Adaptivity in Technology Enhanced Learning with respect to Learning Styles

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What is Technology Enhanced Learning?

- Research:
  - Adaptive and Personalized Learning
  - Social Communities
  - Collaborative Learning
  - Game-based Learning / Educational Robots
  - Ubiquitous Learning
  - ...
- Practice:
  - Learning Management Systems

Learning Management Systems (LMS)

- are often used in TEL
- Examples: Moodle, Blackboard, Sakai, ATutor
- are developed to support teachers to create courses
- provide a lot of different features
- domain-independent
- content can be reused in other LMS
- provide only little or in most cases no adaptivity

Adaptive Systems

- Basic Idea
  - Every student has different needs, characteristics, and situations
  - Considering students' individual differences and providing personalized courses, learning material and/or support help students in learning
  - Adaptivity can focus on different needs/characteristics
    - Prior knowledge
    - Motivation
    - Learning goals / interests
    - Cognitive abilities
    - Learning styles
    - ...

Adaptive Systems

- Examples of current systems
  - AHA!
  - TANGOW
  - INSPIRE
  - ...
- Limitations
  - Consider only few needs/characteristics
  - are either developed for specific content (e.g. accounting) or for specific features (e.g. adaptive quizzes)
  - Lack in supporting teachers' needs
  - content cannot be reused
  - are not often used

My Research Interests

How can individual characteristics and needs of learners be considered in learning systems in order to make learning easier for learners?

Focus on learning styles and cognitive abilities

- How does students with different characteristics behave in TEL?
- How to identify students’ characteristics?
- How to provide suitable adaptive support considering students’ different characteristics

Different contexts:

- Learning Management Systems
- Ubiquitous Learning Environments
- Collaborative and Social Learning

Outline

- How to identify learning styles in LMS?
- How to provide adaptive support with respect to learning styles in LMS?
- How does adaptive courses effect students' learning?

Active experimentation

Learning from listening

Exploratory learning

Competitive learning

Learning from theories

Reflecting

What are Learning Styles?

Collaborative learning

Learning from examples

Learning from written text

Need for guidance

Learning from pictures

Learning Styles

- Complex and partially inconsistent research area
  - More than 70 different learning style models
  - Lot of research in the last 30 years
  - But still several important questions are open
    - What are learning styles?

      "a description of the attitudes and behaviours which determine an individual's preferred way of learning" (Honey & Mumford, 1992)

      "characteristic strengths and preferences in the ways they [learners] take in and process information" (Felder, 1996)

Learning Styles

- Other open issues:
  - Are learning styles stable over time?
  - How can learning styles be measured?
  - Relationships between models are not clear

- Essential questions for incorporating learning styles
  - Does students really prefer different ways of learning?

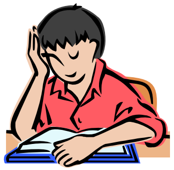
    According to educational theories & experiments → yes

  - Does matching/mismatching courses effect learning?

    According to educational theories → yes
    Experiments provide inconsistent results

