Characterising student exploration strategies using inquiry-based learning resources

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Overview

- Situating this work in the learner analytics landscape
- Theoretical support for discovery learning
- Empirical and theoretical question marks
- This study – comparing discovery and tutorial learning designs
- Initial results showing very little difference
- Reanalysis taking into account exploration strategy showing advantage for systematic discovery
- Alternative approaches to characterising exploration strategies

Definitions

- ***Learning analytics** is concerned with the collection, analysis and reporting of data about learning in a range of contexts. It informs and provides input for action to support and enhance learning experiences, and the success of learners.*
  (Simon Buckingham Shum, The Open University, ascilite 2011 keynote presentation).
- ***Academic analytics** is the application of business intelligence tools and strategies to guide decision-making practices in educational institutions. The goal ... is to help those charged with strategic planning in a learning environment to measure, collect, decipher, report and share data in an effective manner.*
  (http://searchcio.techtarget.com/definition/academic-analytics)

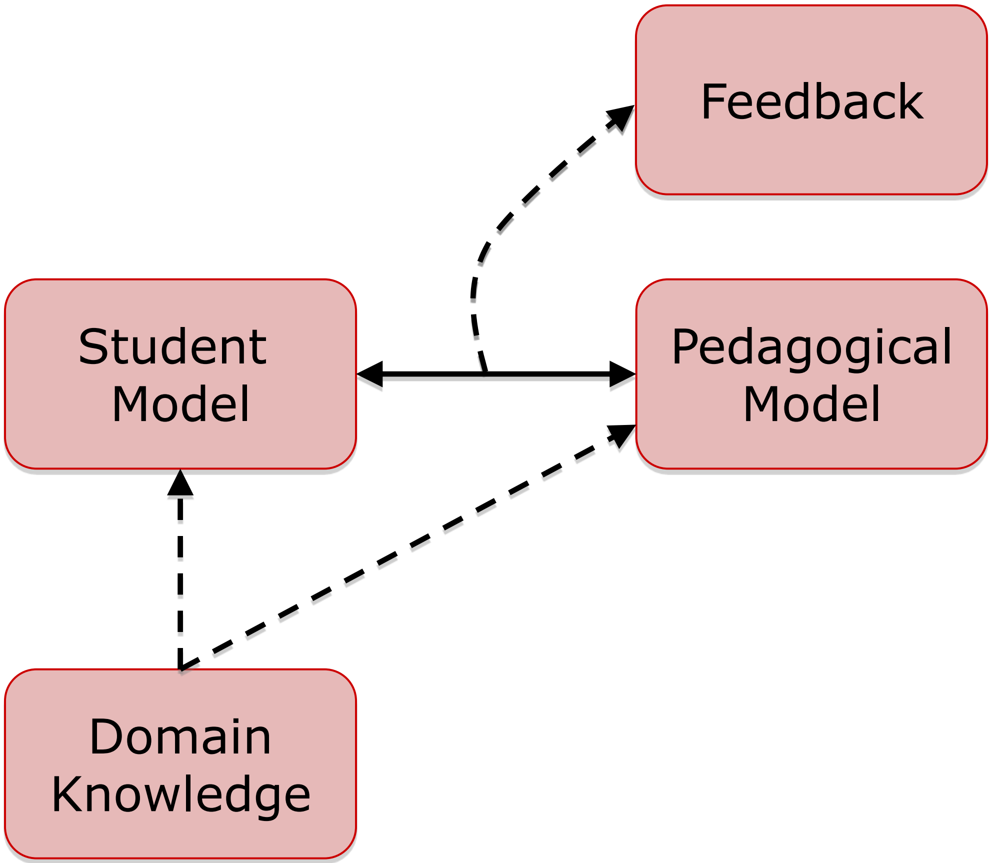
Historical underpinnings

Intelligent Tutoring Systems

Interactivity Research

Historical underpinnings

Intelligent Tutoring Systems



Historical underpinnings

Intelligent Tutoring Systems

- "ITS were recognised as narrow and brittle" (Cumming & McDougall, 2000)
- …they were heavily reliant on educational programs and applications that had defined or discrete stages and steps.
- They were often tied to a program and were not generalisable.

