The acquisition of spatial navigational skills from dynamic versus static visualisations

Olurotimi R. Akinlofa
IDEAS Research Institute
Robert Gordon University
St Andrew Street, Aberdeen
o.r.akinlofa@rgu.ac.uk

Patrik O'Brian Holt
IDEAS Research Institute
Robert Gordon University
St Andrew Street, Aberdeen
p.holt@rgu.ac.uk

Eyad Elyan
IDEAS Research Institute
Robert Gordon University
St Andrew Street, Aberdeen
e.elyan@rgu.ac.uk

Interactions between instruction visualisations and task mental representations in skill acquisition is arguably knowledge-domain dependent. This paper presents the design and preliminary results of an experiment that extends the knowledge-domain dependent model to the acquisition of spatial navigational skills. A between-group design is proposed and tested to compare post-learning navigational performances of different learner groups in a virtual environment. The preliminary results indicate a benefit of dynamic over static visualisations in the acquisition of spatial navigational skills, which is consistent with previous results. A full study with a larger sample size and multi-level comparative analysis is currently underway.

Skill Acquisition, Instruction Design, Spatial Knowledge Representations, Virtual Navigation.

1. VISUALISATIONS AND TASK MENTAL MODELS

Effective training is an important factor in the acquisition of mission-critical skills in many organisations and contexts. Reviews of training design have identified the composition of instructions as a main factor for effective skill transfer in the training curriculum (Day et al., 2006). This has led to extensive research of instructional design methods with emphasis on components and delivery. The aspect of instructional design research of interest in this study is the cognitive benefit of dynamic visualisations in the instructional interface. A meta-analysis of dynamic versus static instructional visualisations currently remains largely inconclusive (Höffler and Leutner, 2008). In previous work, we have argued that the interaction of external percepts and knowledge domains are key to the formation of mental task representations that drive subsequent task performances (Akinlofa, Holt and Elyan, *under revision*). The intuitive view that the role of external percepts in the human problem solving process is underpinned by the formation of mental representations remains widely accepted (Kosslyn and Pomerantz, 1977; Kosslyn and Moulton, 2009; Chandrasekaran et al., 2011). We have proposed a hybrid model of modal and amodal cognitive processing paradigms that include the formation of an abstract mental referent in novel domain-dependent skill acquisition (Akinlofa, Holt and Elyan, *under revision*). Based on this model, empirical evidence suggesting a benefit of dynamic over static visualisations in the acquisition of novel procedural motor skills, has been collected. Furthermore, we have developed computational models with the ACT-R cognitive architecture to investigate the low-level, intertwined role of cognitive processes in post-learning procedural motor task performance (Akinlofa, Holt and Elyan, 2012). In this paper, we present the design and piloting of an experiment, which aims to extend the applicability of our hybrid model to the separate but related domain of the acquisition of spatial navigational skills using a virtual environment.

2. SPATIAL NAVIGATION AS A PROCEDURAL SKILL

Navigational planning is a multi-level problem solving process. The relevant cognitive level processes involved include perceptual scanning, knowledge-based retrieval and memory-based decisions (Reitter and Lebiere, 2011). In Figure 1, we show the memory-based component as the core of this model. It integrates visually perceived information with knowledge retrievals to determine and execute actions in resolving the navigation problem. This central component has been modelled as a multi-layered hierarchy of spatial knowledge representation. Furthermore, neurophysiological research has implicated the posterior parietal cortex (PPC) in the hosting of spatial knowledge for integrating visual and motor signals for executing navigation (Gold and Shadlen, 2007; Andersen and Cui, 2009; Freedman and

