Considering Learning Styles in Technology Enhanced Learning

Sabine Graf
National Central University
Graduate Institute of Learning and Instruction
Jhongli, Taiwan
sabine.graf@ieee.org

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, cognitive abilities, affective states

- 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 Learning
- Game-based Learning

Outline

- How to identify learning styles in LMS?
- How to provide adaptive support with respect to learning styles in LMS?
- How to get more data in order to improving student modelling and adaptivity?
  - Correlations between behaviour and learning style preferences
  - Relationship between learning styles and cognitive traits
  - Students' behaviour and performance in mismatched courses

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?

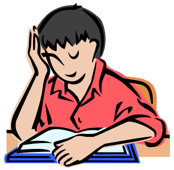
    According to educational theories & experiments → yes

  - Does matching/mismatching courses effect learning?

    According to educational theories → yes
    Experiments provide inconsistent results

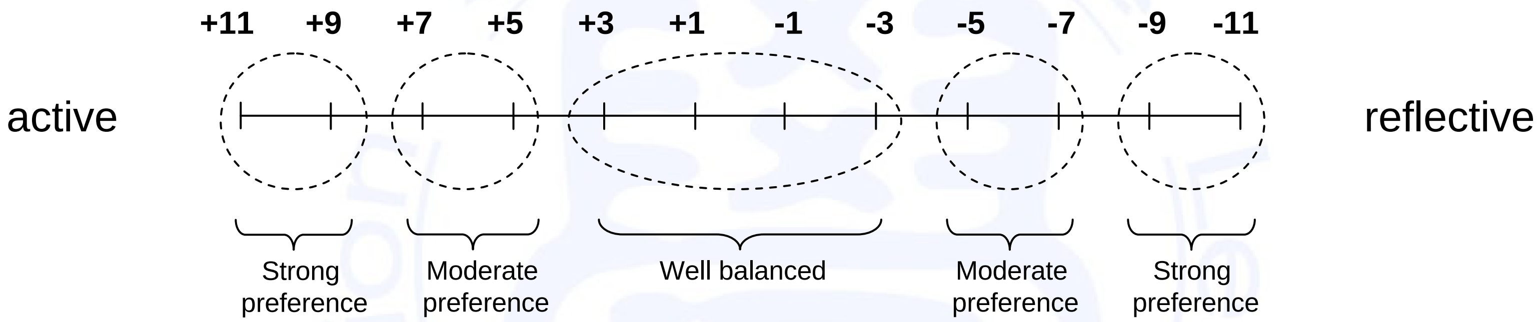
Felder-Silverman Learning Style Model

- 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

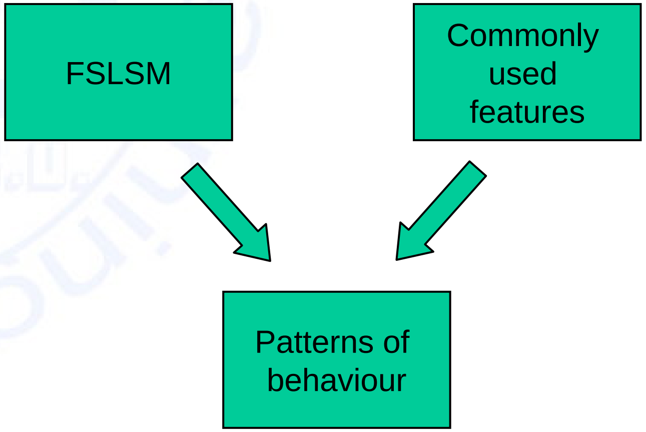
Research Question

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

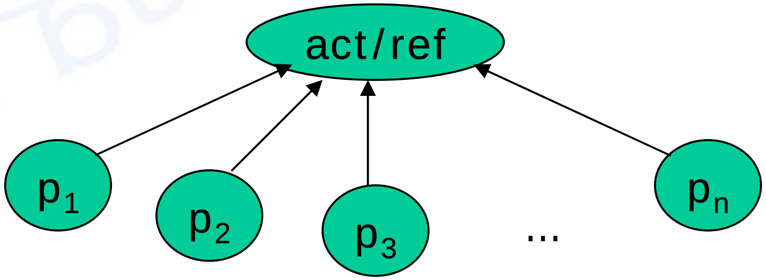
Active/Reflective	Sensing/Intuitive	Visual/Verbal	Sequential/Global
selfass_visit (+)	ques_detail (+)	forum_visit (-)	ques_detail (+)
exercise_visit (+)	ques_facts (+)	forum_stay (-)	ques_overview (-)
exercise_stay (+)	ques_concepts (-)	forum_post (-)	ques_interpret (-)
example_stay (-)	selfass_visit (+)	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:

