Conceptualizing a framework for Adaptive Exercise Selection with Personality as a major Learner characteristic

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ABSTRACT

Effective exercise selection based on learner characteristics is important for Intelligent Tutoring Systems to improve learning. Based on a literature review, we categorize learner characteristics used for adaptation in an ITS. We then present a preliminary framework of the relationship between some of these learner characteristics, with an emphasis on personality, and how they can be used by an ITS to adapt exercise selection.

CCS CONCEPTS

•Human-centered computing → User models; •Applied computing → Computer-assisted instruction;

KEYWORDS

Learning, Adaptation, Exercise Selection, Personality, Learner Characteristics, Conceptual Framework

1 INTRODUCTION

There is much prior research within the Intelligent Tutoring Systems (ITS) community on the automatic adaptation of learning content and instruction to learner characteristics. Many systems have been developed based on one or many of learner characteristics such as cognitive load, effort, and performance [2, 29, 33, 35, 61, 81, 96, 110].

The aim of our research is to investigate how an ITS can adapt *exercise selection* to individual learner characteristics. An instructional exercise engages the learner in an activity so as to develop specific skills [88] and exercise selection is the choosing of exercises for learners to engage in. In any learning process, selecting a suitable exercise plays a major role as it could determine how enjoyable the learning is for the learner and the quality of the learning outcome [79]. Many research studies use the term task selection rather than exercise selection; we adopted the term exercise selection as we were using mathematical exercises in our studies. In this paper, exercise selection and task selection will be used interchangeably.

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It is evident that there has been some use of cognition as a learner characteristic for adaptation and that performance has also been used extensively. However, there has been less research on adaptation to the learner characteristic personality, though other researchers in adaptive learning have shown interest [12, 13, 15, 43, 47, 58, 99]. Our research so far [65–67] has focused on investigating the adaptation of exercise selection to learner personality and learners' cognitive efficiency, so that an intelligent tutoring system can tailor exercise selection to these characteristics.

This paper provides a more theoretical basis for our research by describing a framework for adaptation of exercise selection based on a range of relevant learner characteristics. We hope that this will help to achieve effective learning in an ITS.

In this paper, we first briefly review existing research on adaptations in task selection. Next, we present the conceptual foundation for our adaptive exercise selection framework based on a categorization of learner characteristics used in related work. Finally, we discuss the framework's main concepts and their relationship.

2 BACKGROUND AND FOUNDATIONS

There has been much research on adapting learning content to different learner characteristics as shown in Table 1. In the area of task selection, the focus has been on the design of intelligent tutors that select tasks for the learner based on a learner's past performance, available learning support and more recently, cognitive load (e.g. [11, 18, 19, 45, 84, 89]). [103] explores how the activities and principles in expert performance research can be used to design instructional formats (e.g. correct instruction and adequate feedback) based on cognitive load theory for skills mastery. In this work, they showed that learning tasks can be adaptively selected on the basis of an assessment of learner's expertise. Other studies on exercise selection have provided empirical evidence that students often do not have sufficiently developed self-directed learning skills to select suitable tasks [42]. Furthermore, exercise selection is also regarded as a self-directed learning skill which enables learners to select a task themselves that best fits their learning needs as provided by self-assessment [93]. In this particular study [93], a learner needs to determine if the subsequent task should contain less, equal, or more support, or if it should be less difficult, equally