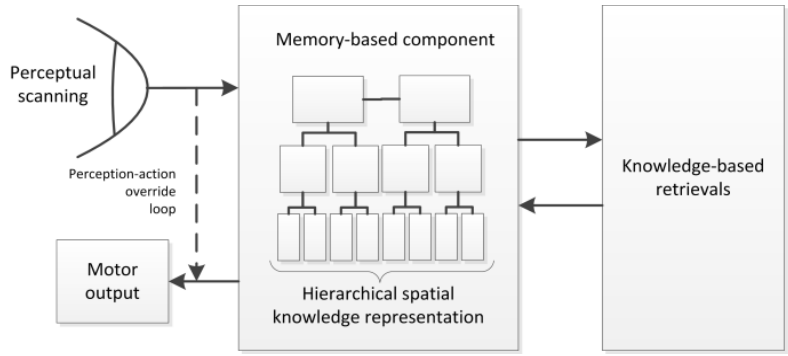


Figure 1: *The association between cognitive processing components in spatial navigation.*

Assad, 2011). More importantly, empirical evidence has suggested that the formation of such spatial knowledge is cognitively sequential (Nitz, 2006; Harvey, Coen and Tank, 2012). This has led to the question of the effect of dynamic versus static manipulations of the visual percept in the creation of novel sequential spatial knowledge and its implications on subsequent navigational performance. In the following sections we describe an experiment designed to compare post-learning navigational performances of independent groups learning a navigational task through dynamic and static instructional interfaces. We further present initial results obtained from a pilot run of the experimental design using a small sample of participants. The experiment involves virtual maze navigation.

3. METHOD

3.1 Participants

Ten students of Robert Gordon University (nine males, one female; mean age = 28.56, *SD* = 1.47) participated voluntarily in the test run of the experiment design.

3.2 Design

A between-groups experiment design was used to compare the post-learning navigation performances of two groups. The independent variable is the level of the dynamic content of the instructional interface with two levels – *static* and *dynamic*. The instructional interface is designed to present equivalent information for acquiring spatial knowledge to navigate a virtual environment in the form of a suggested optimal route. The participant's spatial orientation ability (*spatial_ability*) and *gender* are controlled. The dependent variable is navigational performance measured by the travel path length expressed in virtual environment distance units (*path_length*), the time of travel recorded in seconds (*path_time*) and the route completion rate, which is the ratio of the furthest point reached along the optimal route compared to the total length of the optimal route (*p_route*). All the performance measures are bounded by a specified upper time limit. Travel path length and time have been identified as valid navigation performance measures in previous related research (Richardson, Powers and Bousquet, 2011).

3.3 Materials

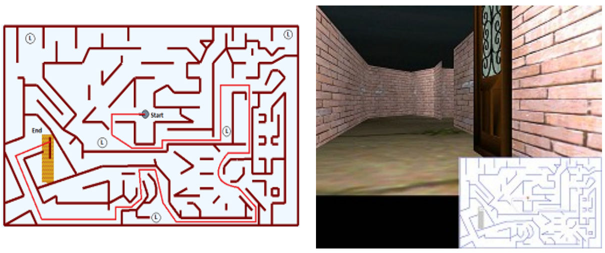
3.3.1. Virtual environment

A 3-D virtual maze was developed using the MazeSuite application (Ayaz et al., 2011) with a single possible optimal path from a start point to a specified end point. The optimal route is divided into one curved and 23 straight-line segments bounded by the start, turning and end points. Movement through the maze is controlled by a Cyborg FLY 5 joystick (www.cyborggaming.com). Translational movements are executed by pushing the joystick forward or backward while turning/rotations are executed by pushing the joystick left or right during translations or when stationary. The virtual maze is presented on an HP Compaq 8200 Elite SFF running under Windows 7 Enterprise 64-bit. The PC is connected to an HP L1950g 19" LCD monitor that affords 110^{o} horizontal X 58^{o} vertical field of view of the virtual navigation environment. A screen shot of the navigation route through the maze is shown in Figure 2.