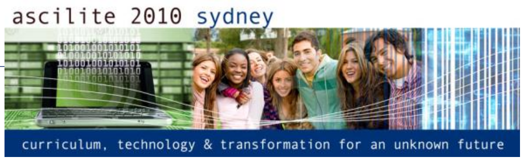
Historical underpinnings

Ascilite 99 5-8 December 1999
Responding to Diversity
The 16th Annual Conference of the Australasian Society for Computers in Learning in Tertiary Education

Interactivity Research

Beyond the comfort zone

ascilite 2011
CHANGING DEMANDS, changing directions.
Wrest Point | Hobart Tasmania Australia | 4–7 December 2011



Historical underpinnings

Interactivity Research

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- Dalgarno, B., Kennedy, G. & Bennett, S. (2010). **Can functional brain imaging be used to explore interactivity and cognition in multimedia learning environments?** *Journal of Interactive Learning Research,* 21(3), 317-342.
- **Key message: analysing interaction in isolation from the learning design is meaningless**

Inquiry-based learning

- In its purest form, students explore learning resources or a physical or virtual space with minimal guidance
- Some elements in common with:
  - Discovery learning
  - Problem based learning
  - Case-based learning
  - Project-based learning
- Common objective of situating the development of a student's knowledge and understanding in the context of authentic activities, problems or scenarios
- Theoretical support from cognitive constructivist theorists such as Piaget (1973) and Bruner (1962)

Empirical and theoretical criticisms of ‘pure’ discovery learning

- Richard Mayer (2004) reviewed three decades of research on discovery learning and concluded that in each case guided discovery learning was more effective than pure discovery learning.
- Paul Kirschner, John Sweller and Richard Clark (2006), reach similar conclusions but based on an argument grounded in current knowledge about cognitive architecture, expert-novice differences and cognitive load.

This study

- Comparing learning performance using a discovery based versus a tutorial based learning design using multimedia learning resources
- The archetypal *discovery* resource allows the learner to *actively* experiment with and manipulate objects within the environment and explore the responses of the simulated entities
- The archetypal *tutorial* resource provides information to the learner in a lock step fashion for passive digestion

