

Addressing Behavioral Disengagement in Online Learning

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DISENGAGED BEHAVIOR – A PROBLEM IN ONLINE LEARNING

In recent years, there has been increasing awareness that behavioral disengagement plays an important role in online learning. Not only are some forms of behavioral disengagement associated with lower learning gains in the short-term (in the case of online learning see Gobel, 2008; Cocea et al., 2009), behavioral disengagement is also associated with lower long-term academic performance (Finn & Owings, 2006; Wang & Eccles, 2012; Pardos et al., 2013) and even whether learners advance in their academic career years later (Ensminger & Slusarcick, 1992; San Pedro et al., 2013).

Correspondingly, there has been increasing interest in developing interventions which address learners' behavioral disengagement, reducing it and/or mitigating its effects on learning and long-term academic achievement. In this chapter, we discuss several types of interventions, and potentially fruitful directions for the next generation of adaptive interventions to reduce behavioral disengagement, discussing how these interventions can be incorporated into the GIFT framework for broad dissemination.

Within this chapter, we conceptualize behavioral engagement (and disengagement) within the framework provided by Fredericks, Blumenfeld, and Paris (2004). They define school engagement in terms of three components: behavioral engagement, emotional/affective engagement, and cognitive engagement. Within this chapter, we focus on behavioral engagement (the other types of engagement are discussed in separate chapters in this volume). Behavioral engagement is defined by Fredericks and colleagues (2004) as participation, effort, persistence, and positive conduct while directly involved in a set of activities: "Behavioral engagement is most commonly defined in three ways. The first definition entails positive conduct, such as following the rules and adhering to classroom norms, as well as the absence of disruptive behaviors such as skipping school and getting in trouble [...] The second definition concerns involvement in learning and academic tasks and includes behaviors such as effort, persistence, concentration, attention, asking questions, and contributing to class discussion [...]. A third definition involves participation in school-related activities such as athletics or school governance," (Fredericks, Blumenfeld, & Paris, 2004, p. 62).

We define behavioral disengagement in terms of the first definition, where students fail to follow the rules or expectations for the activity, engaging instead in behaviors outside of the norms or expectations, such as ceasing to participate in the activity, or participating in it in an undesired and inappropriate fashion.

One of the core types of disengaged behavior, seen across a wide range of interactive learning environments, is gaming the system (Baker, Corbett, Koedinger, & Wagner, 2004). Gaming the system is defined as systemically taking advantage of a software's help and feedback feature to advance through the tutoring curriculum while bypassing actively thinking about the learning material (Baker et al., 2004). Examples include systematic guessing and clicking through hints to obtain answers, but different gaming behaviors such as intentionally making spam posts and

making spam responses to those spam posts are seen in other learning environments (Cheng & Vassileva, 2005). Among disengaged behaviors, gaming the system has been found to be particularly strongly associated with learner outcomes, including short-term learning (Coccea et al., 2009), longer-term learning outcomes (Pardos et al., 2013), and college attendance (San Pedro et al., 2013).

In addition to gaming the system, a range of other disengaged behaviors are seen in online learning environments. For example, learners can go completely off-task (Karweit & Slavin, 1982), ceasing to participate in the learning task. Off-task behavior's relationship to learning is typically negative, but not strongly so (Goodman et al., 1990) – and it may serve as a way of disrupting boredom, which is more strongly associated with negative learning outcomes (Baker, Moore, et al., 2011). Indeed, research has shown that off-task behavior during expert tutoring sessions can improve motivation, build rapport between the tutor and learner, and allow for periodic rest (Lehman, Cade, & Olney, 2010). In online learning, there have been multiple studies finding no relationship between off-task behavior and learning or other outcomes (Coccea et al., 2009; Pardos et al., 2013; San Pedro et al., 2013); the reasons for this are not yet known.

