Adaptivity and Interface Design: A Human-Computer Interaction Study in E-Learning Applications

A Thesis

Submitted in Partial Fulfillment of the Requirements for the Degree Of

DOCTOR OF PHILOSOPHY

By

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DECLARATION

It is certified that the work contained in this thesis entitled "**Adaptivity and Interface Design: A Human-Computer Interaction Study in E-Learning Applications**" has been done by me, a student in the Department of Design, Indian Institute Of Technology Guwahati under the guidance of Prof. Pradeep Yammiyavar and Dr. Samit Bhattacharya for the award of Doctor Of Philosophy and that this work has not been submitted elsewhere for a degree.

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CERTIFICATE

This is to certify that the work contained in this thesis titled

"Adaptivity and Interface Design: A Human-Computer Interaction Study in

E-Learning Applications"

submitted by **Mr. Yogesh Deshpande** to the Indian Institute of Technology Guwahati for the award of the degree of Doctor of Philosophy has been carried out under our supervision. This work has not been submitted elsewhere for the award of any other degree or diploma.

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Abstract

Computer based teaching-learning or e-learning provides more flexible methods of interactions with learning contents compared to the traditional classroom set-up. It motivates learners towards self learning and evaluation in an open virtual environment. However, usefulness of e-learning depends upon learner's beliefs and the degree of adjustments or adaptations shown by him in his learning behavior. The learning goal and the learning interface have a decisive role in influencing learner adaptations. Various researchers have addressed issues in learner adaptations to the (a) cognitive levels of learning goals and the (b) interaction environment. However they have been addressed separately. Also an efficient methodology of quantifying learner adaptations and learner's ability of familiarizing with learning interfaces was lacking. Both these shortcomings have been addressed in this thesis by providing a methodology of measuring adaptations. In this thesis an *adaptation score* that quantifies adaptations and an *adaptivity score* that quantifies ability of adapting have been proposed. The thesis attempts to explain the combined impact of learning task complexity and user interface design on learner adaptations in beliefs, interactions and performance which was not done before. Quantitative data of e-learning interactions involving basic three cognitive levels of learning complexity viz. knowledge, comprehension and application and two types of navigation designs viz. hierarchical horizontal menu and non-hierarchical split menu was analyzed. The empirical data suggest the fact that learning task complexity (cognitive level) affects adaptations in interactions between similar tasks (task adaptation) on same interface. Since these task adaptations did not vary across user interfaces, they were found to be task-dependant. As a result, the cognitive load of learning could be judged by the task adaptation score and utilized to adapt pedagogic strategy or learning content. Results of our study reveal that belief in self e-learning skills (self efficacy) affected adaptations in learning behavior and learning performance. On the other hand, adaptivity to navigation design of user interface was found to be interface-dependant and, interestingly, also influenced learning performance. The beliefs were found to mediate the adaptivity scores. Based on the results of the experiments, the thesis provides recommendations on utilization of these metrics in personalization of e-learning on the bases of the adaptations. The study reveals research on the phenomenon of interactions between human and computer using a multidisciplinary view of Human Computer Interaction (HCI) combining computer science, behavioral science and education.

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Abbreviations used in the thesis

PEOU	Perceived Ease Of Use
PU	Perceived Usefulness
PTLD	Perceived Task Load
PNav	Page Navigation
TNav	Topic Navigation
TCv	Total Chapters Visited
TPv	Total Pages Visited
Top	Total Operations
LO	Learning Outcome
LF	Learning Focus
IE	Interaction Efficiency
CE	Click Efficiency
PE	Page Efficiency
AS	Adaptation Score
TAS	Task Adaptation Score
UAS	User Adaptivity Score
GUI	Graphical User Interface

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Chapter 1

User’s Adaptivity In E-Learning :

An Introduction

Chapter 1

User's Adaptivity In E-Learning - An Introduction

In this chapter the research background, the framework, the definitions and the methodology followed have been stated. The research questions which lead to the formation of the hypothesis have been mentioned. The contribution of this thesis has been stated in detail. The organization of the thesis has been described in terms of chapter summaries at the end this chapter.

1.1. Introduction

The growth of internet and broadband technologies has brought a radical change in the way people learn things using computers. This is termed as e-learning. Personalization of learning content with interactivity has significantly boosted the popularity of e-learning. However, according to the principle of Task Technology Fit (TTF) [24], the e-learning performance of a learner will improve if capabilities of the e-learning application match the tasks a learner needs to perform while learning. Reseachers and practitioners therefore introduced the terms *adaptivity* and *intellegence* into e-learning systems to attain better TTF, though adaptive systems are not beneficial in all situations [48]. There has also been parallel growth in various platforms that support e-learning like discussion forums, Wiki, social networking and bookmarking [19].

This technological evolution has influenced the basic mechanism of learning and the learning tasks, which will be referred to as *learner adaptations* in this thesis. We define *adaptation* as change in user's perception, cognition or interaction behavior in response to the changes in learningcontext. By learning context, we mean the combination of the learning task and the learning application. Research shows that a team which initially used poor-fitting technology over a period of time improved the fit by adapting to technology, thus eliminating the peformance gap that existed earlier between good-fit and poor-fit teams [24]. Similarly, e-learners also show adaptations to fit themselves to the learning environment. By *user adaptivity* we mean capability of a learner to exhibit efficient adaptations for achieving optimised performance in the changed learning context. User's adaptivity in e-learning is driven by charaterictics of the learner, the learning task and the e-learning system.

We can depict user's adaptive behavior as an *adaptivity cycle* shown in figure 1.1. At the beginning, we need to know about system adaptations that influence users. Then we need to understand what do users adapt to, and why? User may show adaptations in beliefs, perceptions, cognition or interactions with menus, dialogs and interactivity of the system. We need to then analyze impact of these adaptations. The adaptations influence effectiveness, efficiency and satisfaction of the user. Finally the success of adaptations need to be evaluated in terms of how well did the user adapt and what were its benefits.

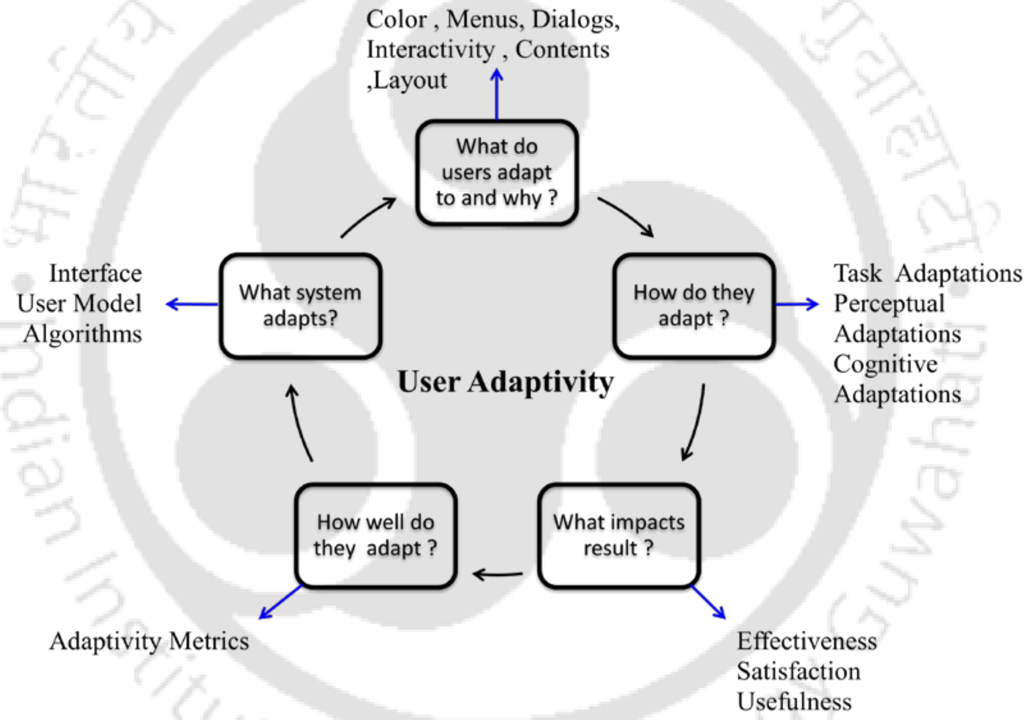


Figure 1.1 User adaptivity cycle in human computer interaction

Understanding Cognitive Load Theory (CLT) is essential to provide explanations to user adaptations in learning context. CLT states that our working memory is limited with respect to the amount of information it can hold, and the number of operations it can perform on that information [65] . Learner has to use his limited working memory efficiently, especially when learning a complex task. *Intrinsic Cognitive Load* is the inherent level of difficulty associated with the complexity of the learning content. Intrinsic cognitive load is determined primarily by the knowledge and skills associated with your instructional objective. *Germane (Relevant) Cognitive Load* is the load devoted to the processing, construction and automation of schemas or instructional activities that benefit the learning goal. This load leads to a better learning outcome. *Extraneous (Irrelevant) Cognitive Load* imposes mental work that is irrelevant to the learning goal and consequently wastes limited mental resources. Extraneous cognitive load is generated by the manner in which information is presented to learners and is under the control of interface designers. Germane load therefore helps a novice learner to become an expert [81]. Figure 1.2 explains the relationship between mental effort , mental resource and performance.

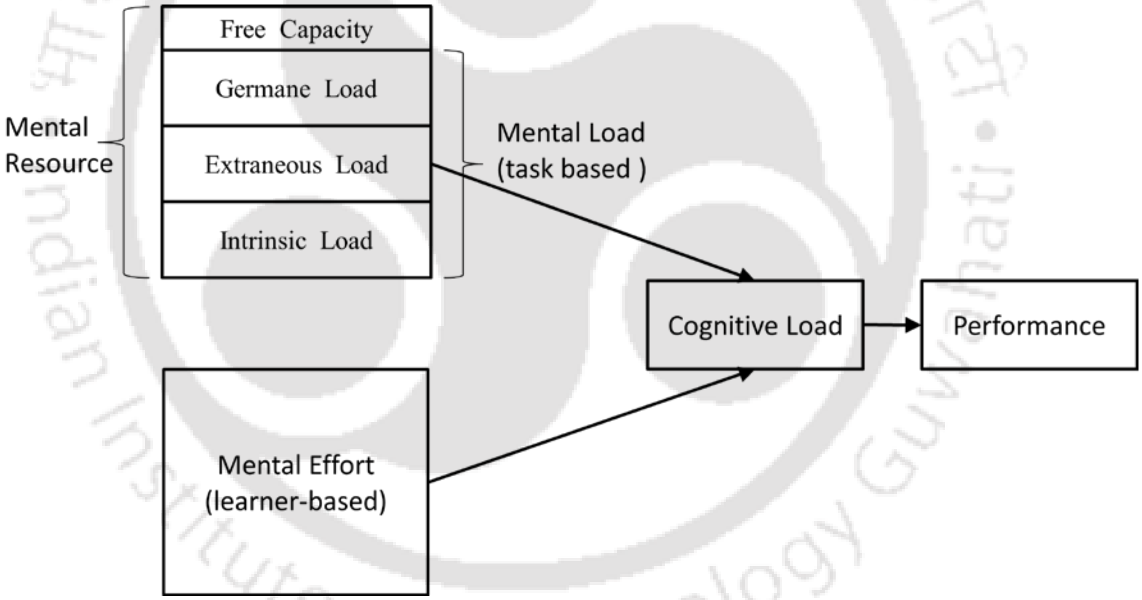


Figure 1.2 Cognitive load of learning

If sum of intrinsic and extraneous load exceeds mental resource, then 'learning' suffers. Variations in cognitive load results due to interaction among instructional environments (user interface), learner's prior knowledge and complexity of learning task.

Literature shows that users give good results with poor systems by adapting their interaction behavior[77]. The adaptation in navigation behavior greatly influences performance[11]. Our research in this thesis aims at analyzing performance benefits of adaptivity and adaptations for (a) hierarchical (linear) and (b) non-hierarchical (non-linear) navigation designs of a learning interface. The intrinsic cognitive load depends on task complexity and learner's task specific expertise [39]. In our study, we have manipulated the intrinsic cognitive load of the task by variations to the cognitive levels of learning required as per Bloom's Taxonomy [64]. This also gave us opportunity to evaluate how a learner manipulates his adaptations to achieve competence in fulfilling different levels of learning objectives[7][35]. Figure 1.3 summarizes the focus and contribution of this thesis.

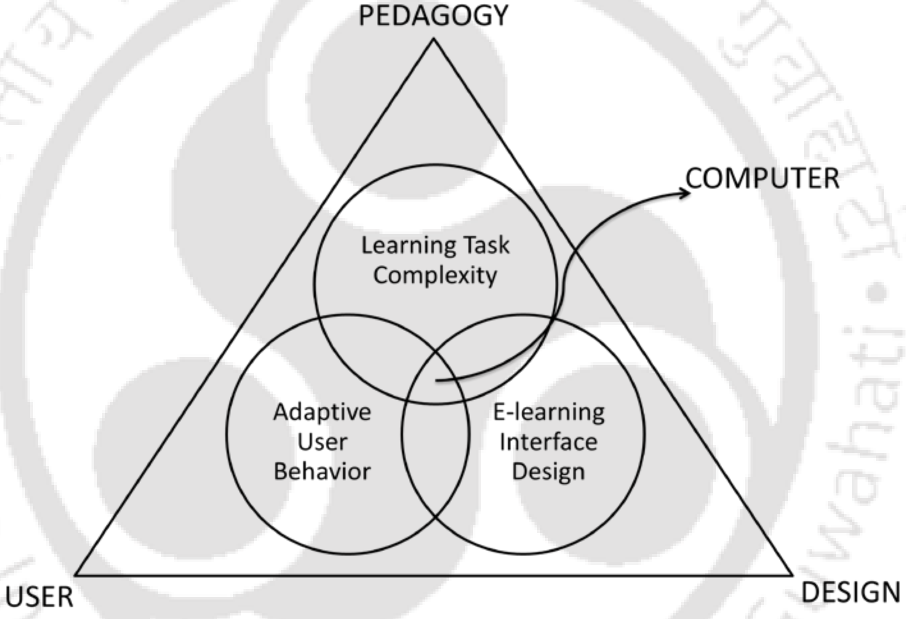


Figure 1.3 Research frame

1.2. Need for Research in User Adaptivity in E-Learning

A user of any technology constantly faces a challenge of adapting to newer interaction modes or interface designs over the time. As new devices replace older ones, an ability to adapt or discard them would be demanded of human skills. Presently it is observed that the duration of usage (lifecycle) of many consumer devices has become short. Hence the device learning or adaptation period needs to be minimum. In such a situation, the ability of adapting efficiently to devices or interfaces can become a measure of success and usefulness of a product or interface. In applications like a smart grid interface (figure 1.4), users with variety of backgrounds need to interact with a common interface. An engineer using a smart grid meter will perceive higher usability of the interface and know the interface features exactly. He will need less effort in completing the intended tasks. On the extreme end, a village farmer will perceive the same smart grid interface as having high complexity. He will need to adapt more in understanding features as well as interacting with the interface as compared to the engineer. He will undergo more adaptations until he familiarizes with the interface and performs well. Figure 1.4 shows how these users adapt differently in relation to the perceived usability of the interface.

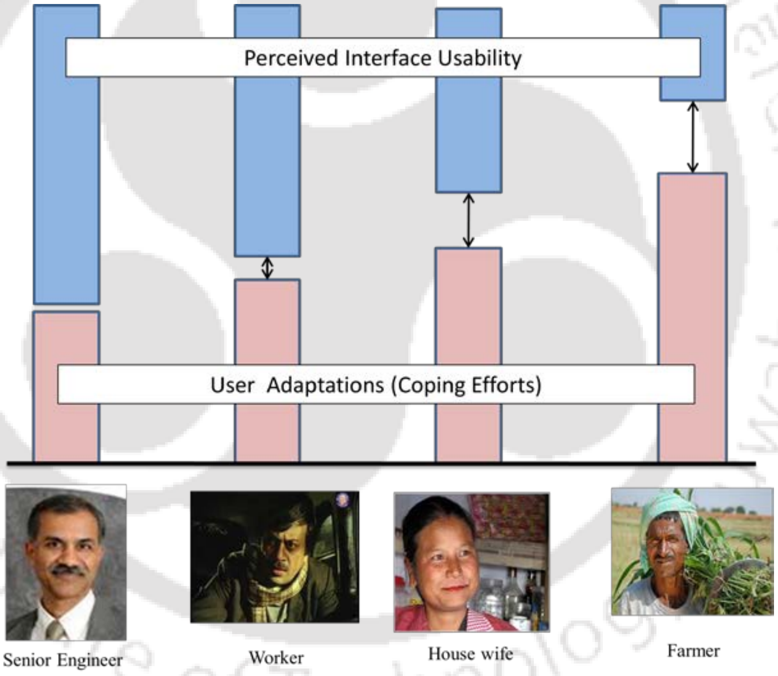


Figure 1.4 User adapations : Case of a smart electric grid

We can assume that users with higher perceived usability or knowledge of features show less acts of adaptations whereas novices have to cope with effort. In such situations, designing for discoverability of features and facilitating user adaptivity to interfaces, may be successfully used. This underlying assumption forms one of the motivation of our research.

Coping Model of User Adaptation (CMUA) [5] explicitly models user adaptation as a form of mediation. Users are forced to adapt in stressful situations of interactions depending on the degree of the stress. It is therefore important to learn how users adapt to systems in order to better respond to their needs. According to CMUA, depending on the threats or opportunities within a situation and the level of personal control, individuals develop coping strategies to stressful events. In e-learning context, knowledge of successful coping strategies under stressful learning situations can be useful to the instructor and peer learners. A study of learner adaptations under combined effect of threats (increasing task complexity) and opportunities (feature rich user interface) in e-learning context can be useful. Since each individual learner interprets the learning task differently, it is necessary to explore how task adaptations help individual learners to gain control over such dynamic situations. E-learners adopt different learning and interaction strategies in different task situations. A behavioral study of such combined mechanisms is therefore needed.

Another issue in adaptable interfaces is the degree to which a user makes use of the adaptation features (interaction methods and learning levels) depend on his level of interface skills as well as interest. A measurement- tool based on an adaptivity measure can be utilized to know user's skill level. This could be used by the system to present adaptable features to the user, based on his skill levels. Measuring user's skill level is a complex multidimensional task. Very few methodologies or measurements (metrics) are evident in literature. There is therefore a need to measure user's adaptivity that could evaluate learner's multidimensional skill level, based on (a) adaptation time (b) degree of feature usage or feature discoverability and (c) degree of expertise.

Task adaptations are adaptations in interactive behavior because of new learning situation. Literature shows that, a new learning interface affects learner's performance which is mediated by his task adaptations [75]. It is also found that task adaptations affect learner's performance under changing scenario of learning task complexity[70]. However, effect of learning task complexity on task-adaptations has not been studied across multiple interface designs. Hence this thesis attempts to fill this research gap by integrating both the approaches. It investigates the impact of learning task as well as interface design on adaptations. In short, an attempt is made to explore and measure user-adaptations to a finer degree and provide guidelines for improving personalization in e-learning interfaces.

1.3. Definitions of Terms Used In Thesis

1.3.1. E-Learning Context (EC)

E-learning context is defined by the learning task and the e-learning application on which the learner is working. In the current study the e-learning context has two e-learning applications with same learning content but different graphical user interfaces(GUI-1 and GUI-2). Knowledge (K), comprehension (C) and application (A) are three types of learning tasks.

1.3.2. User Adaptation (UA)

User Adaptation is the change in user's beliefs, perceptions, cognition, interaction of tasks and performance in response to change in e-learning context.

1.3.3. Task Adaptation (TA)

Task adaptation is the change in user's learning tasks in response to different learning tests.

1.3.4. Learning Focus (LF)

Individual differences significantly influence the way learners navigate through e-learning applications. Learners learning style can be extracted from the trace of his navigation behavior. Learning task characteristics as well as learning interfaces influences the learner's navigation style.

Learning navigation style can be of following types [8]

- *Overviewing*: Learner covers large portion of topics to get an overview
- *Flitting*: Browsing without a strategy or a particular goal and lack of focus
- *Studying*: Partial reading of the topic- pages spends short time on each page.

– *Deepening*: Learner spends long time on a topic , checking in detail the content pages

We are proposing a new measure called *learning focus* in this study. Learning focus measures intermediate style of navigation between overviewing and deepening. Learning focus tells whether the learner's focus is to know topics in details (deep processing - of page commands more than topic commands) or whether the focus is to know topics in brief (overviewing or shallow processing - of topic commands more than page commands). Learner showing deep processing style will navigate through more pages and will be at lowest level of instructional contents to get deeper understanding. He will execute more page navigation commands than topic or chapter level commands. On the other hand a learner having overviewing style only browses the topics and so uses less page commands and higher level of topic commands.

Therefore learning focus is defined as the ratio of page commands to topic commands.

$$\textbf{Learning Focus (LF)} = \frac{\textbf{Total page navigation commands (PNav)}}{\textbf{Total topic navigation commands (TNav)}} \qquad \textbf{(1.1)}$$

Higher focus means deeper interest in pages of topics and lower focus means shallow interest.

1.3.5. Interaction Efficiency (IE)

We define interaction efficiency as the ratio of total pages visited (TP_v) to the total operations or clicks (Top) executed.

$$\textbf{Interaction Efficiency (IE)} = \frac{\textbf{Total pages visited (TPv)}}{\textbf{Total operations or clicks (Top)}} \qquad \textbf{(1.2)}$$

1.3.6. Click Efficiency (CE)

We define click efficiency as the ratio of percentage learning outcome (LO) to the total operations or clicks (Top) executed.

$$\textbf{Click Efficiency (CE)} = \frac{\textbf{Percentage Learning Outcome (LO)}}{\textbf{Total operations or clicks (Top)}} \qquad \textbf{(1.3)}$$

1.3.7. Page Efficiency (PE)

We define page efficiency as the ratio of percentage learning outcome (LO) to the total pages visited (TPv) executed

$$\textbf{Page Efficiency In Pages (PE)} = \frac{\textbf{Percentage Learning Outcome (LO)}}{\textbf{Total page visits (TPv)}} \qquad \textbf{(1.4)}$$

A series of terms with definitions that are used in this thesis have been introduced above. Equations (1.1) to (1.4) are concepts that have been generated and defined in this thesis by the author.

