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Improving Adaptivity in Learning Through Cognitive Modeling

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Adaptivity

Increased user efficiency, effectiveness and satisfaction

by

Improved correspondence between learner, goal and system characteristics

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Adaptive				*Adaptable*
System initiated *adaptivity* (No user control)	System initiated adaptivity with pre-information to the user about the changes	User selection of adaptation from system suggested features	User desired adaptability supported by tools (and performed by the system	User initiated *adaptability* (No system initiation)

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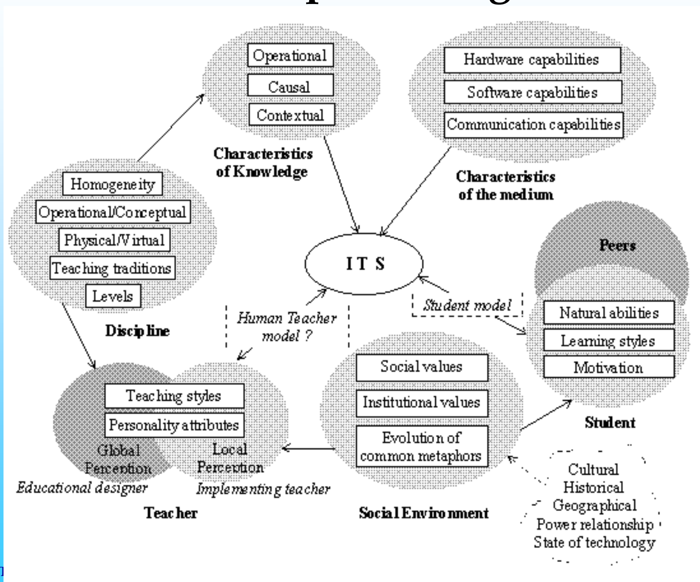
Overall Adaptation Agenda



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Directions in Adaptation

Individualised learning - Bridging the gap among different types of learners

- Human teacher model (designer teacher and local implementer teacher)
- Content based adaptation
- Adaptation in mobile learning
- User exploration adaptation
- Cognitive Trait Model
- Learning Styles & Cognitive Traits

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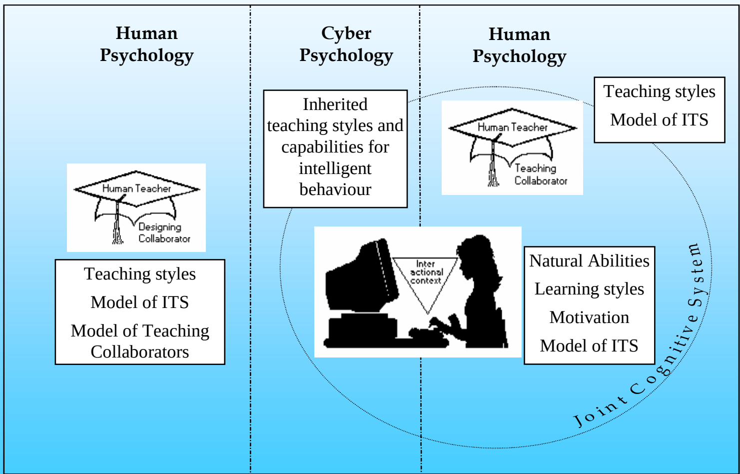
Human Teacher Model



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Content based adaptation

Multiple Representation Approach

- Multimedia object selection
- Navigational object selection
- Integration of multimedia objects

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Adaptation in mobile learning environments

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Traditional E-learning Environment

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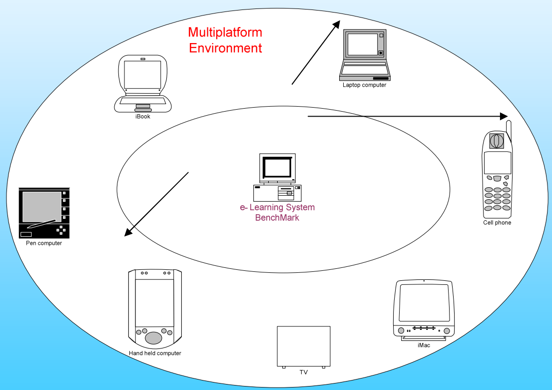
Changing Platforms