Some learners exhibit behaviors within the learning environment that are unrelated to the learning task – this behavior, sometimes called off-task behavior (Rowe et al., 2009) and sometimes called WTF behavior (“without thinking fastidiously” – Wixon et al., 2012), can manifest in many ways. For example, in a multi-user virtual environment, learners may obtain virtual cacti and place them in on a virtual patient, or climb virtual buildings (Sabourin, Rowe, Mott, & Lester, 2013). In a simulation microworld, learners may variables in rapid succession or pause and un-pause a simulation very quickly and repeatedly (Wixon et al., 2012). In one report, no relationship was found between this behavior and learning (Rowe et al., 2009), but its relationship to learning has not been studied in other learning environments.

Learners can also make careless errors, an error that a student makes when answering a question that they know how to do with no obvious reason why they erred (Clements, 1982). Careless errors are seen both in offline learning and assessment (e.g. Clements, 1982), and in online learning (San Pedro, Baker, & Rodrigo, 2011). Careless errors are typically a behavior characteristic of generally more successful learners (Clements, 1982), but are still associated with negative outcomes after learner knowledge is controlled for (Baker et al., 2010; San Pedro et al., 2013).

Though these are the most studied disengaged behaviors in the context of online learning, other behaviors have also been seen, such as killing your teammates in military simulations for no apparent reason (personal communication, Robert Sottolare).

ADDRESSING GAMING THE SYSTEM IN ONLINE LEARNING

Given the relatively strong evidence that gaming the system is associated with worse outcomes for learners, it is perhaps unsurprising that it has been a particular focus of research to address disengaged behaviors in online learning. There have been many approaches to addressing gaming in online learning, including attempting to make gaming more difficult, detecting gaming and employing embodied agents that look unhappy when students game, changing the incentive structure to de-incentivize gaming, giving meta-cognitive messages about how to learn effectively, and using visualizations of the student's behavior to show them how much they have been gaming.

There are several ways to make gaming more difficult. The most popular strategy employed to

accomplish this goal is introducing delays to each level of on-demand hints (clicking rapidly through on-demand hints is one of the most popular ways for learners to game the system). With delayed hints, each time a learner receives a hint, there is a pre-determined amount of time they must wait before they can request another hint (Murray & VanLehn, 2005; Beck, 2005). However, this approach has thus far been ineffective because learners find alternative ways to game the system. In addition, it has the drawback that it discourages some appropriate types of hint use.

Both emotional expressions (on the part of an embodied agent) and changing the incentive structure to de-incentivize gaming were incorporated into Scooter the Tutor (Baker et al., 2006). Scooter the Tutor was an embodied agent that responded when a learner's behavior indicated that they were gaming the system (according to an automated detector of gaming – cf. Baker et al., 2008). Scooter responded by looking unhappy when the learner gamed (and telling the student not to game), and if the gaming behavior persisted, Scooter gave supplementary exercises that slowed the learner down (while also giving the learner an alternate way to learn material bypassed by gaming). In studies in the United States, Scooter reduced gaming and improved learning (Baker et al., 2006; Belmontes et al., 2011), with the supplementary exercises having more effect than the emotional expressions. However, learners disliked Scooter (Rodrigo et al., 2012). In the Philippines, Scooter actually increased the amount of apparent gaming, as learners appreciated Scooter's supplementary exercises and intentionally clicked through hints in order to obtain them (Rodrigo et al., 2012).

A third approach, providing meta-cognitive messages on how to learn more effectively, was adopted by Roll and colleagues (2007). The Help Tutor system responds to gaming the system behavior by giving meta-cognitive feedback, suggesting students should request a hint or slow down and read hints more carefully – for example, “It may not seem like a big deal, but hurrying through these steps may lead to later errors. Try to slow down.” (Roll et al., 2007, p. 205). Although this system reduced gaming behaviors, it did not have a positive impact on learning (Roll et al., 2007).