Having defined the terms we now proceed to the outline of our research objectives.

1.4. Research Questions and Objectives

Having defined and laid the background in which this thesis is framed, we proceed to state the research questions raised. The research is based on finding answers to the following research questions.

1. What is the effect of change in learner characteristics (self efficacy, knowledge), learning task characteristic (cognitive level of learning goals) and learning interface characteristic (navigation design) on user's adaptations in e-learning set-up?
2. Can learners or learning interfaces be evaluated by analyzing user adaptations?
3. Can learning interfaces be evaluated based on user's adaptivity to interfaces?

To answer the above research questions, the following objectives were set :

1. Analyze the effect of
    a. self efficacy and knowledge of learner
    b. navigation designs of user interfaces
    c. cognitive levels of learning goals (learning task complexity)

   on adaptations in beliefs, interactions, tasks and learning performance of learner in e-learning set-up.

2. Compare hierarchical horizontal and non-hierarchical split menu navigation patterns of learning interfaces based on learner adaptations.
3. Compare cognitive levels of learning goals (learning task complexity) based on learner adaptations.
4. Investigate the effects of navigation designs and learning task complexities on user's adaptivity scores.
5. Validate user adaptivity measure using learning curve- equations.

1.5. Research Framework and Hypothesis

The framework of this research is divided in three layers as shown in figure 1.5. The three layers, namely, (a) learner (b) context and (c) user adaptations, are shown inside dotted rectangular boundaries. The independent variables of learner characteristics viz. *e-learning self efficacy (ELSE), prior knowledge (PK) and adaptivity (Adpty)* form the learner layer. The second set of independent variables of task characteristics viz. *task complexity (K, C, A) and navigation design (GUI-1, GUI-2)* makes the context layer as mentioned in section 1.3.1. The third layer is user adaptations which measures adaptations in beliefs, interactions, tasks and performances.

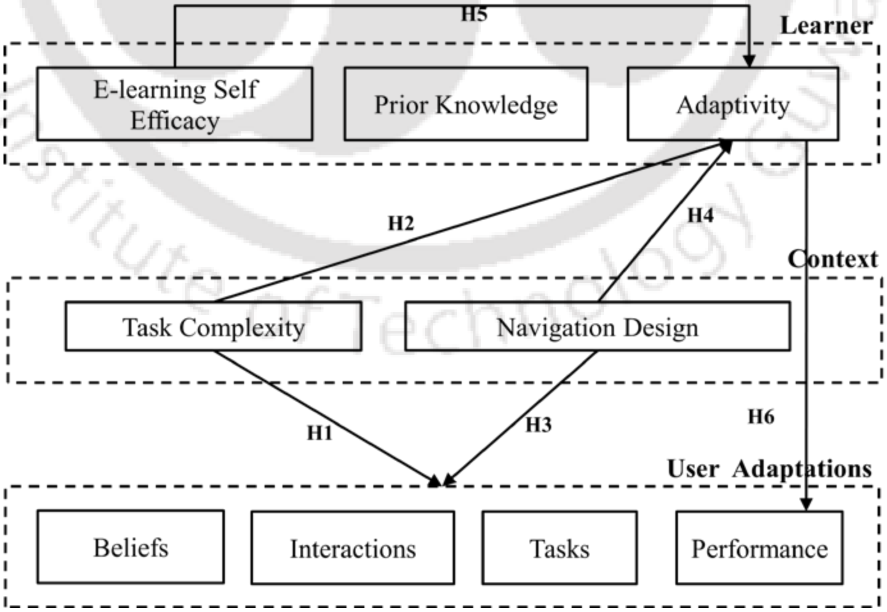


Figure 1.5 Research framework

The literature reviewed (presented in details in chapter 2) showed research on task adaptations and its effect on learner performance. No specific explanation on these adaptations based on cognitive load theory was found. Since learner's perceptions, beliefs, motivations, emotions and thinking also adapted to learning environments, a relevant study of these intangible adaptations was essential. No specific work has been reported on the study of such adaptations and their effect on learning performance. Study of the influence of learning interface design and learner background on adaptations is sparsely reported in literature.

In this research we studied the effect of navigation design on user adaptation along with task complexity. The adaptations in learner's behavior to multiple user interfaces have been investigated under three different complexities of learning tasks. We formed a set of six hypotheses for the investigation, which are discussed next.

Changes in learning- task- complexity affects the intrinsic cognitive load. Depending on an individual's available mental resource, behavioral adaptations result. Based on this, we posit the following hypotheses (H1).

H1. Learning task complexity has significant effect on user adaptations

The effectiveness and efficiency of interactions depend on learner's prior knowledge of the interface. Practicing complex tasks can provide opportunity for better understanding of the underlined interface or for enhancing user adaptivity. Therefore we posit the following hypothesis (H2).

H2. Learning task complexity has significant effect on user adaptivity

Extraneous cognitive load is generated by the manner in which information is presented to the learners and is under the control of instructional and interface designers. Interface design can influence the reduction of extraneous cognitive load. Different navigation patterns selected for learning will impose different amount of cognitive load for different learners. Also the perceived ease-of-use (PEOU) and perceived usefulness (PU) of the navigation design will affect user adaptivity. Thus, we propose the following two hypotheses (H3, H4).

H3. Navigation design has significant effect on user adaptations

H4. Navigation design has significant effect on user adaptivity

Theory of reasoned action (TRA) [3] stated that user's behavior or intention is driven by attitude towards the behavior and perceptions(beliefs) about the behavior. E-leaning self-efficacy reflects learner's confidence in judging one's capabilities of using e-learning for designated goals. This confidence has an impact on his e-learning behavior and adaptivity. Thus, we propose the following two hypotheses (H5, H6).

H5. E-Learning self efficacy has significant effect on user adaptivity

H6. User Adaptivity has significant effect on Learning Performance

1.6. Methodology and Experimental Design

The study required empirical data of learners' adaptations to verify hypothesis. The study undertaken uses a quantitative explanatory research methodology involving statistical analysis of data to find a cause and effect relationship among variables. The research methodology followed in this thesis has been depicted in figure 1.6.

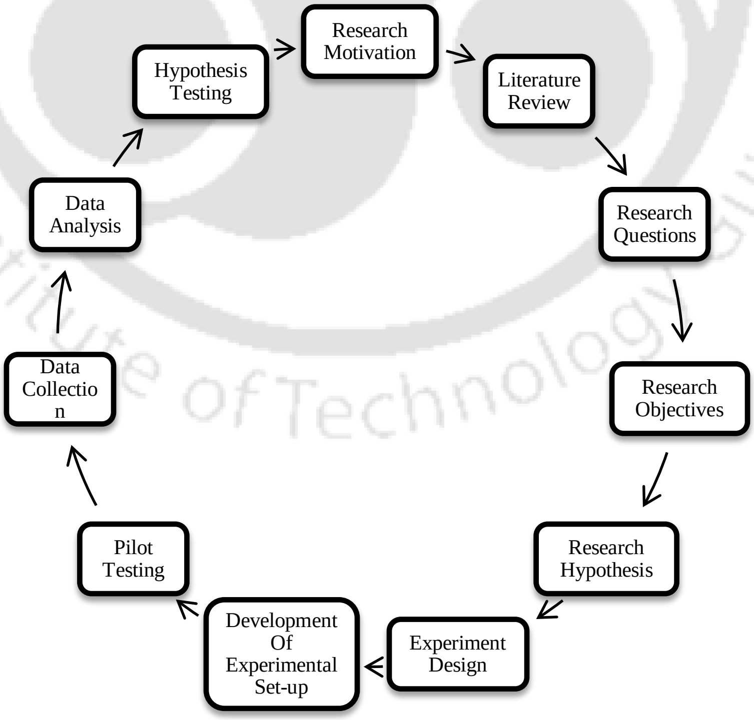


Figure 1.6 Research methodology

Figure 1.7 is an overview of the experimental design. It was a mixed design of *within subjects* (effect of two interfaces) and *between subjects* (effect of three task complexities). There were 15 dependant variables (DV) measured. Questionnaire Q1 was administered for registering demography details and e-learning self-efficacy (ELSE). The participants were then exposed to an application (GUI-1) and were asked to perform three learning tests. In between learning tests, *adaptivity test* was conducted to measure interface skill level. At the end of the three learning tests, questionnaire Q2 was administered to record PEOU, PU and perceived task load (PTLD). The same procedure was then repeated for another application (GUI-2). The data from operation log was utilized for data analysis.

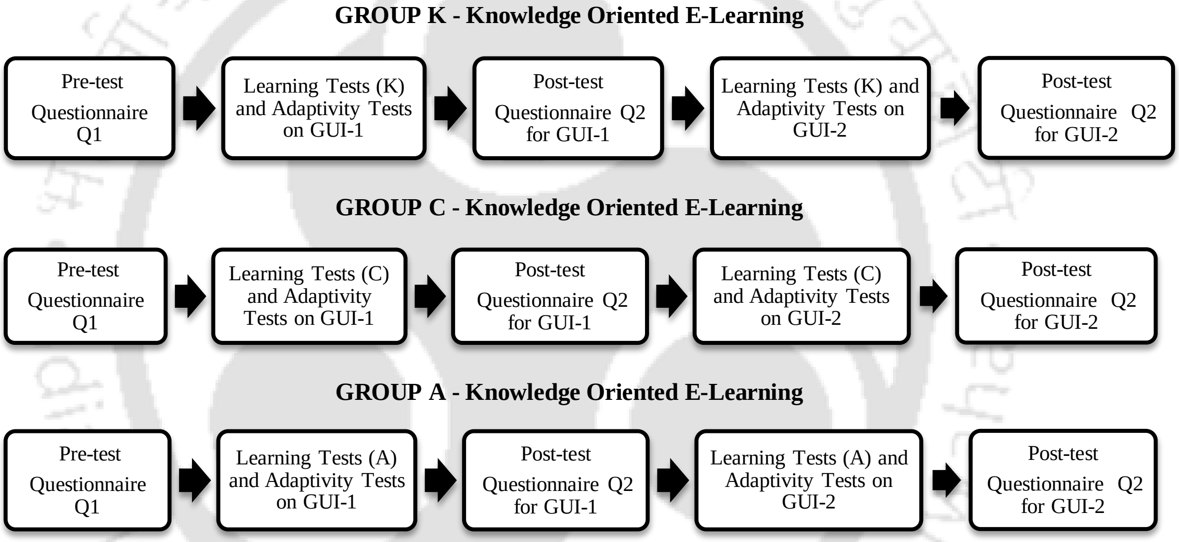


Figure 1.7 Mixed experimental design

1.7. Thesis Contribution

Due to limitations in adaptive interfaces and diverse cognitive levels of learning goals, a learner faces challenges of adapting to learning environments. As seen from published literature, not much is known about the learner's adaptation behavior pattern and adaptivity to learning interfaces. This research studies the learner adaptations in beliefs, interactions and performance, to different user interfaces and learning task complexities. New measures have been proposed to evaluate learners or interfaces based on adaptivity.

The contributions of the thesis are as follows:

1.7.1. *A new measure of task adaptation*

Literature indicates non-availability of an appropriate measure for comparing task adaptations between different contexts. Therefore it was necessary to conceptualize a new measure for capturing and comparing behavioral adaptations under dynamic contexts. The concept of an adaptation indicator *task adaptation score (TAS)* is proposed in this thesis for computing adaptations in interaction behavior between multiple tasks. This indicator is used to compare interface designs on the basis of task adaptation scores of various attributes of learning behavior.

1.7.2. *A new measure of user's adaptivity to user interfaces*

We examined limitations of current techniques to measure user adaptivity to interfaces. We adopted a more practical performance benefit based method for evaluating computing system's adaptivity [71], in our study of user adaptivity to learning interfaces. A new performance index indicating user's degree of interface skill level is proposed. The proposed measure for evaluating user's ability to gain expertise in interface knowledge through practice is called in this thesis as *user adaptivity score (UAS)*.

1.7.3. *Data collection and analysis of user adaptations and adaptivity*

We developed an experimental set-up having two versions of e-learning web applications with two types of user interfaces (GUI-1 and GUI-2). We designed 18 independent learning tests based on three cognitive levels of learning objectives mentioned in the Bloom's Taxonomy. We used the keystroke level model of task analysis for time prediction of 22 unique instructions to be used in the design of the user adaptivity testing- tool. Development of basic e-learning applications and the adaptivity testing tool was done in three months. A pilot study with undergraduate design students was conducted.

We carried out research experiments with a large user population of 287 undergraduate students. Batches of 12 computers were used simultaneously in computer labs of the colleges. The data collection took 3 months time. The interaction data of 6 learning tests and 10 adaptivity tests per individual was stored in MySql database. Total records generated were 220353. We wrote programs in HTML and PHP to process these records stored in MySql database. We used statistical package SPSS to perform t-tests, ANOVA tests and bivariate correlation analysis on the data.

1.7.4. Recommendations for e-learning designers

Important conclusions from the results of the experiments conducted were used to formulate recommendations in the form of a set of guidelines for navigation design of e-learning user interfaces.

The conclusions from this research are valuable for adapting e-learning resources and interface features to user's needs based on adaptivity and coping behavior. Adaptivity measurement technique can be used to drive adaptive mechanisms.

1.8. Organization of the Thesis

Chapter 2 reviews the published literature. It highlights the limitations of technology adaptations in e-learning. It reviews research work on user adaptations in e-learning context, identifies and discusses the research gaps. A review of user adaptivity measurement efforts is also elaborated. The review ends by posing research questions relevant to this research.

Chapter 3 outlines the experiment methodology and research design in detail. Experimental setup and participant groups have been described. Detail process and setup for adaptivity measurement has been laid down. Statistical methods used for data analysis have been mentioned in brief at the end.

Chapter 4 presents data analysis of the study on user's adaptations. The findings and analysis is explained in four broad themes that include beliefs, navigational behavior, learning efficiencies and task adaptations.

Chapter 5 presents data analysis of the study on user's adaptivity. The data collected on user's performance in adaptivity tests has been presented. Effect of user interface designs, learning task complexities and self efficacy on user adaptivity scores has been analyzed. The adaptivity measure is validated by comparing with power curve fitting equations.

Chapter 6 is the discussion and conclusion . It provides a summary of findings, discusses important conclusions and recommends guidelines for e-learning interface design.

Summary: *In this chapter we introduced our motivation of researching adaptations in e-learning context. Definitions of useful terms relating to the research topic have been listed. The research questions which led to research hypothesis have been mentioned. The methodology used for research and experimental design has been explained briefly. Lastly, the contribution of the thesis and organization of chapters of the thesis has been summarized. The research objectives that were set originate from the shortcomings of research in related area. The research gaps identified from the literature review will be explained in detail in next chapter.*

Chapter 2

Literature Review

Chapter 2

Literature Review

This chapter explores the literature relevant to user's adaptations in e-learning and interprets the results of the related work. The first two sections of this review describe the relevant theories from the perspective of user's adaptations. Issues relevant to user modeling and adaptivity limits are discussed from the user's view point. The next part of this review summarizes the research on user's adaptations in the e-learning set-up. Finally, the literature on measurement of user's adaptivity to interfaces is presented. The research-gaps in current methods and directions for further research have been identified.

2.1. Introduction

Adaptivity exists in various forms. Depending on what is adapted and who controls the adaptation, the research space in adaptivity is divided into four quadrants as shown in figure 2.1. The horizontal axis is the adaptation control showing total user control on the extreme left to total system control on the extreme right. The vertical axis is the adaptation axis having user adaptation and technology adaptation as its extremes.

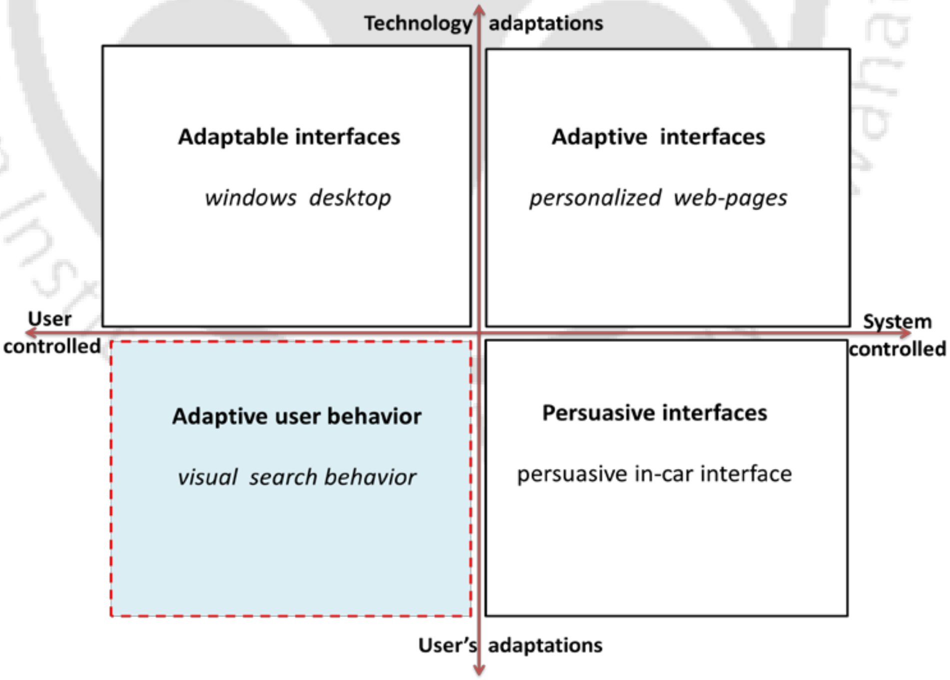


Figure 2.1 Adaptivity research space

The first quadrant of this space will have systems adapting to user needs with entire control over adaptation with itself, like fully adaptive personalized web pages. The second quadrant will have systems that adapt to user needs but adaptation is controlled by its user like adaptable windows desktop interface. User adaptivity is placed in the third quadrant where the user exhibits the adaptations in behavior, which is self- regulated like his visual search behavior. The last quadrant is an emerging area of persuasive systems. These are the technologies that are designed to change the attitudes or the behaviors of the users through persuasion and social influence. A persuasive in-car interface can persuade a driver in driving the car more fuel efficiently. Most of the research in adaptivity space has seen concentrated in the first and the second quadrant. The focus of this thesis is the third quadrant that deals with user adaptivity. User adaptations are caused due to changing task complexity, time pressure, motivation, constraint, context, interface incompatibility or system performance. The user and the system both need to be compatible as well as compensating for one another.

In e-learning, before a learner starts using or adapting, he needs to have a strong belief in accepting e-learning as a mode of education. The technology acceptance model (TAM) by Davis [17] addresses why users accept or reject a technology. TAM is based on the theory of reasoned action (TRA) [3], which says that user behavior or intention is driven by attitude towards the behavior and perceptions (beliefs) about the behavior. It provides a mechanism for identifying influential design parameters of a technology or product for its acceptance and adoption by people. The next section elaborates on how this model was used in e-learning context to find design factors that can predict acceptance and usage of e-learning.

2.2. E-Learning Acceptance and TAM

TAM was used to find relationships between e-learning design features, perceived usefulness, perceived ease-of-use, attitude towards using e-learning, intention to use and the actual usage of e-learning. System design factors like perceived interactivity, perceived flexibility, presentation styles, mobility, system quality, information quality, ease of finding and ease of understanding were studied to find their impact on e-learning acceptance [9, 34, 38]. Individual factors like e-learning self efficacy, enjoyment and computer anxiety [9, 34, 67] ; social factors like subjective norm and organizational factors like facilitating conditions and system accessibility [67] were extensively studied for their influence on e-learning acceptance. Literature shows that a learner's attitudes, intentions and behavior are driven by perceived design attributes of the e-learning system. In one of the studies we performed as part of the present research, we found that PEOU and PU were prominent contributors in generating positive attitudes towards e-learning. However, facilitating conditions played an important mediating role in affecting the final e-learning usage [18].

E-learning acceptance is an essential motivating factor for improving the learning experience. However, its usefulness will depend on fulfillment of learning goals. Usefulness of a technology depends on type of user goals. Current models like TAM, predicting technology success assume that the user goals are simple and constant. However, in e-learning, user goals are complex and layered. Since, variations in cognitive levels of tasks are involved in e-learning, predicting e-learning success just based on usage will not be valid. Other factors contributing to e-learning success need to be investigated.

It is widely considered that the ability of a system to support a task (task-technology fit) plays an important role in its success. The task technology fit (TTF) theory [28] holds that a system will have a positive impact on individual performance if the capabilities of the system match the tasks the user needs to perform. We need to know if TTF theory can be extended to e-learning contexts in predicting learner performance as well as adaptations.

2.3. The Task Technology Fit (TTF) in E-Learning

According to the TTF theory, the learner's performance in e-learning depends on the degree to which e-learning application features fit to his learning tasks. The fitness of different features to learner's tasks will influence PEOU and PU of the system [52]. It was found that the perceived TTF depends on individual characteristics like profession and cultural background [16]. Study by McGill and Klobas [57] revealed that, in addition to TTF, social norms and facilitating conditions also influence utilization of learning applications and learner performance. Cruz [15] suggested a need to combine technology, task, and individual characteristics to design a computer-mediated learning environment that enhances the learning performance.

In situations of poor TTF, learners show adaptations. The poor TTF will be tolerated by the users as they adapt and perform well eventually because of their coping strategies and behavior [22]. Research [24] has shown that TTF may be more relevant as a predictor of effectiveness and efficiency in contexts where the task and the technology are less malleable or flexible. Therefore, TTF may not be a suitable predictor of e-learning performance. As learners move from novice to expert level, their perceived TTF may also change causing proportional changes in their adaptations. Thus, in e-learning context, the learner behavior depends on the dynamic TTF over time as well as across platforms.