Table 1: Categories of Learner Characteristics in Adaptive Learning Environments

Category	Sub category	Characteristic	Adaptive learning examples
Cognition	Style	Cognitive style	[5, 51, 54, 95, 97, 98]
		Learning style	[17, 48, 49, 53, 55, 90]
		Learning pattern	[40]
	Knowledge and skills	Episodic knowledge	[10]
		Problem solving skill	[72]
		Knowledge state/Domain knowledge	[44, 60, 61, 71, 76, 84, 86]
		Logical ability	[10]
		Prior knowledge	[74, 85]
		Knowledge assessment	[16]
	(other)	Mental Effort	[19, 83, 84]
		Degree of concentration	[46, 101]
		Working memory capacity	[34, 52]
Affect		Affective states	[31, 33, 78, 97]
		Learner motivation	[7, 25, 26, 30, 64]
Behaviour	Support used	Hints obtained	[4]
		Instructional support used	[1, 19, 46, 63]
	Performance	Learner progress	[36, 106]
		Education background	[41]
		Learning competence	[14, 19, 24, 74, 101]
		Number of tries	[36]
		Learner errors	[62, 68],
		Learner responses	[28, 41, 61, 62]
Personality		Self-Efficacy	[59]
		Big 5	[27, 102]
		Self-Esteem	[66]
Other		Learner demographics/culture	[28, 77, 78]

difficult or more difficult than the previous task. The differences in self-assessment and task-selection processes between effective and ineffective learners studying in a learner-controlled instructional environment have also been investigated, and results indicated that they used the task aspects to select learning tasks [45].

Many types of learner characteristics have been used in adaptive learning systems. Table 1 categorises these, and provides examples of existing learning systems' research which investigates adaptations to these categories. In six focus group studies, we also investigated learner characteristics that can be considered when selecting the next exercises for learners [65]. Based on the combinations of the literature and our qualitative research, we distinguish four main categories of relevant learning characteristics: cognition, affect, behaviour, and personality, each of which has sub categories and several associated learner characteristics.

3 ADAPTIVE EXERCISE SELECTION FRAMEWORK

Figure 1 shows our conceptual framework for adaptive exercise selection. In this section, we describe the individual concepts for this framework, which have been used in the investigations we carried out on adaptive exercise selection. As shown above, these concepts along with many others have been regarded as important to adapt to in the design of intelligent tutoring systems in general.

We believe that for better understanding of adaptive exercise selection for an Intelligent Tutoring System, a framework of the relationship of all the components for the system should be adequately represented and understood. We therefore attempt to define these concepts as they relate to exercise selection in intelligent tutoring. These concepts have now been used in this paper to structure the framework for adaptive exercise selection.

The framework builds upon existing research on those for adaptive systems [20] which use four major components. The *Domain Model* describes taught instructional content as well as the relationship between the domain contents. The framework describes the domain content and attributes of these exercises such as exercise type and difficulty level.

The *Learner model* contains the learner characteristics as well as the general behaviour of the learner within the system. It does not only monitor the behaviour of the learner within the system updates other individual learner characteristics such as affect and mental effort. Our learner model is grouped into four categories: Personality, Cognition, Affect and Behaviour.