Another approach, visualizing gaming behavior, was combined with text messages (Walonoski & Heffernan, 2006). In this work, a knowledge-engineered gaming detection model was used to select when students would receive interventions. When a learner was assessed to be gaming, the learner received text messages that asked (for example) whether the learner was guessing or actually needed the hint requested. In addition, the screen continually displayed a graphical visualization of learner actions and progress, which displayed gaming behavior as well as other student actions, in a way that was visible to both the student and the teacher. This combined intervention of dynamic active (text messages) and dynamic passive interventions (the visualization) resulted in reduced gaming during the intervention, (Walonoski & Heffernan, 2006). This intervention's effects on domain learning outcomes has not yet been studied.

Another category of gaming intervention is visualizations between problems. In Arroyo et al. (2007), how much the student had gamed the system was visualized between problems, in combination with detailed messages about appropriate meta-cognitive behavior encouraging students to slow down and attentively read problems and hints, e.g., “Dear Ivon, We think this will make you improve even more: Read the problem thoroughly. If the problem is just too hard, then ask for a hint. Read the hints CAREFULLY. When a hint introduces something that you didn't know, write it down on paper for the next time you need it,” (Arroyo et al., 2007, p. 2). The system also included messages that encouraged students to think about the problem and guess at the solution, and ask for hints if the guess was wrong, e.g., “Dear Ivon, Think the problem thoroughly and make a guess. If your guess is wrong, no problem, just ask for a hint. If you need

more hints, keep clicking on help,” (Arroyo et al., 2007, pg. 2).

Arroyo and colleagues (2007) argued that giving feedback on gaming between problems could improve behavior and learning without disrupting problem-solving activity, in addition to increasing the chances of immediate reengagement after seeing an intervention. When evaluated, this intervention led to a lower degree of gaming the system (Arroyo et al., 2007). The between-problem visualizations of how much the student gamed also led learners to spend more time on the subsequent problem. The combined intervention was associated with improved learning of domain content, as well as improving learner attitudes towards the system – a strong contrast to the negative attitudes of students towards Scooter the Tutor.

In a follow-up study, between-problem visualizations were not given, but three types of intervention messages were utilized: attribution interventions, effort-affirmation interventions, and strategic interventions (Arroyo et al., 2010). Attribution interventions messages were given when a student faced a new problem, e.g., “I found out that people have myths about math, think that only some people are good in math. Truth is we can all be good in math if we try,” (Arroyo et al, 2010, p. 5). Effort-affirmation intervention messages were generated when a learner achieves a correct answer; different messages were given depending on whether a correct answer was generated with effort or no effort; for effort: “Keep in mind that when we are struggling with a new skill we are learning and becoming smarter!”; for no effort: “We will learn new skills only if we are persistent. If we are very stuck, let’s call the teacher or ask for a hint from Wayang!” (Arroyo et al., 2010, p. 5). Finally, strategic interventions focused on meta-cognitive strategies that could be used when a student was correct or incorrect; for correct: “We are making progress. Can you think of what we have learned in the last 5 problems?”; for incorrect: “Are we using a correct strategy to solve this? What are the different steps we have to carry out to solve this one?” (Arroyo et al., 2010, p. 5). This system resulted in less gaming the system, less frustration, and more interest as compared to a control condition. However, there was no impact on learning.

A similar result was found by Verginis et al (2011), who incorporated indicators of recent student gaming and other behaviors in a screen separate from the problem (cf. Arroyo et al., 2007), as well as providing comparisons of how much the student engaged in these behaviors compared to other students. Their article found that 39 of 73 students who were initially engaging in gaming behaviors ceased to engage in those behaviors over the course of using their system, a proportion that is not significantly different than chance according to a sign test. They did find that students who reduced their disengaged behavior had significantly better learning than students who did not reduce their disengaged behavior.

Across these papers, it is clear that there are several methods that can effectively reduce gaming the system. However, the only two methods that have been shown to both reduce gaming and improve learning are the types of supplementary exercises given in Scooter the Tutor, and the combination of between-problem visualizations and meta-cognitive messages. Further work may better elucidate the benefits of these approaches, and of other approaches.