From the literature, we can infer that TTF alone is not sufficient in understanding learner performance. User adaptations fill the gap so as to improve the performance. Attempts to model user adaptations can help in (a) knowing learner performance and (b) personalization of e-learning. The next section gives an account of various approaches taken in user modeling in e-learning for personalization.

2.4. Modeling the Learner in E-learning

In e-learning context, modeling of learner means characterization and classification of learner into stereotypes. System's adaptivity is based upon accurate knowledge of learner’s stereotype. Literature shows various demographic, cognitive, behavioral and psychological attributes of the learner, used in building the learner model [2, 4, 10, 20, 25, 29, 31, 40, 41, 45, 47, 54, 73, 83, 88]. New attributes like learner’s search strategy [44], navigational behavior [33], learning curve [55] and short term interest [1] were used in learner modeling. Learners were classified on the basis of learning styles (active, reflexive, theoretical, pragmatic) [63], emotional states (using physiological signals and facial expressions) [63], knowledge states (not learned, learned, mastered) [47], problem solving style (trial-and-error, help-seeking) [47] , cognitive styles (verbal-imagery and holistic-analytical) and learner's multiple intelligences [42] [84]. Mostly models were built using either a query scenario or automatic monitoring of learner interactions [43]. Sumner [78] proposed a learner model with three components, namely (a) knowledge model (b) behavior model and (c) personality model. Based on knowledge about learner's needs, the system provided personalized navigation or content as per preference or mood of the learner[36] .

The existing learner models primarily consider user's knowledge with the system. Modeling system's knowledge with the user has not received the same importance. Therefore, modeling the user's degree of knowledge about the system needs to be explored.

The extent to which a learner needs to adapt to the system depends on the extent of personalization supported by the system. However, the support for personalization has its limits as the literature shows that personalization is not beneficial at all the times. The limits of personalization are discussed in the next section.

2.5. Limits of Learner Personalization

Though adaptive learning interfaces support personalization, the reduction in consistency, high system learning rate, privacy and trust are some of the drawbacks they face [2]. A fully adaptive interface proves to be beneficial only if there is high accuracy in adaptivity [26]. Users of personalized interfaces often do not take efforts to explore or learn overall system or unused features. Lack of such awareness of unused features can affect performance during new tasks in a personalized environment [21]. Personalization also makes the user feel a loss-of-control. Therefore, a *scrutable* (comprehensible) interface is preferred over a personalized one. In *semi adaptive* interfaces, a user can gain control by approving the adaptations (*user-approved adaptations*) each time proposed by the system. But these interruptions can themselves add cost to adaptivity [86]. Support from the system to guide the interface adaptations (adaptable with system support) improves efficiency of adaptations and learning task [66]. But discoverability of these adaptable features is very important from usability perspective. Literature shows that adaptivity improves efficiency but at the cost of learnability [20]. Perceived costs of adaptive interfaces include mental demand, physical demand, frustration, confusion and lack in accuracy [25]. It was observed that if personalized instructional material was provided to learners based on learner's *multiple intelligences*, students learnt more in least preferred conditions than in the most preferred conditions which defeated the very cause of personalization [42].

Personalizing (adaptive) interfaces can be effective provided expected interaction state is maintained within the region of user expectation [69]. System should not adapt very fast or too slow. Both can degrade performance benefits and satisfaction gained because of adaptivity. User-approved adaptations also defocus a learner by adding extra interactivity. Adaptivity can by itself impose additional extraneous cognitive load reducing mental resource of available germane load. The learner's adaptation behavior and ability to adapt to interfaces can be accommodated while designing interfaces. Interfaces can enable gradual improvement in adaptivity based on the learner's adaptations and adaptivity level. In the next section we review related research on user adaptations that can benefit system adaptivity.

2.6. Importance of User's Adaptations in E-learning

We saw that adaptive or personalized interfaces have their own limits. What matters most to a learner is effortless accomplishment of his learning goals with satisfying experience. It is very difficult to build a universal system that adapts to every user, task and situation. If a system or an interface is perceived misfit or unfriendly, users show adaptations to overcome the usability gap and still achieve their goals successfully. For convenience, we restate user's adaptations as changes in user's beliefs, perceptions and cognition or interaction behavior in response to change in e-learning context for the sole purpose of optimizing performance for achieving the learning goal.

User's adaptations are useful when learning in or coping with a new context. Coping Model of User Adaptation (CMUA) [5] explicitly models user adaptation as a form of mediation. As per the CMUA, users are forced to adapt in stressful situations of interaction depending on the degree of the stress. It is important to learn how users adapt to systems or interfaces in order to better respond to their needs. The user shows adaptation when he knows the potential consequences of a stressful event and evaluates it to be of relevance and importance. Therefore, the strategies used for coping can indicate the nature of the stress imposed by the task or the environment. What kinds of user's adaptations take place and to what extent do users adapt or how well do they adapt, are some questions that require further investigation.

Changes in learning contexts invoke adaptations in internal as well as external factors of human behavior. The internal human factors are motivations, perceptions, emotions etc. The external human factors are interactions, speech, eye movements, gestures etc. We have seen earlier in section 2.2 of this chapter that beliefs like PEOU and PU influence e-learning acceptance and adaptations. Adaptations in PEOU or PU can cause change in learning behavior in a new context. We need to explore how internal human factors like motivations, perceptions and emotions adapt to learning contexts. The next section presents a review of the relevant literature.

2.7. Internal Factors of User's Adaptations

Evidences from the literature show, that the internal factors like self regulation, calibration, belief, self efficacy and cognitive architecture, have indirect control over adaptations. We will discuss these factors individually in the next few paragraphs.

Human's have an inherent self regulation mechanism consisting of a cyclic process of (a) monitoring (perception), (b) evaluation (cognition) and (c) action. Users change their way of thinking and interacting so as to suit themselves (self regulation) to the system. They adapt towards attaining optimal human-system-interaction. This human mechanism of adaptation can be modeled and used in interaction design of adaptive systems [22]. Craen et. al. [14] found that accuracy in perceiving complexity of task in hand and accuracy in judging self skills decide the nature and success of adaptations. They defined calibration as the degree to which a user perceives the complexity of the task and the self efficacy. A well calibrated user (expert) adapts adequately to task demands in comparison to a poorly calibrated (novice) user. Users therefore show adaptations in task, technology and are self proportional to their calibration [14, 76]. Calibration therefore reflects ability to adapt i.e. user adaptivity.

Learners’ beliefs influence their adaptation in interaction strategies. Mathieson and Keil [56] showed that PEOU using the same system varied with the task, while PEOU of the same task varied across systems. Therefore it is the interaction of task and interface or system that drives adaptations in PEOU. Also the TAM model [17] predicts behavior based on PEOU and PU. A study of perceived interactivity (PI) and satisfaction showed that, high perceived interactivity increases time to learn the features and their use. Subjects choose the simplest and the most familiar strategies with low perceived interactivity, rather than the most effective strategy when they face decision-making processes under time constraints [80] . PEOU and PU can therefore be used to measure combined effect caused by change in learning task and interface.

Self-efficacy reflects an individual’s confidence in judging one’s capabilities to perform the behavior required to attain designated goals [87]. Self-efficacy is an effective predictor of learner motivation and learning. In the context of e-learning, self-efficacy affects the learner’s behavior, motivation, effectiveness, the choices he makes, efforts, persistence and emotional reactions. Literature shows that computer self-efficacy (CSE) can help individuals cope with technology-mediated (T-M) interruptions. CSE moderates the effect of the frequency of T-M interruptions on individual stress so that the effect is weaker for higher levels of CSE [72]. Self-efficacy mediates relationship between anxiety and perceived ease of use of learning environment [74]. Bica et al. [6] modeled student’s self efficacy and built an adaptive learning interface to enhance self efficacy. Lee and Lee [50] found that learners having high self efficacy had a theoretically high self-study power and perceived learning strategy. Literature shows that e-learning self efficacy can be influential in modulating user adaptations in stressful learning situations.

Cognitive architectures are a set of cognitive resources that underline the behavior consistently across situations, while situated cognition (knowing by doing) approach suggests that all behavior is specific to the situation in which it takes place. Freed et al. [23] proposed an idea of *human-task adaptations* as consistent characteristics of the way the cognitive architecture shapes itself around and adapts to the specific characteristics and demands of a given task. They found these adaptations to be consistent and predictable. Modeling these human-task adaptations can become a new approach towards cognitive modeling.

In the second paragraph of this section, we defined calibration as the degree to which a user perceives complexity of task and self- efficacy. We also concluded that calibration reflects ability to adapt. Learner’s calibration is therefore important in affecting his adaptations to task demands. Effect of calibration on e-learning adaptations need to be explored. PEOU and PU can become indicators of task and interface complexity while e-learning self-efficacy (ELSE) can indicate confidence in e-learning skills. We can utilize these measures to find learner’s calibration level.

In the preceding section, we reviewed works related to internal human factors of user’s adaptations. The coping mechanism of learner can show adaptations of physical or tangible form in interactions, gestures, speech, eye movement and so on. An account of the works related to such external factors affecting e-learning behavior is given in the next section.

2.8. External Factors of User’s Adaptations

There can be various reasons for adaptations in external factors of learner’s behavior. Learners adapt when they encounter either a new learning task, change in learning context or poor system response [79]. Adaptations in different learning contexts reflect the different aspects of a learner or a task or a system. Adaptations in learning effort reflect the cognitive load of learning. Studies show that poor students show more adaptations in their learning effort due to higher cognitive load [77]. Adaptations in browsing behavior of learning material reflects task difficulty or time pressure [85]. A study revealed that significant changes took place in the user’s questioning behavior in response to poor search results from the search engine. Therefore, adaptations can also reflect problems in the system’s performance [77]. Learners also change their level of disengagement with learning content (*disengaged-long* and *disengaged-fast*) when they are not motivated [13]. Experimental results show that user’s adaptations decreased when interface support was provided [66]. Users tend to rely on system/interface and hence do not exert themselves. Overall we observe that, there are various reasons for adaptations in external factor of learner’s behavior which manifest in different forms.

It is seen that changes in the learning contexts predominantly influence the learner’s navigational behavior. Analyzing the learner’s navigational paths for adaptations can provide valuable insights into their coping styles in difficult situations. Work related to deriving inferences from learner’s navigational behavior is presented next.

Navigational paths were analyzed to find irrelevant learning content on website [60]. On the other hand data mining of these paths were done to recommend suitable learning content to the learner [46]. Studying navigational paths were useful in finding student’s interest and personality [12] , motivation deficit [61] , reading behavior [51] or usability short comings in the learning environment [59]. Average page visit times and pages visited from chapters were used as indicators for deducting learning styles [8]. Behavior of using navigation features like main menu, hierarchical map and alphabetical index by novice and experts were studied. It was found that the students’ prior knowledge plays an influential role in their use of the navigation tools. Also, use of the navigation tools showed great impact on the students’ learning performance [58]. Pieschl and Stahl [70] found that adaptation in navigational behavior caused by changing task complexities significantly affect learner’s performance. Adaptations in various interaction parameters for simple, medium, complex tasks were computed. Adaptations in perceived task complexity, number of nodes accessed and use of hierarchical commands (HC) significantly influenced the learner’s performance.

Navigational adaptations can therefore reflect various characteristics. We need to test whether the inferences will be consistent and predictable across various situations. A study of how a learner manipulates navigational adaptations under different contexts of tasks and interfaces needs to be investigated. Learning contexts can be compared on the basis of adaptations in navigational paths.

The navigation design of an e-learning interface may influence learner’s adaptations and coping efforts in adapting to new learning contexts. We carried out a brief review of the general as well as the navigational features and patterns of an e-learning user interface.

A brief summary of e-learning user interface features is presented in table 2.1.

Table 2.1 Summary of e-learning interface design features

No	Parameter	Features
1	Visual Design	Simplistic, Colorful , Consistent (look & feel) , Engaging (multimedia), Appealing
2	Navigation *	Location identifier, Hyperlinked contents, Search(word/text), History, Menus (primary / secondary), Type (hierarchical , non–Hierarchical) , Navigation buttons (next, back, exit, topics, suspend, resume etc) , Tabs , Bookmarks(automatic) , Course undocking , Breadcrumbs , Emphasizing links , Hot-word orientation(how much learnt , how much remaining)
3	Usability	Visual feedback , Undo , Error handling , Shortcuts , Hide/show course progress , Less scroll bars , Less clicks
4	Pedagogy	Course overview , Course prerequisites , Course objectives , Course summary , Course evaluation , Solved problems , Puzzles , Solution analysis, Multiple format ,quizzes
5	Learning Support	Notes taking , Chat rooms ,FAQs , Forums , Language toggles , Additional references, Tutorials , Help , Remedial support , Mail filtering Assignments , Information searching , Books & articles , Resource management, Customized learning path , Games (crosswords, jigsaw puzzles, etc), Simulations, Glossary,
6	Tracking	Time spent , Book markings, Quiz scores, Course status, Learning curve & progress
7	Others	Audio control , Print exercises , Pdfs , Certificate of completion etc.

** The scope of current study is focused only on navigation design*

Subsequently navigational design patterns were studied and used in designing the experimental e-learning set-up. Some important navigational interaction design patterns have been summarized in table 2.2

Table 2.2 Navigational interaction design patterns

Type	Pattern	Usage
TABS	Navigation Tabs	Needs to navigate with clear indication of current section
JUMP	Breadcrumbs	Needs to know his location in the website's hierarchy
	Shortcuts / Search	Needs to access a specific section or functionality quick way
	Home Link	Need to go back to a safe start location of the site
	Fat footer	Needs to access a specific section or functionality quick way
	Search Box	Needs to find an item or specific information
MENUS	Accordion Menu	To find an item in the main navigation
	Horizontal Bar	Navigate sections, but space to show is limited
	Vertical Bar	Navigate sections, but space to show is limited
	Directory Menu	Users need to select an item out of a set

Type	Pattern	Usage
MENUS	Iconic menu	Users need so make a selection from limited items
	Repeated Menu	Users need to access the main navigation
	Split Navigation	The users need to navigate a hierarchical structure
CONTENT	Continuous scrolling	To view subset of data that is not displayed on single page
	Pagination	View a subset of sorted data that is not displayed on one page
MISC	Action button	Users need to take important action
	Stepping	Users need to view/act on a linear ordered set of items.
	Search results	Users need to process a list of search results
	Color coded sections	Users need to recognize that they are in the right place
	Grid based layout	The user needs to scan, read and understand a page quickly

When learning contexts change, initial adaptations are more because of additional load of familiarization with the new environment. The more the learner becomes conversant with the environment, the more will be his learning efficiency. Attempts by researchers in measuring user's ability for adapting to interfaces and skill acquisition are reviewed in the next section.

2.9. Measuring User's Adaptivity to Interfaces

It was observed that when users were given a task and then subsequently its variant task, they performed better the second time by overcoming the difficulties in the interface [49]. This shows that a user may differ in actions in same situations if an increase in knowledge of the interface has occurred. In other words, user's performance improves by adapting to an interface.

Similarly, when an interface acquires knowledge about the user, the interactions become easy and more useful. Trumbley et. al. [82] stated that users perform better if interface features match their computer skill levels. The same can hold good for interface skills also. Learners can learn better if learning interfaces adapt to learner's interface skill levels. For this we need to determine the user's interface skill levels.

Nagasaki and Azuma [62] defined skill as a tendency to select a particular operation. The tendencies were categorized as actions, methods and user operative elements. The first step analyzes the user operations extracted from the interaction log. In the second step, the extracted operations were compared with a typical user model. The method did not consider performance time as a skill attribute, and hence was a task independent- measure with no need to repeat the task.

Ueda and Hayama [32] evaluated user's adaptation to software. Novice users have tendencies to repeat redundant operations that have certain patterns. LZW compression was applied to users' operation logs to find the compression rate. Compression rate represented the rate of repetition of patterns of some character. Thus, the skill level was measured by identifying the occurrences of redundant operational paths. As a user moves from a novice level to an expert, the redundancy count reduces. However, the computation required a long period of user interaction with the system to get the results.

Ghazarian [27] designed an automatic system skill classifier using machine learning algorithm. Since users' skill levels change dynamically as users gain more experience in a user interface, so this classifier was used to build user model for adaptive- interface. User's system skills in low level high frequency events such as mouse motions and menu interactions were extracted. Since it was based on machine learning, its accuracy depended on a large training data.

Reinecke et. al. [71] contributed a framework and methodology for computing benefit based adaptivity metric for computing systems. The adaptivity was defined as an ability of improving performance through adaptations in successive trials of repetitive tasks. Adaptivity was computed as the ratio between the accumulated benefits of the actual system against an optimal system. This metric was more generic and was based on evaluating capacity of achieving ideal performance in minimum trials. The performance index could be developed as per the requirement.

In summary, the literature shows that learning performance is affected by user's skill level of the interface. Usability of an e-learning interface will depend on user's ability of acquiring skills on the interface. Therefore, there is a need of a measure for user's adaptivity to interfaces that could evaluate skill improvement capacity of learners based on (a) adaptation time (b) degree of feature usage or feature discoverability and (c) degree of expertise.

2.10. Conclusions

Figure 2.2 illustrates the issues and related works discussed in this chapter on user's adaptation. A misfit of technology to task or task to technology causes stress which leads to adaptations. Adaptations are controlled by learner's perceived complexity of situation (task + interface) and TTF state. The user adaptations, knowledge of interface features and navigation tools help to improve learning performance.

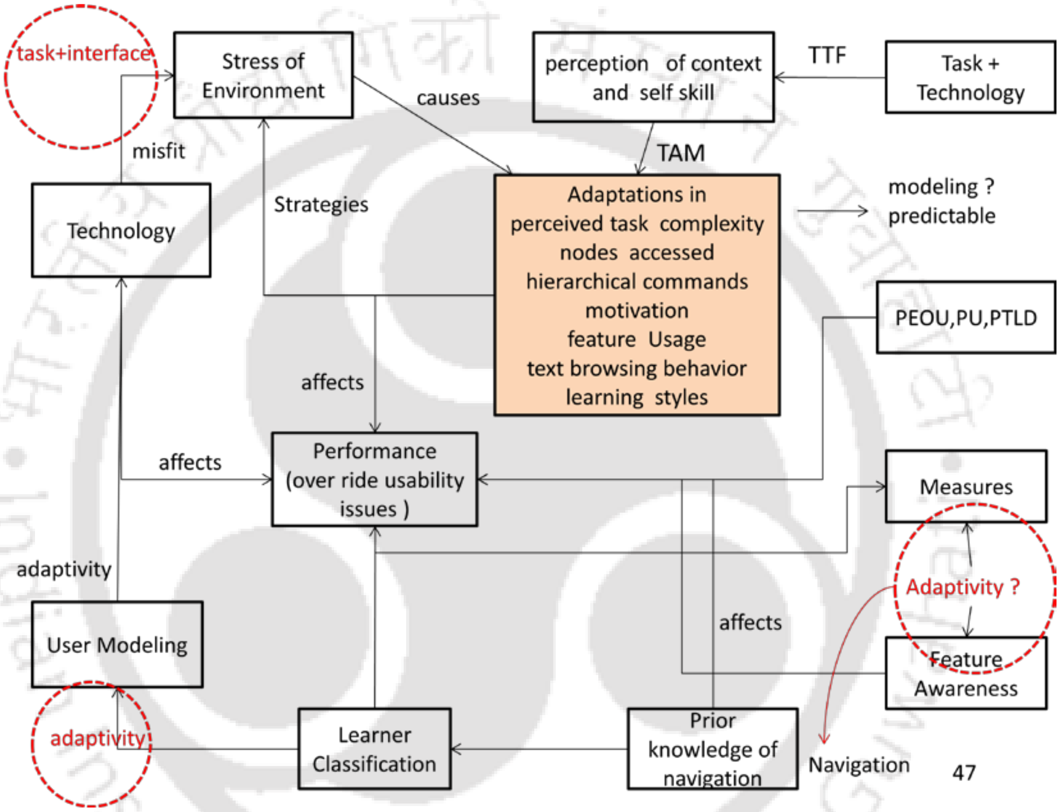


Figure 2.2 Review of research on user's adaptation

The belief in the usefulness of e-learning is an important motivating factor for e-learning. The e-learning success will not merely depend on its usage because it involves variations in cognitive levels of learning tasks. Therefore, TTF theory does not hold good due to the dynamic nature of learning tasks and user adaptation. Learner's adaptation behavior and ability to adapt can be accommodated while designing interfaces. This will need learner models storing user's system- knowledge. Interfaces can provide stepwise- rise in adaptivity based on learner's adaptations and adaptivity level. Various factors influencing user- adaptations need to be considered while designing such systems. Internal factors like self regulation, calibration, belief, self efficacy and cognitive architectures have indirect control over adaptations. An integrated study comparing performance of different interface support mechanisms in situations of different task complexities on the basis of user adaptations is required. Changes to learning contexts mainly affect the learner's navigational behavior. We need to test whether the inferences derived from adaptation behavior are consistent and predictable across various navigation designs. This will also help in comparing learning contexts based on adaptations in navigational paths. Learning performance is effected by user's skill level of application or interface. We need an integrated measure to evaluate user's interface skills and capability for improving it.

Research focus

Since extensive interface adaptivity hinders user motivations and upward movement from novice to expert user, a need of interaction design with knowledge of capabilities and limits of adaptations would be beneficial. Following research needs are identified as an outcome of the literature review.

1. Analyze user beliefs like PEOU, PU and PTLD for their effect on adaptations to new learning contexts need to be investigated.
2. Use of task adaptations as effective predictor of e-learning performance needs to be validated.
3. The extent of influence of learning task complexity and interface navigation design of an interface on task adaptations need to be investigated.
4. A measure of adaptation and adaptivity needs to be developed.

Summary : *The chapter reviewed the research literature on user adaptivity e-learning set-up. Adaptivity was discussed from three angles the learner, the learning task and the learning context. The review suggested a need for developing measures of adaptation and adaptivity. Also the need to validate these measures across differernt learning interfaces and tasks was felt.*

Based on the research needs identified, new measures were proposed and empirical studies were carried out to test and validate them. Detailed methodology of experimentation has been explained in the next chapter.