Experimental design

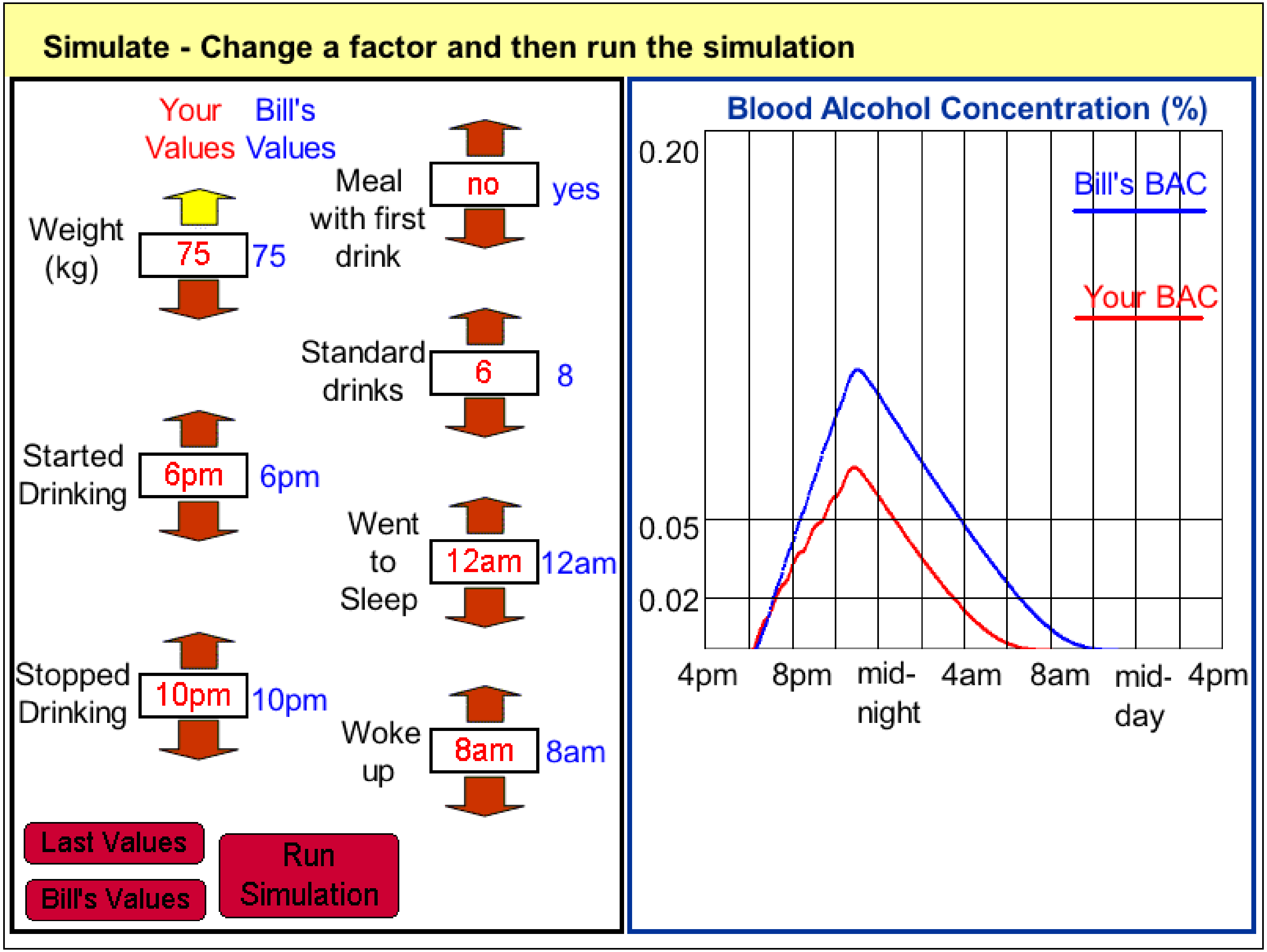
- Two content domains (global warming, blood alcohol concentration, considered separately in the analysis)
- Resources developed using two learning designs (discovery, tutorial) in each content domain
- Each participant (n=158) completed:
  - a pre test on knowledge within each content domain,
  - tasks using one tutorial resource and one discovery resource in two content domains, assigned at random
  - A post test on knowledge within each content domain

	Content Domain	
Condition	Blood Alcohol Concentration	Global Warming
Tutorial	N=73	N=85
Discovery	N=85	N=73