ADDRESSING OTHER DISENGAGED BEHAVIORS IN ONLINE LEARNING

Thus far, there has been considerably less work to address disengaged behaviors beyond gaming the system in online learning systems. One of the few examples of this work is seen in Hughes (2010), which proposed using Scooter the Tutor for off-task interventions as well as for gaming interventions. Specifically, if a student was off-task according to the off-task detector (Baker, 2007), then the screen would go black, and a pop-up would appear with Scooter asking if the student is still at their workstation. The idea behind this intervention is that it would both

encourage the student to return to work and would also attract the attention of a teacher to pay attention to the absent learner (Hughes, 2010). However, these designs were not implemented or tested in a running system.

Interventions for disengaged behaviors other than gaming the system are much more common outside the context of interactive and online learning. Some of these interventions, and the communities producing them, are discussing in the following section on future directions.

FUTURE DIRECTIONS

In this chapter, we have discussed methods that designers of interactive learning environments have used to remediate or otherwise address disengaged behaviors, particularly gaming the system. Some of these efforts have been quite successful, such as providing visualizations of disengaged behaviors between problems (Arroyo et al., 2007). However, this area of research has not scaled as of the time of this writing. Part of the reason for this is that these interventions are time-consuming to implement, and existing intelligent tutoring system infrastructures are typically not designed with these types of interventions in mind. This is an excellent opportunity for a framework such as GIFT. By explicitly incorporating infrastructure-level support for developers to create these types of interventions (messages, visualizations, and embodied agents), and link them to automated detectors, it will become much easier to develop and test these types of interventions.

An additional important future direction comes from the areas of expertise brought to bear on the design of these interventions. The methods of the positive behavior support and behavior modification (Weiss et al., 2009) communities of research and practice are particularly relevant to this type of intervention. These communities have been working to develop classroom practices that reduce and remediate off-task and other disengaged behaviors (termed problem behaviors in these communities) for decades (Weiss et al., 2009). And yet, there has been almost no cross-fertilization between these communities; with the exception of the participation of one behavior modification researcher in the design of Scooter the Tutor, none of the approaches discussed above involved participation from researchers or practitioners in these communities.

Positive Behavior Support (PBS) includes integrating academics, instruction, and achievement with strategies to reinforce discipline, student self-management, and behavior management to promote cooperative and academically engaged learners (Weiss et al., 2009; Knoff, 2012). PBS entails specifying expected behaviors, teaching these expectations to learners, recognizing behavior that meet these expectations, remediating behavior that does not meet expectations through imposed consequences, monitoring and analyzing the implementation of PBS to adjust future PBS strategies, (McKevitt et al., 2012).

Many approaches and findings from these communities have relevance to the problem of reducing disengaged behaviors. For example, Kraemer and colleagues (2012) review two classroom-wide PBS interventions entitled “The Mystery Motivator” and “*Get ‘Em On Task*,” (Kraemer et al., 2012, p. 163). In The Mystery Motivator, students are rewarded for engaging in positive behaviors selected by a teacher or other adult, such as staying in one’s seat or working quietly, and receive a reward from a box corresponding to the day the target behavior is achieved. If the box has a Mystery Motivator symbol, a learner can chose a reward from a special reward menu.

In the *Get ‘Em On Task* intervention, a computer program generates randomly-timed sounds for monitoring student behavior (Kraemer et al, 2012). A teacher can use a classroom computer to

generate random signals from 0 to 100 to sound on the hour as well as program additional random signals throughout the day (Kraemer et al, 2012). When these sounds occur, the teacher assigns points to learners who are on task, students who are off-task receive no points, (Kraemer et al, 2012), and points can subsequently be exchanged for rewards. The effects of the interventions indicated that while both the Mystery Motivator and the *Get 'Em On Task* interventions were effective in decreasing off-task behavior in comparison to no intervention, *Get 'Em On Task* had a difference in decrease of overall off-task behavior of 16.75% as compared to Mystery Motivator, (Kraemer et al, 2012).