Chapter 3

Methodology

Chapter 3

Methodology

This chapter explains the methodology of the study performed for the present research. The design of experiments, choice of participants and configuring of experimental setup are explained in detail. Detail design and implementation of adaptivity testing tool is reported.

3.1. Introduction

In the previous chapter, review of research work related to user adaptation and adaptivity was presented. User's coping behavior in counteracting limitations in system's adaptivity was discussed. A need to explore the consistencies in user adaptations and its predictability in changing e-learning contexts was identified.

Based on this need, our research objective was to analyze the effect of navigation designs and learning task complexities on learner's adaptations in beliefs, interactions, tasks and performance. We conducted an empirical study for the purpose. In this chapter, the study methodology including participants, experiment design, set-up and data collection are presented. The study also focused on measuring the user's adaptivity to interfaces in different learning contexts.

The study required empirical data of learners' adaptations to verify the six hypotheses mentioned in chapter 1, section 1.4. Conclusions were derived based on results of the data collected. Therefore, the study undertaken used a quantitative explanatory research methodology involving statistical analysis of data to find a cause and effect relationship among variables.

3.2. Participants & Sample size

The participants were 287 (165 male and 122 female) undergraduate students of Information Technology from two engineering colleges, located at Guwahati and Pune. Their average age was 20 years and 7 months. Participants had an average computer experience of 6 years with 15 hours per week of internet exposure. However, only 24% of them had firsthand experience on e-learning courses. The participants rated themselves as experts in computer and internet skills, while intermediate in e-learning skills.

3.3. Experimental Design

The study participants were exposed to 2 types of user interface designs and 3 types of learning tests. We used a mixed design approach, where some variables were assessed within participants and others between participants.

An *independent samples between subjects multilevel (3) design* was used to find the effect of learning test types (task complexities) on adaptations and adaptivity. Independent design avoids practice, carry over and fatigue effects. The independent variables (IV) were user interface (GUI-1, GUI-2) and learning task complexity (knowledge, comprehension and application). GUI-1 was an e-learning interface with hierarchical horizontal menu and GUI-2 was an e-learning interface with non-hierarchical split menu. The 3 x 2 multi-level, multivariate factorial design is depicted in table 3.1.

Table 3.1 Independent Samples Design

Task Complexity (IV1) **Interface (IV2)**	**K**	**C**	**A**
GUI-1	K(a)	C(a)	A(a)
GUI-2	K(b)	C(b)	A(b)

To avoid errors due to individual variability in groups and to increase the statistical power, a dependant paired sample within subject (repeated measures) multilevel (2) experiment was also performed to find effect of navigation designs on adaptations and adaptivity. In this experiment design, independent variable was the only user interface (GUI-1, GUI-2). Figure 3.1 illustrates the overall experimental design.

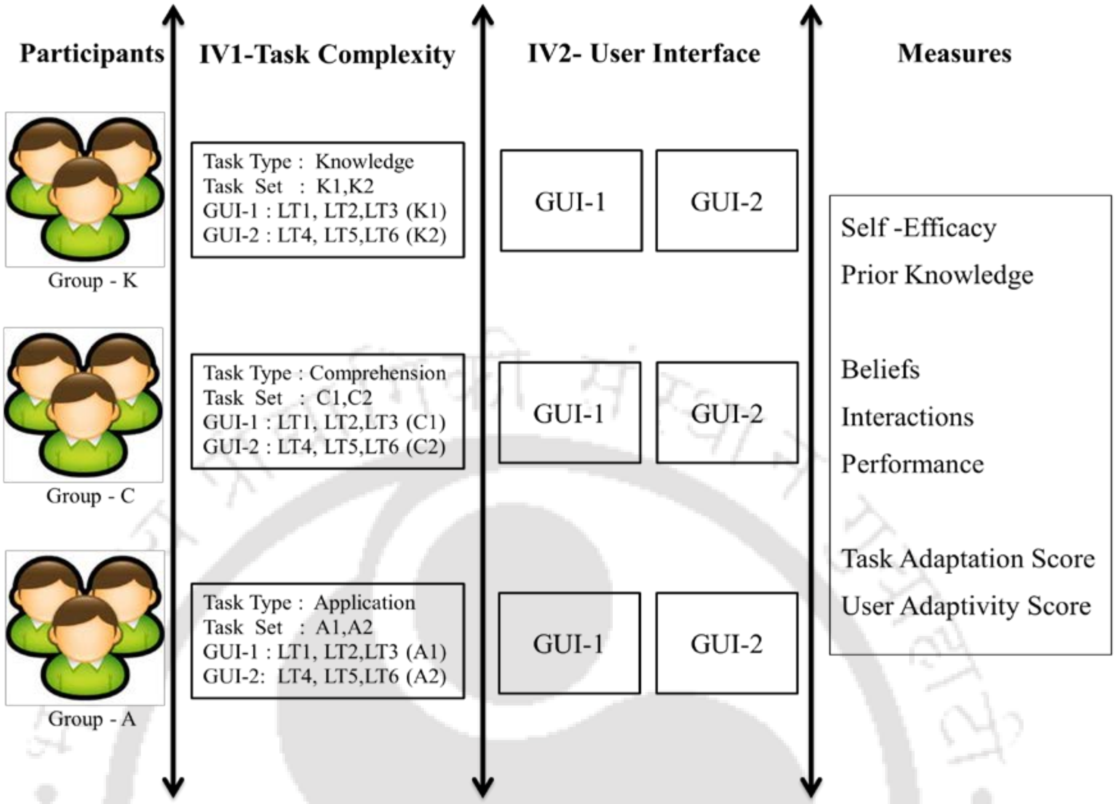


Figure 3.1 Experimental design

Overall it was a mixed design of within subjects (effect of user interfaces) and between subjects (effect of task complexity). There were 15 dependant variables measured which are listed in table 3.2

Table 3.2 Dependent variables

No.	Type	Code	Dependant Variable	Source
1	Belief	PEOU	Perceived Ease Of Use	Questionnaire Davis (1989)
2	Belief	PU	Perceived Usefulness	Questionnaire Davis (1989)
3	Belief	PTLD	Perceived Task Load	Questionnaire Hart et al.(1988)
4	Interaction	PNav	Page Navigation Commands	Operation Log
5	Interaction	TNav	Topic Navigation Commands	Operation Log
6	Interaction	TCv	Total Chapters Visits	Operation Log
7	Interaction	TPv	Total Pages Visits	Operation Log

No.	Type	Code	Dependant Variable	Source
8	Interaction	Top	Total operations	Operation Log
9	Performance	LO	Learning Outcome	Computation
10	Performance	LF	Learning Focus	Computation
11	Performance	IE	Interaction Efficiency	Computation
12	Performance	CE	Click Efficiency	Computation
13	Performance	PE	Page Efficiency	Computation
14	Adaptation	TAS	Task Adaptation Score	Computation
15	Adaptation	UAS	User Adaptivity Score	Computation

3.4. Experimental Set-Up

3.4.1. *Measurement instruments*

The belief attributes were measured using validated questionnaire survey instrument questionnaire Q1 and questionnaire Q2 (Appendix A1 and A2). Scale for perceived ease-of-use (PEOU) and perceived usefulness (PU) were adopted from the Technology Acceptance Model (TAM) of Davis [17]. (Appendix A2)

NASA Task Load Index (NASA-TLX) is a subjective multidimensional perceived workload assessment scale developed by Human Performance Group at NASA's Ames Research Center [30]. It derives an overall workload score based on six sub-scales. This scale was adopted to measure perceived task load (PTLD) of GUI-1 and GUI-2. (Appendix A2)

Learner’s interactions were logged with timestamps and further processed programmatically to compute other dependant variables.

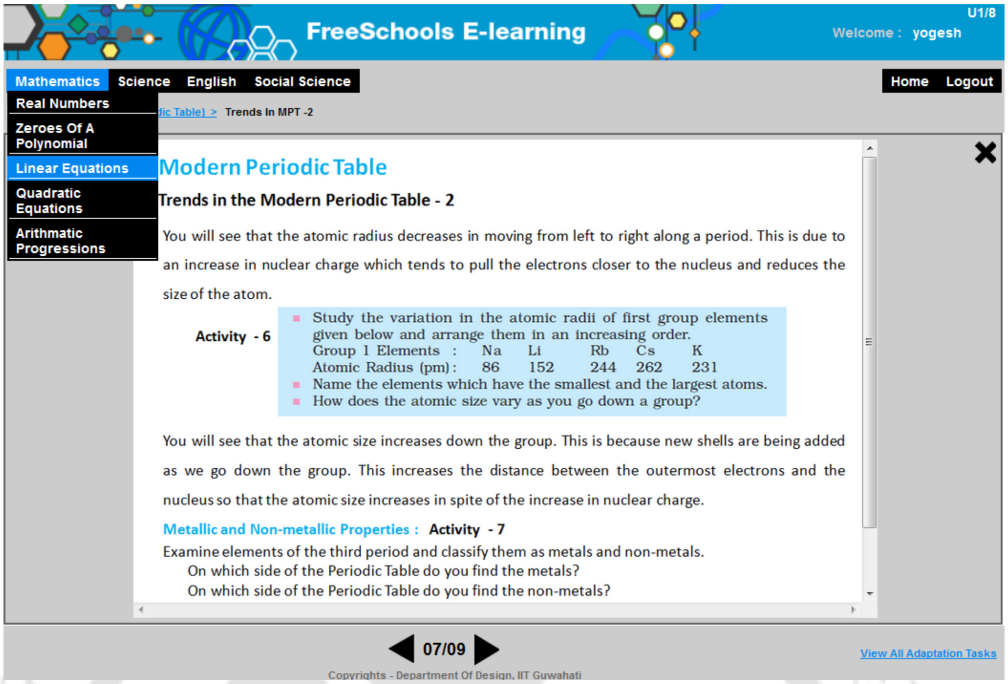
3.4.2. *E-Learning Application*

Two separate e-learning web applications with identical course contents but having different graphical user interfaces (GUI-1 and GUI-2) were developed using HTML, CSS, Java Script, PHP and MYSQL technologies.

The instructional contents were divided into chapters and pages under each chapter. Multiple context views were not essential due to limited learning content, avoiding the need to use navigation tabs. Home, breadcrumbs and history links or buttons were used to facilitate non-hierarchical jumps. Study by Passig and Nadler [68] found that *structural* interfaces (table of contents) improves navigation and speed of locating information while *conceptual* interfaces (menu-type or hyperlinks) improves deeper processing for understanding. Also, interlacing of specific and compatible interfaces make navigation easier (superficial processing) and enhances deep understanding of content (deep processing). Therefore, horizontal menu bar with hierarchical structure was used in GUI-1 while a split menu with hyperlinks (interlaced structure) was used in GUI-2. Scrolling was kept to minimum from usability aspects and page number hyperlinks were provided for quick navigation of content pages. The final design features of user interfaces are shown in table 3.3.

Table 3.3 Interface design parameters

No.	**Parameter**	**GUI-1 Features**	**GUI-2 Features**
1	Jumps	Home – (NH)	Home – (NH)
		Breadcrumbs (NH)	
		Restore page (NH)	Restore page(NH)
2	Menus type , position	Hierarchical	Non-Hierarchical
		Horizontal Drop down (Top)	Vertical Split Menu (Left)
3	Page Navigation	Buttons (Next , Back)	Pagination (Hyper links)
4	Navigation Bar Position	Top	Top
5	Control Bar Position	Bottom	Bottom
6	Progress Identification	Page - 1/15	None



Modern Periodic Table

Trends in the Modern Periodic Table - 2

You will see that the atomic radius decreases in moving from left to right along a period. This is due to an increase in nuclear charge which tends to pull the electrons closer to the nucleus and reduces the size of the atom.

Activity - 6

- Study the variation in the atomic radii of first group elements given below and arrange them in an increasing order.

Group 1 Elements :	Na	Li	Rb	Cs	K
Atomic Radius (pm) :	86	152	244	262	231

- Name the elements which have the smallest and the largest atoms.
- How does the atomic size vary as you go down a group?

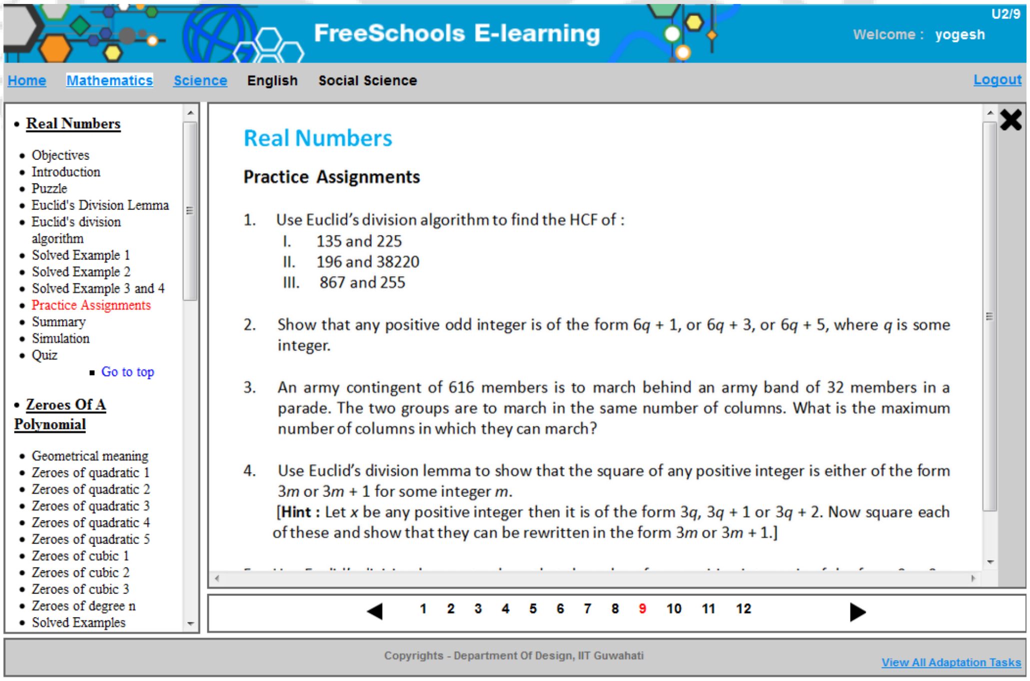
You will see that the atomic size increases down the group. This is because new shells are being added as we go down the group. This increases the distance between the outermost electrons and the nucleus so that the atomic size increases in spite of the increase in nuclear charge.

Metallic and Non-metallic Properties : Activity - 7

Examine elements of the third period and classify them as metals and non-metals.
On which side of the Periodic Table do you find the metals?
On which side of the Periodic Table do you find the non-metals?

Figure 3.2 Hierarchical horizontal menu - GUI-1

GUI-1, shown in figure 3.2, had a simplistic design with hierarchical drop down menu, only next and back page navigation buttons, progress indicator and breadcrumb feature.



Real Numbers

Practice Assignments

1. Use Euclid's division algorithm to find the HCF of :
   I. 135 and 225
   II. 196 and 38220
   III. 867 and 255
2. Show that any positive odd integer is of the form $6q + 1$, or $6q + 3$, or $6q + 5$, where q is some integer.
3. An army contingent of 616 members is to march behind an army band of 32 members in a parade. The two groups are to march in the same number of columns. What is the maximum number of columns in which they can march?
4. Use Euclid's division lemma to show that the square of any positive integer is either of the form $3m$ or $3m + 1$ for some integer m.
   [**Hint :** Let x be any positive integer then it is of the form $3q$, $3q + 1$ or $3q + 2$. Now square each of these and show that they can be rewritten in the form $3m$ or $3m + 1$.]

Figure 3.3 Non-Hierarchical split menu – GUI-2

GUI-2, shown in figure 3.3, had a complex design with non-hierarchical design having a split menu consisting of horizontal menu bar for subject selection and vertical hyperlinked sub-menu for topic and page selection. Differences in navigation focus of both the designs are stated in table 3.4.

Table 3.4 Navigation focus of GUI1 and GUI2

Interface	**Control**	**Purpose**	**Tool Used**
GUI-1	Sequence Control	To allow students to decide sequence of topic pages to be learned	Hierarchical menu Backward-forward buttons
GUI-2	Content Control	To allow students to control the selection of contents they wish to learn	Main Menu Sub-Menu (hyper-linked)

The domain knowledge chosen for this study were Mathematics and Chemistry. The topics chosen within these subjects were not part of the engineering curricula, diminishing the possible influence of learners' prior knowledge. The contents were taken from standard text books of mathematics and science and were converted to web pages for use in the online system.

The learning course included five chapters of each subject. The topics of the chapters had no prerequisites. Each chapter had the same structure starting with the introduction, followed by a detailed explanation with examples and practice assignments at the end. The page length of the chapters was also kept short i.e. between 9 pages to 15 pages. The explanations were illustrative and were kept brief to avoid scrolling of contents as much as possible. Each content page had proper identification of chapter name and topic name at the top and page number at the bottom.

3.4.3. *Learning Test – Based on Bloom's Taxonomy*

Bloom's Taxonomy [64] divides educational objectives into three domains viz. cognitive, affective and psycho motor. The cognitive levels of educational objectives are presented in table 3.5. In the current study, three levels of cognitive activities namely knowledge, comprehension and application have been selected. These will be referred as *learning* *task complexities*. These levels require participants to remember, comprehend and apply knowledge. Remembering involves recognizing and retrieving from previously learnt concepts. Comprehension involves understanding and interpretations. Application involves use of the concept learnt in a new situation or providing a solution. The learning test questions for the three sample groups were based on these three levels of cognitive complexities.

Table 3.5 Blooms' taxonomy of educational objectives

No.	Type	Description
1	Knowledge	recall or recognize information
2	Comprehension	understand meaning, re-state data in one's own words, interpret, extrapolate, translate
3	Application	use or apply knowledge, put theory into practice, use knowledge in response to problems
4	Analysis	interpret elements, organizational principles, structure, construction, internal relationships, quality, reliability of individual components
5	Synthesis	develop new unique structures, systems, models, approaches, ideas; creative thinking,
6	Evaluation	assess effectiveness of whole concepts, in relation to values, outputs, efficacy, viability; critical thinking, strategic comparison and review; judgment relating to external criteria

Richard, P. (1985). Bloom's taxonomy and critical thinking instruction. *Educational Leadership*, *42*(8), 36-39.

Knowledge based, comprehension based and application based learning tasks (tests) were developed for three independent sample groups labeled K, C and A respectively. Each learning task (LT) was a test having 5 predefined objective type questions. One set of three learning tests (LT1, LT2 and LT3) were developed for GUI-1 and another set of three for GUI-2. The sets were given labels K1-K2 for knowledge type, C1-C2 for comprehension type and A1-A2 for application type (Appendix A3).

3.4.4. *User Adaptivity Testing Tool*

We designed a separate repetitive task for measuring adaptivity. We developed a PHP program to log learner's performance on this repetitive task in terms of completion time and number of clicks required. The participants executed a set of predefined instructions given in table 3.6 and 3.7 in a sequence as the repetitive task. The instructions were purposely chosen, to expose the participant, to each functionality of the interface. We designed different repetitive tasks for GUI-1 (having 13 instructions) and GUI-2 (having 19 instructions). The participant performed each trial of this repetitive task as part of adaptivity test, after each learning test was completed.

Table 3.6 and 3.7 show repetitive task sets for GUI-1 and GUI-2 respectively.