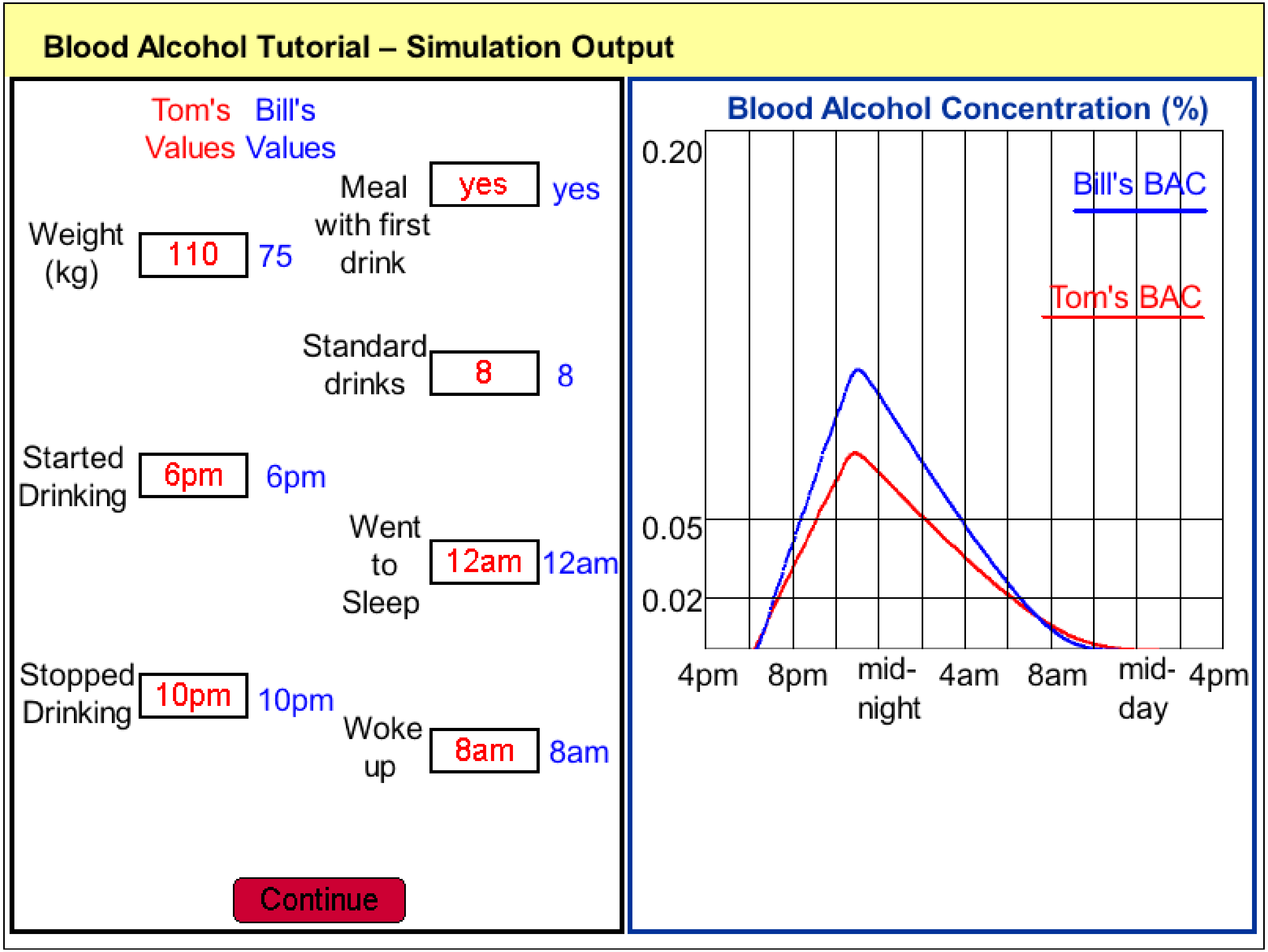
Resource designs

- Discovery
  - A series of instructional screens providing background to the content domain and explanation of terminology but not including explanation of key concepts
  - A series of screens allow for setting of simulation parameters and mental *prediction* of output, *observation* of results, and mental *explanation.*
- Tutorial
  - The same series of instructional screens as the discovery resources
  - A series of simulation output screens showing the effect of different input parameters