Another approach, the *response to intervention* model (National Center on Response to Instruction, 2010), integrates positive behavioral supports into learning experiences. In this approach, the first line of intervention includes *surface management techniques* for behavior management (Sayesk & Brown, 2011). Surface management techniques include the following: (1) ignoring attention seeking behavior; (2) signal interference: nonverbal signals such as a sound or flicker of lights, to remind learners about rules; (3) proximity and touch control: presence of a teacher nearby; (4) directly addressing a learner by name when their attention is wandering; (5) deliberate, sincere attention by instructor demonstrating concern for learner; (6) tension decontamination through humor; (7) hurdle help: providing instructional support in place of a reprimand; (8) interpretation as interference: helping students understand a confusing or frustrating experience; (9) regrouping: physically reconfiguring a space in the classroom; (10) restructuring: changing an activity to stem off disruptive behavior; (11) direct appeal: reminder of rules; (12) limitation of space and tools: limiting learners access to materials that might tempt problem or disengaged behaviors; (13) removing a learner from the classroom to complete a neutral task without the negative connotation of being thrown out of a class; (14) permission and authoritative verboten (“No!”): clearly and succinctly communicating a particular behavior is not tolerated; and (15) promises and rewards: delivered randomly and at unexpected times, (Sayesk & Brown, 2011). While some of these approaches may not be immediately feasible in online learning, many could be realized by a pedagogical or non-player character (NPC) agent in some form.

By bringing in the ideas and successful approaches from other communities, we may be able to find better ways to address disengaged behaviors, guiding learners to engage in appropriate behaviors, and helping them to learn more effectively as a result. By embedding support for creating effective interventions into architectures like GIFT, we may be able to realize these interventions at scale, creating significant positive impact on learners.

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REFERENCES

Aleven, V. (2001) Helping Students to Become Better Help Seekers: Towards Supporting Metacognition in a Cognitive Tutor. Paper presented at *German-USA Early Career Research Exchange Program: Research on Learning Technologies and Technology-Supported Education*. Tubingen, Germany.

Aleven, V., McLaren, B., Roll, I., & Koedinger, K. (2006). Toward meta-cognitive tutoring: A model of help seeking with a Cognitive Tutor. *International Journal of Artificial Intelligence and Education*. 16, 101-128.

Arroyo, I., Ferguson, K., Johns, J., Dragon, T., Meheranian, H., Fisher, D., Barto, A., Mahadevan, S., & Woolf, B.P. (2007) Repairing Disengagement with Non-Invasive Interventions. *Proceedings of the 13th International Conference of Artificial Intelligence in Education*. IOS Press.

Arroyo, I., Woolf, B., Royer, J., Tai, M., Muldner, K., W., Cooper, D. (2010). Gender Matters: The Impact of Animated Agents on Students' Affect, Behavior and Learning. Technical report UM-CS-2010-020. Computer Science Department, UMASS Amherst.

Babin, L., Tricot, A., & Mariné, C. (2008). Seeking and providing assistance while learning to use information systems. *Computers & Education*. 53, 1029-1039.

Baker, R.S.J.d., Corbett, A.T., Gowda, S.M., Wagner, A.Z., MacLaren, B.M., Kauffman, L.R., Mitchell, A.P., Giguere, S. (2010). Contextual Slip and Prediction of Student Performance After Use of an Intelligent Tutor. *Proceedings of the 18th Annual Conference on User Modeling, Adaptation, and Personalization*. 52-63.

Baker, R., Corbett, A., Koedinger, K., Evenson, S., Roll, I., Wagner, A., Naim, M., Raspat, J., Baker, D., & Beck, J. (2006). Adapting to when student game an intelligent tutoring system. *Proceedings of the 8th International Conference on Intelligent Tutoring Systems*. 392-401.

Baker, R., Corbett, A.T., Koedinger, K.R., Wagner, A.Z. (2004). Off-Task Behavior in the Cognitive Tutor Classroom: When Students "Game The System." *Proceedings of ACM CHI 2004: Computer-Human Interaction*. 383-390.