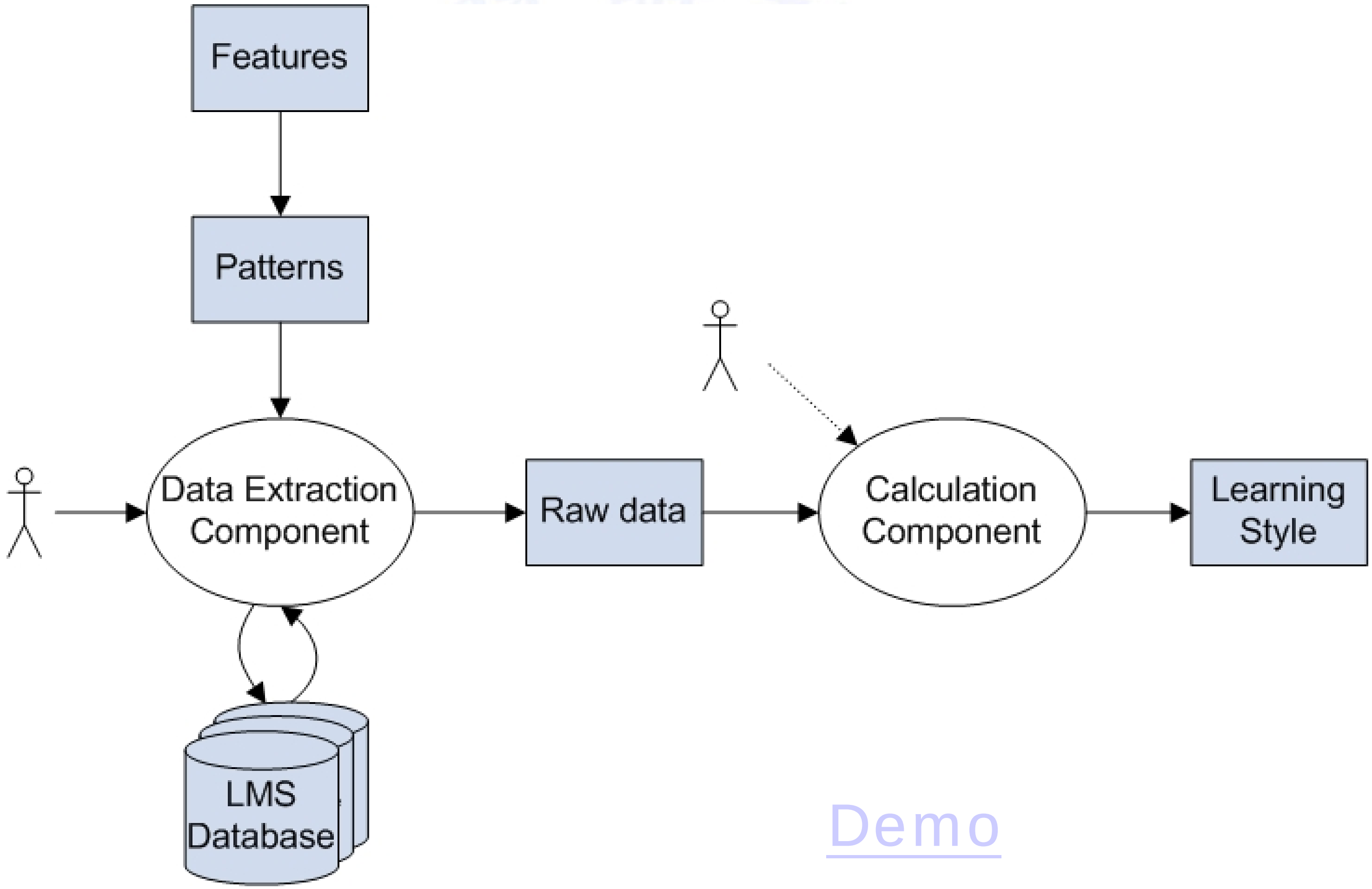
	act/ref	sen/int	vis/ver	seq/glo
data-driven	62.50%	65.00%	68.75%	66.25%
literature-based	**79.33%**	**77.33%**	**76.67%**	**73.33%**

- 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



Demo

Part 2:

How to provide adaptivity?

Research Question

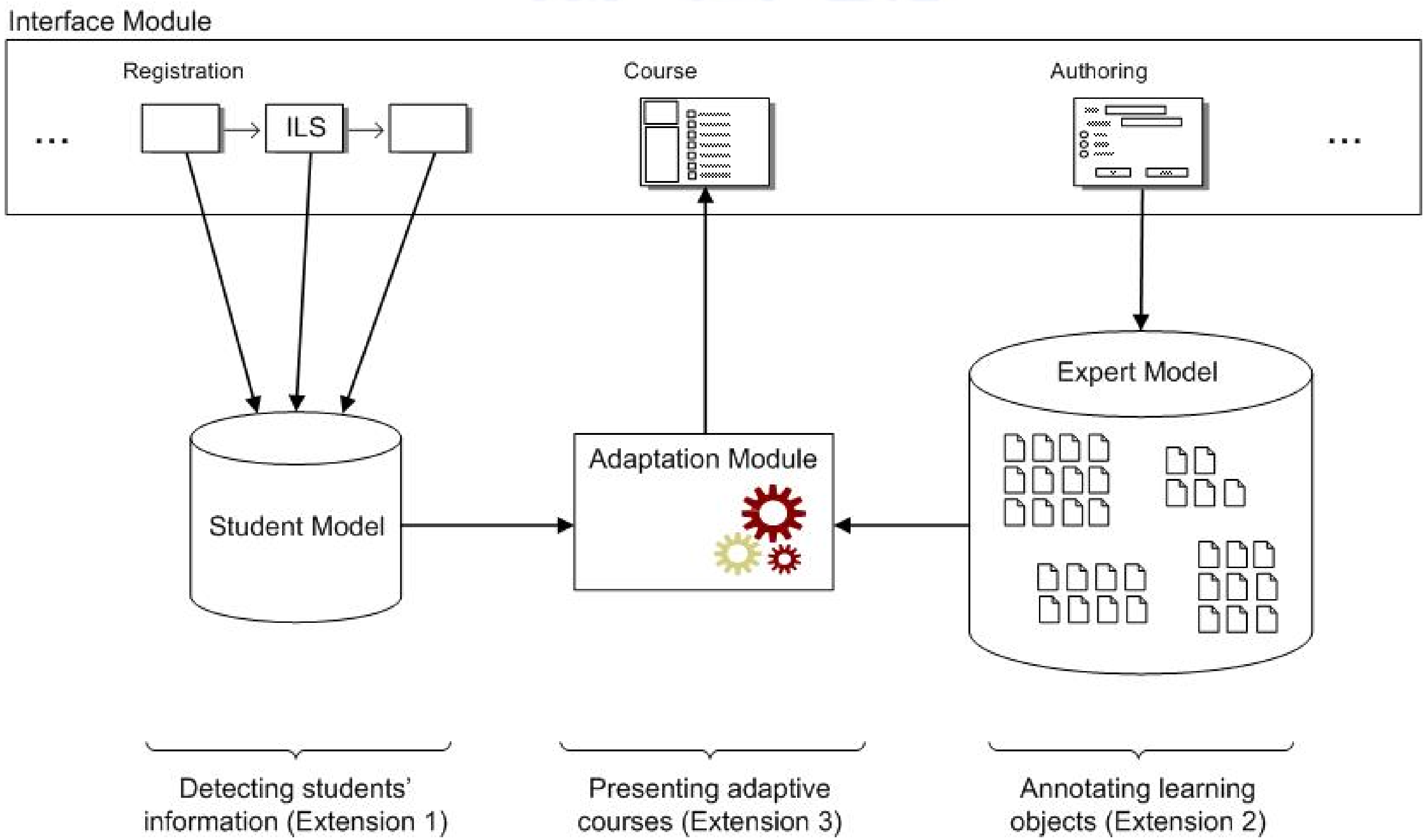
How to extend LMS with adaptivity?