Figure 2: *Screen shot of the virtual environment.*

3.3.2. Navigation instructions

The instruction for learning the optimal route is presented as a Microsoft PowerPoint 2007 slideshow consisting of 10 slides. Slides 1-4, 7, and 10 provide textual instructions for guidance. Slides 6, and 9 are blank spacer slides for procedural control while the different navigation instruction based on the experiment groups is interchangeably presented on slide 8. Practice instruction corresponding to the experimental groups is also presented through slide 5. The *static* instruction is a map of the virtual maze with a white background and on which the optimal route is depicted with a red trace. The map also shows the location of reference landmarks such as static objects or maze walls with distinct texture/colour different from that of surrounding walls. A screenshot of the *static* instruction interface is shown in Figure 3a. The *dynamic* instruction on the other hand is an animation of a single navigational run along the optimal route superimposed in the lower left corner with a dynamically updated map showing synchronised navigation progress. The superimposed map however does not show reference landmarks, which have to be acquired from the main view during the playback of the animation. The participant is able to pause, rewind or fast-forward the playback as desired. A screenshot of the *dynamic* instruction interface is shown in Figure 3b.



(a) *(b)*

Figure 3: *(a) Static and (b) Dynamic instruction interfaces.*

3.3.3. Pre and post test questionnaires

The pre-test questionnaire asks the participants to report their age, gender, dominant hand used and any disability (specifically dyslexia, epilepsy and related photo-sensitivity). The post-test questionnaires report participant's self-assessment of performance on five scales of the NASA Task Load Index (TLX)[1]. The physical demand scale of the NASA TLX was excluded, as the physical effort required for the navigation task is considered negligible and irrelevant for subsequent analysis.

3.3.4. Card rotations test

The card rotations test (Eskrom et al., 1976) is used to measure participant's spatial orientation ability as a confounding covariate. It is a two-part test of 10 problems each. For each problem, the test taker is asked to compare a uniquely shaped card with eight other cards of different orientations and required to determine if the first card can be made to look like each of the subsequent eight cards. The first card may be mentally rotated for comparison but cannot be flipped or reshaped.

3.4 Procedure

Participants are randomly assigned to either of the two levels of the independent variable – *static* or *dynamic* instruction groups. The experiment is conducted in individual sessions lasting 30 minutes on the average. The participant starts by completing the pre-test questionnaire followed by the card rotations test. Thereafter, the participant interacts with the instructional presentation seated in front of the monitor. The participant is allowed up to five minutes to practice navigating the virtual environment using a different example maze but with instructions corresponding to the experimental group. The practice session is followed by interaction with the group's navigation instruction for the actual experimental maze for up to eight minutes. The virtual task environment is then loaded and participants are allowed a further seven minutes to complete navigation to the end points. Participants may choose to proceed from interacting with the instruction to actual navigation at any time before the expiration of the learning time allowed or would be automatically switched to the navigation phase if the time is exceeded. It is important to note that no participant exceeded the allowed learning time. Additionally, the participant controls pacing through the slide sequence without interference except for when the participant requests to terminate the practice session or load the navigation environment earlier than the expiration of the times allowed respectively. Navigational performance was automatically recorded by the MazeSuite application as individual files for subsequent analysis. Lastly, the participant completes the NASA TLX to end the session.

4. ANALYSIS

Navigational performance was measured on the dependant variables of *path_length*, *path_time* and *p_route* as described in the design subsection above. The dependant variable measures were extracted and recorded for each participant by analysing the performance log files created by the MazeSuite application. Potential performance confounding variables of *spatial_ability* and *gender* were obtained from analysing card rotations test scores and responses to the pre-test questionnaires respectively. Due to the volume of data recorded, the analysis was particularly labour intensive with about 30 minutes required on the average to complete each participant's performance log.

5. RESULTS

The data was analysed with SPSS version 17™. Means and standard deviations for the path length (in maze units), path time (seconds), route completion rate (% of optimal route) and spatial orientation ability scores for the static and dynamic groups are shown in Table 1.