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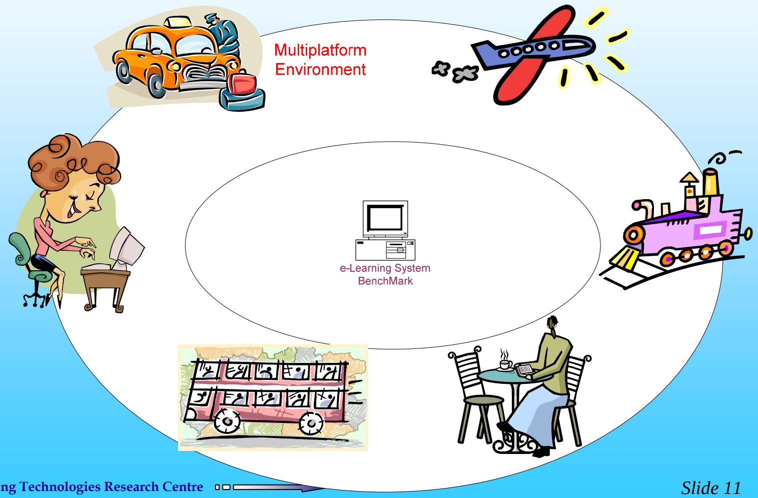
Changing Environment



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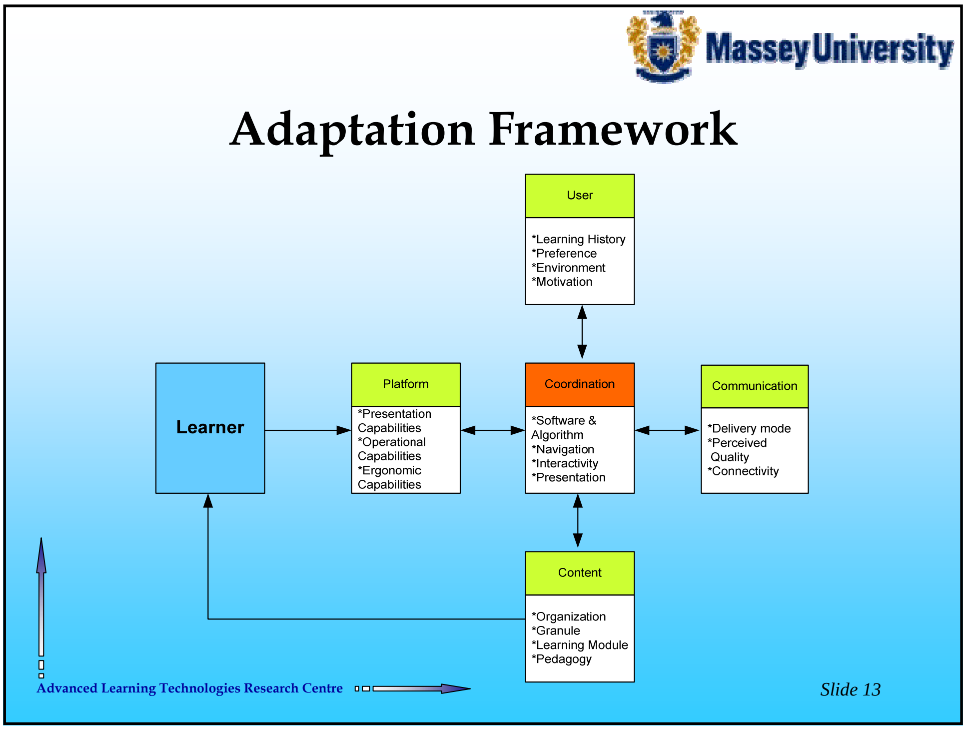
Motivation