Table 3.6 Repetitive task set for GUI-1

No.	Instruction
1	Open chapter linear Equations of Mathematics
2	Go to page no 4 of chapter Real Numbers of Mathematics
3	Go to home page
4	Open recently referred page
5	Go to last page of chapter Quadratic Equations of Mathematics
6	Move 3 pages backward
7	Go to first page of current chapter(Quadratic Equations)
8	Close this chapter
9	Go to page no 5 of chapter Arithmetic Progressions of Mathematics
10	Go to first page of current chapter(Arithmetic Progressions)
11	Go to home page
12	Open recently referred page
13	Logout

Table 3.7 Repetitive task set for GUI-2

No.	Instruction
1	Select Science
2	Move 3 pages forward
3	Close this chapter
4	Open chapter Metals and Non-Metals of Science
5	Jump to page 5 of this chapter
6	Jump to start of Science topic index
7	Select Mathematics
8	Select Linear Equations chapter
9	Open practice assignments page of chapter Linear Equations
10	Go to home page

No.	Instruction
11	Open recently referred page
12	Open page Acids And Bases >>> Reactions with metals
13	Jump to page 8 of this chapter
14	Move 2 pages backward
15	Open page Covalent Bond >>> Quiz
16	Close this chapter
17	Open chapter Modern Periodic Table
18	Check out activity 2 in chapter Acids and Bases
19	Logout

Keystroke Level Model (KLM) was used to predict completion time for each instruction of the repetitive task. The total predicted time (T_{opt}) for adaptivity test was computed as *27600ms* for GUI-1 and *27000ms* for GUI-2. Also minimum number of clicks (C_{opt}) required by an expert user to complete adaptivity test was computed to be 28 mouse clicks for GUI-1 and 25 mouse clicks for GUI-2. A sample KLM analysis of the instruction, *'Go to page no 4 of chapter Real Numbers of Mathematics'* on GUI-1 is shown in table 3.8. The analysis computes the completion time as *11300 mili seconds.*

Table 3.8 KLM analysis of 2nd instruction of the repetitive task set for GUI-1

Task	Description	Key	M	P	BB	Time
2	***Go to page no 4 of chapter Real Numbers of Mathematics***					
1	Think to point to maths	M	1200			1200
2	Point to "maths" menu item from top menu bar	P		1100		1100
3	Think to point to real numbers	M	1200			1200
4	Point to "real numbers" submenu item from "maths" drop-down menu	P		1100		1100
5	Click on "real numbers" submenu item from "maths" drop-down menu	BB			200	200
6	Check page number	M	1200			1200
7	Point to "next page" button	P		1100		1100
8	Click "next page" button (on page 2)	BB			200	200
9	Check page number	M	1200			1200
10	Click "next page" button (on page 3)	BB			200	200
11	Check page number	M	1200			1200

Task	Description	Key	M	P	BB	Time
12	Click "next page" button (on page 4)	BB			200	200
13	Check page number	M	1200			1200
	K= Keystroke (280 ms)	0		0		
	P= Pointing mouse (1100ms)	3		3300		
	B= Press or release mouse (100ms)	0		0		
	BB= Click mouse button (200ms)	4		800		
	M= Estimated mental operation (1200 ms)	6		7200		
Total						**11300**

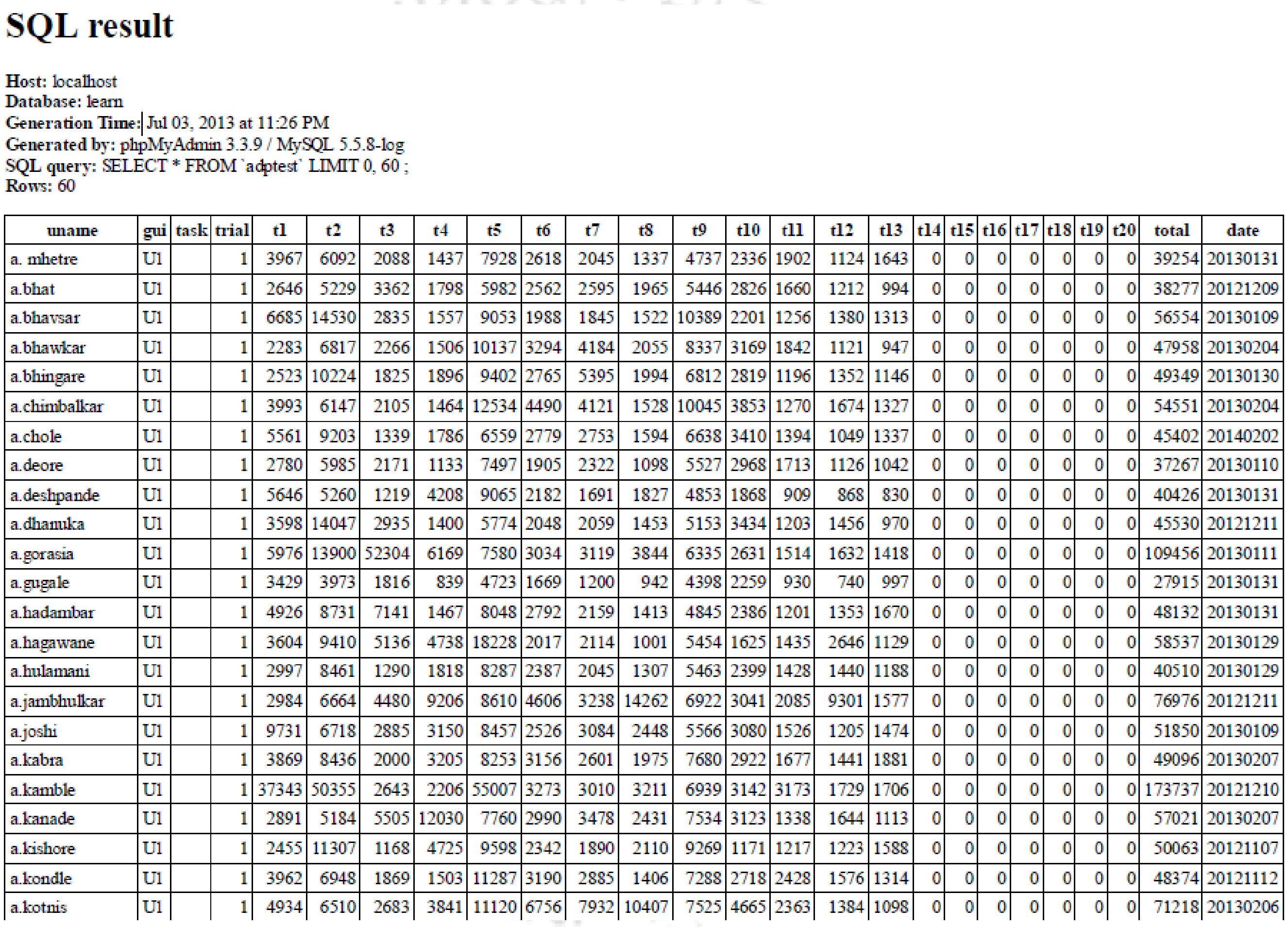
Since adaptivity test was required to be repeated 5 times, the sequence of instructions within the repetitive task was randomly changed to nullify the memorizing or skill effect.

The adaptivity test tool was also developed using HTML, CSS, Java Script, PHP and MYSQL technologies. A screen shot of the adaptivity test on GUI-2 is shown in figure 3.4. A window with instructions to be executed in sequence can be seen in the figure.

T1 - Select Science
T2 - Move 3 pages forward
T3 - Close this chapter
T4 - Open chapter Metals and Non-Metals of Science
T5 - Jump to page 5 of this chapter
T6 - Jump to start of Science topic index
T7 - Select Mathematics
T8 - Select Linear Equations chapter
T9 - Open practice assignments page of chapter Linear Equations
T10 - Go to home page
T11 - Open recently referred page
T12 - Open page Acids And Bases >>> Reactions with metals
T13 - Jump to page 8 of this chapter
T14 - Move 2 pages backward
T15 - Open page Covalent Bond >>> Quiz
T16 - Close this chapter
T17 - Open chapter Modern Periodic Table
T18 - Check out activity 2 in chapter Acids and Bases
T19 - Logout

Figure 3.4 Screen shot of adaptivity test on GUI-2

The performance data on repetitive task in adaptivity test was stored in a MySql table. Figure 3.5 shows the partial data from the table ADPTEST for GUI-1.



SQL result

Host: localhost
Database: learn
Generation Time: Jul 03, 2013 at 11:26 PM
Generated by: phpMyAdmin 3.3.9 / MySQL 5.5.8-log
SQL query: SELECT * FROM `adptest` LIMIT 0, 60 ;
Rows: 60

uname	gui	task	trial	t1	t2	t3	t4	t5	t6	t7	t8	t9	t10	t11	t12	t13	t14	t15	t16	t17	t18	t19	t20	total	date
a. mhetre	U1		1	3967	6092	2088	1437	7928	2618	2045	1337	4737	2336	1902	1124	1643	0	0	0	0	0	0	0	39254	20130131
a.bhat	U1		1	2646	5229	3362	1798	5982	2562	2595	1965	5446	2826	1660	1212	994	0	0	0	0	0	0	0	38277	20121209
a.bhavsar	U1		1	6685	14530	2835	1557	9053	1988	1845	1522	10389	2201	1256	1380	1313	0	0	0	0	0	0	0	56554	20130109
a.bhawkar	U1		1	2283	6817	2266	1506	10137	3294	4184	2055	8337	3169	1842	1121	947	0	0	0	0	0	0	0	47958	20130204
a.bhingare	U1		1	2523	10224	1825	1896	9402	2765	5395	1994	6812	2819	1196	1352	1146	0	0	0	0	0	0	0	49349	20130130
a.chimbalkar	U1		1	3993	6147	2105	1464	12534	4490	4121	1528	10045	3853	1270	1674	1327	0	0	0	0	0	0	0	54551	20130204
a.chole	U1		1	5561	9203	1339	1786	6559	2779	2753	1594	6638	3410	1394	1049	1337	0	0	0	0	0	0	0	45402	20140202
a.deore	U1		1	2780	5985	2171	1133	7497	1905	2322	1098	5527	2968	1713	1126	1042	0	0	0	0	0	0	0	37267	20130110
a.deshpande	U1		1	5646	5260	1219	4208	9065	2182	1691	1827	4853	1868	909	868	830	0	0	0	0	0	0	0	40426	20130131
a.dhamka	U1		1	3598	14047	2935	1400	5774	2048	2059	1453	5153	3434	1203	1456	970	0	0	0	0	0	0	0	45530	20121211
a.gorasia	U1		1	5976	13900	52304	6169	7580	3034	3119	3844	6335	2631	1514	1632	1418	0	0	0	0	0	0	0	109456	20130111
a.gugale	U1		1	3429	3973	1816	839	4723	1669	1200	942	4398	2259	930	740	997	0	0	0	0	0	0	0	27915	20130131
a.hadambar	U1		1	4926	8731	7141	1467	8048	2792	2159	1413	4845	2386	1201	1353	1670	0	0	0	0	0	0	0	48132	20130131
a.hagawane	U1		1	3604	9410	5136	4738	18228	2017	2114	1001	5454	1625	1435	2646	1129	0	0	0	0	0	0	0	58537	20130129
a.hulamani	U1		1	2997	8461	1290	1818	8287	2387	2045	1307	5463	2399	1428	1440	1188	0	0	0	0	0	0	0	40510	20130129
a.jambhulkar	U1		1	2984	6664	4480	9206	8610	4606	3238	14262	6922	3041	2085	9301	1577	0	0	0	0	0	0	0	76976	20121211
a.joshi	U1		1	9731	6718	2885	3150	8457	2526	3084	2448	5566	3080	1526	1205	1474	0	0	0	0	0	0	0	51850	20130109
a.kabra	U1		1	3869	8436	2000	3205	8253	3156	2601	1975	7680	2922	1677	1441	1881	0	0	0	0	0	0	0	49096	20130207
a.kamble	U1		1	37343	50355	2643	2206	55007	3273	3010	3211	6939	3142	3173	1729	1706	0	0	0	0	0	0	0	173737	20121210
a.kanade	U1		1	2891	5184	5505	12030	7760	2990	3478	2431	7534	3123	1338	1644	1113	0	0	0	0	0	0	0	57021	20130207
a.kishore	U1		1	2455	11307	1168	4725	9598	2342	1890	2110	9269	1171	1217	1223	1588	0	0	0	0	0	0	0	50063	20121107
a.kondle	U1		1	3962	6948	1869	1503	11287	3190	2885	1406	7288	2718	2428	1576	1314	0	0	0	0	0	0	0	48374	20121112
a.kotnis	U1		1	4934	6510	2683	3841	11120	6756	7932	10407	7525	4665	2363	1384	1098	0	0	0	0	0	0	0	71218	20130206

Figure 3.5 Adaptivity test data in mysql table – ADPTEST

3.5. Experiment Procedure

Total participants were divided into three sample groups based on the type of learning tasks given to them. Participants were assigned randomly to these groups. Different sample groups were administered different types of learning tasks (tests) having different complexities such as knowledge (K), comprehension (C) and application (A).

The three sample population groups were as follows:
(1) Group-A - Application oriented learning group
(2) Group-C - Comprehension oriented learning group
(3) Group-K - Knowledge oriented learning group

All the three sample populations were similar in their background. Analysis of demographic details of the three sample groups is shown in table 3.9 and the corresponding questionnaire used for data collection is shown in Appendix A1

Table 3.9 Demographic details of sample groups

Sample Group	**Size**	**Age (years. month)**	**Gender**	**Computer (Internet) Usage (hours/week)**	**Self Rated Knowledge In Maths (out of 5)**	**Self Rated Knowledge In Chemistry (out of 5)**	**E-learning Self Efficacy (out of 120)**
A	96	20.10 (SD=1.74)	M=55 F= 41	15 (13)	M = 4.70 (SD=1.162)	M=3.82 (SD=1.465)	M=95.21 (SD=13.9510)
C	106	20.7 (SD=1.59)	M=55 F= 51	14 (10)	M = 4.58 (SD=1.286)	M=3.81 (SD=1.235)	M=93.26 (SD=11.285)
K	85	20.7 (SD=1.51)	M=55 F= 30	16 (11)	M = 4.76 (SD=1.13)	M=3.86 (SD=1.05)	M=95.56 (SD=9.579)

Each sample population group-A (*n*=96), group-C (*n*=106) and group-K (*n*=85) were further randomly divided in two subgroups each viz. K(a), K(b), C(a), C(b), A(a) and A(b). The treatments given to these sub-groups are summarized in table 3.10.

Table 3.10 Learning test treatments to sub-groups

Interface	**Learning Test Set**					
	K1	K2	C1	C2	A1	A2
GUI-1	K(a)	K(b)	C(a)	C(b)	A(a)	A(b)
GUI-2	K(b)	K(a)	C(b)	C(a)	A(b)	A(a)

Participants were randomly assigned to sub-groups. The order effect of GUI-1 and GUI-2 was counter balanced by changing the sequence of GUIs for half the subgroup population. Since same learning test could not be repeated for both GUIs, the participants of sub-group K(a) solved 3 learning tests (LT1,LT2,LT3) from set K1 using GUI-1 and then solved three more learning tests (LT1,LT2,LT3) from set K2 using GUI-2. For sub-group K(b) everything else was same except the order of GUIs, which were reversed. This was done to create two independent sample sub-groups for comparing effect of different GUIs on task adaptation scores under similar learning test conditions. Similar tests were administered for other sample groups as given in table 3.10.

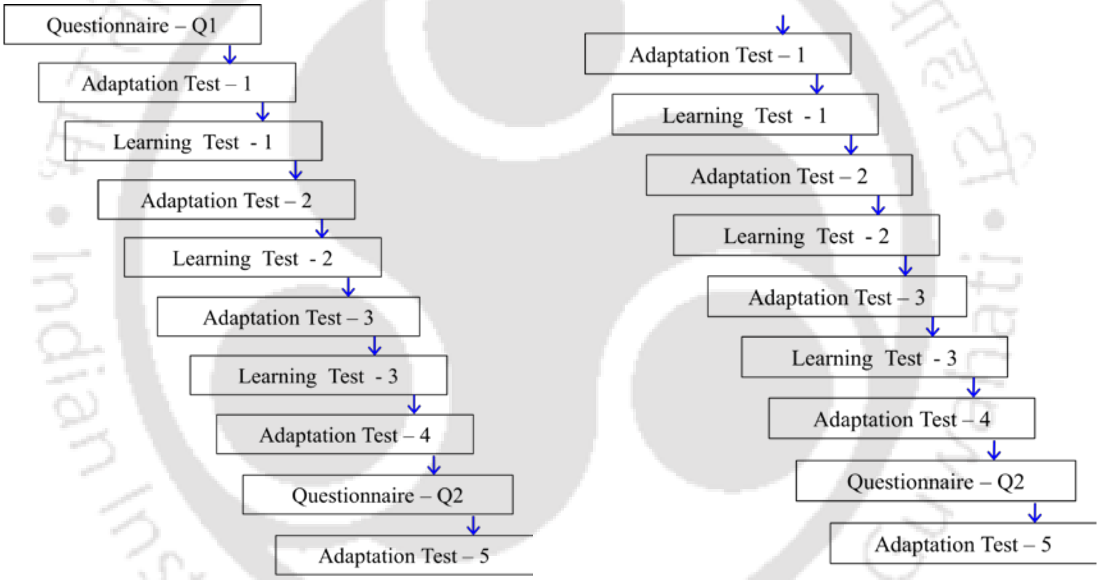
The experimentation was divided in two parts. Part A was – *study of user's adaptations* in beliefs, interactions, tasks and performance on GUI-1 and GUI-2 in the three sample groups. Part B was - *study of user's adaptivity to* GUI-1 and GUI-2 in the three sample groups.

In order to illustrate, we present as an example the procedure followed to collect data from group-K.

1. In the beginning, participants responded to questionnaire Q1 which recorded their personal information.
2. Participants then performed first trial of adaptivity test (AT1) on GUI-1. They were instructed to complete the tasks as fast as possible.
3. Learning test-1(LT1) was then solved from set K1.
4. The participants then solved LT2 and LT3 from K1 in succession interlaced with adaptivity tests AT2 and AT3.

5. Participants familiarized and learnt GUI features during each learning test which reflected in their performance in adaptivity test.
6. After adaptation test-4 participants responded to questionnaire Q2 that recorded PEOU, PU and PTLD of the GUI under test.
7. At the end adaptation test-5 was performed.
8. The same experimental steps were then repeated with second GUI and a new set of learning tests. The entire e-learning experiment was completed in 80 minutes.

The experimental procedure is depicted in figure 3.6.



Using GUI-1 and test set K1 **Using GUI-2 and test set K 2**

Figure 3.6 Experimental procedure

Figure 3.7 Pictures of participants working on experiments

3.6. Statistical and Mathematical Methods Used for Data Analysis

In the statistics, the missing data values from the questionnaire are called as *missing completely at random* (MCAR) if the event that leads to the particular missing data-item is independent of observable variables and unobservable parameters of interest. When data is MCAR, the analysis performed on the data is unbiased. In this study, Little's MCAR [53] test was run on data to find out whether the missing values occurred at random. Simple mean imputation strategy was adopted to replace these missing values. The outliers in data were identified using z-scores. The effective outlier cases were deleted. Since the sample size of the smallest sample population including all sub-groups was greater than 30, Central Limit Theorem was invoked and thus normal distribution was assumed for inferential statistics.

The measurement scales were tested for internal consistency or reliability using Cronbach's Alpha (α) coefficient. The results of the tests are shown in the table 3.11.

Table 3.11 Reliability of questionnaire scales

No	Sample Group	Interface	Scale	Cronbach's Alpha
1	K	GUI-1	Perceived Ease-Of-Use (PEOU)	0.908
2	K	GUI-1	Perceived Usefulness (PU)	0.920
3	K	GUI-1	Perceived Task Load (PTLD)	0.747
4	K	GUI-2	Perceived Ease-Of-Use (PEOU)	0.879
5	K	GUI-2	Perceived Usefulness (PU)	0.909
6	K	GUI-2	Perceived Task Load (PTLD)	0.707
7	C	GUI-1	Perceived EaseOfUse (PEOU)	0.856
8	C	GUI-1	Perceived Usefulness (PU)	0.901
9	C	GUI-1	Perceived Task Load (PTLD)	0.722
10	C	GUI-2	Perceived EaseOfUse (PEOU)	0.818
11	C	GUI-2	Perceived Usefulness (PU)	0.842
12	C	GUI-3	Perceived Task Load (PTLD)	0.692
13	A	GUI-1	Perceived EaseOfUse (PEOU)	0.902
14	A	GUI-1	Perceived Usefulness (PU)	0.909
15	A	GUI-1	Perceived Task Load (PTLD)	0.785
16	A	GUI-2	Perceived EaseOfUse (PEOU)	0.820
17	A	GUI-2	Perceived Usefulness (PU)	0.856
18	A	GUI-2	Perceived Task Load (PTLD)	0.742

Results showed all scales to be highly reliable with a mean value of alpha = 0.828. Descriptive statistics including mean, median, range, standard deviation, skewness were used to summarize the sample data.

Two independent learning groups were given the same set of learning tests to solve on different GUIs. The significance of differences in these observed values were analyzed using independent-samples t-test. For adaptivity tests, the performance of participants from the same group was compared between GUI-1 and GUI-2. Paired-samples t-test was therefore used on the adaptivity data to analyze the significance of differences within the group. ANOVA test was performed to find whether the observed mean values of various parameters varied significantly across the three sample groups K,C and A. Finally, bivariate analysis using Pearson product-moment correlation coefficient (Pearson's r) was performed to find the empirical relationship or causality checking between variables.

Power Law of Practice was used to model the user's adaptation behavior and validate the usefulness of the proposed user adaptivity score. According to this law, the performance time on a task can be described as a power function of practice, as indicated by

$$\mathbf{T = T_{min} + AN^{\propto}} \qquad \mathbf{(3.1)}$$

Where,

T_N = Trial completion time at N^{th} trial
T_{min} = Minimum time that a task can be performed
A = Constant
N = Trial number
α = Learning rate, a value usually between 0 and -1

We plotted the learning curves i.e. adaptivity test completion time against trial number. We did power curve fitting to this graph using the inbuilt Excel feature. Also the equation of the fitted curve was obtained in the form of Eqn. (2.1). The parameters 'A' and 'α' gave the initial effort and the learning rate. We correlated these parameters with the adaptivity scores to conclude on the validity of the score.

Summary: *This chapter discussed the research methodology used to carry out the research experiments. Details of experiment design, participants, measuring scales, experimental set-up and procedure are elaborated. Detail design of user adaptivity testing tool has also been outlined. The empirical data collected from the experiments and analysis are presented in the next two chapters.*

Chapter 4

Data Analysis of the Study on User's Adaptations

Chapter 4

Data Analysis of the Study on User's Adaptations

E-learning experiments with 287 participants were conducted in two parts using the methodology described in the previous chapter. Part A studied the user's adaptations to two types of user interface designs and part B studied the user's adaptivity to these two user interfaces. This chapter defines the task adaptation measure at the beginning and then presents the data collected and analysis of part A of the experiment i.e. the study of user's adaptations. Conclusions are derived on the basis of statistical significance of the results obtained.

4.1. Introduction

In the previous chapter, we described the methodology of experimental design, data collection and analysis that was adopted for this research. In this chapter, we will present the data collection and analysis of the user's adaptations. The objective of this part of the experiment was to validate whether learning task complexity has significant effect on user adaptations *(hypothesis H1)* and whether navigation design has significant effect on user adaptations *(hypothesis H3)*. For this purpose, we divided the participants in three sample groups (K, C and A) based on the type of learning tests given to them. We administered knowledge based tests to group-K, comprehension based tests to group-C and application based tests for Group-A.

As it may be recalled, in Part-A of the experiment, participants initially responded to questionnaire Q1 (Appendix-A1). The participants then solved three learning tests using the e-learning application having GUI-1. After the learning tests, they responded to questionnaire Q2 (Appendix-A2) which recorded PEOU, PU and PTLD on GUI-1. We repeated the same process for the same participants on GUI-2 with a different set of learning tests of same type. We logged the interaction data of all participants in MySql database. We preprocessed the belief data from the questionnaire for the missing values and outliers. We computed the interaction data from the operation log in database. Both the data were entered into SPSS package for statistical analysis.

In order to compare user's adaptations, we propose a new measure in this thesis. The proposed measure is described next.

4.2. The Measure of Task Adaptation Score (TAS)

The learning-contents of the e-learning application are organized into pages and chapters within courses as they appear on the computer screen in front of the participants. A learning test (LT) is a test having objective type questions based on the contents of the e-learning courses. We define task adaptations as adaptations in learning tasks (chapters visited, pages visited, total operations etc.) between learning tests carried out on the same learning interface.