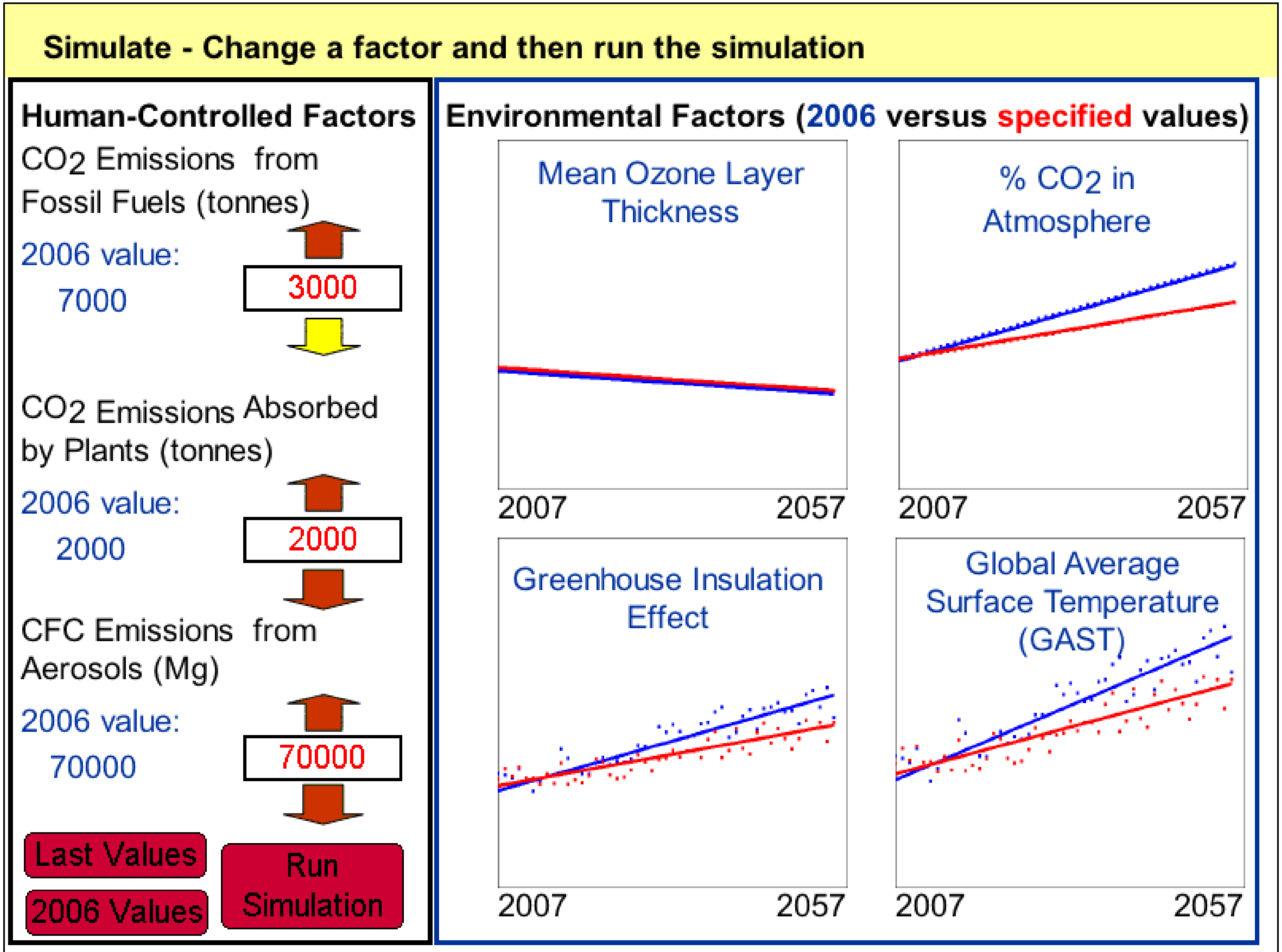
Blood Alcohol Concentration - Simulation



