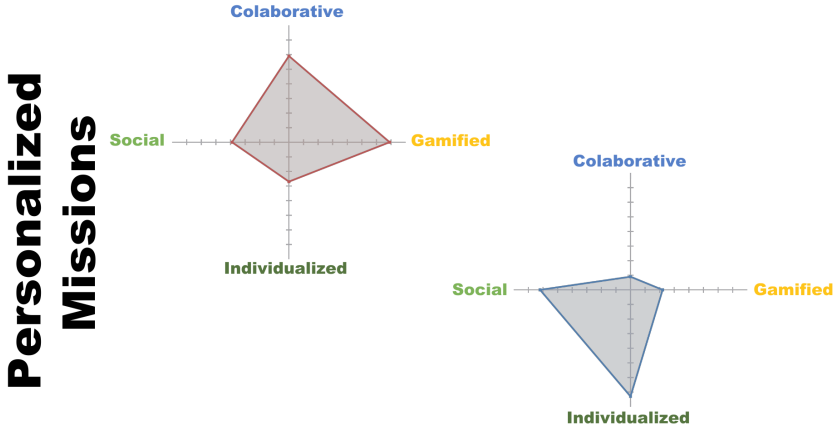
Orji, R., Vassileva, J., Mandryk, R. Modeling the efficacy of persuasive strategies for different gamer types in serious games for health. User Modeling and User-Adapted Interaction. (2014) doi: 10.1007/s11257-014- 9149-8

Cognitive Gamification
Meu Tutor: A Brazilian ITS



Paiva, R.; Bittencourt, I.; Tenório, T.; Isotani, S. ; Jacques, P.. What do students do on-line? Modeling students' interactions to improve their learning experience. Computers in Human Behavior, v. 64, p. 769-781, 2016.

Cognitive Gamification
Meu Tutor: A Brazilian ITS



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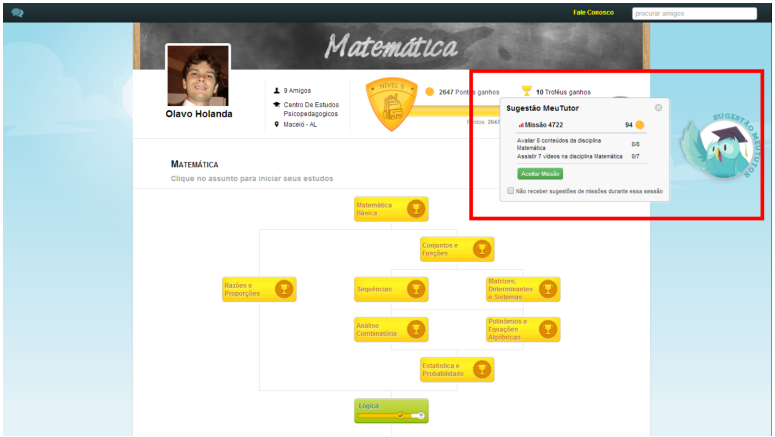
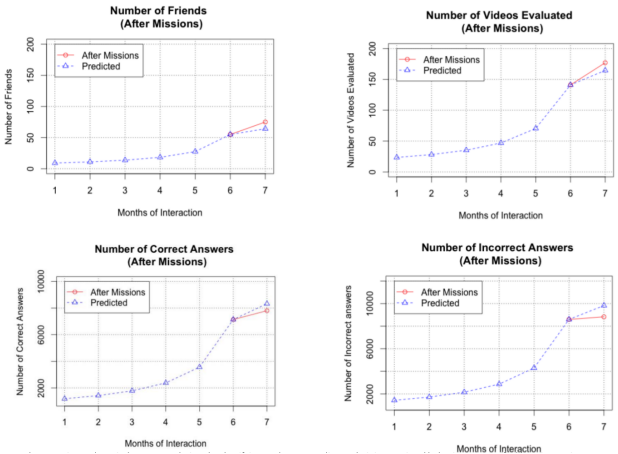


Paiva, R.; Bittencourt, I.; Tenório, T.; Isotani, S. ; Jacques, P.. What do students do on-line? Modeling students' interactions to improve their learning experience. Computers in Human Behavior, v. 64, p. 769-781, 2016.

