# Spatial Ability and Other Predictors of Gameplay Time: Understanding barriers to learning in Game-based Virtual Environments

Megan Frankosky
Eric Wiebe
Philip Buffum
Kristy Elizabeth Boyer

North Carolina State University

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**Abstract**
The ENGAGE project is a game-based virtual environment where students engage in problem-based learning experiences centered around computational thinking and broader computer science education learning objectives that require students to participate in cognitively demanding tasks. Cognitive Load Theory (Ayres & van Gog, 2009; Sweller, et al., 1998) provides a robust framework to characterize these cognitive demands as intrinsic and extrinsic load. Here we examined the role of three factors that may impact either the intrinsic or extraneous load experienced by students as they work through learning scenarios in the game. Spatial orienting ability, previous video game experience, and previous programming experience had differential impacts on game performance based on the type of puzzle and its temporal sequence in the game.

## 1. Introduction

Creating activities that engage K-12 students with computer science education curriculum has received the attention of the education community (CWCT, 2010). Recently, computer science outreach programs facilitated by visual programming languages (e.g., Scratch and Alice) have been successfully implemented at the middle school level (Roger, et al., 2009; 2010). Visual programming languages have been paired with game-based instructional design strategies as a way of motivating and engaging students who otherwise might not be intrinsically inclined to learn about programming and computational thinking (e.g., Repenning, 2012; Roger, et al., 2010; Werner, Campe & Denner, 2012). While one approach is to have students create games using the visual programming language, another approach is to embed the programming tasks as part of challenges within a game-based environment. This latter approach is used by the ENGAGE project to create a compelling narrative around problem-solving tasks within a game based virtual environment (Figure 1; Intellimedia, 2013).

ENGAGE is an immersive game-based learning environment for middle school computer science education. The curriculum underlying ENGAGE is based on the AP Computer Science Principles course (CS Principles, 2013) with learning objectives that are developmentally appropriate for middle school students. The learning environment was designed to expose students to problems that encourage the development of computational thinking skills. Computational thinking is a problem-solving process involving abstraction and algorithmic thinking and leverages the use of computational tools for data analysis, modeling, or simulations (Barr & Stephenson, 2011). The goal of the ENGAGE project is to increase computational fluencies for all middle school students through collaborative exploration and problem-solving within an engaging game-based narrative-driven virtual environment.

Game-based learning environments have considerable potential as learning tools (Boyle, et al., 2011; Spires, et al., 2011), due to their ability to appeal to a broad range of students with diverse backgrounds, and to motivate students to participate in activities that they may not otherwise engage in when presented in traditional formats (Steinkuehler & King, 2009). However, in some circumstances, characteristics inherent in a virtual environment, such as the nature of 3D tasks, wayfinding, and spatial orienting, may be a barrier for users with low spatial abilities (e.g., Savage, et al., 2004; Wiebe & Converse, 1996, Marsh, et al, 2013). Similarly, even if an individual's general spatial ability is strong, there are specific cognitive costs when interacting with a new, unfamiliar interface (Marsh, et. al., 2014; Shneiderman, 1998; Zanbaka et. al., 2005). However research has not investigated the impacts of these costs on other co-occurring cognitive tasks, or their relationship to spatial ability within a game-based learning environment.