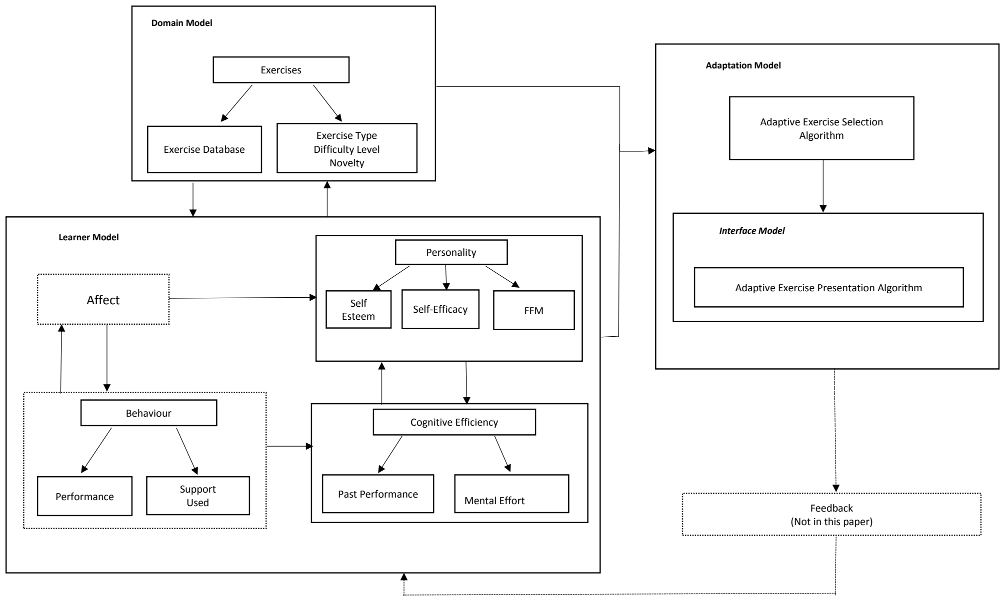

Figure 1: Conceptual Framework for Adaptive Exercise Selection

The *Adaptation model* describes the tutoring strategies as depicted by the methodology used to achieve adaptation. This model controls the workings of the adaptive system.

The *Interface Model* is often seen as part of the adaptive model. It manages the communication between learner and computer, and the presentation of the instructional content.

We now discuss the learner model concepts in particular.

3.1 Personality

Personality refers to a person's psychological structure including their temperament, character, intelligence, sentiments, attitudes, interests, beliefs, ambitions and ideals. A person's personality is shown by their disposition [37]– their response to experiences. Personality can obtained through self-reporting questionnaires, or automatically recognized (see review in [107]).

3.1.1 Five factor model. The five factor model of personality (also known as the 'Big Five') [32], is the most scientifically validated and complete measure of the personality of an individual [57]. The dimensionality of the FFM does not only cut across all cultures [57], it has remained stable over time [23, 39, 87]. Personality is expressed as scores across the five traits: Extraversion (how talkative, energetic, assertive); Agreeableness (how good natured, cooperative, trustful); Conscientiousness (how orderly, responsible, dependable); Emotional Stability (how calm vs neurotic); Openness to Experience (how intellectual, imaginative, independent minded). Adaptive exercise selection may consider a learner's Openness to Experience, as this may impact on a learner's willingness to try new exercises. It may consider a learner's Emotional Stability, as this may determine the level of support and scaffolding needed. Conscientiousness may also be relevant, as perhaps conscientious learners can be given more exercise repetitions and it may determine the mental effort put in. Extraversion may affect the type of exercise (group vs individual), as recently investigated by [3].

3.1.2 Self-Esteem. Self-esteem is defined as how favourably a person regards oneself [80]. For a learner to achieve better learning outcomes in a specific domain, they must believe in their abilities and this belief in the fact that they can produce a favourable outcome will in turn serve as motivation to learn. Self-esteem is seen as an important component of personality [56]. Self-esteem is one of the most widely studied personality concepts in psychology [38] such that in 2001, 20,203 articles had self-esteem as a keyword which made self-esteem the most researched personality concept in comparison with concepts like neuroticism with 20,026 articles and locus of control with 13,428 articles. Significant associations can be found between self-esteem and all personality traits such as openness, conscientiousness, extraversion, agreeableness and neuroticism [32]. Adaptive exercise selection may aim to boost learner's self-esteem, for those learners with low self-esteem. In our own recent research, we have shown the importance of adapting the difficulty level of exercises to self-esteem [67].

3.1.3 Self Efficacy. Self efficacy describes confidence in one's abilities [6]. In line with Bandura's social cognitive theory [6], students' confidence in the performance of academic tasks can predict their ability to be successful [70]. These beliefs have also been hypothesized to influence other determinants of learning outcomes such as competence, past achievements, and skills. Confident learners usually exhibit a sense of responsibility for their learning thereby reducing boredom and distraction during learning. Confidence in a learner's ability to accomplish certain tasks is called self-efficacy. Adaptive exercise selection may aim to boost learner's confidence, for learners with low self-efficacy.

3.2 Cognition

Cognition is the mental process of learning that leads to the acquisition of knowledge [21, 92]. Cognition has been found to be an important aspect of learning and academic performance [22, 73].