Personalized Missions



Paiva, R.; Bittencourt, I.; Tenório, T.; Isotani, S. ; Jacques, P.. What do students do on-line? Modeling students' interactions to improve their learning experience. Computers in Human Behavior, v. 64, p. 769-781, 2016.

Amplified Gamification

Combine Gamification with Artificial and Human Intelligence into an Educational Environment

Amplified Gamification

Int J Artif Intell Educ (2016) 26:600–614
DOI 10.1007/s40593-016-0105-0

CrossMark

ARTICLE

Stupid Tutoring Systems, Intelligent Humans

Ryan S. Baker[1]

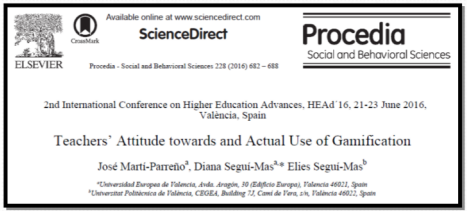
...

So let me pose the possibility of a different way that the excellent online learning systems of tomorrow could be developed. Perhaps we do not in fact need intelligent tutoring systems. Perhaps instead what we need, what we are already developing, is ***stupid tutoring systems***.[3] Tutors that do not, themselves, behave very intelligently. But tutors that are ***designed intelligently***, and that ***leverage human intelligence***.

In other words, perhaps what we need is stupid tutoring systems, and intelligent humans.

Baker, R.; Stupid Tutoring Systems, Intelligent Humans. International Journal of Artificial Intelligence in Education. (2016). 26:600-614.

Amplified Gamification
Teachers' attitudes towards use of gamification



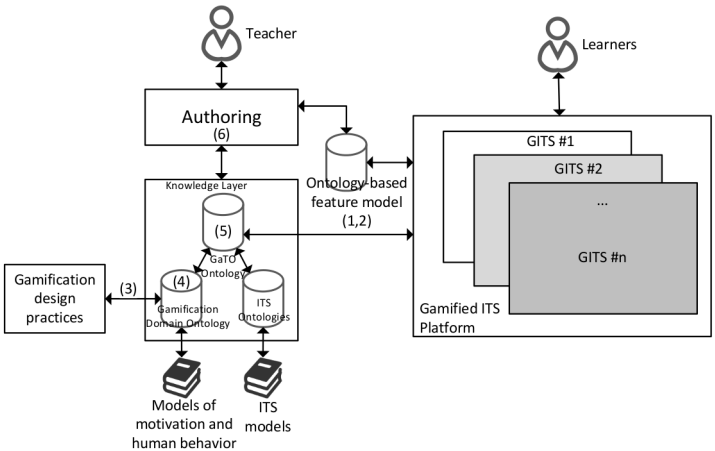
(Martí-Parreño et al., 2016)

(Sánchez-Mena and Martí-Parreño, 2016)

- **Motivate students**
- **Facilitate students' learning**;
- Show a **positive attitude** towards gamification;
- Main barrier: **the lack of time and resources** available.";