- 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



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

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

Evaluation of the Concept

- 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

Part 3:

How to get more data in order to improve student modelling and adaptivity?

Research Question

How does students with different learning style preference really behave in an online course?

→ Correlations between behaviour and learning style preferences

- This study is based on the data from the object-oriented modelling course
  - Learning Management Systems
  - using only data from the standard course
  - By incorporating only behaviour which is common in TEL, we aim at making our results applicable for TEL in general

Motivation

- Currently, our work and most of the other research works about student modelling and adaptivity are based on the learning style model's description about how students with specific learning styles typically behave
- But most learning style models (including FSLSM) are developed for traditional learning rather than online learning

Benefits from more detailed information

- Student Modelling
  - Automatic approach has several advantages over using learning style questionnaires
    - free of problems regarding inaccurate self-conception
    - Considering data from a time span → more accurate
    - Consideration of changes of learning styles
  - More detailed information about how students really behave in an online environment can make the automatic student modelling approach more accurate
- Adaptive Course Generation
  - More detailed information about how students really prefer to behave can help in developing more precise adaptation features
- Potential of adaptivity regarding learning styles
  - The existance of correlations between behaviour and learning styles gives another indication for the potential of adaptive learning with respect to learning styles

Learning Style Preferences

- Characteristic Preferences within Felder-Silverman Learning Style dimensions (Graf, Viola, Kinshuk, and Leo, 2007)

	active		reflective	
Student 1	Trying things out	Collaborate with others	Reflect about the material	Work alone
Student 2	Trying things out	Collaborate with others	Reflect about the material	Work alone
Student 3	Trying things out	Collaborate with others	Reflect about the material	Work alone

Learning Style Preferences

- Derived Semantic Groups from the learning style model (Graf, Viola, Kinshuk, Leo, 2007)
- Verifying Semantic Groups by Fisher Linear Discriminant Analysis and empirical frequencies analysis

Style	Semantic group	ILS questions (answer a)	Style	Semantic group	ILS questions (answer b)
Active	trying something out social oriented	1, 17, 25, 29 5, 9, 13, 21, 33, 37, 41	Reflective	think about material impersonal oriented	1, 5, 17, 25, 29 9, 13, 21, 33, 41, 37
Sensing	existing ways concrete material careful with details	2, 30, 34 6, 10, 14, 18, 26, 38 22, 42	Intuitive	new ways abstract material not careful with details	2, 14, 22, 26, 30, 34 6, 10, 18, 38 42
Visual	pictures	3, 7, 11, 15, 19, 23, 27, 31, 35, 39, 43	Verbal	spoken words written words difficulty with visual style	3, 7, 15, 19, 27, 35 3, 7, 11, 23, 31, 39 43
Sequential	detail oriented sequential progress from parts to the whole	4, 28, 40 20, 24, 32, 36, 44 8, 12, 16	Global	overall picture non-sequential progress relations/connections	4, 8, 12, 16, 28, 40 24, 32 20, 36, 44

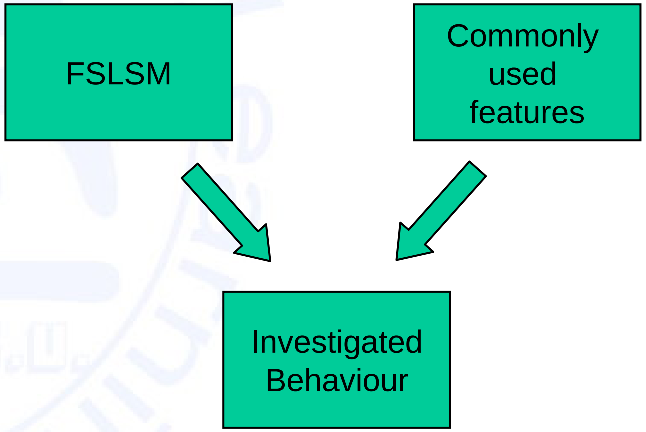
→ Allows building a more accurate model of the student