Task adaptations are changes in a task type (say T) between different learning tests given on the same user interface. If a learner attempts 'n' different learning tests in sequence as $\{LT_1, LT_2 \ldots LT_n\}$, then the number of tasks of type T performed during the tests would be $\{T_1, T_2 \ldots T_n\}$ respectively. Task adaptations score will be computed as below:

$$\text{Task Adaptation Score in T} = \frac{\text{Task adapations of type T}}{\text{Total tasks of type T}}$$

$$\text{Task Adaptations of type T} = |T_1 - T_2| + |T_2 - T_3| + \ldots |T_{n-1} - T_n| = \sum_{i=2}^{n} |T_{i-1} - T_i|$$

$$\text{Total tasks of type T} = T_1 + T_2 + \ldots T_n = \sum_{i=1}^{n} T_i$$

$$\textbf{Task Adaptation Score} = \frac{\sum_{i=2}^{n} |T_{i-1} - T_i|}{\sum_{i=1}^{n} T_i} \qquad (4.1)$$

In the current study, we considered task types (T) of (a) the total chapters visited (TC_v) (b) the total pages visited (TP_v) and (c) the total operations done (T_{op}) by the learner during a learning task.

We also computed adaptations across GUI-1 and GUI-2 for all the dependant variables (table 3.2 chapter 3). The expressions of adaptation score (AS) for all the variables are shown in Eqns. (4.2)-(4.16).

$$AS\_PEOU = \frac{|PEOU_{GUI-1} - PEOU_{GUI-2}|}{PEOU_{GUI-1} + PEOU_{GUI-2}} \quad (4.2)$$

$$AS\_PU = \frac{|PU_{GUI-1} - PU_{GUI-2}|}{PU_{GUI-1} + PU_{GUI-2}} \quad (4.3)$$

$$AS\_PTLD = \frac{|PTLD_{GUI-1} - PTLD_{GUI-2}|}{PTLD_{GUI-1} + PTLD_{GUI-2}} \quad (4.4)$$

In Eqns. (4.2), (4.3) and (4.4), PEOU, PU and PTLD represent group mean values of belief variables for a specific GUI (GUI-1 or GUI-2).

$$AS\_TNav = \frac{|TNav_{GUI-1} - TNav_{GUI-2}|}{TNav_{GUI-1} + TNav_{GUI-2}} \quad (4.5)$$

$$AS\_PNav = \frac{|PNav_{GUI-1} - PNav_{GUI-2}|}{PNav_{GUI-1} + PNav_{GUI-2}} \quad (4.6)$$

$$AS\_TPv = \frac{|TPv_{GUI-1} - TPv_{GUI-2}|}{TPv_{GUI-1} + TPv_{GUI-2}} \quad (4.7)$$

$$AS\_Top = \frac{|Top_{GUI-1} - Top_{GUI-2}|}{Top_{GUI-1} + Top_{GUI-2}} \quad (4.8)$$

In Eqns. (4.5), (4.6),(4.7) and (4.8), TNav, PNav, TPv and Top represent group mean values of sum of respective tasks in all the three learning tests (LT1,LT2 and LT3) for a specific GUI (GUI-1 or GUI-2).

$$AS\_LO = \frac{|LO_{GUI-1} - LO_{GUI-2}|}{LO_{GUI-1} + LO_{GUI-2}} \quad (4.9)$$

$$AS\_LF = \frac{|LF_{GUI-1} - LF_{GUI-2}|}{LF_{GUI-1} + LF_{GUI-2}} \quad (4.10)$$

$$AS\_IE = \frac{|IE_{GUI-1} - IE_{GUI-2}|}{IE_{GUI-1} + IE_{GUI-2}} \quad (4.11)$$

$$AS\_CE = \frac{|CE_{GUI-1} - CE_{GUI-2}|}{CE_{GUI-1} + CE_{GUI-2}} \quad (4.12)$$

$$AS\_PE = \frac{|PE_{GUI-1} - PE_{GUI-2}|}{PE_{GUI-1} + PE_{GUI-2}} \quad (4.13)$$

$$TAS\_TCv = \frac{|TCv_{LT1} - TCv_{LT2}| + |TCv_{LT2} - TCv_{LT3}|}{TCv_{LT1} + TCv_{LT2} + TCv_{LT3}} \quad (4.14)$$

$$TAS\_TPv = \frac{|TPv_{LT1} - TPv_{LT2}| + |TPv_{LT2} - TPv_{LT3}|}{TPv_{LT1} + TPv_{LT2} + TPv_{LT3}} \quad (4.15)$$

$$TAS\_Top = \frac{|Top_{LT1} - Top_{LT2}| + |Top_{LT2} - Top_{LT3}|}{Top_{LT1} + Top_{LT2} + Top_{LT3}} \quad (4.16)$$

In Eqns. (4.14), (4.15) and (4.16) TCv, TPv and Top represent the group mean values of the respective tasks for a specific learning test (LT1, LT2 or LT3).

We performed the data analysis on the four broad themes, namely, beliefs, navigational behavior, learning efficiencies and task adaptations, which are presented in the remainder of this chapter.

4.3. Adaptations in Beliefs

We recorded participant's beliefs in perceived ease-of-use (PEOU), perceived usefulness (PU) and perceived task load (PTLD) for GUI-1 and GUI-2. We measured PEOU and PU using 6 items each of 7 point likert scales i.e. TAM questions (Appendix A2) and measured PTLD using 6 items of a 20 point NASA-TLX scale (Appendix A2). The group means (M) and standard deviations (SD) of the recorded data for the 3 variables are summarized in tables 4.1-4.3.

In order to explain the table organization, let us consider table 4.1. The first column of the table describes independent variables GUI-1 and GUI-2 and the dependant variable adaptation score (AS). K1 and K2 are the two sets of learning tests administered to the sub-groups K(a) and K(b) in group-K. The group means (M) and standard deviations (SD) of PEOU, PU and PTLD for both these test conditions K1 and K2 are shown in the next columns. The last row shows the computed adaptation scores across GUIs in the beliefs based on Eq. (1.5) of chapter 1. Similar structure is followed in the other two tables 4.2 and 4.3

Table 4.1Adaptations in beliefs (Group-K, N=85)

Beliefs (DV) / User Interface (IV)	PEOU (7 point scale)				PU (7 point scale)				PTLD (120 point scale)			
	K1		K2		K1		K2		K1		K2	
	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
Hierarchical Horizontal Menu (GUI-1)	5.59	0.91	5.43	0.99	5.2	0.89	5.33	1.04	44.57	18.07	43.21	17.43
Non-hierarchical Split Menu (GUI-2)	5.67	0.86	5.85	0.82	5.62	0.97	5.62	0.74	40.1	14.04	37.54	17.34
Adaptation Score (AS)	0.0071		0.0373		0.0381		0.0265		0.0527		0.0701	

Table 4.2 Adaptations in beliefs (Group-C, N=106)

Beliefs (DV) / User Interface (IV)	PEOU (7 point scale)				PU (7 point scale)				PTLD (120 point scale)			
	C1		C2		C1		C2		C1		C2	
	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
Hierarchical Horizontal Menu (GUI-1)	5.34	0.86	5.62	0.95	5.09	0.97	5.53	0.99	45.20	16.81	32.74	17.07
Non-hierarchical Split Menu (GUI-2)	5.85	0.68	5.65	0.76	5.72	0.67	5.54	0.76	37.04	15.77	40.58	16.06
Adaptation Score (AS)	0.0457		0.0023		0.0580		0.0010		0.0992		0.1068	

Table 4.3 Adaptations in beliefs (Group-A, N=96)

Beliefs (DV) / User Interface (IV)	PEOU (7 point scale)				PU (7 point scale)				PTLD (120 point scale)			
	A1		A2		A1		A2		A1		A2	
	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
Hierarchical Horizontal Menu (GUI-1)	5.71	0.70	5.12	1.21	5.50	0.81	4.95	1.10	45.76	19.13	43.60	22.02
Non-hierarchical Split Menu (GUI-2)	5.59	0.70	5.88	0.74	5.56	0.68	5.80	0.68	42.19	18.02	48.80	22.03
Adaptation Score (AS)	0.0111		0.0692		0.0055		0.0787		0.0405		0.0563	

We observe low adaptation scores in PEOU, PU and PTLD induced by the two interface designs in all the three sample groups K, C and A. Adaptation scores for PEOU and PU are similar and lower compared to adaptation scores for PTLD. This indicates a greater influence of the task as compared to the interface designs on user adaptations. Non-hierarchical split-menu interface (GUI-2) has greater PEOU and PU and lower PTLD as compared to the hierarchical horizontal menu interface (GUI-1). Participants therefore perceive GUI-2 to be better than GUI-1 for learning. PEOU, PU and PTLD across GUIs within the participants of the same sample group are summarized in table 4.4.

Table 4.4 Adaptations in beliefs within participants

Group	**Beliefs (DV)** **User Interface (IV)**	**PEOU**		**PU**		**PTLD**	
		M	**SD**	**M**	**SD**	**M**	**SD**
K (N=85)	Hierarchical Horizontal Menu (GUI-1)	5.51	0.95	5.26	0.96	43.94	17.68
	Non-hierarchical Split Menu (GUI-2)	5.76	0.84	5.62	0.85	38.72	15.87
C (N=106)	Hierarchical Horizontal Menu (GUI-1)	5.46	0.91	5.29	1.00	39.68	17.96
	Non-hierarchical Split Menu (GUI-2)	5.74	0.73	5.62	0.73	39.01	15.96
A (N=96)	Hierarchical Horizontal Menu (GUI-1)	5.42	1.02	5.23	1.00	44.70	20.51
	Non-hierarchical Split Menu (GUI-2)	5.74	0.73	5.68	0.69	45.56	20.33

We performed paired-samples t-tests to check whether significant adaptations occurred in PEOU, PU and PTLD within participants as a consequence of change in user interfaces of the e-learning application.

Effect of GUI on Perceived Ease of Use

PEOU was significantly higher for GUI-2 (M=5.7647, SD=0.83622) as compared to GUI-1 (M=5.5137, SD=0.94568) in group-K [t(84)=-3.094, p=0.003, d=0.281, r=0.139]. For group-C also, the t-test results showed PEOU to be significantly higher for GUI-2 (M=5.7374, SD=0.72810) than for GUI-1 (M=5.4638, SD=0.90968); [t(105)=-3.481, p=0.001, d=0.332, r=0.164]. The same trend continued for group-A participants, having significantly higher PEOU for GUI-2 (M=5.7361, SD=0.73056) as against GUI-1 (M= 5.4219, SD=1.02283) ; [t(95) = -3.002, p=0 .003, d= 0.3535, r= 0.174].

Overall t-test results of group K, C and A show an overwhelming evidence to infer that the user interface designs (GUI-1 and GUI-2) induce significant adaptations in PEOU.

Effect of GUI on Perceived Usefulness

Participants of group-K showed significantly higher PU for GUI-2 (M=5.6196, SD=0.84774) than for GUI-1 (M=5.2627, SD=0.95997); [t(84)=-4.390, p<0.001, d=0.39, r=0.19]. PU in group-C was also significantly higher for GUI-2 (M=5.6211, SD=0.72504) compared to GUI-1 (M=5.2877, SD=0.99935) ; [t(105)=-4.55, p<0.001 ,d=0.382, r=0.188]. Similarly, the t-test results for group-A revealed a significantly higher PU for GUI-2 (M=5.6788, SD=0.68835) than for GUI-1 (M=5.2292, SD=0.99685); [t(95)=-5.078, p< 0.001, d=0.525, r= 0.254].

Similar to the PEOU t-test results, all the three sample groups show a strong evidence to infer that the user interface designs induce adaptations in perceived usefulness.

Effect of GUI on Perceived Task Load

Participants of group-K experienced significantly higher PTLD for GUI-1 (M=43.9412, SD=17.68329) compared to GUI-2 (M=38.7176, SD=15.87122); [t(84)=2.834, p=0.006, d=0.31, r=0.15]. However, in group-C, there was no significant difference between PTLD of GUI-1 (M=39.6792, SD=17.95844) and GUI-2 (M=39.0094, SD=15.95678) ;[t(105)= 0.526, p=0.600]. The same effect was observed for participants of group-A, having no significant difference between PTLD of GUI-1 (M=44.6979, SD=20.51296) and that of GUI2 (M=45.5625, SD=20.33240) ; [t(95)=-0.458, p=0.648].

T-test results for PTLD suggest that user interface designs cause significant adaptations in perceived task load only during knowledge oriented learning.

We quantified adaptations in beliefs across GUI-1 and GUI-2 into respective adaptation scores AS_PEOU, AS_PU and AS_PTLD as per Eqn. (4.1). Since adaptation score values were widely spread, we compared their medians. Figures 4.1-4.3 shows adaptation scores of PEOU, PU and PTLD across GUIs.

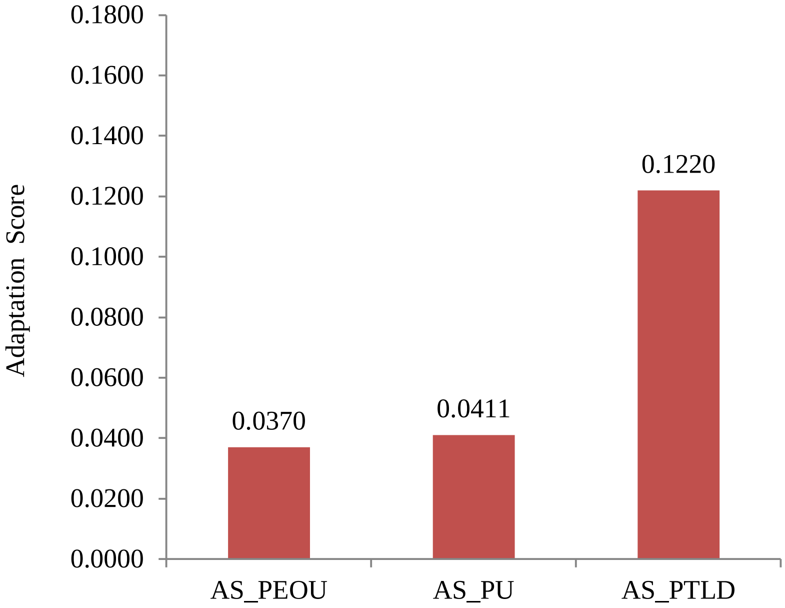


Figure 4.1 Adaptation scores of belief attributes (Group-K)

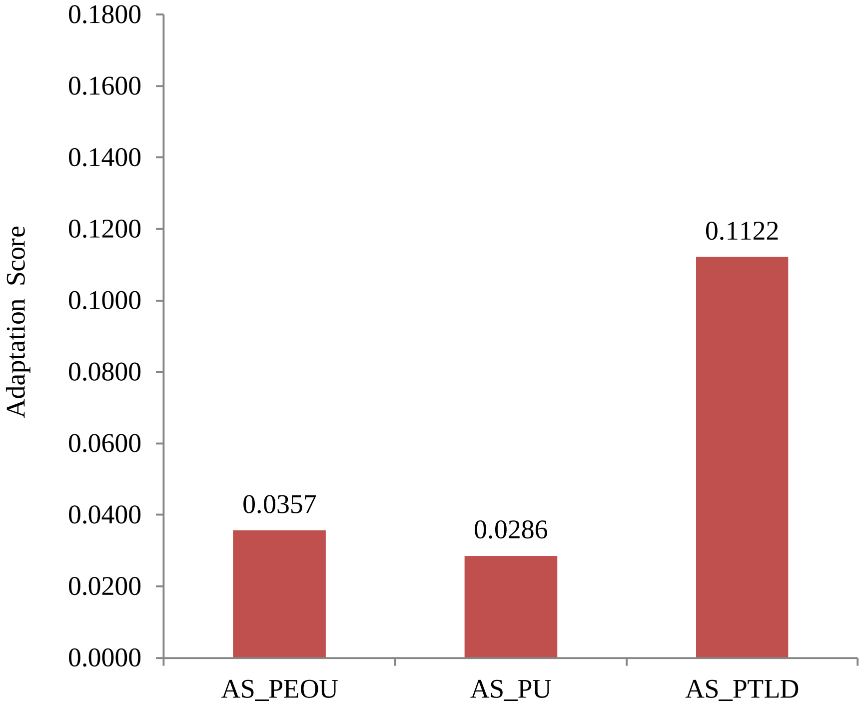


Figure 4.2 Adaptation scores of belief attributes (Group-C)

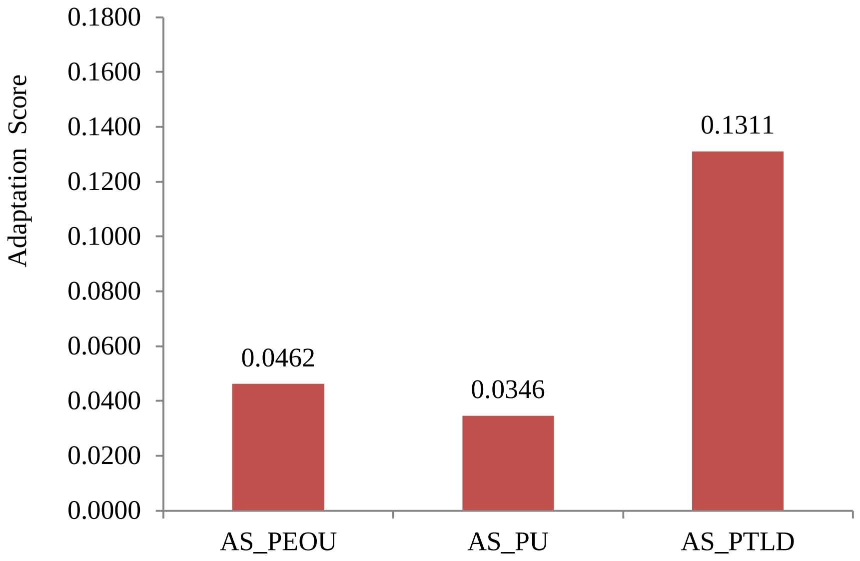


Figure 4.3 Adaptation scores of belief attributes (Group-A)

It may be noted that within participants adaptations across GUIs in PEOU and PU are lower than adaptations in PTLD for all the three groups K, C and A. This suggests that the participants perceived GUI-1 and GUI-2 to have similar usability and usefulness. However the perceived mental workload was quite different for GUI-1 and GUI-2. This indicates that interfaces perceived are similar from usability angle, but may require different efforts while learning similar contents.

Correlations

We correlated adaptation scores (AS), e-learning self-efficacy (ELSE), prior knowledge and the sum of the learning test scores on GUI-1 and GUI-2. AS_PTLD and ELSE in group-K were significantly correlated [r(85)=0.270, p=.012], suggesting that during knowledge oriented learning, higher self-efficacy learners exhibit more adaptations in perceived task load caused due to the change in user interfaces. During comprehension oriented learning, AS_PTLD and learning test scores were correlated [r(96)=0.227, p=.026], reflecting that adaptations in PTLD benefit learning test results. Same was the case with the participants of group-A, where AS_PTLD and learning test scores were also correlated [r(106)=0.251, p=.009].

Beliefs influence learners' motivations, attitudes, intentions and actual usage. We will now investigate the consequences of adaptations in beliefs and learning contexts on the external factor of user adaptation i.e. navigational behavior.

4.4. Adaptations in Navigational Behavior

We measured adaptations in learning by tracing the participants' navigational behavior. We extracted the participant's topic processing behavior from the total topic commands used (TNav), the page processing behavior from the total page commands used (PNav), the content processing behavior from the total pages visited (TPv) and the entire interaction effort from the total mouse clicks (Top). We computed these navigational attributes for GUI-1 as well as GUI-2 from the operation log data. The data extracted was also helpful in understanding the participants' learning styles. The group means (M) and standard deviations (SD) of navigational attributes TNav, PNav, TPv and Top are presented in tables 4.5-4.7.

Table 4.5 Adaptations in navigational behavior (Group-K, N=85)

Navigation Attributes / GUI	**Topic processing -TNav**				**Page processing - PNav**				**Content processing - TPv**				**Interaction Effort - Top**			
	K1		**K2**		**K1**		**K2**		**K1**		**K2**		**K1**		**K2**	
	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
GUI-1	12.38	5.928	10.14	3.655	69.02	39.364	54.03	23.83	59.64	30.534	49.6	17.495	87.96	44.301	70.63	26.363
GUI-2	8.46	4.01	8.58	4.319	24.91	23.011	29.26	23.45	39.31	19.146	44.42	20.39	53.6	26.631	62.58	31.62
AS	0.1883		0.0835		0.4695		0.2974		0.2054		0.0551		0.2427		0.0604	

Let us consider table 4.5 in order to understand table organization. The first column of the table 4.5 describes independent variables GUI-1 and GUI-2 and the dependant variable adaptation score (AS). K1 and K2 are the two sets of learning tests administered to the subgroups K(a) and K(b) in group-K. The group means (M) and standard deviations (SD) of TNav, PNav, TPv and Top for both the test conditions K1 and K2 is shown in next columns. The last row depicts computed adaptation scores across GUIs of the navigational attributes based on Eq. (1.5) of chapter 1. Similar structure is followed in the other two tables 4.6 and 4.7.