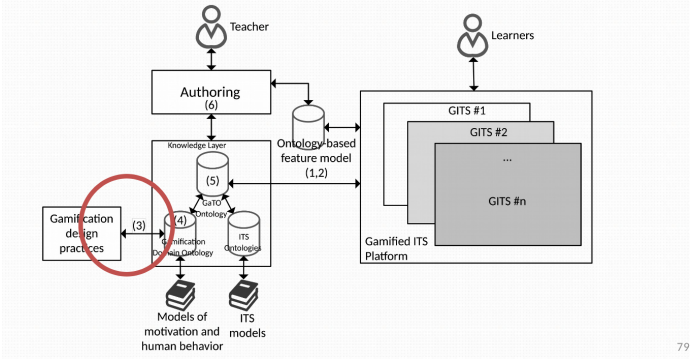
Dermeval, D. ; Paiva, R. ; Borges, D. ; Bittencourt, I.; Vassileva, J. . Authoring Tools for Designing Intelligent Tutoring Systems: a Systematic Review of the Literature. International Journal of Artificial Intelligence in Education, v. 1, p. 1-49, 2017.

Amplified Gamification
AGITS: Authoring Gamified ITS



Dermeval, D.; Bittencourt, I.; et al. Amplifying Teachers Intelligence in the Design of Gamified Intelligent Tutoring Systems. Lecture Notes in Computer Science. 1ed.: Springer International Publishing, 2018, v. , p. 68-73..

GaTO: Gamified Tutoring Ontology



- Dermeval, D.; Bittencourt, I.; Vassileva, J.; Isotani, S.. GaTO: an Ontological Model to Apply Gamification in Intelligent Tutoring Systems. Frontiers in Artificial Intelligence: AI for Human Learning Behavior Change. (To be Submitted)

#3 Identify evidence-supported combinations of game design elements for achieving particular behaviors in the e-learning domain;

- For each empirical paper in the e-learning domain reported by three SLRS on gamification:
  - **Hamari et al. (2014)**. Does gamification work?--a literature review of empirical studies on gamification;
  - **Borges et al. (2014).** A systematic mapping on gamification applied to education;
  - **Seaborn and Fels (2015).** Gamification in theory and action: A survey.

- We identified the **behaviors** with **positive evidence** and the **set of game elements** used for achieving it. 80

Dermeval, D.; Bittencourt, I.; Vassileva, J.; Isotani, S.. GaTO: an Ontological Model to Apply Gamification in Intelligent Tutoring Systems. Frontiers in Artificial Intelligence: AI for Human Learning Behavior Change. (To be Submitted)

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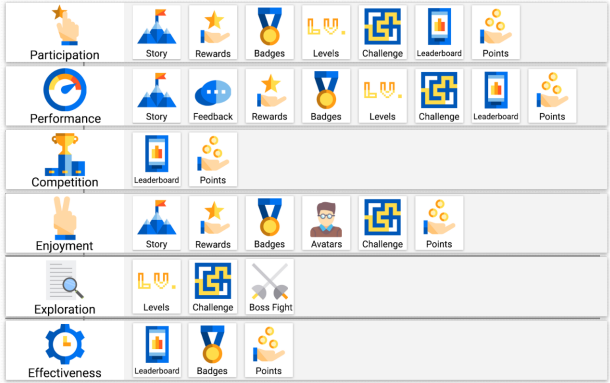

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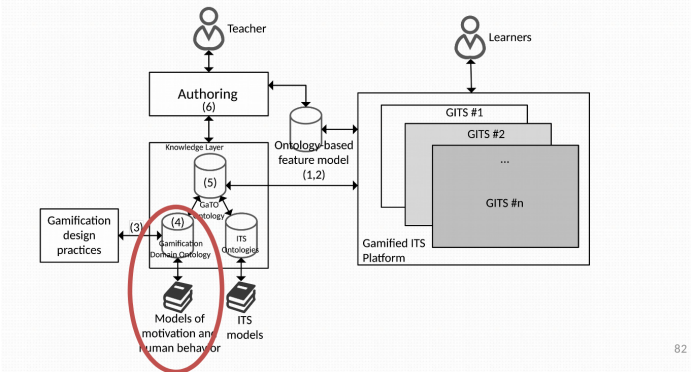
GaTO: Gamified Tutoring Ontology