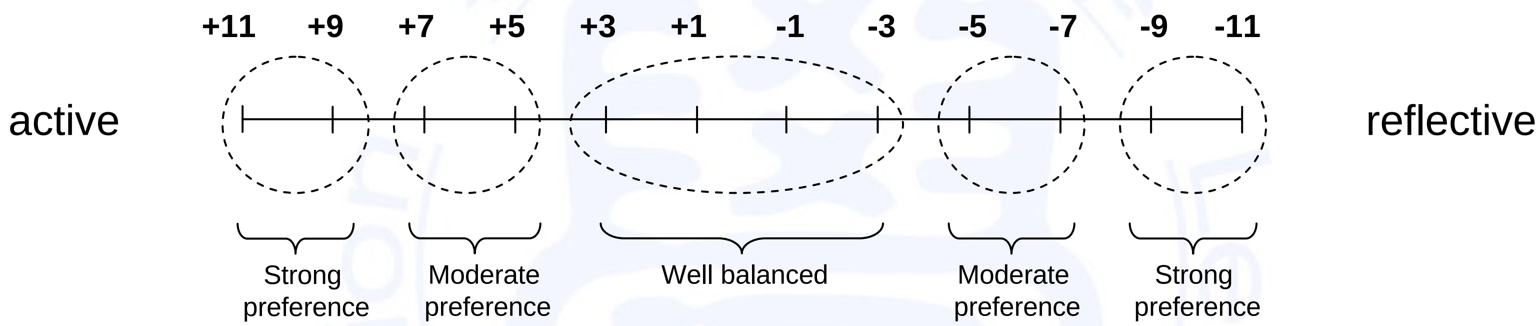
Felder-Silverman Learning Style Model

- Each learner has a preference on each of the dimensions
- Dimensions:
  - Active – Reflective
    learning by doing – learning by thinking things through
    group work – work alone
  - Sensing – Intuitive
    concrete material – abstract material
    more practical – more innovative and creative
    patient / not patient with details
    standard procedures – challenges
  - Visual – Verbal
    learning from pictures – learning from words
  - Sequential – Global
    learn in linear steps – learn in large leaps
    good in using partial knowledge – need „big picture“
    serial – holistic



Felder-Silverman Learning Style Model

- Scales of the dimensions:



→ Strong preference but no support → problems

- Differences to other learning style models:
  - Combines major learning style models (Kolb, Pask, Myers-Briggs Type Indicator)
  - New way of combining and describing learning styles
  - Describes learning style in more detail (Types <-> Scale)
  - Represents also balanced preferences
  - Describes tendencies

Part 1:

How to identify learning styles?

How to identify learning styles?

- Collaborative student modelling
  - "Index of Learning Styles" (ILS) questionnaire
    - 44 questions (11 for each dimension)
    - Online available
  - Problems with questionnaires
    - Motivate students to fill it out
    - Non-intentional influences
    - Can be done only once

How to identify learning styles?

- Automatic student modelling
  - What are students really doing in an online course?
  - Infer their learning styles from their behaviour
  - Advantages:
    - no additional work for students
    - direct and free from the problem of inaccurate self-conceptions of students
    - analyses data from a specific time span → more accurate & allows tracking changes in learning styles
  - Problem/Challenge:
    - Get enough reliable information to build a robust student model

      → certain amount of data about the behaviour

      → use information related to learning styles as additional source

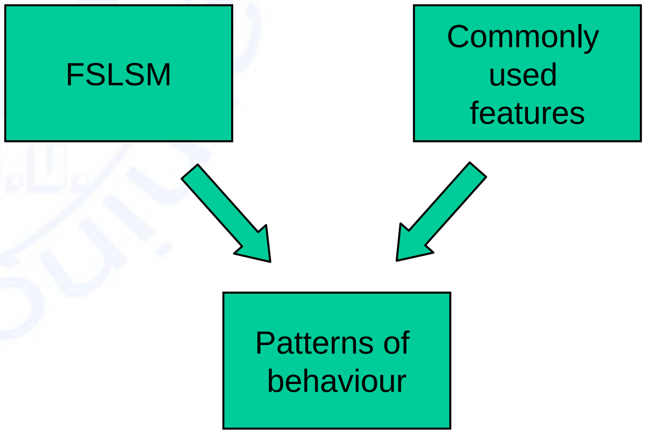
Research Question

How to automatically identify learning styles in LMS?