Table 1: *Descriptive statistics for performance variables.*

Performance Variables	Instruction type					
	Static			*Dynamic*		
	N	*M*	*SD*	*N*	*M*	*SD*
Path length	5	343.24	65.28	5	200.81	86.09
Path time	5	376.10	75.99	5	255.96	190.18
Route Rate(%)	5	39.20	3.51	5	69.75	3.56
Spatial ability	5	84.60	26.81	5	83.50	7.33

Three independent samples t-test were conducted to compare the dependent performance measures of path length, path time and spatial orientation ability. There was a significant difference in the path length for the static and dynamic groups $t(8) = 2.83$, $p < .02$ (two-tailed), eta squared = .5. However, the differences in the path time and spatial orientation ability were not significant $t(8) = 1.19$, $p > .05$ (two-tailed), eta squared = .17 and $t(8) = .08$, $p > .05$ (two-tailed), eta squared = 0 respectively.

Two one-way between groups ANCOVAs were further conducted on the dependent variables of path length and time with the spatial orientation ability as the potential confounding variable. The independent variables remained the instructional group (*static* vs *dynamic*). After adjusting for the spatial orientation ability in the first ANCOVA, there was a significant difference in the path length, $F(1, 7) = 7.6$, $p < .05$, partial eta squared = .56. The effect of the spatial orientation ability was not significant, $F(1, 7) = .53$, $p > .05$, partial eta squared = .08. Following adjustment for the spatial orientation ability in the second ANCOVA however, no significant difference was observed in the path time, $F(1, 7) = 1.7$, $p > .05$, partial eta squared = .22. The effect of the spatial orientation ability was also not significant, $F(1, 7) = .72$, $p > .05$, partial eta squared = .11.

A Fisher's Exact Probability test revealed no significant association between the instructional group and the route completion rate, $p > .05$, phi = .32.

6. DISCUSSION

The result presented is from a test run of the experiment design and is limited by the small sample used. However, the results provide some insight into the cognitive effects of dynamic interface visualisations in the acquisition of novel spatial navigational skills. In general, learners in the *dynamic* group recorded shorter path lengths and completed the navigation task faster than those in the *static* group. However, only the difference in path length was statistically significant. The evidence suggests that *dynamic* group learners were able to develop more effective mental task representations that drive their subsequent better navigation performance. This is arguably due to the intrinsic characteristic of the dynamic interface to provide enhanced perceptual input including transitions between points and relative positioning of landmarks. This is consistent with the results of our earlier study in the motor skills knowledge domain. Furthermore, the *dynamic* group also completed a larger percentage of the optimal route. This reflects the acquisition of robust spatial knowledge of the task that enabled faster recovery to deviations from the optimal route.

The results as noted are limited by the low sample size used and a larger sample size would be required in the main experiment to enable the generalisation of the results. Furthermore, the current experimental design cannot account for an expected convergence of the learning performances of the different groups due to a reinforcement effect. The design is also defective for investigating any effect due to task complexity. We will improve the experiment design to include multiple navigational runs of the optimal route to investigate expected convergence of performance. A multi-level design of different virtual environments of increasing navigational complexity may also help to investigate the effect of task complexity on performance.

Our results factor in the spatial orientation abilities of the participants as a performance confounding variable. However, previous research has established other confounding variables of virtual navigational task performance including gender (Dabbs et al., 1998; Moffat et al., 1998; Waller, 2000), age (Driscoll et al., 2005) and video game play experience (Richardson, Powers and Bousquet, 2011). We will redesign the pre-questionnaire to capture participant's video game play experience as a composite of the duration and intensity of the experience. We will also vary the recruitment of participants to control for the gender effect on navigational performance.

In general, our results show that the experimental design appears valid for investigating the cognitive effects of interface dynamism in the acquisition of novel spatial navigational skills. Substantial revisions of the design are required to investigate reinforcement learning effects and performance variations due to navigational task complexity. The improved design will also control for the confounding effects of gender and video game play experience on navigational performance in a virtual environment.

7. ACKNOWLEDGEMENT

This study was supported by the Petroleum Technology Development Fund (PTDF), Nigeria Grant: PTDF/TR/PhD/AOR/206/09.