- Need of an adaptation framework in multiplatform environment.
- There is a need to identify **environmental factors** that influence learning experience in a multiplatform environment.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Adaptation Framework
User
*Learning History
*Preference
*Environment
*Motivation
Learner
Platform
*Presentation Capabilities
*Operational Capabilities
*Ergonomic Capabilities
Coordination
*Software & Algorithm
*Navigation
*Interactivity
*Presentation
Communication
*Delivery mode
*Perceived Quality
*Connectivity
Content
*Organization
*Granule
*Learning Module
*Pedagogy
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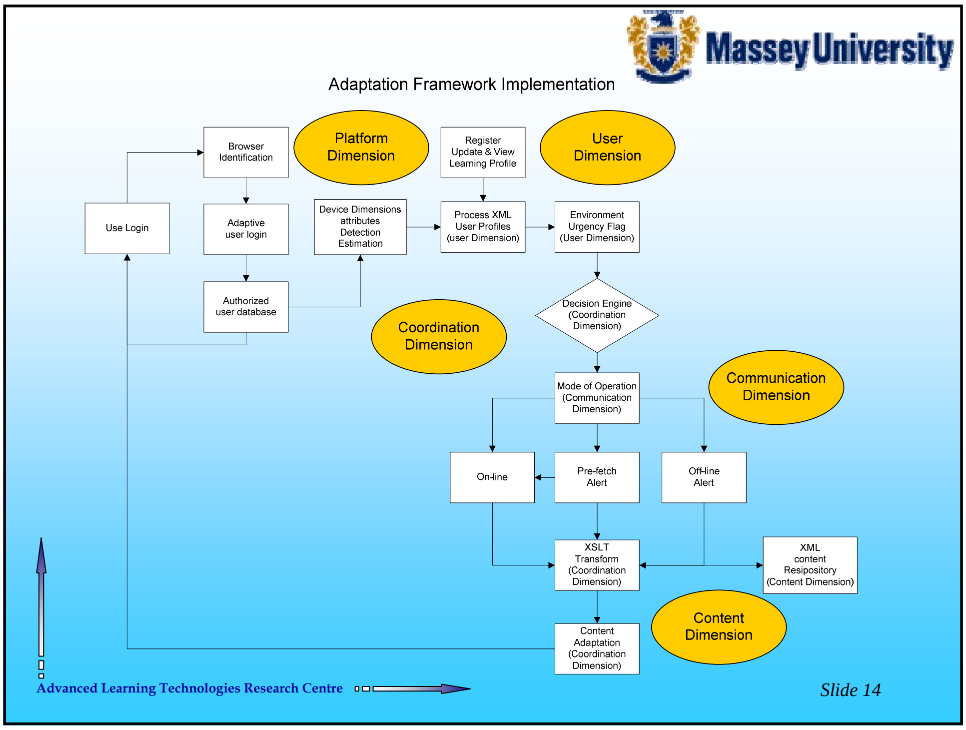
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Adaptation Framework Implementation
Browser Identification
Platform Dimension
Register Update & View Learning Profile
User Dimension
Use Login
Adaptive user login
Device Dimensions attributes Detection Estimation
Process XML User Profiles (user Dimension)
Environment Urgency Flag (User Dimension)
Authorized user database
Coordination Dimension
Decision Engine (Coordination Dimension)
Mode of Operation (Communication Dimension)
Communication Dimension
On-line
Pre-fetch Alert
Off-line Alert
XSLT Transform (Coordination Dimension)
XML content Resipository (Content Dimension)
Content Dimension
Content Adaptation (Coordination Dimension)
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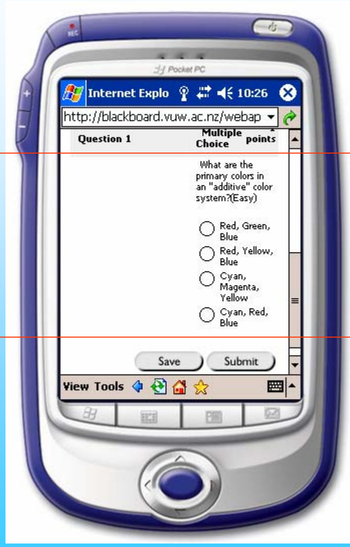
Blackboard PDA Access



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- Adapted version
- Learner directed to assessment page.
- Layout is better.

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- Adapted version
- System provides animated gif if no flash was detected.

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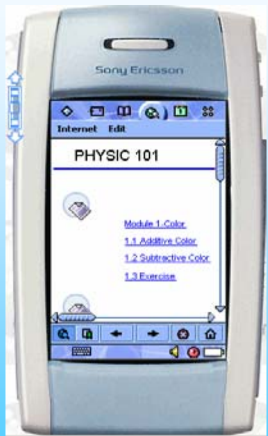

- No script support
- Unable to access Blackboard site.
- Able to access Adapted site.