Design of the Study

- Object oriented modelling course at an university in Austria
- Only data from students in the standard course were used (75 students)
- Moodle was used to provide additional learning material and learning opportunities
- Students need to perform 5 assignments and a final exam
- Student interaction with Moodle was tracked
- Students filled out the ILS questionnaire for providing information about their learning style preferences

Investigated Behaviour

- Incorporates only behaviour based on commonly used features in TEL
  - Content
  - Outlines
  - Examples
  - Self-assessment tests
  - Exercises
  - Discussion Forum
  - Navigation
  - General Patterns



Patterns of Behavior

- Content objects
  - Number of visits
  - Time student spent on content objects
  - Time student spent on content objects including graphics
  - Time student spent on content objects including only text
- Outlines
  - Number of visits
  - Time spent on outlines
- Self-assessment tests (SA-Tests)
  - Number of tests performed
  - Whether all available tests were performed at least once
  - Results on tests
  - Number of questions a learner answers twice wrong
  - Number of revisions before submission
  - Time spent on the test
  - Time a learner checked his/her results
  - Results on specific kinds of questions (facts/concepts, detail/overview, graphics/text, interpreting predefined solutions/generating new solutions)

Patterns of Behavior

- Exercises
  - Number of visits
  - Time students spent on exercises
  - Results on exercises
  - Number of revisions before submission (in combination with SA-Tests)
  - Results on questions about interpreting predefined solutions/generating new solutions (in combination with SA-Tests)
- Examples
  - Number of visits
  - Time spent on examples
- Discussion Forum
  - Number of visits
  - Time spent in the forum
  - Number of postings

Patterns of Behavior

- Navigation
  - Number of times, students skipped learning objects
  - Number of times, students jumped back to the previous learning object
  - Number of visits of the course overview page
  - Time students spent on the course overview page
- General Patterns
  - Scores on final exam
  - Scores on compulsory assignments
  - Overall time students spent in the course
  - Number of logins
  - Overall number of visited learning objects

Method of Analysis

- For calculating correlations between behaviour and learning style preferences, rank correlation analysis was used (Kendall‘s tau)

Results – Active/Reflective Dimension

trythingsout	social oriented	think about material	impersonal oriented
	forum_visit (-)		forum_visit (+)
	forum_stay (-)		forum_stay (+)
	quiz_que_codedev (-)		exercise_score (+)
	content_stay (-)		content_stay (+)
	nav_skip (-)		nav_skip (+)

Results – Sensing/Intuitive Dimension

existing ways	concrete material	careful with details	new ways	abstract material	not carefule with details
exercise_score (-)	exercise_score (-)	forum_visit (+)	selfass_visit (-)	exercise_score (+)	selfass_ques_detail (-)
slides_visit_diff (+)		selfass_ques_detail (+)	exercise_score (+)	quiz_ques_codedev (+)	selfass_ques_conceptual (-)
		selfass_ques_factual (+)	slides_visit_diff (-)		selfass_ques_text (-)
		selfass_ques_conceptual (+)	course_time (-)		selfass_visit (-)
		selfass_ques_graphics (+)			selfass_score (-)
		selfass_ques_text (+)			exercise_visit (-)
		selfass_visit (+)			exercise_stay (-)
		selfass_visit_diff (+)			quiz_ques_codeint (-)
		selfass_score (+)			exam_score (-)
		exercise_visit (+)			course_time (-)
		exercise_stay (+)			course_activities (-)
		quiz_ques_codeint (+)			
		slides_visit_diff (+)			
		nav_overview_stay (+)			
		course_time (+)			
		course_login (+)			
		course_activities (+)			

Results – Visual/Verbal Dimension

pictures	spoken words	written words	difficulty with visual style
	selfass_ques_overview (+)	example_visit (-)	forum_post (+)
		example_visit_diff (-)	exercise_visit (-)
		example_stay (-)	exercise_stay (-)
			outine_stay (-)

Results – Sequential/Global Dimension

detail oriented	sequential progress	from parts to the whole	overall picture	non-sequential progress	relations/connections
navigation_back (-)	forum_visit (+)	quiz_revision (-)	nav_back (+)	forum_visit (-)	slides_visit_diff (-)
navigation_overview_visit (-)	forum_stay (+)	assignment_score_avg (-)		forum_stay (-)	
	selfass_ques_graphics (+)			forum_post (-)	
	selfass_visit (+)			selfass_ques_overview (-)	
	selfass_visit_diff (+)			selfass_ques_factual (-)	
	slides_visit_diff (+)			selfass_ques_conceptual (-)	
	nav_overview_stay (+)			selfass_ques_graphics (-)	
	course_time (+)			selfass_ques_text (-)	
	course_login (+)			selfass_visit (-)	
	course_activities (+)			selfass_score (-)	
				selfass_visit_diff (-)	
				nav_skip (-)	
				nav_overview_stay (-)	
				course_time (-)	
				course_login (-)	
				course_activities (-)	

Conclusions from this Study

- Comparison of our results with other studies (e.g., usage of adaptation features, automatic student modelling, ...)
  - Some of our results are in agreement with existing studies
  - Some are in agreement with FSLSM but are not typically used by studies
  - Some are not explicitly mentioned by FSLSM but appear in our data
- Resulting correlations can contribute in adaptive learning by
  - showing that students with different learning style preferences behave differently in TEL
    → give another indication for the potential of adaptivity based on learning styles
  - providing more information in order to develop more precise adaptation features
  - providing more information in order to improve automatic student modelling

Research Question

How to improve the detection process of learning styles by the use of additional sources?