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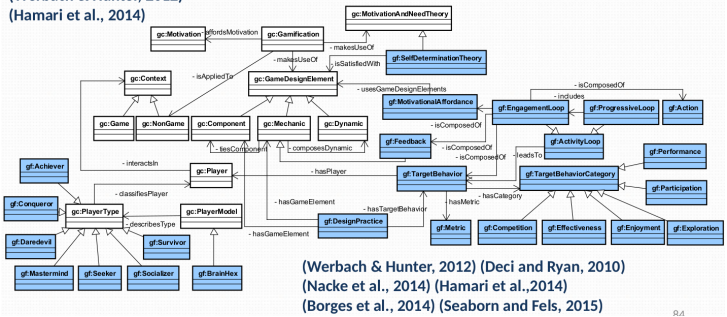
#4 Develop a Gamification Domain Ontology (GaDO)

- GaDO is composed by two sub-ontologies:
  - GaDO-core: represent **core gamification concepts** (e.g., gamification definition, game design element, player model, and so on);
  - GaDO-full: represent gamification concepts (e.g., gamification design framework, particular combination of game design elements, specific player models, and so on) of **particular theories and frameworks;**
- Each ontology was developed using the using an ontology engineering methodology (METHONTOLOGY). **(Gómez-Pérez 1996; Fernández et al. 1997)**

Dermeval, D.; Bittencourt, I.; Vassileva, J.; Isotani, S.. GaTO: an Ontological Model to Apply Gamification in Intelligent Tutoring Systems. Frontiers in Artificial Intelligence: AI for Human Learning Behavior Change. (To be Submitted)

#4 Develop a Gamification Domain Ontology (GaDO)

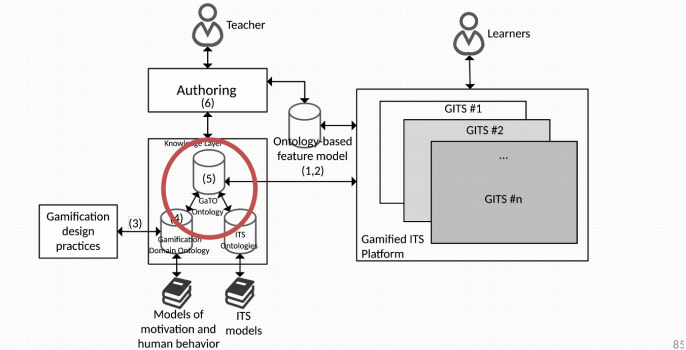
(Deterding et al., 2011)
(Werbach & Hunter, 2012)
(Hamari et al., 2014)



(Werbach & Hunter, 2012) (Deci and Ryan, 2010)
(Nacke et al., 2014) (Hamari et al.,2014)
(Borges et al., 2014) (Seaborn and Fels, 2015)

Dermeval, D.; Bittencourt, I.; Vassileva, J.; Isotani, S.. GaTO: an Ontological Model to Apply Gamification in Intelligent Tutoring Systems. Frontiers in Artificial Intelligence: AI for Human Learning Behavior Change. (To be Submitted)

GaTO: Gamified Tutoring Ontology



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#5 Develop an integrated ontological model of Gamified Tutoring Ontology (GaTO)

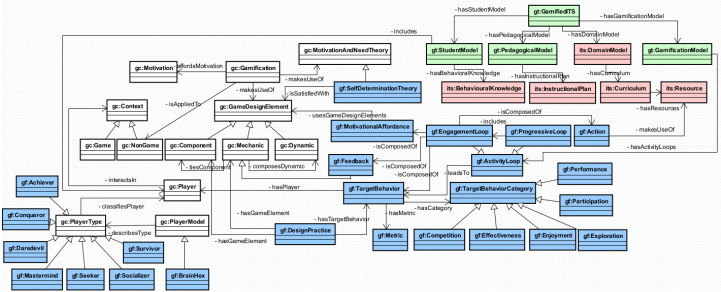
- GaTO:
  - It was also developed using the METHONTOLOGY;
  - Connects gamification and ITS concepts;
  - Reuse the Gamification Domain Ontology;
  - Reuse an existing ITS ontology.