- General aims
  - Developing an approach for LMSs in general
  - Implementing and evaluating this approach in Moodle
  - Developing a tool which can be used by teachers in order to identify students' learning styles

Determining Relevant Behaviour

- Felder and Silverman describe how learners with specific preferences act in learning situations
- Mapped the behaviour to online learning
- Only commonly used features are considered:
  - Content objects
  - Outlines
  - Examples
  - Self-assessment tests
  - Exercises
  - Discussion Forum



Determining Relevant Behaviour

- Content objects
  - Visits, time
- Outlines
  - Visits, time
- Examples
  - Visits, time
- Self-assessment tests
  - Visits, time on test, time on results
  - Revisions, answering a question twice wrong
  - Performance on questions about facts or concepts, details or overview, graphics or text, interpreting or developing solutions
- Exercises
  - Visits, time on exercises, time on results
  - Revisions
  - Performance on questions about interpreting and developing solutions
- Discussion Forum
  - Visits, time, postings
- Navigation
  - Skipping learning objects
  - Visits and time on course overview page

Determining Relevant Behaviour

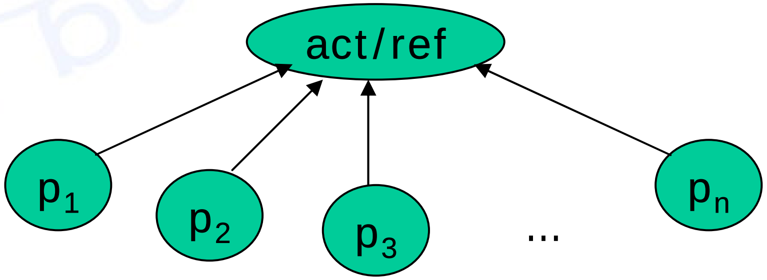
Active/Reflective	Sensing/Intuitive	Visual/Verbal	Sequential/Global
selfass_visit (+)	ques_detail (+)	forum_visit (-)	ques_detail (+)
exercise_visit (+)	ques_facts (+)	forum_stay (-)	ques_overview (-)
exercise_stay (+)	ques_concepts (-)	forum_post (-)	ques_interpret (-)
example_stay (-)	selfass_visit (+)	ques_graphics (+)	ques_develop (-)
content_visit (-)	selfass_result_duration (+)	ques_text (-)	outline_visit (-)
content_stay (-)	selfass_duration (+)	content_visit (-)	outline_stay (-)
outline_stay (-)	exercise_visit (+)		navigation_skip (-)
selfass_duration (-)	ques_rev_later (+)		overview_visit (-)
selfass_result_duration (-)	ques_develop (-)		overview_stay (-)
selfass_twice_wrong (+)	example_visit (+)		
forum_visit (-)	example_stay (+)		
forum_post (+)	content_visit (-)		
	content_stay (-)		

Building an model for inferring learning styles

- Data-driven approach
  - Using Bayesian Networks in order to build a model to identify learning styles
  - Train the model with data about behaviour and learning styles

→ can represents dependencies in the model more accurate

→ very much dependent on data



Building an model for inferring learning styles

- Literature-based approach
  - Building a model based on literature
  - Based on the idea that behaviour of learners provide hints on their learning styles
  - Using indications from data and a simple rule-based approach to identify learning styles

→ is very general since it is based on literature

→ dependencies in the model might be less accurate

Evaluation

- Study with 75 students
  - Let them fill out the ILS questionnaire
  - Tracked their behaviour in an online course
- Aim was to identify learning styles on a 3-item scale (e.g., active, balanced, reflective)
- Investigated the efficiency of the data-driven approach and the literature-based approach
- Using a measure of precision

$$\text{Precision} = \frac{\sum_{i=1}^{n} Sim(LS_{predicted}, LS_{ILS})}{n}$$

- Looking at the difference between results from ILS, data-driven approach and literature-based approach

Evaluation

Correctly detected learning styles:

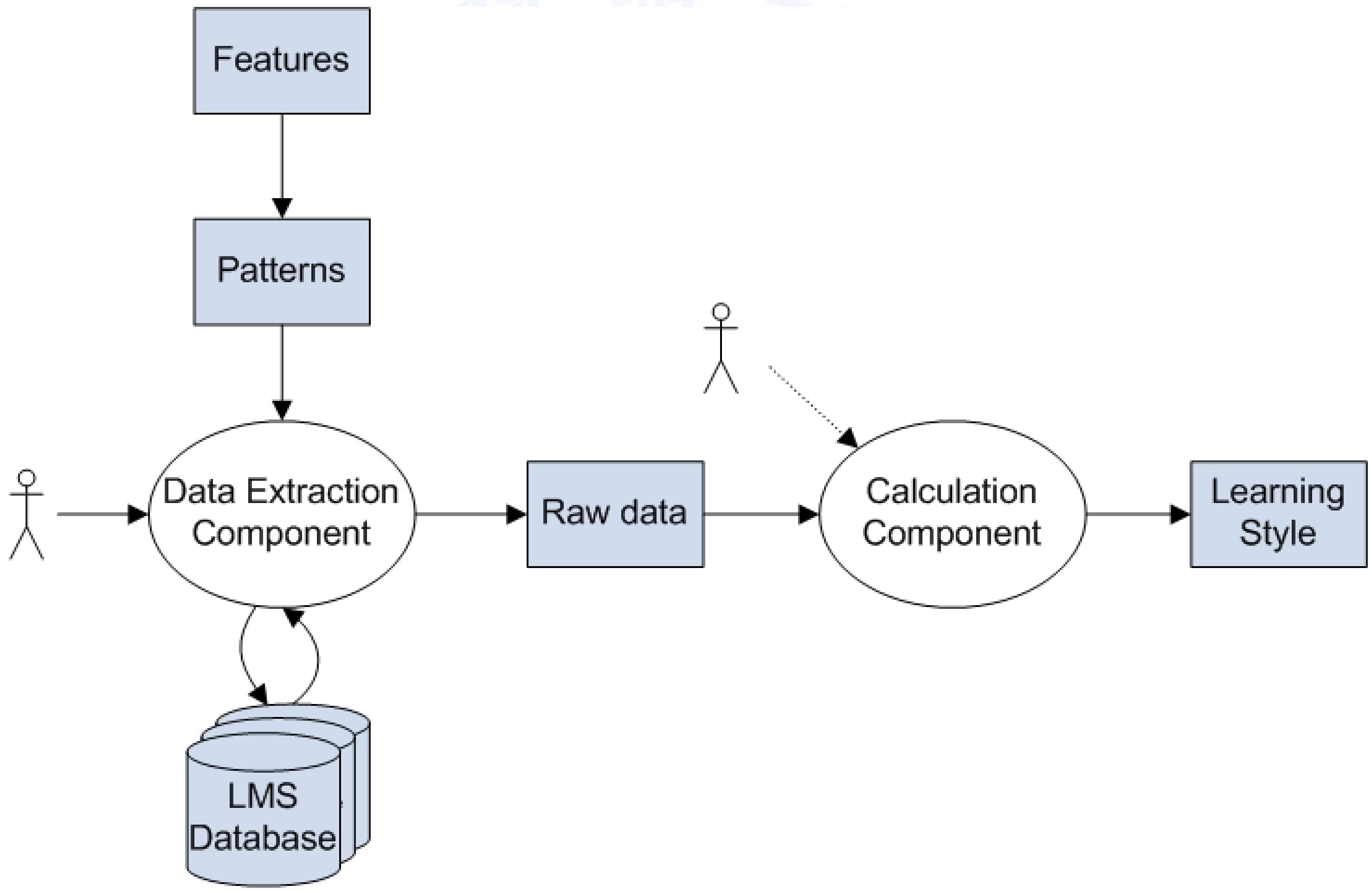
	act/ref	sen/int	vis/ver	seq/glo
data-driven	62.50%	65.00%	68.75%	66.25%
literature-based	**79.33%**	**77.33%**	**76.67%**	**73.33%**

- Literature-based approach → suitable instrument for identifying learning styles

DeLeS – A tool to identify learning style in LMS

- DeLeS = **De**tecting **Le**arning **S**tyles
- Basic concept
  - Define relevant patterns of behaviour
  - Extract data about patterns from the LMS database
  - Use literature-based approach to calculate learning styles based on the gathered data
- Requirements
  - Applicable for LMS in general
    → Usable for different database schemata
    → Deal with missing data since maybe not all information can be tracked by each LMS

Tool Architecture



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Part 2:

How to provide adaptivity?