Baker, R.S.J.d., Gowda, S.M., Corbett, A.T. (2011). Automatically Detecting a Student's Preparation for Future Learning: Help Use is Key. *Proceedings of the 4th International Conference on Educational Data Mining*. 179-188.

Baker, R.S.J.d., Mitrovic, A., Mathews, M. (2010). Detecting Gaming the System in Constraint-Based Tutors. *Proceedings of the 18th Annual Conference on User Modeling, Adaptation, and Personalization*. 267-278.

Baker, R.S.J.d., Pardos, Z., Gowda, S., Nooraei, B., Heffernan, N. (2011). Ensembling Predictions of Student Knowledge within Intelligent Tutoring Systems. *Proceedings of 19th International Conference on User Modeling, Adaptation, and Personalization*. 13-24.

Baker, R.S.J.d., Rossi, L.M. (2013). Assessing the Disengaged Behavior of Learners. In Sottolare, R., Graesser, A., Hu, X., & Holden, H. (Eds.) *Design Recommendations for Intelligent Tutoring Systems -- Volume 1 -- Learner Modeling*. U.S. Army Research Lab, Orlando, FL, 155-166.

Beck, J. (2005). Engagement tracing: using response times to model student disengagement. *Proceedings of the 12th International Conference on Artificial Intelligence in Education*. Amsterdam. 88-95.

Belmontes, R., Fontaine, S., & Genato, R. (2011). Gaming in middle schools: An interactive qualifying project report. Unpublished masters thesis. Worcester Polytechnic Institute, Worcester, MA.

Betoret, F., & Artiga, A. (2011). The relationship among student basic need satisfaction: Approaches to learning, reporting of avoidance strategies and achievement. *Electronic Journal of Research in Educational*

Psychology. 9(2), 463-496.

Clements, K. (1982). Careless errors made by sixth-grade children on written mathematical tasks. *Journal for Research in Mathematics Education*. 13, 136-144.

Ebner, M. & Holzinger, A. (2007). Successful implementation of user-centered game based learning in higher education: An example from civil engineering. *Computers & Education*. 49(3), 873-890.

Ensminger, M. E., & Slusarcick, A. L. (1992). Paths to high school graduation or dropout: A longitudinal study of a first-grade cohort. *Sociology of Education*. 65, 95-113.

Finn, J. D., & Owings, J. (2006). The adult lives of at-risk students: The roles of attainment and engagement in high school, statistical analysis report. NCEs, National Center for Education Statistics, U.S. Department of Education, Institute of Education Science, 2006-328.

Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. *Review of Educational Research*. 74, 59-109.

Garris, R., Ahlers, R., & Driskell, J. E. (2002). Games, motivation, and learning: a research and practice model. *Simulation & Gaming*. 33, 441-467.

Habgood, M., & Ainsworth, S. (2011). Motivating children to learn effectively: Exploring the value of intrinsic integration in educational games. *Journal of the Learning Sciences*. 20(2), 169-206.

Hughes, K. (2010). Educational software for off-task behavior. (Unpublished Major Qualifying Project). Worcester Polytechnic Institute, MA.

Karweit, N., & Slavin, R. E. (1982). Time-on-task: Issues of timing, sampling, and definition. *Journal of Educational Psychology*, 74(6), 844-851.

Kraemer, E., Davies, S., Arndt, K., & Hunley, S. (2012). A comparison of the mystery motivator and the get 'em on task interventions for off-task behaviors. *Psychology in the schools*. 49(2), 163-175.

McKevitt, B. C., Dempsey, J. N., Ternus, J., & Shriver, M. D. (2012). Dealing with behavior problems: The use of positive behavior support strategies in summer programs. *Afterschool Matters*. (15), 16-25.

Pardos, Z., Baker, R.S.J.d., San Pedro, M.O.Z., Gowda, S.M., & Gowda, S. (2013). Affective states and state tests: Investigating how affect throughout the school year predicts end of year learning outcomes. In *Proceedings of the 3rd International Conference on Learning Analytics and Knowledge*. 117-124.