(Bittencourt et al., 2009)

Dermeval, D.; Bittencourt, I.; Vassileva, J.; Isotani, S.. GaTO: an Ontological Model to Apply Gamification in Intelligent Tutoring Systems. Frontiers in Artificial Intelligence: AI for Human Learning Behavior Change. (To be Submitted)

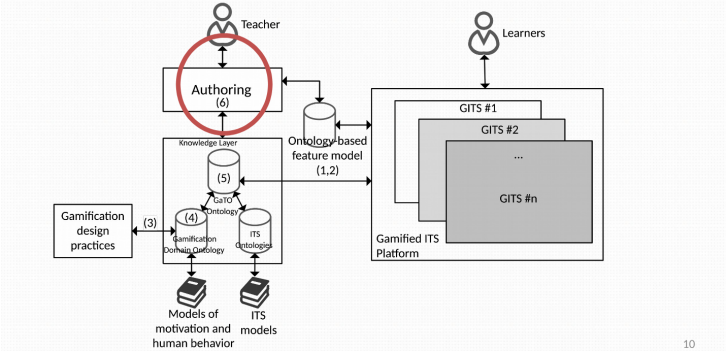
#5 Develop an integrated ontological model of Gamified Tutoring Ontology (GaTO)

Du Boulay & Luckin (2001), Self (1998), Costa et al. (1998), Dillebourg & Self (1992) and Self (1990), Bittencourt et al., 2009



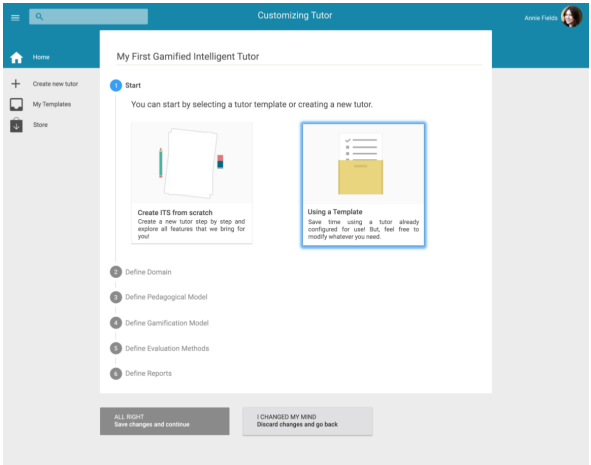
- Dermeval, D.; Bittencourt, I.; Vassileva, J.; Isotani, S.. GaTO: an Ontological Model to Apply Gamification in Intelligent Tutoring Systems. Frontiers in Artificial Intelligence: AI for Human Learning Behavior Change. (To be Submitted)

AGITS: an authoring solution for designing gamified intelligent tutoring systems



Dermeval, D.; Bittencourt, I.; et al. Amplifying Teachers Intelligence in the Design of Gamified Intelligent Tutoring Systems. Lecture Notes in Computer Science. 1ed.: Springer International Publishing, 2018, v. , p. 68-73..

Amplified Gamification
AGITS: Authoring Gamified ITS



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Amplified Gamification
AGITS: Authoring Gamified ITS

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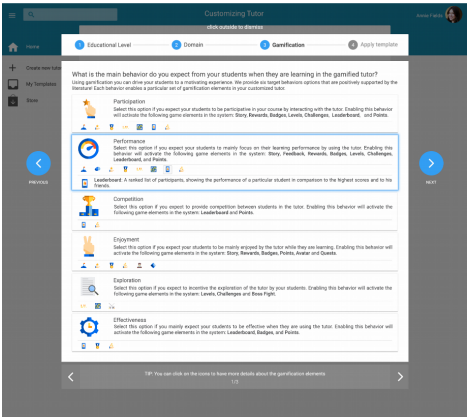
Amplified Gamification
AGITS: Authoring Gamified ITS