Research Question

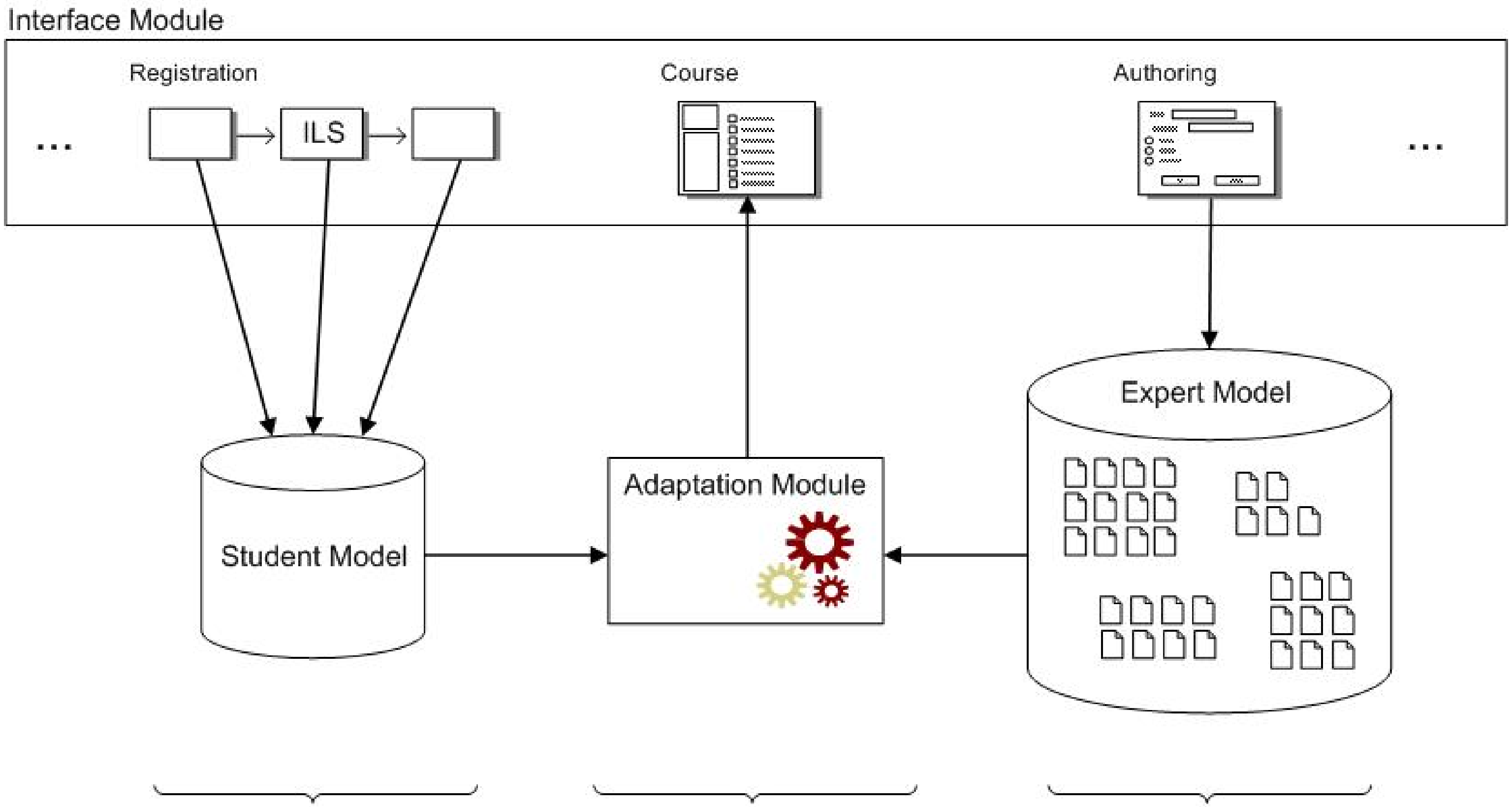
How to extend LMS with adaptivity?