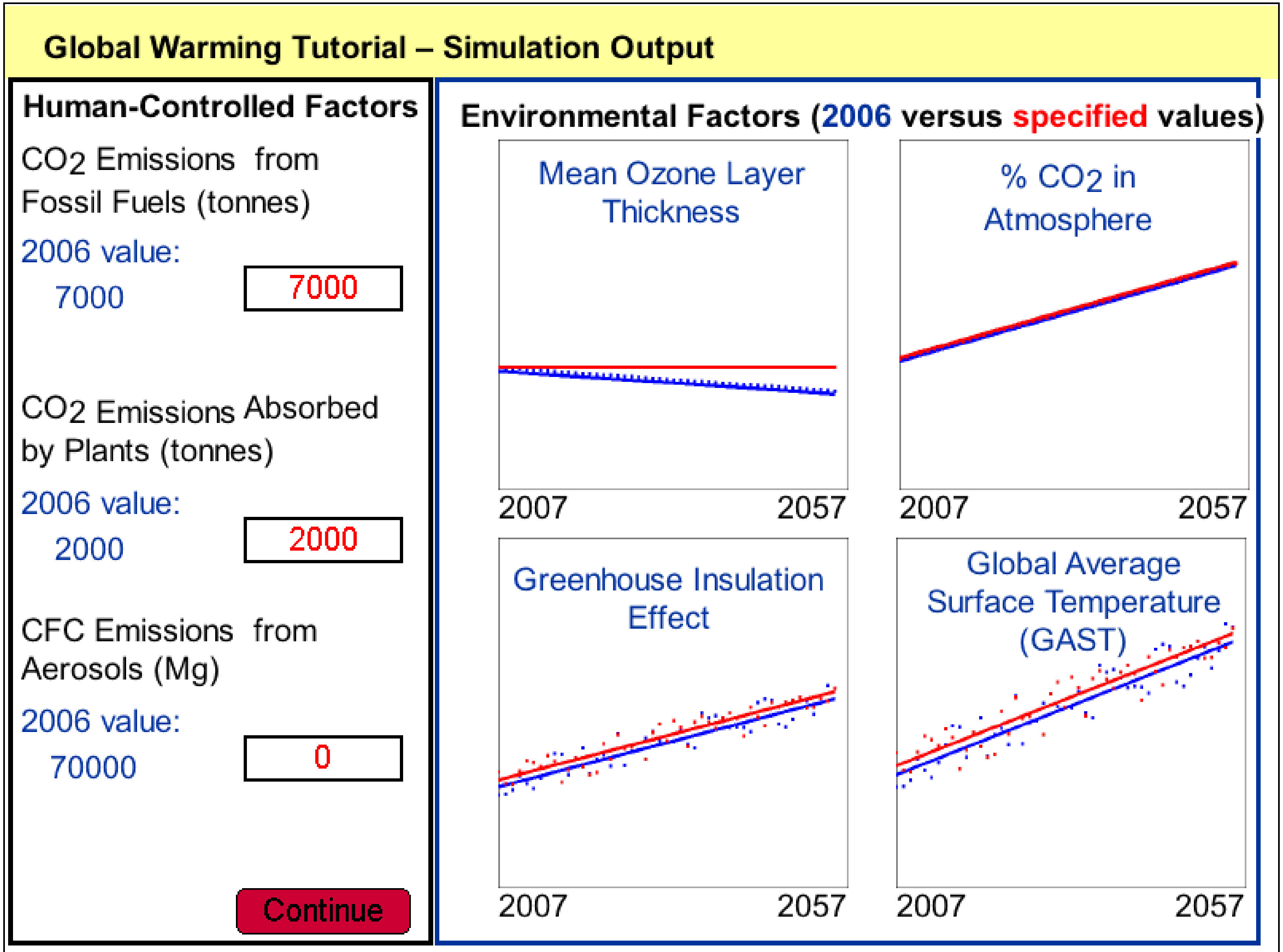
Blood Alcohol Concentration - Tutorial



Global Warming - Simulation



Global Warming - Tutorial



Data collection

- Identical pre-test and post-test on conceptual understanding within these learning domains
  - Global warming – 7 items
  - Blood alcohol concentration – 9 items
- Questionnaires on cognitive load and engagement
- Student actions within the learning resources were also logged to allow later analysis of their exploration strategies

Results

Content Domain	Condition	Pre-Test M (SD)	Post Test M (SD)	T
Global Warming	Tutorial (n=85)	1.82 (1.51)	1.42 (1.29)	2.26 (p=0.027)
	Discovery (n=73)	1.68 (1.42)	1.72 (1.85)	0.20 (p=0.841)
Blood Alcohol	Tutorial (n=73)	3.55 (1.25)	3.42 (1.31)	0.60 (p=0.552)
	Discovery (n=85)	3.60 (1.24)	3.93 (1.40)	2.33 (p=0.022)

- Little or no improvement on post test
- Main effect of learning condition for Blood Alcohol ($F(1, 155) = 5.52$; $p = .02$)
- No effect of learning condition for Global Warming ($F(1,155) = 2.40$; $p = .124$)

Is this the end of the story?