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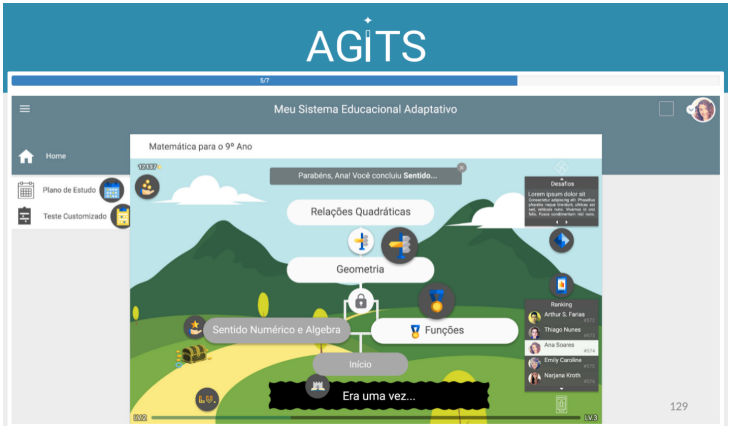
Amplified Gamification
AGITS: Authoring Gamified ITS



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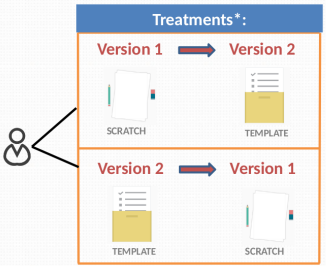
2nd Experimental evaluation with teachers: design



Dependent variables**:
Perceived ease of use (PEU)
Usability (U)
Complexity (C)
Usefulness (USE)
Behavioral intention to use (BIU)
Perceived system support (PSS)
Credibility (CR)
Time for authoring (T)
Representability (R)
Satisfaction (S)
Utility (UTI)

N(Version 1) = 36
N(Version 2) = 41

Authored tutor

* Order is randomized
** Questionnaires for each version are answered

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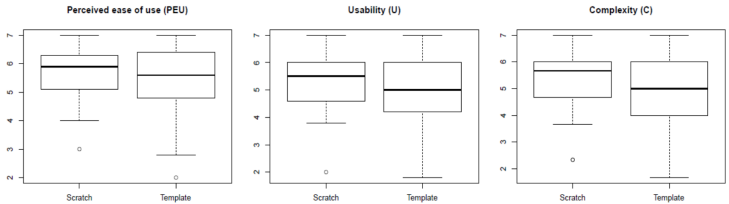
Amplified Gamification
AGITS: Authoring Gamified ITS



Metric	Null hypothesis	Alternative hypothesis	Method	p-value
Perceived ease of use (PEU)	H1-0: V1 = V2	H1-1: V1 ≠ V2	Wilcoxon test	0.643764588
Usability (U)	H2-0: V1 = V2	H2-1: V1 ≠ V2	Welch Two Sample t-test	0.535877832
Simplicity (C)	H3-: V1 = V2	H3-1: V1 ≠ V2	Wilcoxon test	0.387900237
Time for authoring (T)	H9-0: V1 = V2	H9-1: V1 ≠ V2	Wilcoxon test	0.00081419

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Amplified Gamification
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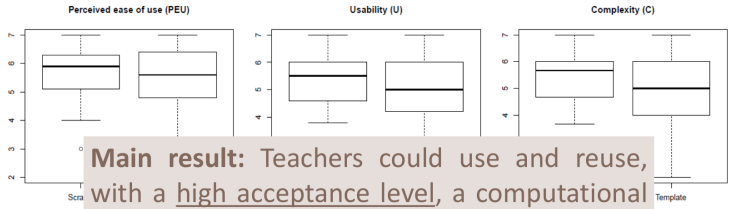

Main result: Teachers could use and reuse, with a high acceptance level, a computational solution that considers the high complexity of designing gamified ITS in less than 5 minutes.