- Develop a concept which enables LMS to automatically generate adaptive courses
- Incorporates only common kinds of learning objects
  - Content
  - Outlines
  - Conclusions
  - Examples
  - Self-assessment tests
  - Exercises

Aims and Benefits

- Teachers can continue using their courses in LMS
- Students get personalized support with respect to their learning styles
- Requirements for teachers
  - Teachers shall have as little as possible additional effort
  - Provide learning objects
    → Excluded the visual/verbal dimension
  - Annotate learning objects (distinguish between the objects)

General Concept for Providing Adaptivity in LMS



Detecting students' information (Extension 1)

Presenting adaptive courses (Extension 3)

Annotating learning objects (Extension 2)

Structure of a course

Chapter 1:

- Examples
- Self-assessment
- Exercises
- Outline
- Content with / without outlines between subchapters
- Conclusion
- Examples
- Self-assessment
- Exercises
- Conclusion

Chapter 2:

...

Adaptation features

- Sequence of examples (before or after content)
- Sequence of exercises (before or after content)
- Sequence of self-assessments (before or after content)
- Sequence of outlines (only once before content or between content)
- Sequence of conclusion (after content or at the end of the chapter)
- Number of examples
- Number of exercises

Adaptations for active/reflective learners

- Active learners
  - Self-assessments before and after content
  - High number of exercises
  - Low number of examples
  - Outline only at the begin of content
  - Conclusions at the end of the chapter
- Reflective learners
  - Outlines between content
  - Conclusion after content
  - Avoid self-assessments before content
  - Examples after content
  - Exercises after content
  - Low number of exercises

Adaptations for sensing/intuitive learners

- Sensing learners
  - High number of examples
  - Examples before content
  - Self-assessment after content
  - High number of exercises
  - Exercises after content
- Intuitive learners
  - Self-assessment before content
  - Exercises before content
  - Low number of exercises
  - Low number of examples
  - Examples after content
  - Outlines only at the begin of content

Adaptations for sequential/global learners

- Sequential learners
  - Outlines only at the begin of content
  - Examples after content
  - Self-assessment after content
  - Exercises after content
- Global learners
  - Outlines between content
  - Conclusion after content
  - High number of examples
  - Avoid self-assessment before content
  - Avoid examples before content
  - Avoid exercises before content

Ambiguous Learning Preferences

- Active/Reflective = +11 → strong active style
- Sensing/Intuitive = -11 → strong intuitive style
- Sequential/Global = -11 → strong global style
- Number of Exercises
  - Active → high number
  - Intuitive → low number
  - Global → no preference

  → Moderate number of exercises

Part 3:

How does adaptive courses effect students' learning?

Evaluation of the Concept

- Implemented add-on for Moodle (Version 1.6.3)
- Evaluated with more than 400 students participating in a course about object-oriented modelling
- Course consisted of
  - Lecture (optional)
  - Practical part - 5 Assignments (compulsory)
  - Online Course in Moodle (optional)
  - Final Exam (compulsory)
- The aim of using a LMS was to provide students with additional learning material and learning opportunities

Evaluation of the Concept

- Randomly assigned to 3 groups:
  - Courses that fit to the students' learning styles (matched group)
  - Courses that do not fit to the students' learning styles (mismatched group)
  - Standard course which includes all learning objects (standard group)
- Procedure
  - Students filled out a learning style questionnaire
  - Adaptive course is automatically generated and presented
  - Students were nevertheless able to access all learning objects and take a different learning path

General Analysis

- Investigated differences of three gropus with respect to
  - Average score on assignments
  - Score on final exam
  - Time spent on learning activities
  - Number of logins
  - Number of visited learning activities
  - Number of requests for additional LOs