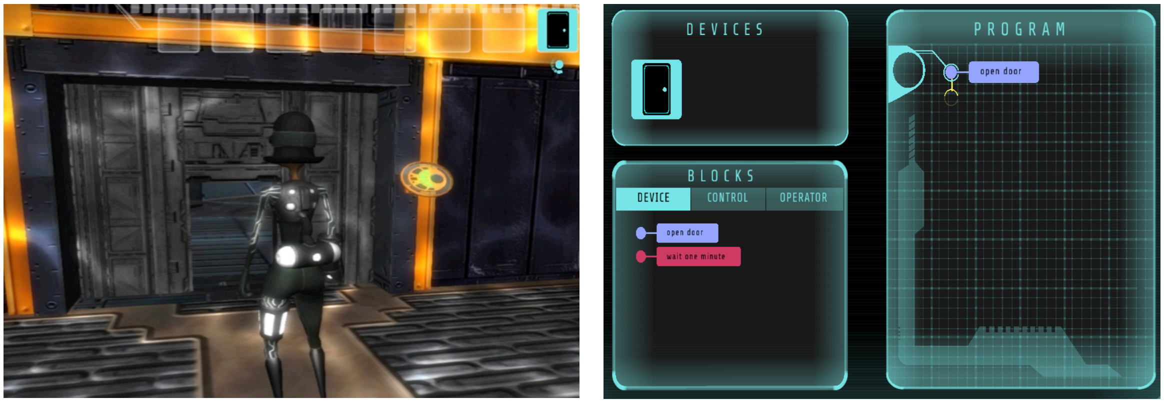
## 2. Theoretical Framework

The ENGAGE virtual game environment requires students to engage in a number of cognitively demanding tasks, only some of which are directly related to the learning goals. Cognitive Load Theory (Ayres & van Gog, 2009; Sweller, et al., 1998) provides a robust framework to characterize these cognitive tasks and their interactions. The inherent difficulty level associated with computer science problem-solving tasks within the game can be thought of as intrinsic cognitive load, while game-mechanic elements not directly related to the learning tasks can be thought of as extraneous load. The challenges presented to the students as they move through the virtual game space have components of 3D spatial orientation and wayfinding, spatial memory, and computational logic. All three of these components are recognized, distinct loads on visual processing, working memory, and fluid reasoning abilities (Flanagan & Harrison, 2012; McGrew, 2009; Woodcock, et al., 2001). Cognitive Load Theory postulates that the actual intrinsic cognitive load experienced by the student will be an interaction of current ability and the intrinsic demands of the task. Therefore, individuals with low spatial ability or low programming logic expertise—in general, or in the specific task they are being asked to do—will experience higher intrinsic load. Similarly, less experience with video game mechanics, in general, or the types used in this game will raise extraneous cognitive load. Cognitive Load Theory works from an understanding of finite working memory that can be allocated between these intrinsic and extraneous cognitive tasks. Therefore, high levels of cognitive load from both intrinsic and extraneous factors may hinder progress in a game that requires solving cognitive challenges. Direct empirical evidence of this is seen in studies looking at individual differences in perspective taking ability and how it impacts performance on a spatial task within a virtual environment. Those with lower spatial ability performed worse on a navigation task that involved a concurrent spatial memory task (Marsh, et al, 2013).

**3. Method**

As part of an iterative design-based development cycle (Barab & Squire, 2004; Collins, Joseph & Bielaczyc, 2004), we have used Cognitive Load Theory, design heuristics, as well as results from pilot studies to make user-centered design improvements to the interface, game mechanics, and problem based learning experiences in the game. In the version of the game piloted for this study, students are required to navigate a platform across a body of water through planning out and writing a program to control a moving platform (See Figure 1a for an illustration of one of these puzzles). This puzzle which is high in intrinsic spatially-focused cognitive load can be contrasted with a non-spatially focused puzzle within the game involving programming a door device to open (See Figure 1b for an illustration of this puzzle). As a first step in evaluating the effectiveness of the ENGAGE game environment, analyses were conducted to explore the role of spatial abilities and previous experiences in both programming and with video games on game performance.


(a)




(b)

*Figure 1.* (a) spatial programming task in first moving platform room (b) non-spatial programming task in hallway.

*Participants*

Fifty-nine eighth graders (35 males, 24 females) from four classes were randomly assigned to pairs before beginning the activity. Of these 59, a total of 38 (26 males, 12 females) completed surveys and assessments that were used in the analyses below.

*Measures & Procedure*

*Spatial Ability Test.* The PTSOT, a test to measure spatial orienting ability (Kozhevnikov & Hegarty, 2001), was administered to the students before they began playing the game. Instructions were explained to the whole class, and then they were given 5 minutes to complete as many of the 12 items on the test as they could. The PTSOT presents an arrangement of objects at the top of the page and asks students to indicate where a specific object would be if they were oriented in a certain direction by drawing an arrow on a circle. PTSOT scores were then calculated by using the average degrees difference between the individuals' given response, and the actual location of the third object. The reliability for the PTSOT, calculated with this data, was acceptable (Cronbach's alpha = .80).

*Knowledge Assessment & Engagement.* Before beginning gameplay, each student completed a pre knowledge assessment. After reaching the last room in the game level students completed a post knowledge assessment and engagement survey. The six multiple choice items administered assessed knowledge of programming concepts we expected students to master during the specific section of the game that they played during this study. Students also completed an engagement questionnaire, the User Engagement Scale (UES; O'Brien & Toms, 2010). Thirty-one items were measured as a 5-point Likert scale and were aggregated according to the recommended subscales when engagement is being assessed within the context of a gaming environment (Wiebe, Lamb, Hardy, & Sharek 2014).

*Gameplay & Metrics.* Students were randomly paired students to play the ENGAGE game. We encouraged a paired programming style of gameplay where students alternate between controlled character movement (being the driver) and who was advising the player controlling the character (the navigator). The amount of time it took each team to progress successfully through each room within the level is referred to as *gameplay time*).