Metr…	…	…	…	p-value
Perceived ease of use (PEU)	H1-0: V1 = V2	H1-1: V1 ≠ V2	Wilcoxon test	0.643764588
Usability (U)	H2-0: V1 = V2	H2-1: V1 ≠ V2	Welch Two Sample t-test	0.535877832
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Gamification as Research Area

There is no well-grounded theory about gamification.

Gamification as Research Area

There is no well-grounded theory about gamification.

Stereotyped Gamification

Gamified environments are (uncousciously) been gender-stereotyped.

Gamification as Research Area

There is no well-grounded theory about gamification.

Stereotyped Gamification

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Long-term Motivation

There is no evidence

Gamification as Research Area

There is no well-grounded theory about gamification.

Stereotyped Gamification

Gamified environments are (uncousciously) been gender-stereotyped.

Long-term Motivation

There is no evidence

Autotelic Learning Experience

There are no strong evidences about gamification and flow theory

Gamification as Research Area

There is no well-grounded theory about gamification.

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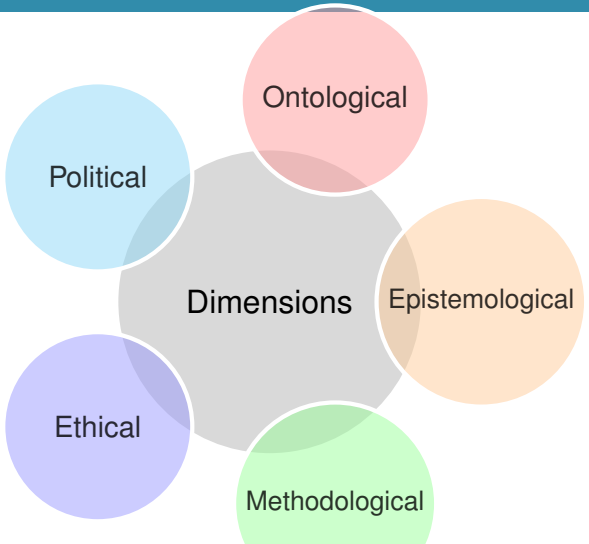
Editorial

The maturing of gamification research

Keywords:
Gamification
Gameful design
Motivational design

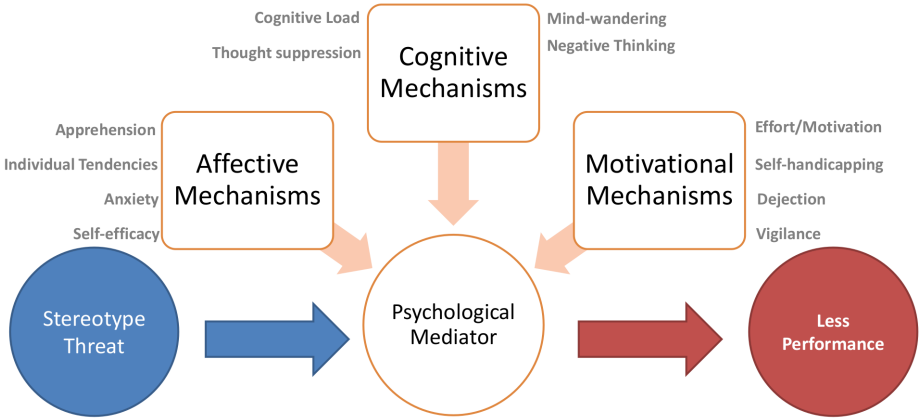
crowdsourcing, and word-of-mouth-marketing, all of which make employee customer engagement a crucial capacity for organisations. Meanwhile, policy-makers around the globe awake to motivation, engagement, and user experience as vital levers for public policy goals in health, education, or civic engagement. Taken together, these technical, cultural, economic, and political forces afforded and demanded a design practice that harnessed the potential of computing technology for improving user experience and engagement across domains and industries – and gamification filled this niche (Deterding, 2015).