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Directions in Adaptation

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- Cognitive Trait Model
- Learning Styles & Cognitive Traits

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Adaptation in Exploration

Exploration Space Control
and
Cognitive Modelling

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Problems in educational exploration

- Learners should be free to explore to "construct" learning (Carroll et al.,1985).
- However, learners may not know what to and how to explore.
- Cognitive overload - Excessive mental efforts in integrating information from different resources.
- Exploration space too wide – *Lost in Hyperspace*.

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Exploration space

Extent of the exploration activity

=

Extent of the information resources (including the domain concepts/knowledge)

+

Exploration operations (such as search, selection, apply, integration etc.)

This is called exploration space.

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Need for Cognitive Support

Exploration Space Control

- Prevents discouragement to learning caused by cognitive overload.
- Prevents boredom of learning caused by oversimplified content.
- Supports both cognitively challenged and active learners.

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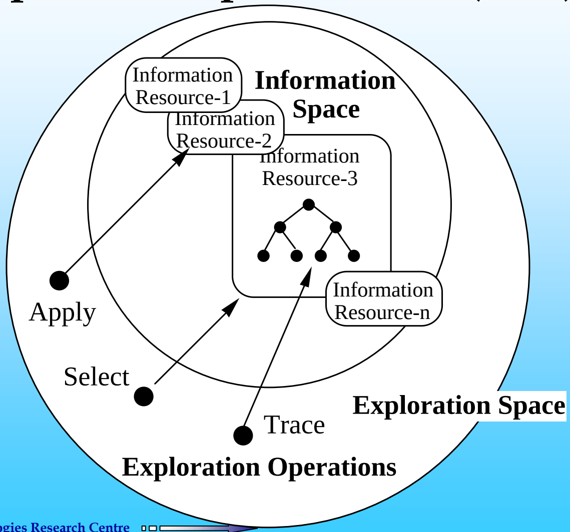
Exploration space control (ESC)



ESC Control Levels

- Embedding information: This facilitates the creation of information space and involves scaffolding.
- Limiting information resources:
  - Limiting number of information resources
  - Selecting types of information resources appropriate for looking into current domain material

ESC Control Levels

- Limiting exploration paths:
  - Limiting the number of feasible exploration paths to be looked into
  - Limiting the exploration paths which are non-feasible or are unrelated to the current domain material
- Limiting information to be presented:
  - Limiting the amount of information.
  - Adapting the contents of information to each learner

Designing systems with ESC

1. Identification of learning goals to be accomplished by the learners
2. Selection of scaffolding methods
   a. Selecting various information resources (e.g. hypertext, simulation, images)
   b. Developing the information resources based on amount of information and contents of information
   c. Selecting various exploration operations

Designing systems with ESC

3. Deciding application of control levels according to learner and domain models

Learner model factors:

- Preferences
- Knowledge Levels
- Competence
- Exploration Process
- Cognitive Load (Mental Efforts)

Domain model factors:

- Type of knowledge (know-how, know-why …)
- Degree of detail (Granularity)
- Depth (Deep or Shallow)

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ESC and Student Model

- ESC assumes that the system is able to correctly identify the information about a particular student.
- Existing student models are good in inferring competency level and external preferences, but there is a need for better modelling of individual differences in cognitive processing.

Cognitive Trait Model

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Cognitive Trait Model

Attempts to create profiles of learners in terms of their cognitive traits such as **working memory capacity**, **inductive reasoning ability**, etc. in order to allow learning systems to provide adaptivity accordingly.

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CTM could

- be transferable across different domains;
- be persistent and stays valid in long duration of time;
- be used to provide adaptivity to suit individual learner's cognitive capacity;
- be used to supplement existing performance-based models.

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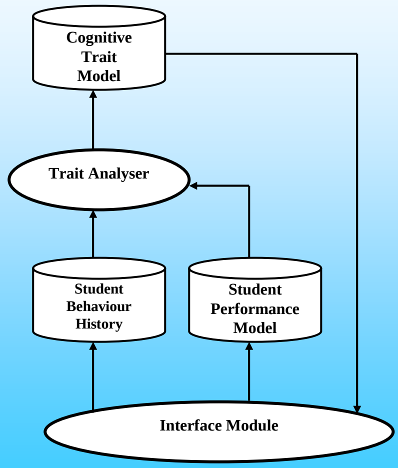
Cognitive Traits

- **Working Memory Capacity:** allows us to keep active a limited amount of info (7+/-2 items) for short time (Miller, 1956).
- **Inductive Reasoning Ability:** is the ability to construct concepts from examples.
- **Information Processing Speed:** determines how fast the learners acquire the information correctly.
- **Associative Learning Skill:** is the skill to link new knowledge to existing knowledge.
- **Domain Experience:** is the familiarity of the domain concepts and skills.
- **Domain Complexity:** is the student perception regarding difficulty of the concepts in the domain.