**4. Results**

There were no gender differences in spatial ability scores, gameplay time, or self reported engagement ratings, programming experience, or learning gains as revealed by independent samples t-tests. Means and standard deviations for each of these variables can be found in Table 1. Multiple regressions were run to predict gameplay time from PTSOT scores and self-reported programming experience (coded as having relevant experience or not). These analyses were ran for total gameplay time, for time within two rooms with a spatial programming component (*first platform one,* and *second platform)*, as well as for one room that had a non-spatial programming component (*hallway)*.

**Table 1.**
Means and standard deviations

| | Females | | Males | | Overall | |
|---|---|---|---|---|---|---|
| | M | SD | M | SD | M | SD |
| Video Game Experience | 3.00 | .85 | 3.65 | 1.13 | 3.45 | 1.08 |
| Programming Experience | .23 | .45 | .54 | .51 | .45 | .50 |
| Spatial Ability | 84.61 | 60.06 | 68.93 | 54.13 | 73.89 | 55.73 |
| Pre Score | 3.33 | 1.07 | 2.93 | 1.74 | 3.05 | 1.56 |
| Post Score | 3.25 | 1.28 | 3.65 | 1.41 | 3.53 | 1.37 |
| Overall Engagement | 3.01 | .72 | 3.00 | .529 | 3.00 | .59 |
| Focused Attention | 2.94 | .87 | 2.93 | .75 | 2.93 | .78 |
| Perceived Usability | 2.43 | .80 | 2.40 | .48 | 2.41 | .58 |
| Aesthetics | 3.32 | 1.01 | 3.25 | .90 | 3.27 | .92 |
| Satisfaction | 3.52 | 1,71 | 3.60 | .79 | 3.58 | .91 |
| Total Game Time* | 58.31 | 9.72 | 51.17 | 11.05 | 53.4 | 11.05 |
| Hallway Time* | 2.5 | 1.41 | 2,2 | .9 | 2.30 | 1.08 |
| First Platform Time* | 5.61 | 2.48 | 4.85 | 1.61 | 5.08 | 1.93 |
| Second Platform Time* | 24.43 | 10.66 | 15.86 | 6.78 | 18.41 | 8.92 |

*game time is in minutes

The model predicting total game time was significant F(3,37) = 4.08, $p$ = .014, $R^2$ = .20. However only self reported video game experience contributed statistically significantly to the prediction, $p$ =.008. For the *hallway*, the overall model predicting game time in this room was not significant F(3,37) = 2.57, $p$ = .07, $R^2$ = .13. However, self reported programing experience contributed statistically significantly to the prediction, $p$ =.026. The overall model predicting game time the *first platform* room was significant F(3,37) = 2.89, $p$ = .049, $R^2$ = .11. However only spatial ability scores contributed statistically significantly to the prediction, $p$ =.035. Finally, the overall model predicting game time in the *second platform* room was significant F(3,36) = 4.41, $p$ = .01, $R^2$ = .23. Here, the only statistically significant variable in the model is video game experience, $p$ =.003. Regression coefficients, standard errors, and partial eta squares for each model can be found in Table 2.

**Table 2.**
Regression results predicting game time

| Location / Predictor | B | SE | Beta | t | p | Partial $R^2$ |
|---|---|---|---|---|---|---|
| *Total Game (N = 38)* | | | | | | |
| **VG Exp** | **-280.181** | **99.482** | **-0.458**** | **-2.816** | **0.008** | **0.17** |
| Prog Exp | 98.922 | 234.139 | 0.075 | 0.422 | 0.675 | 0 |
| Spatial Ability | 2.423 | 2.004 | 0.204 | 1.209 | 0.235 | 0.03 |
| *Hallway (N = 38)* | | | | | | |
| VG Exp | -5.797 | 10.278 | -0.096 | -0.564 | 0.576 | 0 |
| **Prog Exp** | **-56.479** | **24.191** | **-0.437*** | **-2.335** | **0.026** | **0.13** |
| Spatial Ability | -0.193 | 0.207 | -0.165 | -0.932 | 0.358 | 0.02 |
| *First Platform (N = 38)* | | | | | | |
| VG Exp | -1.842 | 18.136 | -0.017 | -0.102 | 0.92 | 0 |
| Prog Exp | -24.579 | 42.685 | -0.107 | -0.576 | 0.569 | 0 |
| **Spatial Ability** | **0.800** | **0.365** | **0.384*** | **2.191** | **0.035** | **0.11** |
| *Second Platform (N = 37)* | | | | | | |
| **VG Exp** | **-255.168** | **79.287** | **-0.522**** | **-3.218** | **0.003** | **0.22** |
| Prog Exp | 79.61 | 191.933 | 0.075 | 0.415 | 0.681 | 0 |
| Spatial Ability | 1.123 | 1.659 | 0.117 | 0.677 | 0.503 | 0.01 |