Stereotyped Gamification

Gamified environments are (uncousciously) been gender-stereotyped.

Grand Challenges about Gamification
Stereotyped Gamification



Grand Challenges about Gamification
Stereotyped Gamification

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Computers & Education
Volume 115, December 2017, Pages 161-170

Does gender stereotype threat in gamified educational environments cause anxiety? An experimental study

Josmario Albuquerque [a], Ig I. Bittencourt [a], Jorge A.P.M. Coelho [b], Alan P. Silva [a]

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https://doi.org/10.1016/j.compedu.2017.08.005

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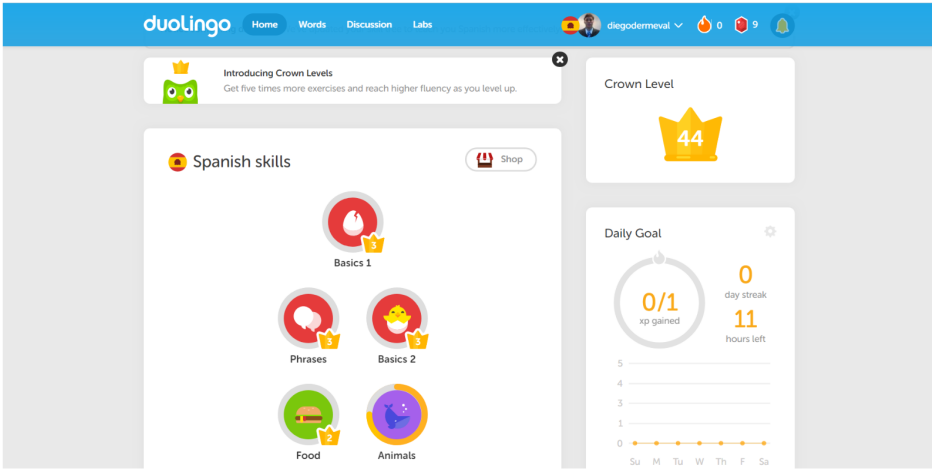
Highlights

- An experimental study about gender stereotype threat and anxiety is conducted.
- The experiment was conducted in a gamified educational environment.
- Male-stereotyped environments increased females' anxiety.

Long-term Motivation

There is no evidence

Grand Challenges about Gamification
Long-term Motivation

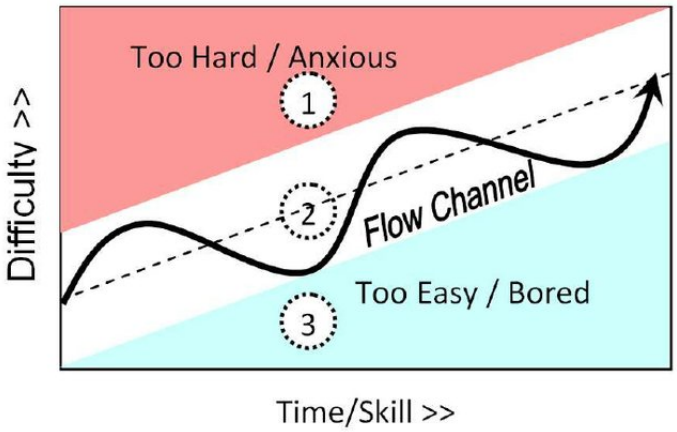


Grand Challenges about Gamification
Long-term Motivation

Autotelic Learning Experience

There are no strong evidences about gamification and Flow Channel

Grand Challenges about Gamification
Autotelic Learning Experience



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Gamification and Intelligent Learning Environments

From Theories to Evidences

Ig Ibert Bittencourt

ig.ibert@ic.ufal.br

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