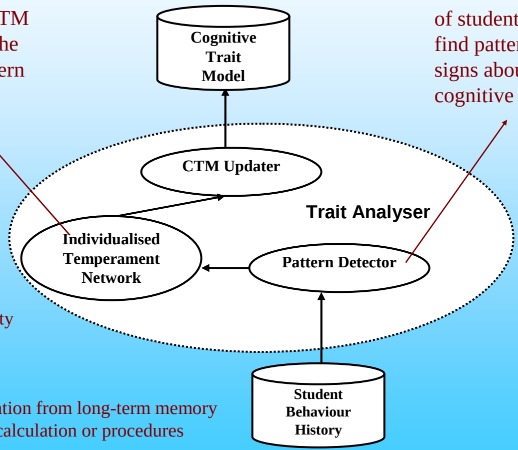
Incorporation of Cognitive Trait Model



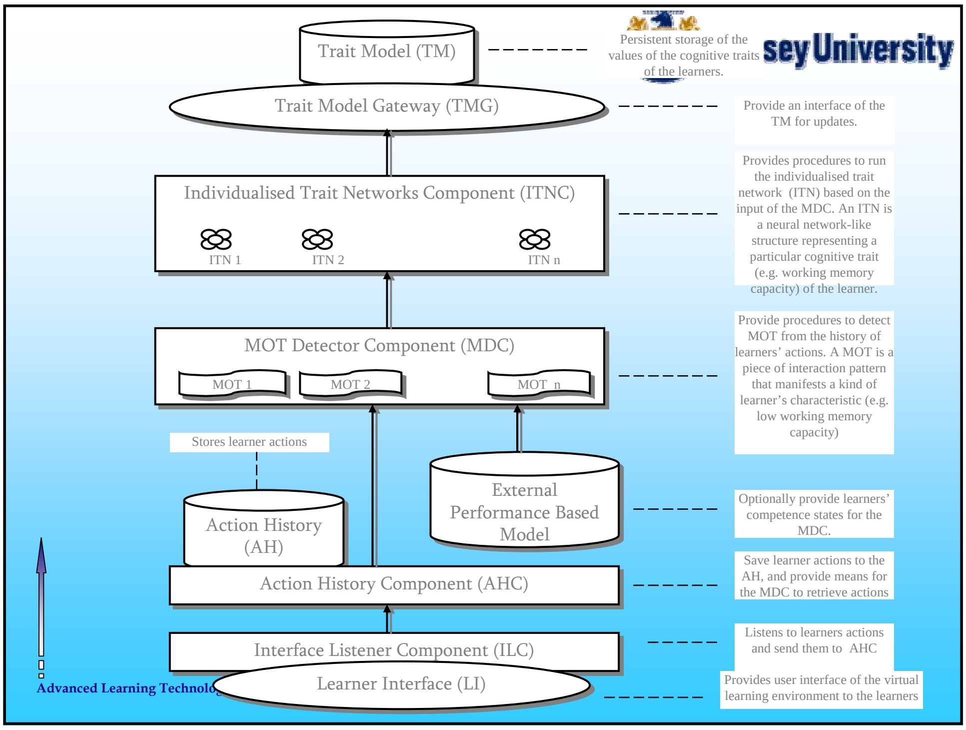
Trait Analyser

Neural network that adjusts CTM according to the results of pattern detector

Examines the records of student's actions to find patterns that give signs about student's cognitive ability



Pattern examples:
- Navigational linearity
- Reverse navigation
- Excursions
- Simultaneous tasks
- Retrieval of information from long-term memory
- Long sequences of calculation or procedures



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Exploration Space Control Elements

- Navigational Path:
  - **Number**
  - **Relevance**
- Content:
  - **Amount (Detail)**
  - **Concreteness**
  - **Structureness**
- Information Resources:
  - **Number**

Cognitive Traits and ESCEs?