- We noticed that variance in post-test scores for discovery participants were quite high
- In looking at the log files we noticed that some participants had explored the simulation systematically and others had not
- Exploring the data by eye suggested that those who explored the simulation systematically may have performed better
- Consequently we looked at ways we might characterise participants based on their exploration strategies

Characterising exploration strategies

- The log file data provided us with a number of variables that could be used to characterise learners' strategies
- For example:
  - Time spent on the task as a whole
  - Time spent on specific screens representing aspects of the task (eg. planning, manipulating, reviewing output)
  - The number of iterations through the simulation
  - The number of variables changed during each iteration
  - The values chosen

Characterising exploration strategies

- Our initial analysis (see Dalgarno, Kennedy & Bennett, 2012), led to simple intuitively sound rule based characterisation:
- Systematic Discovery Participants:
  - 4 or more cycles with only one variable changed from previous cycle
    or
  - 4 or more cycles with only one variable changed from the provided example (‘Bill’s values’ or ‘2006 values’)
- Non Systematic Discovery Participants:
  - All other discovery participants

Results by strategy

Content Domain	Post-Test Tutorial M (SD)	Post-Test Non Systematic Discovery M (SD)	Post-Test Systematic Discovery M (SD)	F	p
Global Warming	1.42 (1.29)	1.33 (1.52)	2.48 (2.20)	4.17	.017
Blood Alcohol	3.42 (1.31) [a]	3.51 (1.30) [a]	4.56 (1.33) [b]	8.69	<.001

- Significant main effect of learning condition for both content domains
- In each case
  Systematic Discovery > Non Systematic = Tutorial

Characterising exploration strategies

- There are a number of alternative approaches that have been used by others:
  - Thompson and Reimann (2010), drawing on Levy and Wilensky (2005), **used rules** based on the values chosen by learners, the time spent and the number of iteration, and characterised learner strategies as 'straight to the point', 'homing' or 'oscillating', in manipulating an agent-based model .
  - Kennedy and Judd (2004) used **Cluster Analysis** to identify clusters of students with interaction patterns illustrating distinct learning strategies in the context of exploration of a digital learning resource
  - Kennedy et al. (2012) developed **Hidden Marcov Models** of characterising expert and novice performance in a surgical simulator and dynamically provided feedback to learners depending on which model their actions best matched

Characterising exploration strategies

- The key potential limitation of the simple rule based method used in our earlier analysis is that there may be a range of different strategies used with varying efficacies and so a simple systematic/unsystematic characterisation may be too simplistic

Characterising exploration strategies

- Our second approach was to use cluster analysis, drawing on the following variables:
  - time spent on the background material preceding the simulation,
  - total time spent on the simulation
  - number of cycles in which exactly one variable was changed from the previous cycle
  - number of cycles in which exactly one variable was changed from the provided base values
  - number of cycles where at least one variable was changed from the previous cycle
  - the sum of the number of variables changed per cycle across all cycles.

Characterising exploration strategies

- Cluster analysis for the Blood Alcohol condition led to a three-cluster solution, discriminated by:
  - by time spent on the simulation, and
  - the degree to which the student manipulated single variables in the simulation.
- Cluster analysis for the Global Warming condition led to a four-cluster solution, using the same variables as above.
- The additional cluster in the Global Warming condition contained students with interaction patterns that were indicative of a complete lack of engagement with the program.

Take home messages for learning analytics

- Learning designers and academic staff need more sophisticated understandings of the relationship between learning activities and outcomes
- Techniques such as Cluster Aalysis and use of Hidden Marcov Models have promise in characterising learning strategies
- We need tools that make it easier to
  - Develop empirically informed characterisations of successful and unsuccessful strategies in specific discipline/learning design contexts
  - Automatically provide tailored support based on this characterisation

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