- The aim is to use additional source in order to get more information to identify learning style more accurately
- Examplarily, we investigated the relationship between learning styles and working memory capacity

Cognitive Abilities/Traits

- Cognitive abilities are abilities to perform **any of the functions involved in cognition** whereby cognition can be defined as the mental process of knowing, including aspects such as awareness, perception, reasoning, and judgment (Colman, 2006; Pickett, 2001)
- Cognitive abilities are more or less stable over time
- Important abilities for learning
  - Working memory capacity
  - Inductive reasoning ability
  - Information processing speed
  - Associative learning skills

Relationship between Cognitive Traits (CT) and Learning Styles (LS)

Why shall we relate cognitive traits and learning styles?

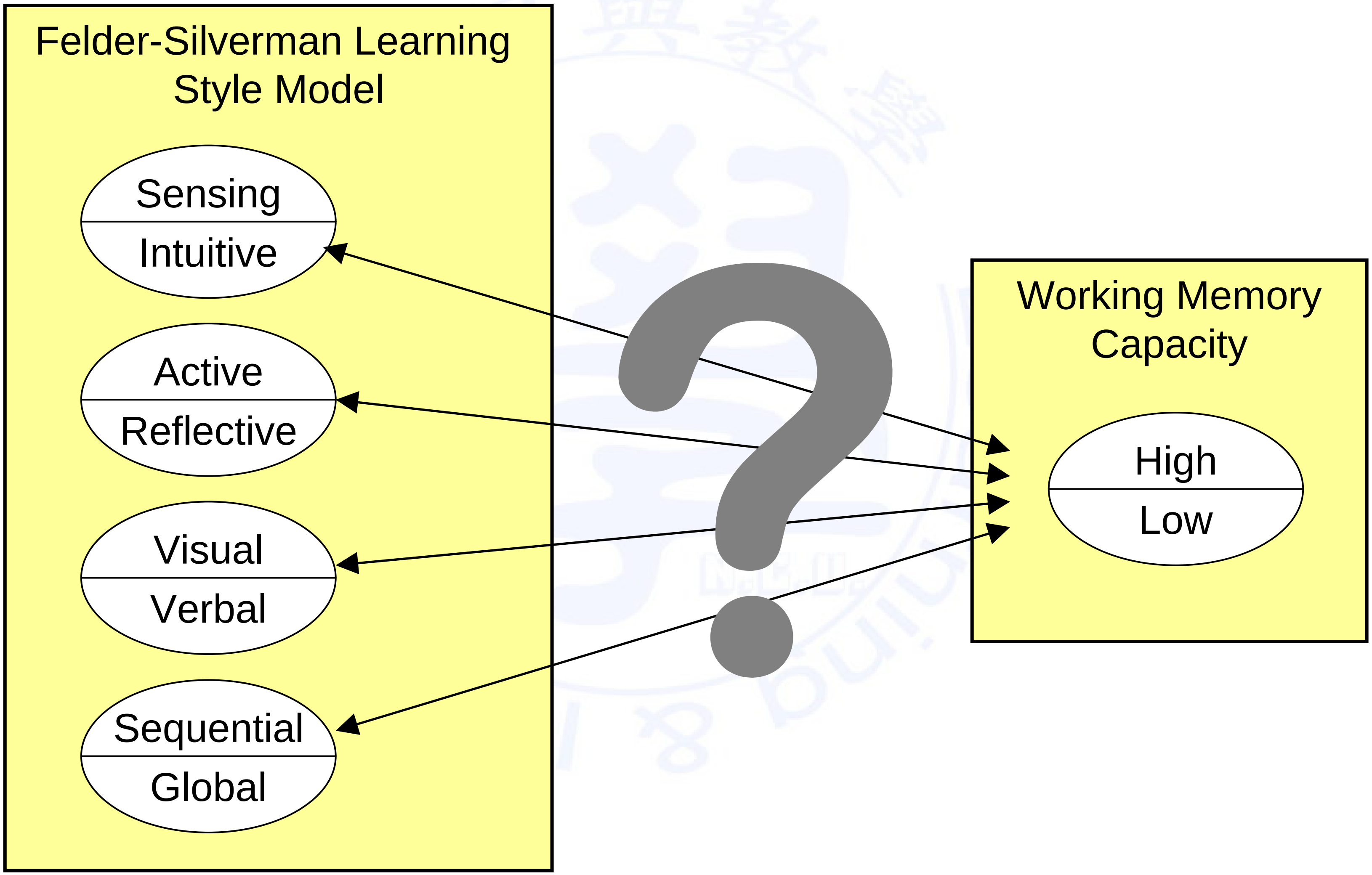
- Case 1: Only one kind of information (CT and LS) is considered
  → Get some hints about the other one

CT → LS or LS → CT

- Case 2: Both kinds of information are considered
  → The information about the one can be included in the identification process of the other and vice versa
  → The student model becomes more reliable