3.2.1 Cognitive Efficiency. Cognitive efficiency is the amount of mental effort invested in a certain task in combination with the quality of the indicated performance [94]. Cognitive efficiency is also an important aspect of learning and academic performance in the context of assessment. Cognitive efficiency is calculated using learner performance and learner mental effort [11]. Mental effort is an indicator of the load imposed on the mental capacity of the learner by a task [91]. The mental effort invested in doing exercises can be defined as the total amount of cognitive process. This is seen as the cognitive cost of learning [69]. Performance (which is part of the behavioural characteristics, see below) has proved to have a good influence in determining learning outcomes.

3.2.2 Domain mastery. Another aspect to consider is the learner's domain mastery level. According to Bloom [8], there is a gradual progression of mastery. Therefore, teaching content such as exercises tend to be presented in stages and in a gradual progression from easy to difficult. As learners work on gradually more complex tasks, it enhances their understanding of the solution strategies. However, how difficult a task is, depends on factors affecting both the learner and the task. Learners with more mastery of a task will invest less mental effort in performing the task. Learning tasks selected must be at the right cognitive level for the learner, meaning that the tasks administered to the learners must neither be too easy, as this could bore the learner due to the lack of challenge in the learning content, nor too difficult, as this could overwhelm the learner due to excessive cognitive load. What is the right cognitive level depends on a model of the learner's domain mastery complemented by an observation of a learner's recent performance.

3.3 Behaviour

3.3.1 Performance. For adaptive exercise selection, performance describes how well a learner did on previous exercises (or tests), e.g. mistakes made and time taken. Academic performance is determined by factors relating to the opportunity to perform, willingness to perform and capacity to perform [75, 103]. Willingness to perform portrays a stimulation to act which is usually triggered by an incentive and reflects personality [9, 75]. Furthermore, factors associated with willingness to perform such as initiative, sporting activities, motivation and attitudes to study [73, 100, 111] have also been shown to predict academic performance. Therefore it is logical to expect for personality and affective state to be correlated with academic performance. Performance has been largely used by researchers to determine learning outcomes [21, 92]. Most adaptative ITSs have used learner performance as a core characteristic for adaptation. We have previously investigated performance and personality on adaptive exercise selection and performance has proved to be a strong determinant with exercise difficulty being adapted to past performance [66, 67].

3.3.2 Support used. The use the learner has made of available support in doing past exercises (for example, use of hints) should also be considered by an adaptive exercise selection algorithm, as it impacts on mental effort used, and learning achieved.

3.4 Affect

Affect describes learner emotional state before or after a cognitive process[50]. [27] outlined a model of how affective states impacts on motivation and personality and learner performance. Affective states are usually placed on a scale of two dimensions, positive and negative [108]. Positive affect reflects the extent to which a person feels enthusiastic, active and alert. Negative affect is the general dimension of subjective distress and unpleasurable engagement resulting in moods such as disgust, guilt, anger, contempt or fear. Both positive and negative affective states have an impact on learning, and are experienced as a result of learning [112].

3.5 Relationship between Concepts

Several studies have shown personality and cognitive efficiency to be associated with academic performance, with significant correlations between academic performance and agreeableness, conscientiousness and openness [75, 82]. Reasearch has shown that personality could predict mental well-being [82, 104] which implies personality also influences cognitive abilities. Affective states such as attentiveness has been shown to be related to personality and conscientious individuals are likely to exhibit guilt when they fail to meet goals [109]. Therefore the relationship between personality, cognitive efficiency and academic performance can be treated and understood as a composite entity, hence their use in our conceptual framework.

4 CONCLUSION

In this paper, we have presented a literature review of adaptive interventions in learning, showing various learner characteristics that have been investigated in order to inform our work on adaptive exercise selection. We have concluded that personality, mental effort and performance should be considered jointly in adaptive learning interventions. In response to the call by [105] for a practical-based framework for intelligent learning systems which would facilitate better structured and systematic empirical research, we have presented a conceptual framework for Adaptive exercise selection which considers personality as a core learner characteristic.

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