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Low Working Memory Capacity 1/3

- Number of paths: "decrease" (protect learners from getting lost in too much information, from overloading the working memory with complex hyperspace structure)
- Relevance of paths: "increase" (give important information directly without irrelevant info)
- Amount of information: "decrease" (important information only, protect from information overload, give more time to review essential content if necessary)

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Low Working Memory Capacity 2/3

- Structure of information: "unchanged"

  The increase of structure-ness could facilitate the building of mental model and thus assist future recall of the learned information. But versatile learners tend to have smaller short-term memory than serial learners, and the increase of structure-ness limits versatile learners' navigational freedom, which is the primary way they learn. So the net effect cancels out.

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Low Working Memory Capacity 3/3

- Concreteness of information: "increase" (grasp the fundamental concepts first and use them to generate higher-order concepts)
- Number of information resources: "increase" (choose the media resources that work best along their cognitive styles)

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Working Memory Formalisation

	Path		*Content*			*Info Resource*
Level	**Number**	**Relevance**	**Amount**	**Concrete-ness**	**Structure**	**Number**
Low	-	+	-	+	\	+
High	\+	\-	+	-	\	\

"+" → should increase

"-" → should decrease

"\+" → could increase

"\-" → could decrease

"\" → stay unchanged

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Looking at Induction with

- Domain Knowledge
- Analogy
- Hypothesis
- Working Memory

Domain Knowledge and Induction

Generic Knowledge / Domain Knowledge	High (HGK)	Low (LGK)
High (HDK)	Start with Hypothesis Space, only goes into Experiment Space to test the validity of hypothesis.	Constant switching between Hypothesis Space and Experiment Space
Low (LDK)	Start with Experiment Space and gradually into Hypothesis Space	Stay and Struggle in the Experiment Space

Learner Categorisation (SGW, 1996)

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Analogy and Induction

- In VLEs, use of analogies means the learner has higher possibility to induce new concept.
- The ability to learn from analogy can be detected from the navigation trace of the learner in a pattern that includes visit to analogous concepts and success in assessment of new concept.

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Hypothesis and Induction

- In VLEs, learner can navigate to a concept's example node, which is the primary arena for the hypothesis generation process.
- Confirmation of hypothesis would typically require tracing back from example to concept.
- Thus, this navigational pattern can be used to detect inductive reasoning ability.

Working Memory and Induction

- Transferability of learning is an important part of how people develop competencies (Bransford et al., 2000)
- Inducing which learned mental model to apply in a situation requires matching and thus comparison operations.
- Comparison speed is known to determine performance of working memory (Salthouse & Babcock, 1991).

MOTs of Inductive Reasoning Ability

- Higher generalisation ability → higher inductive reasoning ability.
- Ability to learn from analogy → higher inductive reasoning ability.
- Activities to confirm hypotheses → higher inductive reasoning ability.
- Higher working memory capacity → higher inductive reasoning ability.

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ESC Formalisation Matrix

Student Attributes	Level	Path: No	Path: Rel	Content: Amt	Content: Con	Content: Str	Info Res: No
Work mem capacity	Low	-	+	-	+	\	+
	High	\+	\-	+	-	\	\
Induct reason skill	Poor	\+	\-	+	+	+	\
	Good	\-	\	-	\-	\	\
Info process speed	Slow	-	+	-	\	\+	\
	Fast	+	-	+	\	\	\
Assoc learn skill	Poor	+	+	\	\	+	+
	Good	\-	-	\	\	\-	\
Domain Experience	Little	-	+	\-	+	+	\+
	Many	+	\	+	\-	\	\
Domain Complexity	Low	\+	-	\	\	\-	\-
	High	\-	+	+	+	+	+