Detection of CT ← … … … LS and Detection of LS ← … … … CT

Relationship between FSLSM and WMC

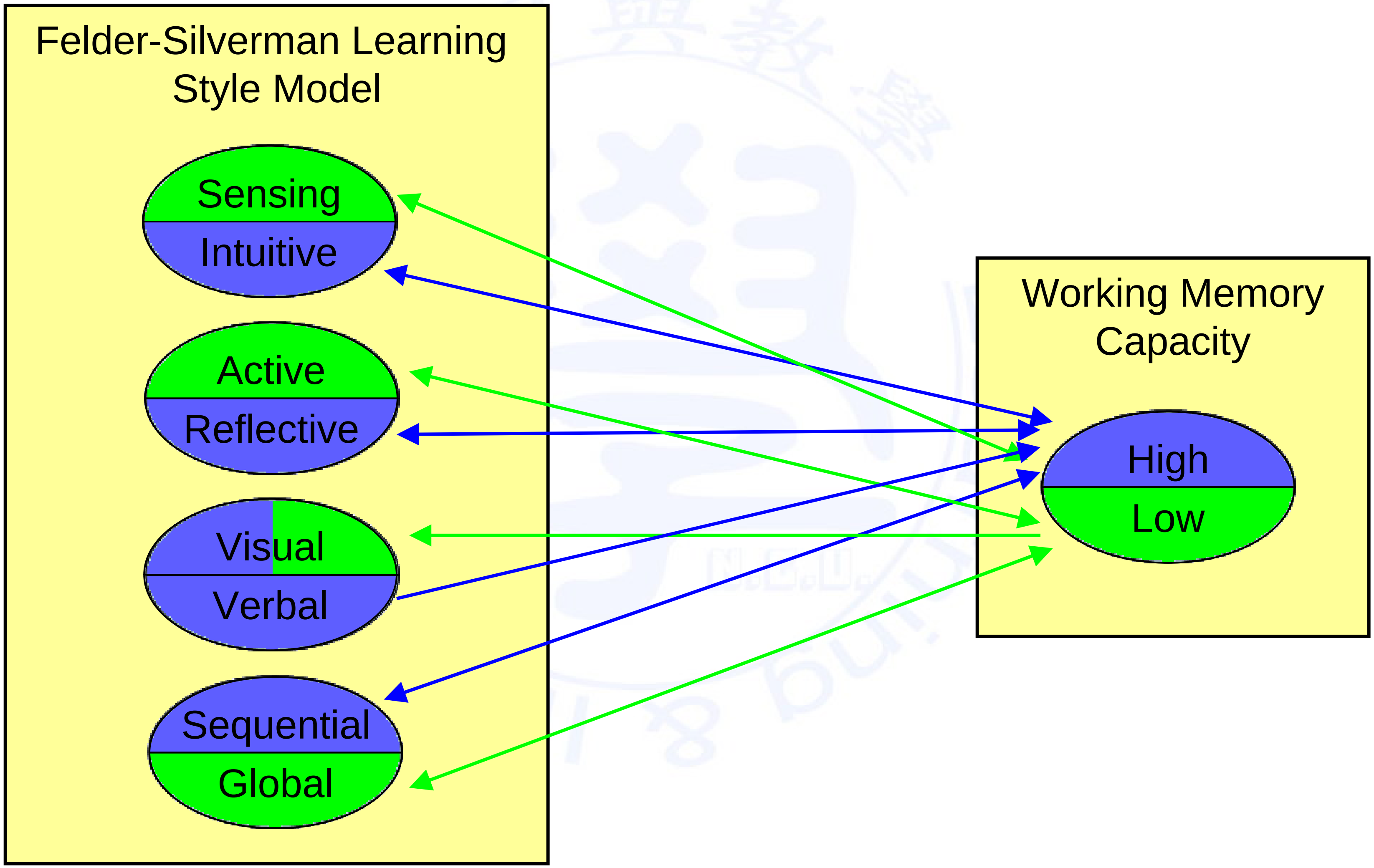


Literature Research

	High WMC	Low WMC
Felder-Silverman Learning Style Dimensions	**Reflective**	**Active**
	Beacham, Szumko, and Alty (2003) Hadwin, Kirby, and Woodhouse (1999) Kolb (1984) Summervill (1999) Witkin et al. (1977)	
	Intuitive	**Sensing**
	Bahar and Hansell (2000) Davis (1991) Ford and Chen (2000) Hudson (1966) Kinshuk and Lin (2005) Scandura (1973) Witkin et al. (1977)	
	Verbal or Visual	**Visual**
	Beacham, Szumko, and Alty (2003) Simmons and Singleton (2000) Wey and Waugh (1993)	
	Sequential	**Global**
	Beacham, Szumko, and Alty (2003) Ford and Chen (2000) Huai (2000) Liu and Reed (1994) Mortimore (2003) Witkin et al. (1977)	

	High WMC	Low WMC
Cognitive Styles	Field-independent	Field-dependent
	Al-Naeme (1991) Bahar and Hansell (2000) El-Banna (1987) Pascual-Leone (1970)	
	Divergent	Convergent
	Bahar and Hansell (2000)	
	Serial	Holistic
	Huai (2000)	