## 5. Discussion

With a game that requires players to work through problem-based learning scenarios in a way that can utilize cognitive resources—both intrinsic and extraneous load—we found that previous gaming experience seems to be more important than either spatial ability or previous programming experience as players progress through the game. Only previous gaming experience was a significant predictor for overall game time and the time spent in the later room, the second moving platform. However, early in the game as players encounter the *first moving platform* puzzle, the only significant predictor of game time is spatial ability. This puzzle possesses an intrinsic load with high spatial demands, thus orienting ability plays an important role in predicting performance time. Those with higher spatial abilities are able to complete the *first moving platform* puzzle room more quickly than those with lower spatial abilities. As players progress in the game, the impact of spatial ability on completion time is not present in the *second moving platform puzzle*, while video game experience continues to be predictive of game time. This finding indicates that players are able to adjust to the spatial demands, decreasing their intrinsic load related to spatial orienting. Interestingly, in the hallway, where the students presented with a puzzle that does not involve a spatial component (writing a program to open a door), neither video game experience nor spatial ability are predictive of the gameplay time. Yet having previous programming experience seems to give players a jump-start in this room, as they complete this room more quickly than those without experience.

## 6. Conclusions

While game based learning environments hold great promise for delivering motivating and engaging learning experiences, individual differences may contribute to performance within the learning environment. Scenarios within a 3D virtual environment, like ENGAGE, that tax cognitive resources in ways that are both intrinsically and extraneously related to the central learning task make it necessary to consider the role of previous experience and cognitive abilities when evaluating game-based learning environments. Specifically, the impact of spatial demands on performance within virtual game based learning environments should be investigated. Here we examined the role of three factors that may impact either the intrinsic or extraneous load experienced by students as they work through problem based learning scenarios within our virtual game environment, but may also evolve as they gain experience. A specific type of spatial ability, orienting, combined with previous experience in playing video games, and previous experience with programming had differential impacts on game performance based on the type of puzzle and its temporal sequence in the ENGAGE game. Unique cognitive resource demands within the game merge spatial ability, with programming ability. As a lesson for future game design, in our environment too high an emphasis on spatial abilities required to solve the puzzles combined with too high requirements for programming knowledge could result in longer completion times and potential user frustration. While players seemed to gain experience that lessened the intrinsic load of the spatially focused puzzles, the distribution of these cognitive demands must be balanced and paced over the arc of game play in order to optimize the learning experience.

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## References

Ayres, P., & van Gog, T. (2009). State of the art research into Cognitive Load Theory. *Computers in Human Behavior, 25*(2), 253-257.

Barab, S. A., & Squire, K. (2004). Design-based research: Putting a stake in the ground. *Journal of the Learning Sciences, 13*(1), 1-14.

Barr, V., & Stephenson, C. (2011). Bringing Computational Thinking to K-12: What is Involved and What is the Role of the Computer Science Education Community? *ACM Inroads,* 2(1), 48–54.

Boyle, E., Connolly, T. M., & Hainey, T. (2011). The role of psychology in understanding the impact of computer games. *Entertainment Computing, 2*(2), 69-74. doi: 10.1016/j.entcom.2010.12.002

Collins, A., Joseph, D., & Bielaczyc, K. (2004). Design research: Theoretical and methodological issues. *The Journal of the Learning Sciences, 13*(1), 15-42.

Conference on Innovation and Technology in Computer Science Education (ITiCSE '10) (p. 234). New York, New York, USA: ACM Press.

CS Principles. (2013). *Homepage*. Retrieved July, 2014, from www.csprinciples.org

CWCT, Committee for the Workshops on Computational Thinking. (2010). *Report of a Workshop on The Scope and Nature of Computational Thinking*. Washington, DC: National Research Council.

Flanagan, D. P., & Harrison, P. L. (Eds.). (2012). *Contemporary intellectual assessment: Theories, tests, and issues*. New York: Guilford Press.