→ t-test and u-test

General Analysis

- Results:
  - Average score on assignments & score on final exam
    - no significant difference
  - Time spent on learning activities
    - Standard (5h 34 min) > Matched (3h 47min)
    - Mismatched (5h 33min) > Matched (3h 47min)
  - Number of logins
    - Standard (32 logins) > Matched (28 logins)
  - Number of visited learning activities
    - no significant difference
  - Number of requests for additional LOs
    - Mismatched (8.30%) > Matched (6.59%)

→ Students from the matched group spent significant less time in the course but achieved in average equal grades
→ Demonstrates positive effect of adaptivity

Analysis considering Learning Styles

- Does students with different learning styles benefit from adaptivity in different ways (with respect to performance and behaviour)?
  → Effects of adaptivity for students with different learning styles

- Which students can be supported more effectively by using adaptivity comparing their learning styles?
  → Effectiveness of adaptivity comparing different learning styles

Effects of Adaptivity

- Comparing data from matched and mismatched course with respect to learning styles and behaviour/performance variables
- Learning Styles:
  - Two groups for each dimension (e.g., active and reflective)
- Performance
  - Scores of final exam
- Behaviour
  - Time spent on learning activities
  - Number of logins
  - Number of visited learning activities
  - Number of requests for additional LOs

Effects of Adaptivity

- Results:

4.45 (matched)
6.29 (mism.)

		active	reflective	sensing	intuitive	sequential	global
final_exam	F	2.276	0.451	3.613	0.174	0.793	0.937
	p	0.136	0.504	0.06	0.678	0.376	0.336
time	F	**7.888 ***	3.856	1.754	0.339	**4.271 ***	0.038
	p	**0.006**	0.054	0.189	0.563	**0.043**	0.846
numlogin	F	3.937	0.11	1.28	0.012	1.356	0.014
	p	0.052	0.741	0.262	0.915	0.249	0.906
numLO	F	1.54	**4.639 ***	**4.084 ***	0.509	2.173	0.29
	p	0.219	**0.035**	**0.047**	0.479	0.145	0.592
numALO_p	F	1.486	**4.531 ***	**4.442 ***	1.668	0.867	**5.741 ***
	p	0.227	**0.037**	**0.038**	0.202	0.41	**0.019**

3.81 (ma
6.00 (n

624.73 (m
433.83 (r

413.33 (m
545.17 (r

5.46% (ma
7.91% (m

6.07 (matched)
8.27 (mism.)

6.25 (matched)
8.99 (mism.)

Effectiveness of Adaptivity

- Which students can be supported more effectively by using adaptivity comparing their learning styles?
- Looking only at data from matched course and comparing the students‘ performance and behaviour with respect to their learning styles

Effectiveness of Adaptivity

		act/ref	sen/int	seq/glo
final_exam	F	**8.862 ***	**5.127 ***	0.490
	p	**0.004**	**0.027**	0.486
time	F	**8.063 ***	0.018	0.180
	p	**0.006**	0.893	0.672
numlogin	F	**4.586 ***	3.866	2.806
	p	**0.036**	0.054	0.099
numLO	F	**6.635 ***	1.370	0.003
	p	**0.012**	0.246	0.953
numALO_p	F	2.649	0.131	0.055
	p	0.108	0.718	0.816

166.07 (act.)
184.37 (ref.)

169.98 (sen.)
185.43 (int.)

3.81 (act.)
6.68 (ref.)

27.24 (act.)
31.08 (ref.)

415.21 (act.)
624.73 (ref.)

Conclusions

- Adaptivity based on learning styles can help students in learning
- Adaptivity seems to have different effects for learners with different learning styles
- Findings give a deeper insight in the effects and effectiveness of adaptivity
- Findings show that for some learning styles adaptivity works better than for others, in terms of encouraging them to use the course more intensively and/or letting them achieve better scores.

Questions

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