Relationship between FSLSM and WMC

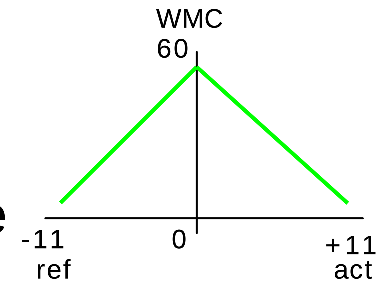


Verifying the relationship

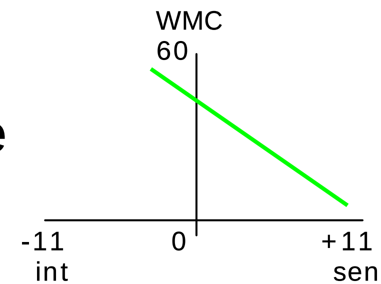
- Participants
  - 225 students from Austria
- Detecting learning style
  - ILS questionnaire
- Detecting working memory capacity
  - WebOSpan Task

Results

- Active/reflective:
  - Low WMC <-> strong active preference
  - Low WMC <-> strong reflective preference
  - High WMC <-> balanced learning preference



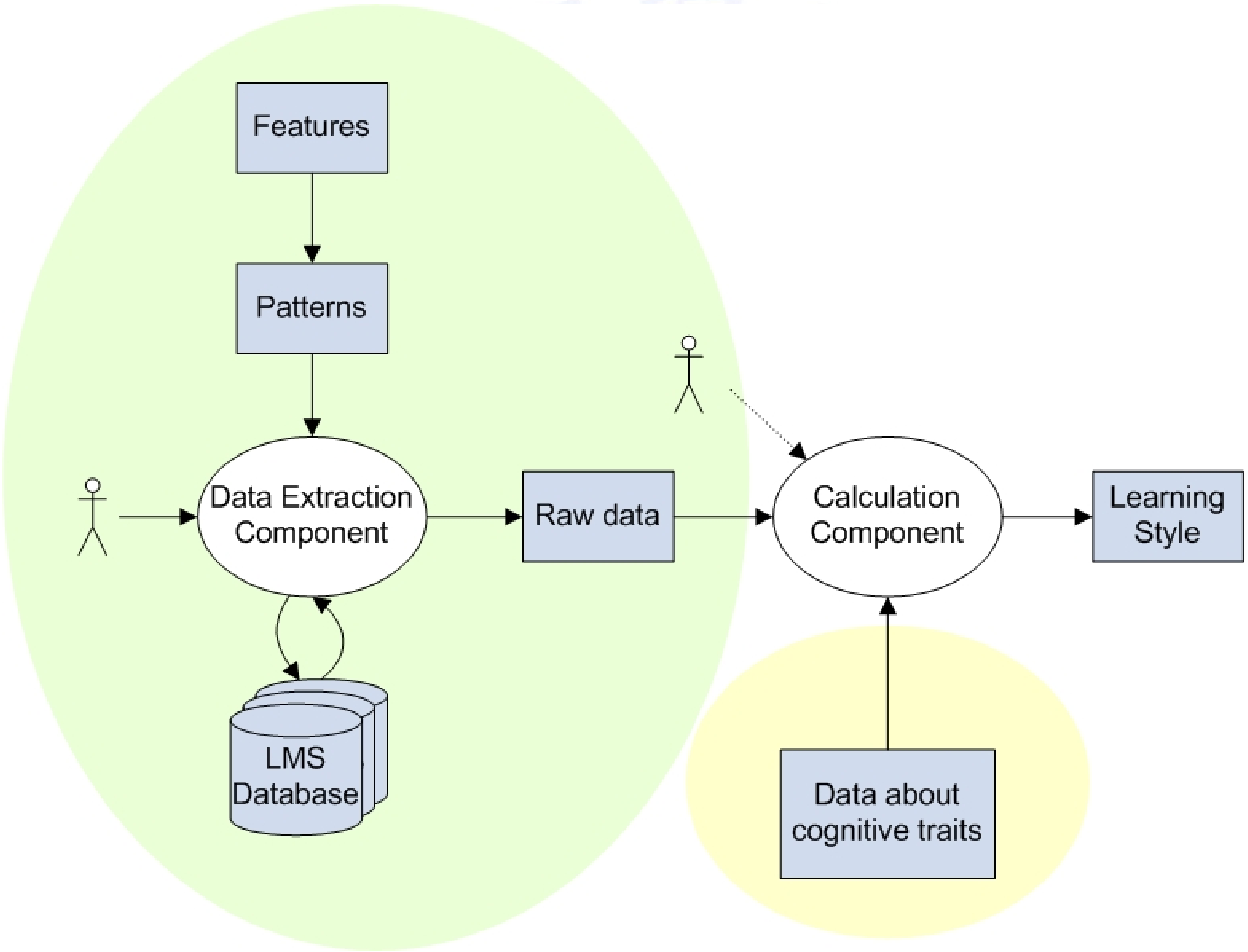
- Sensing/intuitive:
  - Low WMC <-> sensing learning preference
  - High WMC <-> balanced learning preference



- Visual/verbal:
  - Low WMC -> visual learning preference
  - Verbal learning preference -> high WMC
- Sequential/Global:
  - No relationship found

→ Identified relationships can be included in the detection process of learning styles and cognitive traits

Using the information in DeLeS



國立中央大學學習與教學研究所
Graduate Institute of Learning & Instruction
National Central University

Research Question

How does students in mismatched courses behave and learn?