Table 4.6 Adaptations in navigational behavior (Group-C, N=106)

Navigation Attributes / GUI	**Topic processing -TNav**				**Page processing - PNav**				**Content processing - TPv**				**Interaction Effort - Top**			
	C1		**C2**		**C1**		**C2**		**C1**		**C2**		**C1**		**C2**	
	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
GUI-1	10.22	4.56	10.77	5.41	55.64	29.23	52.17	37.61	51.14	22.26	46.83	23.65	72.34	31.68	69.38	40.76
GUI-2	8.66	4.12	8.42	4.54	15.87	20.74	21.8	22.17	34.64	17.94	36.47	16.63	47	25.23	50.22	24.21
AS	0.0827		0.1221		0.5561		0.4106		0.1923		0.1243		0.2123		0.1602	

Table 4.7 Adaptations in navigational behavior (Group-A, N=96)

Navigation Attributes / GUI	**Topic processing -TNav**				**Page processing - PNav**				**Content processing - TPv**				**Interaction Effort - Top**			
	A1		**A2**		**A1**		**A2**		**A1**		**A2**		**A1**		**A2**	
	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
GUI-1	8.41	5.65	5.77	2.8	60.12	38.21	40.72	25.33	56.06	31.36	36.13	17.9	74.84	43.04	52.89	28
GUI-2	15.6	75.82	5.55	3.05	11.79	16.14	23.98	24.64	27.11	19.69	33.53	21.17	46.81	80.48	51.53	37.19
AS	0.2994		0.0190		0.6722		0.2588		0.3482		0.0373		0.2304		0.0131	

From the data in tables 4.5-4.7, we may conclude that higher learning effort is required on part of the participants when hierarchical horizontal menu (GUI-1) is used for navigation as compared to non-hierarchical split menu (GUI-2). We observe significant adaptation scores for all the navigational attributes in all the three sample groups K, C and A. It may be noted that, the change in user interfaces induces large differences in page processing (AS_PNav) as compared to the other attributers. Non-hierarchical navigation design therefore, reduces the page processing significantly, enhancing learning efficiency in terms of effort.

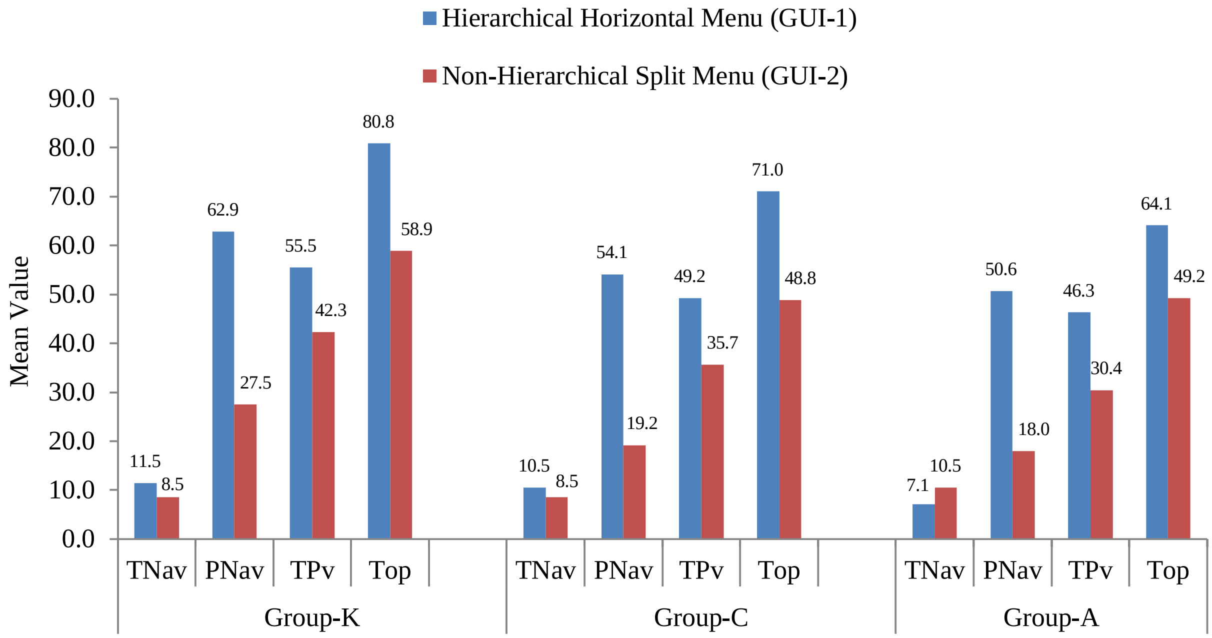


Figure 4.4 Adaptations in navigational behavior within participants

TNav, PNav, TPv and Top across GUIs within participants of same sample group are shown in figure 4.4. We verified whether the adaptations in these attributes across GUIs were significant, by performing paired-samples t-tests. The results are discussed below.

Effect of GUI on Topic Navigation Commands

In knowledge oriented learning, TNav was significantly higher for GUI-1 (M=11.46, SD=5.209) than for GUI-2 (M=8.53, SD=4.171); [t(84)=4.957, p<0.001, d=0.62, r=0.296]. Similarly the participants showed significantly higher TNav for GUI-1 (M=10.46, SD=4.940) as compared to GUI-2 (M=8.53, SD=4.339); [t(105)=3.447, p=.001, d=0.415, r=0.203] in comprehension oriented learning. However, the difference in TNav for GUI-1 (M=7.11, SD=4.659) and GUI-2 (M=10.47, SD=53.042) was not statistically significant; [t(95)=-0.618, p=0.538] for participants of group-A.

We may infer that user interface designs, which are under study, induce significant adaptations in topic command usage during knowledge and comprehension oriented learning. The interfaces did not affect topic command usage in application oriented learning.

Effect of GUI on Page Navigation Commands

Participants exhibited significantly higher PNav using GUI-1 (M=62.85, SD=34.479) as against GUI-2 (M=27.47, SD=23.232); [t(84)=10.591, p<0.001, d=1.20, r=0.515] in group-K. In group-C also, PNav was significantly higher for GUI-1 (M=54.10, SD=33.089) as compared to GUI-2 (M= 19.17, SD= 21.649); [t(105)=11.218, p<0.001, d=1.25, r=0.53]. The same trend was observed in group-A where, PNav was significantly higher for GUI-1 (M=50.63, SD=33.813) than for GUI-2 (M=18.01, SD=21.690); [t(95)=10.035, p<0.001, d=1.148, r=0.4979].

It may be concluded that the user interface designs under study invoke significant adaptations in page command usage.

Effect of GUI on Total Pages Visited

Group-K participants recorded a significantly higher TPv for GUI-1 (M=55.51, SD=26.314) than for GUI-2 (M=42.32, SD=19.932); [t(84)=5.059, p=<.001, d=0.565, r=0.271]. TPv was also found significantly higher for GUI-1 (M=49.23, SD=22.877) as compared to GUI-2 (M=35.66, SD=17.165); [t(105)=6.105, p<.001, d=0.671, r=0.318] in group-C. Finally the same result was repeated for group-A participants, showing significantly higher TPv for GUI-1 (M= 46.30, SD=27.426) as compared to GUI-2 (M=30.39, SD=20.606); [t(95) =6.674, p<.001, d=0.6558, r=0.3116].

In the conclusion, it may be noted that there was an overwhelming evidence to infer that the user interface designs, which are under study, induce significant adaptations in pages visited.

Effect of GUI on Total Operations

Total operations (Top) done by the participants were significantly higher for GUI-1 (M=80.82, SD=38.727) as compared to GUI-2 (M=58.88, SD=29.833); [t(84)=6.352, p=<.001, d=0.634, r=0.302] in knowledge oriented learning. While in group-C, Top was also significantly higher for GUI-1 (M=71.03, SD=35.838) than for GUI-2 (M=48.79, SD=24.600); [t(105)=6.669, p<.001, d= 0.723, r= 0.34]. Group-A participants also exhibited, a significantly higher Top for GUI-1 (M=64.09, SD=37.910) as against GUI-2 (M=49.22, SD=61.976); [t(95)=2.327, p=.022, d=0.2894, r=0.1432].

It is observed collectively that, the interface designs, which are under study, invoke significant adaptations in total operations or clicks.

Similar to the participants' belief data, we also computed adaptation scores (AS) of their navigational data across GUI-1 and GUI-2 using Eqn. (4.1). We used median values of adaptation scores for comparison since standard deviations were large. Figures 4.5-4.7 show adaptation scores AS_TNav, AS_PNav, AS_TPv and AS_Top across GUIs for the three sample groups K, C and A respectively.

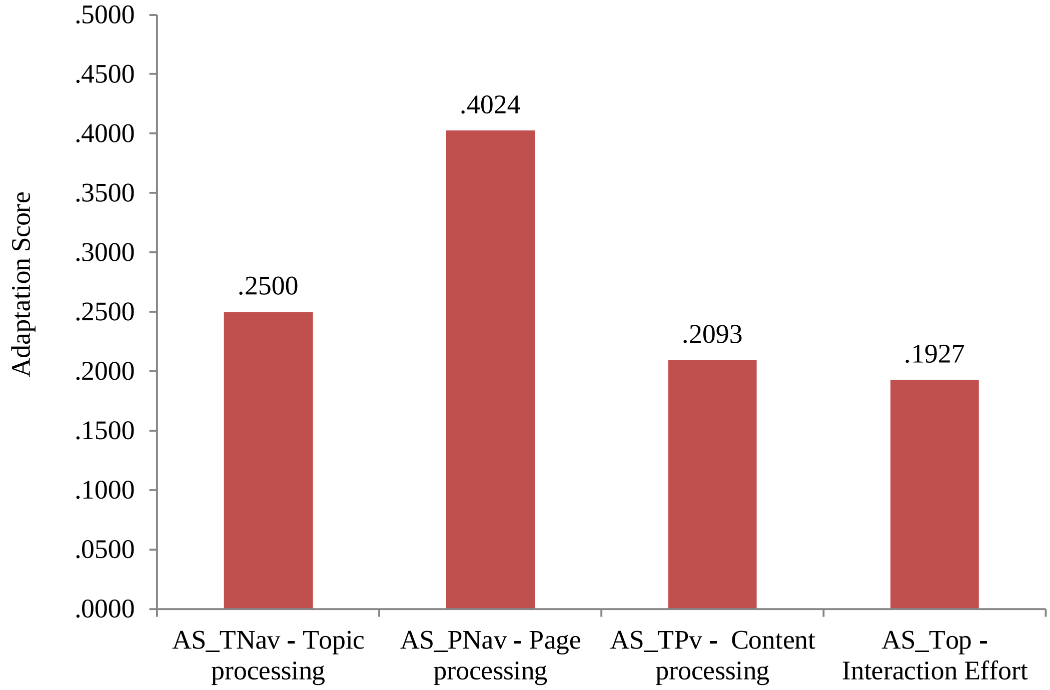


Figure 4.5 Adaptation scores of navigational attributes (Group-K)

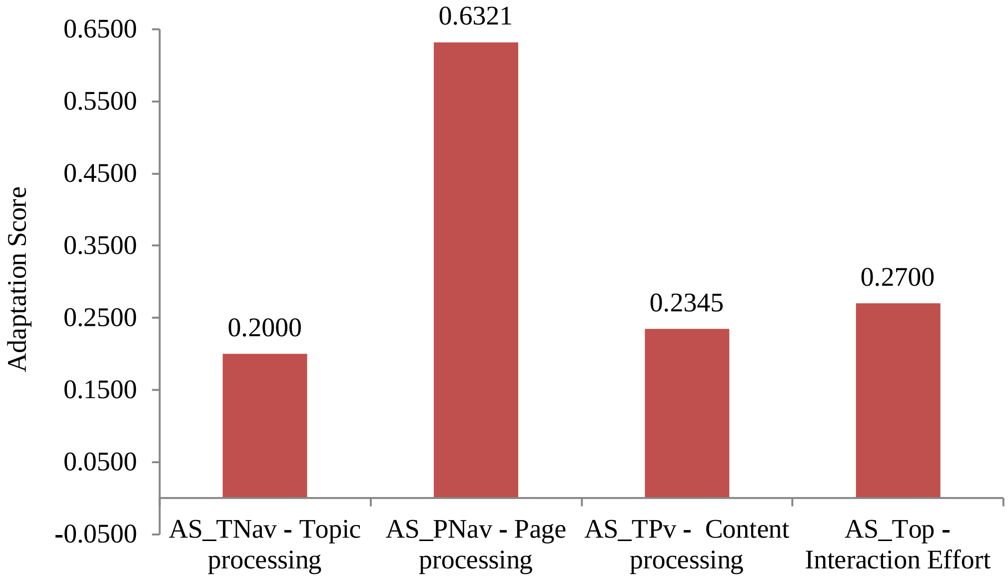


Figure 4.6 Adaptation scores of navigational attributes (Group-C)

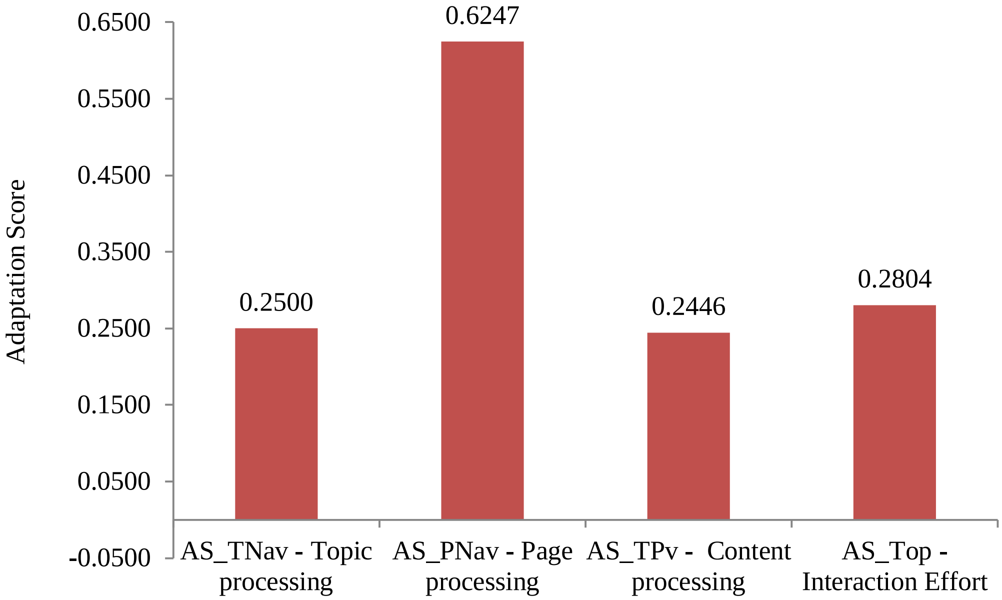


Figure 4.7 Adaptation scores of navigational attributes (Group-A)

We may conclude that, the navigation designs of interfaces, which are under study, induce significant adaptations in TNav, PNav, TPv and Top. Specifically, adaptations in page command usage (PNav) are much higher (40% in group-K and 63% in group-C and group-A) as compared to other attributes. Therefore, non-hierarchical split menu interface (GUI-2) reduces the page command usage compared to hierarchical horizontal menu interface (GUI-1) by a significant degree.

Correlations

We also checked for the correlations of adaptation scores (AS) of navigational attributes with e-learning self-efficacy (ELSE), prior knowledge and the sum of learning test scores on GUI-1 and GUI-2. There were no significant correlations found in the knowledge oriented learning group. There was significant correlation found of prior knowledge with AS_TNav [r(106)=-.373, p<.01], AS_TPv [r(106)=-.308, p=.001] and AS_Top [r(106)=-.220, p=.024] suggesting that prior knowledge influences adaptations in comprehension based learning. AS_PNav and learning test scores were significantly correlated [r(96)=.204, p=.047] indicating that adaptations in page command usage affects the learning outcomes during application oriented learning.

The investigations of the participants' navigational behavior show that the navigation design of a learning interface significantly influences the learning process. Since participants adapt their learning process across GUIs, we investigated its effect on their learning outcomes and efficiency. The analysis of this is presented in the next section.

4.5. Adaptations in Learning Outcome and Efficiencies

We computed adaptations in learning outcomes and efficiencies (section 1.3, chapter 1) under the various learning contexts. Based on the learning test results and the operation log data we computed learning focus (LF), interaction efficiency (IE), click efficiency (CE) and page efficiency (PE) using Eqns. (1.1),(1.2),(1.3) and (1.4) of chapter 1 respectively, for GUI-1 and GUI-2. We computed the learning outcome (LO) by normalizing the sum of the learning test scores obtained in the three learning tests performed on each GUI.

Tables 4.8-4.10 represent the group means (M) and standard deviations (SD) of attributes LO, LF, IE, CE and PE. In order to explain the table organization, let us consider table 4.8. The rows of the table indicate dependant variable i.e. learning efficiency (LO, LF, IE, CE and PE) for GUI-1 and GUI-2. The columns indicate the independent variable i.e. learning test set (K1 and K2). The last row of each dependant variable shows the computed adaptation scores across GUIs for that attribute. Similar structure is followed in the other two tables 4.9 and 4.10

Table 4.8 Adaptations in learning outcome and efficiencies (Group-K, N=85)

Test Set **Efficiency**		**K1**		**K2**	
	GUI	**M**	**SD**	**M**	**SD**
Learning Outcome (LO)	GUI-1	59.333	21.894	49.524	16.433
	GUI-2	55.810	16.257	57.600	21.115
	AS	0.031		0.075	
Learning Focus (LF)	GUI-1	5.588	2.200	5.472	2.285
	GUI-2	3.121	2.554	3.568	2.620
	AS	0.283		0.211	
Interaction Efficiency (IE)	GUI-1	0.671	0.127	0.711	0.108
	GUI-2	0.738	0.102	0.713	0.111
	AS	0.047		0.001	
Click Efficiency (CE)	GUI-1	0.974	0.857	0.896	0.766
	GUI-2	1.440	1.042	1.287	1.160
	AS	0.193		0.179	
Page Efficiency (PE)	GUI-1	1.722	2.400	1.319	1.429
	GUI-2	1.981	1.464	1.989	2.335
	AS	0.070		0.202	

Table 4.9 Adaptations in learning outcome and efficiencies (Group-C, N=106)

Test Set / Efficiency		C1		C2	
	GUI	**M**	**SD**	**M**	**SD**
Learning Outcome (LO)	GUI-1	48.588	21.507	46.099	17.276
	GUI-2	39.716	19.444	52.684	19.293
	AS	0.100		0.067	
Learning Focus (LF)	GUI-1	5.711	2.691	4.912	2.962
	GUI-2	1.720	2.027	2.611	2.865
	AS	0.537		0.306	
Interaction Efficiency (IE)	GUI-1	0.722	0.106	0.693	0.156
	GUI-2	0.746	0.079	0.730	0.079
	AS	0.016		0.026	
Click Efficiency (CE)	GUI-1	0.861	0.576	1.196	1.612
	GUI-2	1.076	0.708	1.583	1.588
	AS	0.111		0.139	
Page Efficiency (PE)	GUI-1	1.192	0.726	1.913	4.293
	GUI-2	1.420	0.927	2.267	2.592
	AS	0.087		0.085	

Table 4.10 Adaptations in learning outcome and efficiencies (Group-A, N=96)

Test Set / Efficiency		A1		A2	
	GUI	M	SD	M	SD
Learning Outcome (LO)	GUI-1	55.782	28.372	41.489	23.019
	GUI-2	63.121	29.063	39.796	21.467
	AS	0.062		0.021	
Learning Focus (LF)	GUI-1	7.713	2.795	6.828	2.54
	GUI-2	2.389	2.929	4.446	3.958
	AS	0.527		0.211	
Interaction Efficiency (IE)	GUI-1	0.756	0.113	0.696	0.108
	GUI-2	0.724	0.156	0.694	0.128
	AS	0.021		0.001	
Click Efficiency (CE)	GUI-1	1.264	1.738	1.15	1.287
	GUI-2	3.001	3.207	1.365	1.476
	AS	0.407		0.086	
Page Efficiency (PE)	GUI-1	2.015	4.725	1.68	1.877
	GUI-2	4.96	7.914	2.036	2.61
	AS	0.422		0.096	

We find adaptation scores for LO to be low. This is because the participants performed equally well in the learning tests on both the GUIs, which indicates their adaptations to user interfaces. It may be noted that there is an equal drop in pages visited and operations done when participants switched over from GUI-1 to GUI-2. Therefore the adaptation score of IE is low. We observed significant adaptations in CE and PE due to differences in total operations required for GUI-1 and GUI-2. The CE and PE of GUI-2 are higher compared to GUI-1. Higher adaptation scores of the learning focus reflect that the interface designs impose a significant change in the page commands required for learning i.e. learning depth.

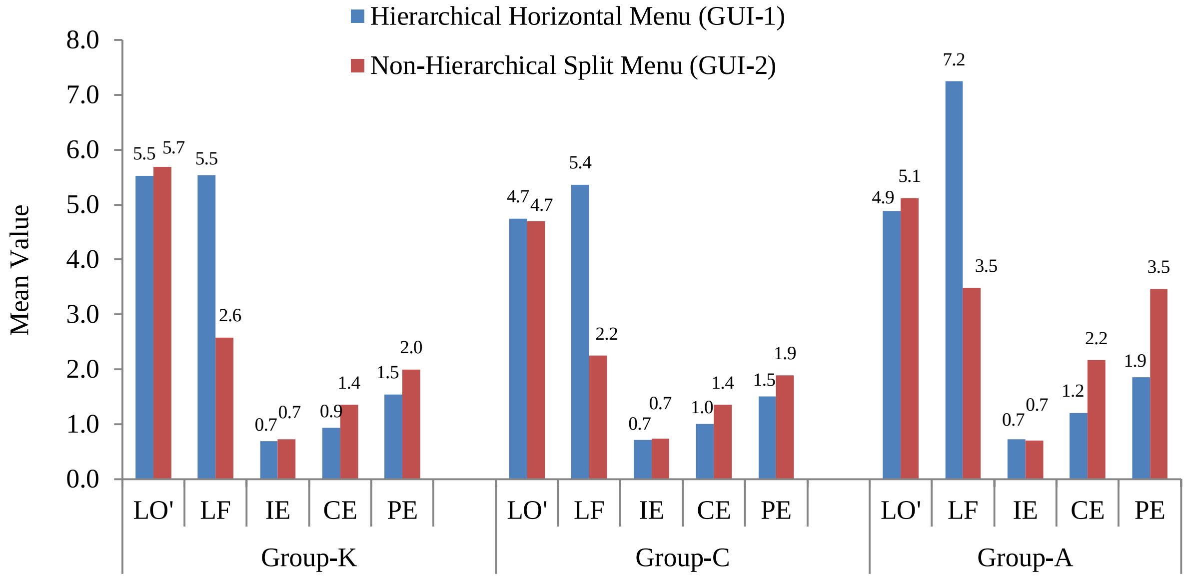


Figure 4.8 Adaptations in learning efficiencies within participants

LO', LF, IE, CE and PE across GUIs within participants of the same sample group are presented in figure 4.8 (where LO'= LO/10). We performed paired-samples t-tests to verify whether significant adaptations occurred across GUIs in learning efficiencies within participants. We have discussed its results in next paragraphs.