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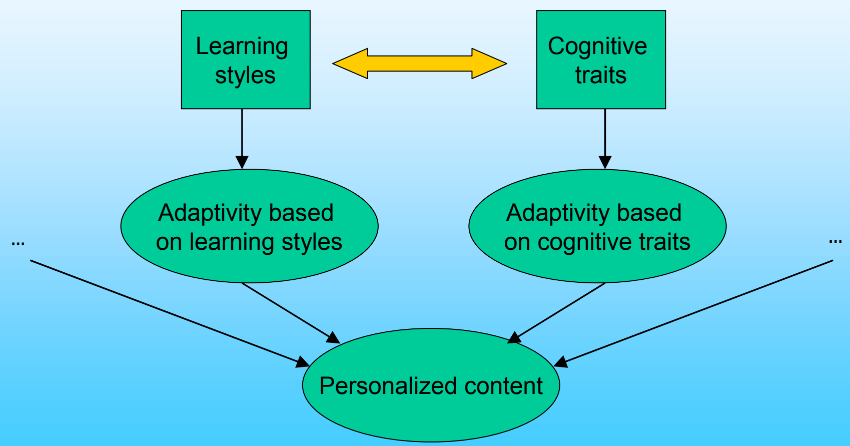
Combining Learning Styles and Cognitive Traits

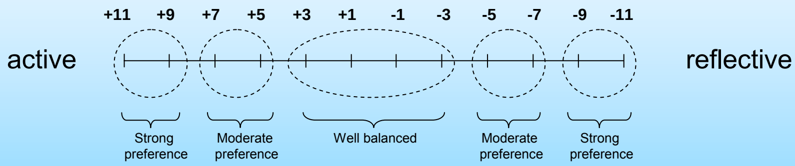


Felder-Silverman Learning Style Model

- Dimensions:
  - *Active – Reflective*
    learning by doing – learning by thinking things through
    group work
  - *Sensing – Intuitive*
    concrete material – abstract material
    more practical – more innovative and creative
    better in single answer-tests – better in open-end tests
    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

FSLSM – How to find out the learning style?

- Index of Learning Style (Felder & Soloman, 1997)
  - 44-item questionnaire (11 questions per dimension)



- Track learners behavior and infer the learning style from it
  - Using Bayesian networks to detect learning styles
  - Detecting learning styles in learning managment systems

Adaptivity based on learning styles

Some examples:

- Number of exercises (active, sensing)
- Number of examples (reflective, sensing)
- Incorporating discussions (active, verbal)
- Sequencing of the course
  - Examples first (sensing)
  - Exercises/tests at the end of a course (global)
- Use of overviews (global)
- …

Benefits

Why relate cognitive traits and learning styles?

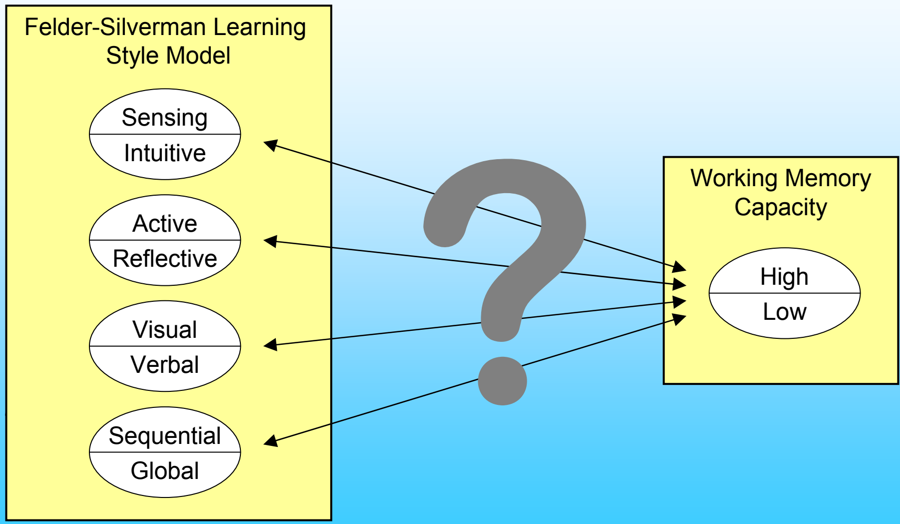
- Case 1: Only one kind of information (CT and LS) is included
  → Get some hints about the other one

  CT → ~LS   or   LS → ~CT

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

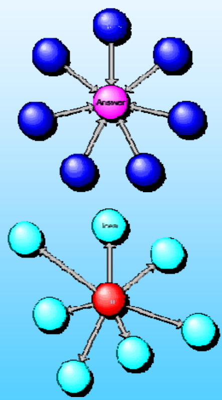
Detection of CT ← … … … LS   and   Detection of LS ← … … … CT