8. REFERENCES

Akinlofa, O.R., Holt, P.O. and Elyan, E. (under revision). Effect of interface dynamism on learning procedural motor skills.

Akinlofa, O.R., Holt, P.O. and Elyan, E. (2012). Performance modelling of interface dynamism in motor skills acquisition. In: N. Rußwinkel, U. Drewitz & H. van Rijn (eds.), *Proceedings of the 11th International Conference on Cognitive Modeling*. 13-15 April 2012. Berlin: Universitaetsverlag der TU Berlin. pp. 129-130.

Andersen, R.A. and Cui, H. (2009). Intention, action planning, and decision making in parietal-frontal circuits. *Neuron,* 63, 568–583.

Ayaz, H., Shewokis, P.A., Curtin, A., Izzetoglu, M., Izzetoglu, K. and Onaral, B. (2011). Using mazesuite and functional near infrared spectroscopy to study learning in spatial navigation. *Journal of Visualized Experiments,* 56, e3443.

Chandrasekaran, B., Banerjee, B., Kurup, U. and Lele, O. (2011). Augmenting cognitive architectures to support diagrammatic imagination. *Topics in Cognitive Science,* 3, 760–777.

Dabbs Jr., J.M., Chang, E, Strong, R.A. and Milun, R. (1998). Spatial ability, navigation strategy, and geographic knowledge among men and women. *Evolution and Human Behavior,* 19, 89–98.

Day, E.A., Blair, C., Daniels, S., Kligyte, V. and Mumford, M.D. (2006). Linking instructional objectives to the design of instructional environments. The integrative training design matrix. *Human Resource Management Review,* 16, 376–395.

Driscoll, I., Hamilton, D.A., Yeo, R.A., Brooks, W.M. and Sutherland, R.J. (2005). Virtual navigation in humans: the impact of age, sex, and hormones on place learning. *Hormones and Behavior* 47, 326–335.

Ekstrom, R., French, J., Harman, H. and Derman, D. (1976). *Kit of factor-referenced cognitive tests*. Educational Testing Service, Princeton, NJ.

Freedman, D.J. and Assad, J.A. (2011). A proposed common neural mechanism for categorization and perceptual decisions. *Nature Neuroscience,* 14, 143–146.

Gold, J.I. and Shadlen, M.N. (2007). The neural basis of decision making. *Annual Review of Neuroscience,* 30, 535–574.

Harvey, C.D., Coen, P. and Tank, D.W. (2012). Choice-specific sequences in parietal cortex during a virtual-navigation decision task. *Nature,* 484, 6268.

Höffler, T.N. and Leutner, D. (2007). Instructional animation versus static pictures: A meta-analysis. *Learning and Instruction*, 17, 722–738.

Kosslyn, S.M. and Pomerantz, J.R. (1977). Imagery, propositions, and the form of internal representations. *Cognitive Psychology,* 9, 52–76.

Kosslyn, S. and Moulton, S. (2009). Mental imagery and implicit memory. In: K. Markman, W. Klein & J. Suhr (eds), *Handbook of Imagination and Mental Simulation*. New York: Hove.

Moffat, S.D., Hampson, E. and Hatzipantelis, M. (1998). Navigation in a ”virtual” maze: Sex differences and correlation with psychometric measures of spatial ability in humans. *Evolution and Human Behavior*, 19, 73–87.

Nitz, D.A. (2006). Tracking route progression in the posterior parietal cortex. *Neuron,* 49, 747–756.

Reitter, D. and Lebiere, C. (2010). A cognitive model of spatial path-planning. *Computational and Mathematical Organization Theory*, 16, 220–245.

Richardson, A.E., Powers, M.E. and Bousquet, L.G. (2011). Video game experience predicts virtual, but not real navigation performance. *Computers in Human Behavior*, 27, 552–560.

Waller, D. (2000). Individual differences in spatial learning from computer-simulated environments. *Journal of Experimental Psychology Applied*, 6, 307–321.

[1] http://humansystems.arc.nasa.gov/groups/TLX/