→ Investigate the relationship between students' learning styles, their behaviour in the course, and their achievement in a mismatched course

- Find out which learners need more help in mastering mismatched courses
- Get a better understanding about how students with good and poor achievement learn, considering their learning styles
- Provide information about how to identify learners who might have difficulties in learning

Motivation and Aim

- Two different ways to provide adaptivity based on learning styles
  - Provide students with courses that fit their learning styles → short-term goal
  - Provide students with guidance and help them to develop skills to be able to learn from mismatched courses → long-term goal
- Most adaptive systems focus on the short-term goal, namely providing courses which are matched to their learning styles
- This study focuses on what happens if learning styles are not considered/matched

Sub-Questions

1. Does the strength of learning style preferences have an impact on students' achievement?

2. Which learning styles have an impact on students' achievement?

3. How does students with different learning styles and different achievement behave in a mismatched course and does their strategies give indications about their achievement?

Experiment Design

- Study was done within a project about enriching learning management systems with adaptivity regarding learning styles
- Course about object-oriented modelling
- In the project, learners were divided into 3 groups and presented with a
  - Matched course
  - Mismatched course
  - Standard course
- In this study, we focus only on data from the mismatched course (72 students)

Impact of Strengths of Learning Styles

Sub-Question:
Does the strength of learning style preferences have an impact on students' achievement?

Method:
- Based on the results of ILS, two groups were built:
  - Students who have a strong learning style preference (greater than +5 or smaller than -5) at least for one dimension
  - Students who have only weak learning style preferences
- Scores of the final exam were used for measuring the achievement

Impact of Strengths of Learning Styles

Results:

	N	Mean Scores	T	p
One or more strong preferences	39	174.26	**2.521**	**0.014**
Only weak preferences	33	190.97		

→ Learners with at least one strong learning style preference achieve significantly lower scores than learners with only weak preferences

→ Learners with strong learning style preferences need more support in a mismatched course

Correlations between Learning Styles and Achievement

Sub-Question:

Which learning styles have an impact on students' achievement?

Method:

Rank correlation analysis between achievement (scores on final exam) and learning style preferences (ILS questionnaire)

Correlations between Learning Styles and Achievement

Results:

		active/reflective	sensing/intuitive	sequential/global
Kendall	tau	**-0.187**	-0.063	-0.006
	p	**0.028**	0.456	0.941
Spearman	rho	**-0.266**	-0.095	-0.015
	p	**0.024**	0.425	0.900

→ act/ref dimension is significantly correlated with achievement, indicating that active learners have more problems in mismatched courses than reflective learners

Students' behaviour in relation to their learning styles and achievement

Sub-Question:

How does students with different learning styles and different achievement behave in a mismatched course and does their strategies give indications about their achievement?

Method:

- Behaviour:
  - Time students spent in the course
  - Number of logins
  - Number of visited learning objects (LO)
  - Number of requests for additional learning objects
- Achievement: scores on final exam (building two groups based on average score)
- Learning style preferences: ILS values (building two groups, using a threshold of 0)

Students' behaviour in relation to their learning styles and achievement

Method:

Analysis 1:

looking at difference in behaviour patterns between students with the same achievement but different learning style preferences on a dimension

e.g., active (high score) and reflective (high score)
active (low score) and reflective (low score)

Analysis 2:

looking at differences in behaviour patterns between students with same learning styles but different achievement

e.g., active (low score) and active (high score)
reflective (low score) and reflective (high score)

Analysis 3:

looked at correlations between behaviour patterns and achievement for each of the six learning styles

Summary of Results

- Students with different learning styles and different achievement chose different strategies of behaviour in the mismatched course

- Analysis1:
  - Seq_{high} visited more LOs than Glo_{high}
    → sequential learners like to go through the LOs step by step without skipping them
  - Glo_{low} asked more often for additional LOs than Seq_{low}
    → although global learners like little guidance, it seems that they easily search too much for additional LOs which has a negative effect on their learning outcome
  - Seq_{high} logged in more often than Glo_{high}
  - Seq_{low} logged in more often than Glo_{low}

Summary of Results

- Analysis2:
  - Ref_{high}, Int_{high}, and Seq_{high} spent more time in the course and visited more LOs than learners with low scores
  - Glo_{high} asked less often for additional LOs than Glo_{low}

Analysis1 & Analysis2:

→ Show which strategies are used by learners with high and low scores, considering different learning styles

→ Only allows to infer behaviour from learning styles and achievement

Summary of Results

- Analysis3 additionally
  - allows to predict the achievement from the behaviour
  - shows which strategies lead to good achievement for each learning style and therefore are able to recommend good strategies
  - shows which strategies lead to poor achievement and helps therefore to identify student who might have difficulties in learning

Summary of Results

- Results of Analysis 3 show
  - Positive correlation for reflective, sensing and sequential learners between achievement and time as well as number of visited LOs

    → good indicator for identifying learning difficulties/frustration (since their behaviour is then not in line with their typical behaviour)
  - Positive correlation for sequential learners between achievement and requests for additional LOs

    → Shows that seq. learners can benefit from not going step-by-step through a mismatched course (although they would prefer it)

Conclusions of this Study

- Learners with strong learning style preferences have more difficulties
- Active learners have more difficulties than reflective learners
- Learners with different learning style and achievement behave differently in the course
- Differences help in getting a better understanding about the relationship between students' learning styles, behaviour, and achievement
- Correlations were found between behaviour and achievement for some learning styles, allowing conclusions from the behaviour to the achievement and therefore identifies behaviour which leads to learning difficulties as well as shows which behaviour leads to positive learning outcome

Questions

Sabine Graf
http://lrn.ncu.edu.tw/sabine/
sabine.graf@ieee.org