Relationship between FSLSM and WMC



Sensing-Intuitive Dimension and WMC

- Sensing and intuitive learners have similar characteristics to convergent and divergent learners
  - Hudson, 1966 (thinking style)
    - Convergent:
      - Good in seeing information leading to a restricted answer or solution
      - Score better in single answer tests
    - Divergent:
      - More creative
      - Good in finding a greater variety of answers to a problem
      - Score better in open end tests



[http://www.learningandteaching.info]

Sensing-Intuitive Dimension and WMC

- Several experiments about FD/FI and high/low WMC
  - Al-Naeme, 1991
  - Bahar and Hansell, 2000
  - El-Banna, 1987
  - → FD ↔ low WMC
  - → FI ↔ high WMC

→Sensing ↔ field dependent ↔ low WMC

→Intuitive ↔ field independent ↔ high WMC

Active-Reflective Dimension and WMC

- Kolb's learning style theory (1984)
  - Convergers
    - More practical
    - Finding one solution to a problem
    - More attracted to technical problems than to social or interpersonal issues
    - Active experimentation
  - Divergers
    - Perform well in idea-generation
    - Reflective observations
  - → similar to Hudson's definition
  - Relation to active and reflective dimension
    - Convergers tend to be more active – by doing something
    - Divergers tend to be more reflective – by watching

→ Active ↔ convergers ↔ low WMC

→ Reflective ↔ divergers ↔ high WMC

Sequential–Global Dimension and WMC

- Study by Huai, 2000
  - Relationship between working memory capacity and long-term memory capacity to serial and holistic learning style
  - Serial learning style is strongly related to a sequential one
    Holistic learning style is strongly related to a global one
  - About 140 students
  - Results:

    serial ↔ high WMC (but poor results in the long run)

    holistic ↔ low WMC (but good results in the long run)

→ Sequential ↔ serial ↔ high WMC

→ Global ↔ holistic ↔ low WMC

Sequential–Global Dimension and WMC

- Relation to field-dependency and field-independency
  - FI learners can learn material that is separated from its context and perceives information analytically
    → sequential
  - FD learners learn best when given a larger context, in which to embed new learning and perceives information globally
    → global

→ Sequential ↔ field-independent ↔ high WMC

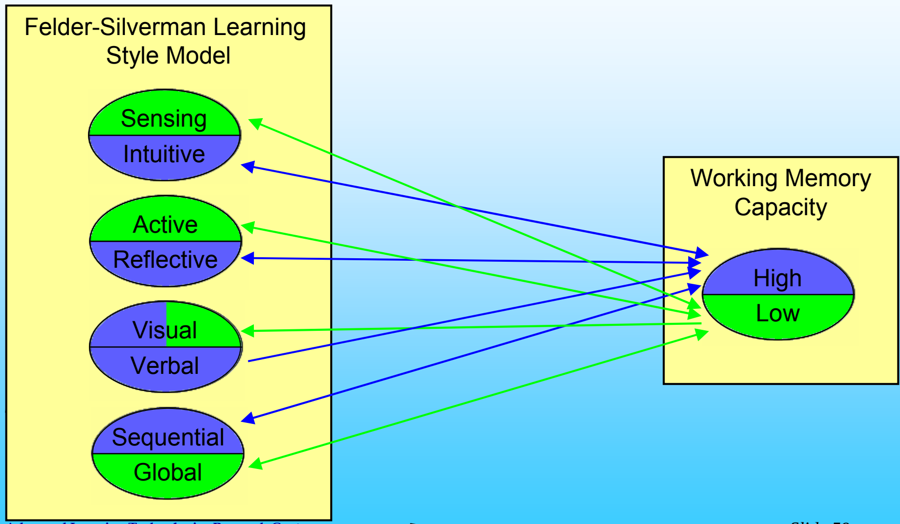
→ Global ↔ field-dependent ↔ low WMC

- Study by Beacham, Szumko and Alty, 2003 (dyslexia)
  - Higher preference (14 % higher) of global learning style among dyslexic learners (low WMC)

→ Sequential ↔ high WMC

→ Global ↔ low WMC

Relationship between FSLSM and WMC



Synopsis

In exploration based learning, adaptation requires analysis of student's competence, behaviour, and cognitive processing.

Exploration Space Control, existing competency based student modelling techniques, learning styles and Cognitive Trait Model provide an integrative solution towards this requirement.

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http://is-alt.massey.ac.nz