Puustinen, M., Volckaert-Legrier, O., Coquin, D., & Bernicot, J. (2008). An analysis of students' spontaneous computer-mediated help-seeking: A step toward the design of ecologically valid supporting tools. *Computers & Education*. 53(4), 1040-1047.

Roll, I., Alevan, V., McLaren, B.M., & Koedinger, K.R. (2007). Can help seeking be tutored? Searching for the secret sauce of metacognitive tutoring. *Proceedings of the 13th International Conference on Artificial Intelligence in Education*, 203-210.

Rowe, J., McQuiggan, S., Robison, & J., Lester, J. (2009). Off-Task Behavior in Narrative-Centered Learning Environments. *Proceedings of the 14th International Conference on AI in Education*. 99-106.

Roscoe, R., Segedy, J., Sulcer, B., Jeong, J., & Biswas, G. (2013). Shallow strategy development in a teachable agent environment designed to support self-regulated learning. *Computers & Education*. 62, 286-297.

Sabourin, J., Rowe, J., Mott, B., & Lester, J. (2011). When Off-Task in On-Task: The Affective Role of

- Off-Task Behavior in Narrative-Centered Learning Environments. *Proceedings of the 15th International Conference on Artificial Intelligence in Education*. 534-536.
- Sabourin, J., Rowe, J., Mott, B., & Lester, J. (2013). Considering Alternate Futures to Classify Off-Task Behavior as Emotion Self-Regulation: A Supervised Learning Approach. *Journal of Educational Data Mining*. 5(1), 9-38, 2013.
- San Pedro, M.O.Z., Baker, R.S.J.d., Bowers, & A.J., Heffernan, N.T. (2013). Predicting College Enrollment from Student Interaction with an Intelligent Tutoring System in Middle School. *Proceedings of the 6th International Conference on Educational Data Mining*. 177-184.
- San Pedro, M.O.C., Baker, R., Rodrigo, M.M. (2011) Detecting Carelessness through Contextual Estimation of Slip Probabilities among Students Using an Intelligent Tutor for Mathematics. *Proceedings of 15th International Conference on Artificial Intelligence in Education*. 304-311.
- Schwartz, D., Chase, C., Chin, D., Kwong, H., Opezzo, M., Okita, S., Roscoe, R., Jeong, H., Wagster, J., & Biswas, G. (2009). Interactive metacognition: Monitoring and regulating a teachable agent, in D.J. Hacker, J. Dunlosky, & A.C. Graesser (Eds.), *Handbook of Metacognition in Education*. New York, NY: Routledge.
- Sayeski, K. L., & Brown, M. R. (2011). Developing a classroom management plan using a tiered approach. *Teaching Exceptional Children*. 44(1), 8-17.
- Verginis, I., Gouli, E., Gogoulou, A., & Grigoriadou, M. (2011). Guiding learners into reengagement through the SCALE environment: An empirical study. *IEEE Transactions on Learning Technologies*. 4(3), 275-290.
- Villalta, M., Gajardo, I., Nussbaum, M., Andreu, J. J., Echeverría, A., & Plass, J. L. (2011). Design guidelines for classroom multiplayer presential games. *Computers & Education*. 57(3), 2039-2053.
- Wang, M. S. & Eccles, J. (2012). Adolescent Behavioral, Emotional, and Cognitive Engagement Trajectories in School and Their Differential Relations to Educational Success. *Journal Of Research On Adolescence*. 22(1), 31-39.
- Weiss, M. J., DelPizzo-Cheng, E., LaRue, R. H., & Sloman, K. (2009). ABA and PBS: The dangers in creating artificial dichotomies in behavioral intervention. *Behavior Analyst Today*. 10(3), 12.
- Wixon, M., Baker, R.S.J.d., Gobert, J., Ocumpaugh, J., & Bachmann, M. (2012) WTF? Detecting Students who are Conducting Inquiry Without Thinking Fastidiously. *Proceedings of the 20th International Conference on User Modeling, Adaptation and Personalization (UMAP 2012)*. 286-298.