Hegarty, M. & Waller, D. (2004). A dissociation between mental rotation and perspective-taking spatial abilities. *Intelligence*, *32*, 175-191

Intellimedia. (2013). *ENGAGE Project homepage*, from http://projects.intellimedia.ncsu.edu/engage/

Kozhevnikov, M. & Hegarty, M. (2001). A dissociation between object manipulation spatial ability and spatial orientation ability. *Memory & Cognition*, *29*(5), 745-756.

Kizhevnikov, M., Motes, M. A., Rasch, B., & Blajenkova, O. (2006). Perspective-taking vs. mental rotation transformations and how they predict spatial navigation performance. *Applied Cognitive Psychology*, *20*, 397-417. doi: 10.1002/acp.1192

Marsh, W., Kelly, J., Dark, V., & Oliver, J. (2013). Cognitive Demands of Semi-Natural Virtual Locomotion. *Presence*, *22*(3), 216-234.

McGrew, K. S. (2009). CHC theory and the human cognitive abilities project: Standing on the shoulders of the giants of psychometric intelligence research. *Intelligence*, *37*(1), 1-10.

Neale, D. C. (1996). *Spatial perception in desktop virtual environments.* Paper presented at the Proceedings of the human factors and ergonomics society 40th annual meeting, Philadelphia, PA.

O'Brien, H. L., & Toms, E. G. (2010). The Development and Evaluation of a Survey to Measure User Engagement. *Journal of the American Society for Information Science*, *61*(1), 50–69. doi:10.1002/asi

Rodger, S. H., Bashford, M., Dyck, L., Hayes, J., Liang, L., Nelson, D., et al. (2010). Enhancing K-12 Education With Alice Programming Adventures. Proceedings of the 15th Annual SIGCSE

Rodger, S. H., Hayes, J., Lezin, G., Qin, H., Nelson, D., Tucker, R., . . . Slater, D. (2009). *Engaging middle school teachers and students with Alice in a diverse set of subjects*. Proceedings of the 40th ACM technical symposium on Computer science education (SIGCSE), Chattanooga, TN, USA.

Savage, D. M., Wiebe, E. N., & Devine, H. A. (2004). *Performance of 2D versus 3D topographic representations for different task types.* Paper presented at the Human Factors and Ergonomics Society 48th Annual Meeting, New Orleans, LA.

Shneiderman, B. (1998). *Designing the user interface: Strategies for effective human-computer interaction* (3rd ed.). Reading, MA: Addison-Wesley.

Spires, H., Rowe, J., Mott, B., & Lester, J. (2011). Problem Solving and Game-Based Learning: Effects of Middle Grade Students' Hypothesis Testing Strategies on Learning Outcomes. [10.2190/EC.44.4.e]. *Journal of Educational Computing Research, 44*(4), 453-472.

Steinkuehler, C., & King, B. (2009). Digital literacies for the disengaged: Creating after school contexts to support boys' game-based literacy skills. *On the Horizon, 17*(1), 47-59.

Stephenson, C., Wilson, C. (2012) Reforming K-12 Computer Science Education… What Will Your Story Be? *ACM Inroads*. 3, 43–46.

Sweller, J., Merrienboer, J. J. G. v., & Paas, F. G. W. C. (1998). Cognitive architecture and instructional design. *Educational Psychology Review, 10*, 251-296.The College Board. (2010) AP CS Principles: Learning Objectives and Evidence Statements.

Repenning, A. (2012). Programming goes back to school. *Communications of the ACM, 55*(5), 38-40. doi: 10.1145/2160718.2160729

Werner, L., Campe, S., & Denner, J. (2012). Children Learning Computer Science Concepts via Alice Game-Programming. In ACM (Ed.), *Proceedings of the 43rd ACM technical symposium on Computer science education (SIGCSE '12)*. New York, NY: ACM.

Wiebe, E. N., & Converse, S. A. (1996). *Recognition of shape and metric changes in 3-D computer models.* Paper presented at the Human Factors and Ergonomics Society 40th Annual Meeting, Philadelphia, PA.

Wiebe, E. N., Lamb, A., Hardy, M., & Sharek, D. (2014). Measuring engagement in video game-based environments: Investigation of the User Engagement Scale. *Computers in Human Behavior*, *32*, 123–132. doi:10.1016/j.chb.2013.12.001

Woodcock, R. W., McGrew, K. S., & Mather, N. (2001). Woodcock-Johnson III Tests of Cognitive Abilities. Itasca, IL: Riverside.

Zanbaka, C. A., Lok, B. C., Babu, S. V., Ulinski, A. C., & Hodges, L. F. (2005). Comparison of path visualizations and cognitive measures relative to travel technique in a virtual environment. *Visualization and Computer Graphics, IEEE Transactions on*, *11*(6), 694-705.