Effect of GUI on Learning Outcome

In group-K, there was no significant difference between LO on GUI-1 (M=55.2941, SD=20.31038) and that on GUI-2 (M=56.8627, SD=19.17859); [t(84)=-0.698, p=0.487]. Same was the case with group-C, where no significant difference was observed between LO on GUI-1 (M=47.4843, SD=19.69240) and GUI-2 (M=46.9340, SD=20.32557); [t(105) = 0.308, p=0.758]. Similarly no significant difference was observed between LO on GUI-1 (M=48.7847, SD=26.73727) and GUI-2 (M= 51.2153, SD=27.91432); [t(95)=-0.749, p=0.456] in group-A.

Learners therefore performed equally well under both GUI conditions.

Effect of GUI on Learning Focus

Participants of group-K exhibited significantly higher LF using GUI-1 (M=5.54003, SD=2.222034) than using GUI-2 (M=2.583106, SD=2.3334837); [t(81)=10.618, p<.001, d=1.28, r= 0.544]. Also learning focus was significantly higher for GUI-1 (M=5.36500, SD=2.825316) as compared to GUI-2 (M=2.247253, SD=2.5694948); [t(103)=10.053, p<.001, d=1.154, r=0.499] for participants of group-C. It was also observed that group-A participants showed significantly higher LF using GUI-1(M=7.244379, SD=2.7070454) than using GUI-2 (M=3.48157, SD=3.645739); [t(91)=8.650, p<.001 d=1.172, r=0.505].

So we may conclude that, there was evidence to infer that the user interfaces, which are under study, induce significant adaptations in learning focus.

Effect of GUI on Interaction efficiency

Interaction efficiency in knowledge oriented learning group was significantly higher for GUI-2 (M=0.723023, SD=0.1075545) than for GUI-1 (M=0.687549, SD=0.1205777); [t(84)=-2.603, p=0.011, d=0.31, r=0.153]. It was also observed in group-C, that IE was significantly higher for GUI-2 (M=0.736835, SD=0.0790581) as compared to GUI-1 (M=0.709341, SD=0.1306920); [t(105)=-2.118, p=0.037, d=0.254, r=0.126]. However, in group-A, there was no significant difference between IE on GUI-1 (M=0.726485, SD=0.1143348) and GUI-2 (M=0.708792, SD=0.1423570); [t(95)=0.971, p=.334].

We find that the interface designs under study affect IE across GUIs in knowledge and comprehension based learning.

Effect of GUI on Click Efficiency

The click efficiency of participants in group-K was significantly higher for GUI-2 (M=1.359545, SD=1.1199394) than for GUI-1 (M=0.935177, SD=0.8127894); [t(84)=-3.741, p<.001, d=0.433, r=0.211]. It was observed that CE was significantly higher for GUI-2 (M=1.358081, SD=1.2948158) than for GUI-1 (M=1.009874, SD=1.1619649); [t(105)=-2.422, p=0.017, d=0.283, r=0.140] of participants in group-C. The same trend was observed in group-A where, CE was significantly higher for GUI-2(M=2.166193, SD=2.5996144) than for GUI-1 (M=1.208196, SD=1.5266848); [t(95)=-3.434, p=0.001, d=0.449, r=0.219].

We may conclude that, there were significant adaptations in CE caused by the two user interfaces which are under study.

Effect of GUI on Page Efficiency

In group-K, PE was significantly higher for GUI-2 (M=2.000969, SD=2.0273518) than for GUI-1 (M=1.546244, SD=2.0519604); [t(84)=-2.638, p=0.010, d=0.223, r=0.11. However, there was no significant difference between PE of GUI-1 (M=1.507667, SD=2.8977445) and that of GUI-2 (M=1.889824, SD=2.0753902); [t(104)=-1.218, p=0.226] in group-C. Finally in group-A, PE was significantly higher for GUI-2 (M=3.467432, SD=5.9940853) as compared to GUI-1 (M=1.851089, SD=3.6080223); [t(95)=-2.351, p=0.021, d=0.32, r=0.16].

The above results indicate that interface designs, which are under study, induce significant adaptations in PE across GUIs for knowledge and application based learning.

We computed adaptation scores (AS) of learning efficiencies across GUI-1 and GUI-2 using Eqn. (4.1). Since the adaptation scores were dispersed widely, we have used median values for their comparison. Figures 4.9-4.11 show adaptation scores AS_LF, AS_IE, AS_CE and AS_PE across GUIs for the three sample groups K, C and A. Since the learning outcome was the same across interfaces, the adaptation score of LO is not shown in figures 4.9-4.11.

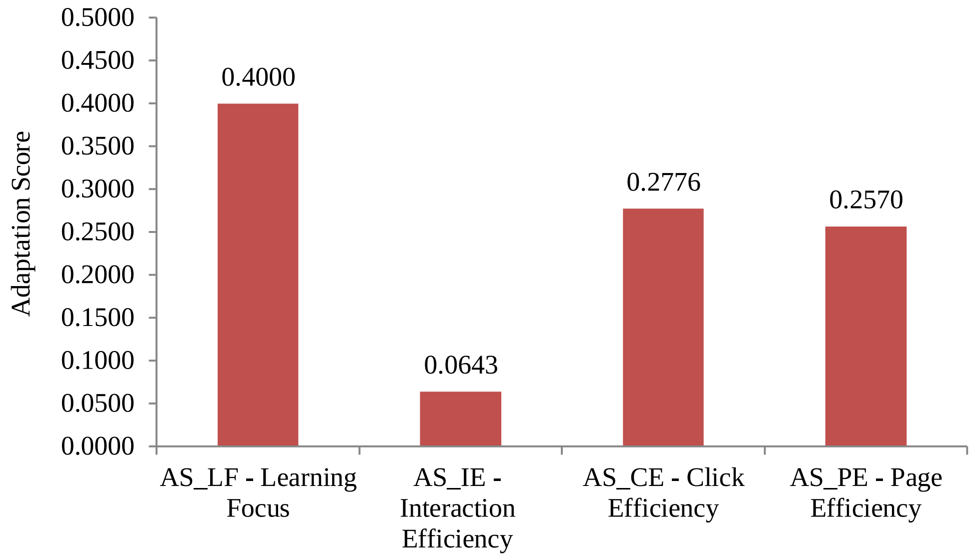


Figure 4.9 Adaptation scores of learning efficiencies (Group-K)

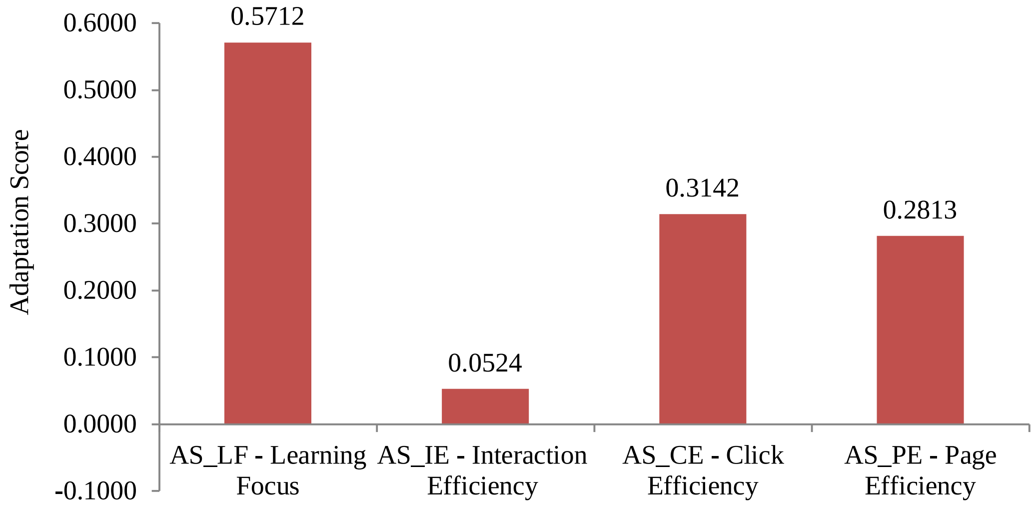


Figure 4.10 Adaptation scores of learning efficiencies (Group-C)

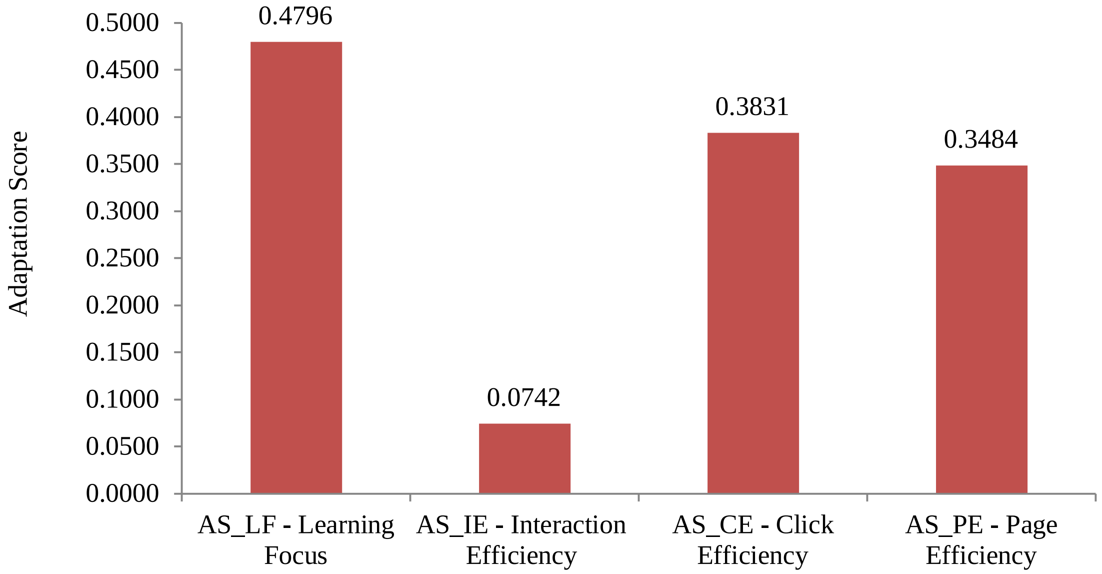


Figure 4.11 Adaptation scores of learning efficiencies (Group-A)

We observe significant adaptations across GUIs in learning efficiencies. Interface designs GUI-1 and GUI-2 induce high adaptations in learning focus. A large AS_LF indicates that more page commands per topic are used while navigating the learning content using horizontal hierarchical menu (GUI-1) as compared to split non-hierarchical menu (GUI-2). It is also observed that GUI-2 is superior in terms of click and page efficiencies as compared to GUI-1. Since the adaptation score of interaction efficiency is low we may conclude that the pages referred for learning remained almost same in GUI-1 and GUI-2. However a large adaptation in learning focus is due to the fact that more pages were visited more than once on GUI-1 i.e. multiple visits as against GUI-2.

Correlations

We did a correlation analysis between adaptation scores (AS) of learning efficiencies, e-learning self-efficacy (ELSE), prior knowledge and the sum of learning test scores on GUI-1 and GUI-2. There were no significant correlations found in the knowledge oriented learning group. In comprehension oriented learning group AS_CE was significantly correlated with learning test scores [r(106)=-3.25, p=.001] and AS_PE was also correlated with learning test scores [r(106)=-.343, p<.001]. This means learners with lower learning test scores show greater difference (adaptations) in operations and page visits across GUIs while those with high learning test scores have consistent behavior across GUIs. In group-A, adaptation in learning focus (AS_LF) was correlated with learning test scores [r(96)=.262, p=.01]. This suggests that the adaptations in content browsing directly influence the test results.

Learners also adapt their behavior within an application. The change in such a behavior is due to the change in learning task or due to the experience gained from the learning environment. The next chapter gives a detailed account of how learners gain experience of the learning user interface. Here we will investigate the task adaptations and their behavior across user interfaces and in situations of different types of learning tasks.

4.6. Task Adaptations within GUI

We defined task adaptations (section 1.3.3 chapter 1) as changes in learning tasks in response to different learning tests i.e. adaptations between learning tests. Learners change their navigational behavior depending on the learning goal and the interface used. We gave three learning tests (section 3.4.3 chapter 3) to each participant on GUI-1 and GUI-2. We investigated the learning task types which are the total chapters visited (TCv), the total pages visited (TPv) and the total mouse clicks (Top) between the three learning tests.

The group means (M) and standard deviations (SD) of TCv, TPv and Top are presented in Tables 4.11-4.13. Let us consider table 4.11, in order to explain table organization. The rows of the table represent the various task types for GUI-1 and GUI-2. The column represents mean (M) and standard deviation (SD) of each task during the learning test LT1, LT2 and LT3. The learning task data has been represented for two sets of learning tests K1 and K2 administered to independent subgroups within sample group-K. A similar structure is followed in the other two tables 4.12 and 4.13

Table 4.11 Task adaptations (Group-K, N=85)

Tasks \ Test Set		K1						K2					
		LT1		LT2		LT3		LT1		LT2		LT3	
		M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
Chapters Visited (TCv)	GUI-1	3.54	1.72	3.06	1.86	3.48	2.04	2.77	1.21	3.09	1.22	3.06	1.43
	GUI-2	3.34	1.37	3.51	1.98	3.74	2.05	3.30	1.79	3.94	1.72	3.80	1.71
Pages Visited (TPv)	GUI-1	21.54	12.99	17.76	11.77	20.34	16.63	18.17	7.75	14.54	7.11	16.89	8.13
	GUI-2	12.89	6.66	12.89	9.18	13.54	7.75	15.40	8.40	12.90	7.71	16.12	8.76
Total Operations (Top)	GUI-1	34.44	20.19	24.88	16.52	28.64	21.14	27.51	13.63	19.86	10.72	23.26	12.62
	GUI-2	18.89	11.83	17.06	12.30	17.66	9.45	22.80	14.05	17.16	10.95	22.62	14.75

Table 4.12 Task adaptations (Group-C, N=106)

Tasks \ Test Set		C1						C2					
		LT1		LT2		LT3		LT1		LT2		LT3	
		M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
Chapters Visited (TCv)	GUI-1	3.47	1.42	2.54	1.37	2.68	1.62	2.85	1.43	2.98	1.39	2.89	1.88
	GUI-2	3.49	1.33	3.21	1.44	3.26	1.48	3.22	1.67	3.05	1.57	3.41	1.69
Pages Visited (TPv)	GUI-1	21.34	13.44	15.00	8.81	14.80	9.37	14.64	8.14	15.94	9.77	16.32	10.94
	GUI-2	12.74	7.76	12.06	7.15	9.83	5.99	13.41	7.82	11.10	6.41	11.97	6.97
Total Operations (Top)	GUI-1	30.78	19.01	20.95	11.26	20.61	13.11	22.70	14.77	23.77	17.50	22.91	14.94
	GUI-2	17.68	12.13	16.83	10.72	12.49	7.17	18.78	12.10	15.20	9.69	16.24	9.85

Table 4.13 Task adaptations (Group-A, N=96)

Tasks \ Test Set		A1						A2					
		LT1		LT2		LT3		LT1		LT2		LT3	
		M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
Chapters Visited (TCv)	GUI-1	2.31	1.28	2.55	2.18	2.04	1.81	1.45	0.97	1.72	1.02	2.09	1.41
	GUI-2	2.26	1.34	1.91	1.54	1.79	1.91	1.90	1.52	2.53	1.67	2.29	1.57
Pages Visited (TPv)	GUI-1	18.12	9.11	21.43	18.26	16.51	14.15	9.47	6.89	11.45	7.40	15.21	11.65
	GUI-2	9.09	5.97	9.53	7.28	8.49	9.86	10.06	8.38	13.35	10.26	10.12	8.45
Total Operations (Top)	GUI-1	23.80	12.39	30.67	25.41	20.37	16.63	14.64	11.13	16.26	11.23	22.00	16.48
	GUI-2	12.06	7.36	13.09	10.50	21.66	75.31	15.49	15.34	20.27	18.29	15.78	13.51

The tables show that there are no significant differences in the chapters visited (TCv) between GUI-1 and GUI-2 for all the learning tests and in all the three sample groups K, C and A. This is because the participants only focus and browse the learning content that is relevant to the test questions which are the same for GUI-1 and GUI-2. Hence the chapters visited will remain the same. On the other hand we observe significant differences in the page visits and the total operations across GUIs. This shows that the two navigation designs significantly influence the learner's page processing behavior while learning. Higher page visits and operations are observed in case of hierarchical horizontal menu (GUI-1) as compared to non-hierarchical split menu (GUI-2) for LT1, LT2 and LT3 in all the sample groups.

We computed task adaptation scores (TAS) for the chapters visited (TAS_TCv), the pages visited (TAS_TPv) and the total operations (TAS_Top) between the learning tests for GUI-1 and GUI-2 for the participants within the same sample group, using Eqn. (1.5) of chapter 1. Figures 4.12-4.14 show mean of task adaptation scores of groups for GUI-1 and GUI-2 Within participants for all the three sample groups K, C and A.

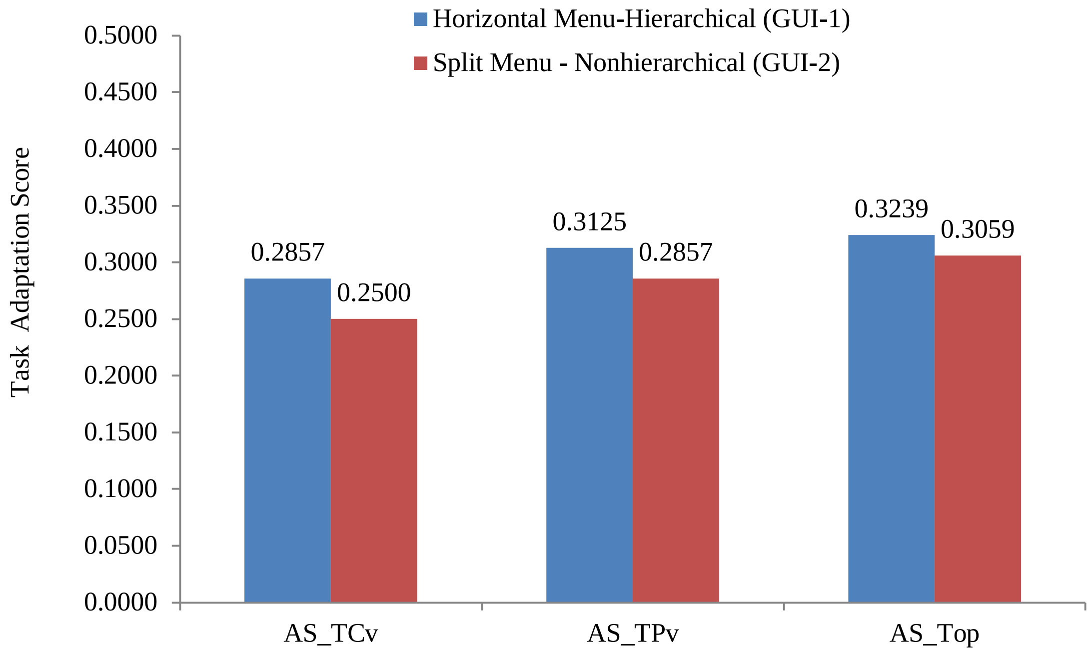


Figure 4.12 Task adaptation scores (Group-K)

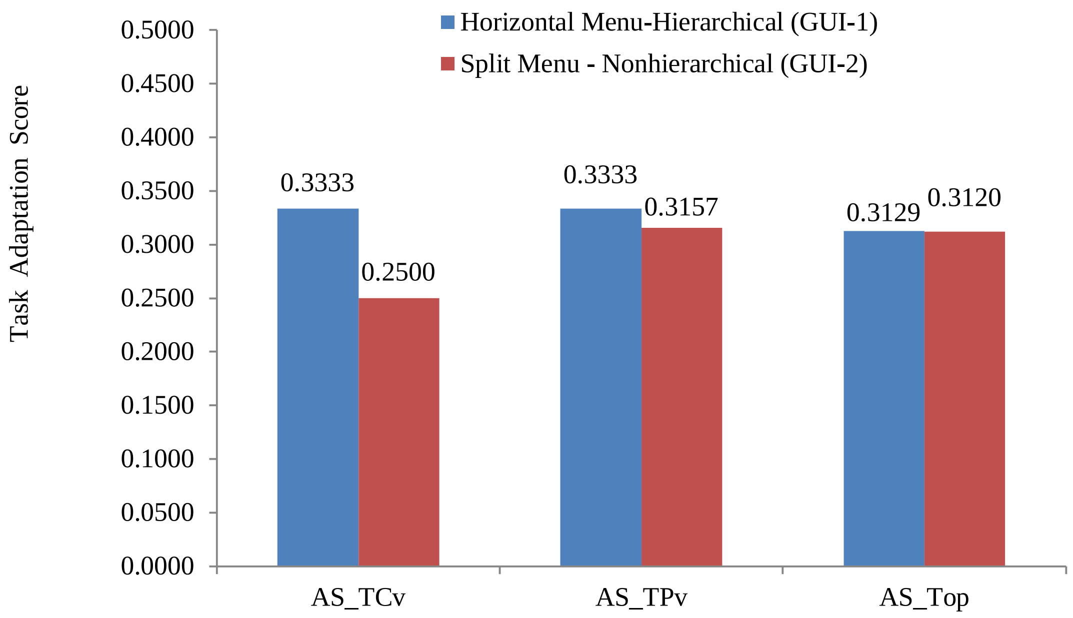


Figure 4.13 Task adaptation scores (Group-C)

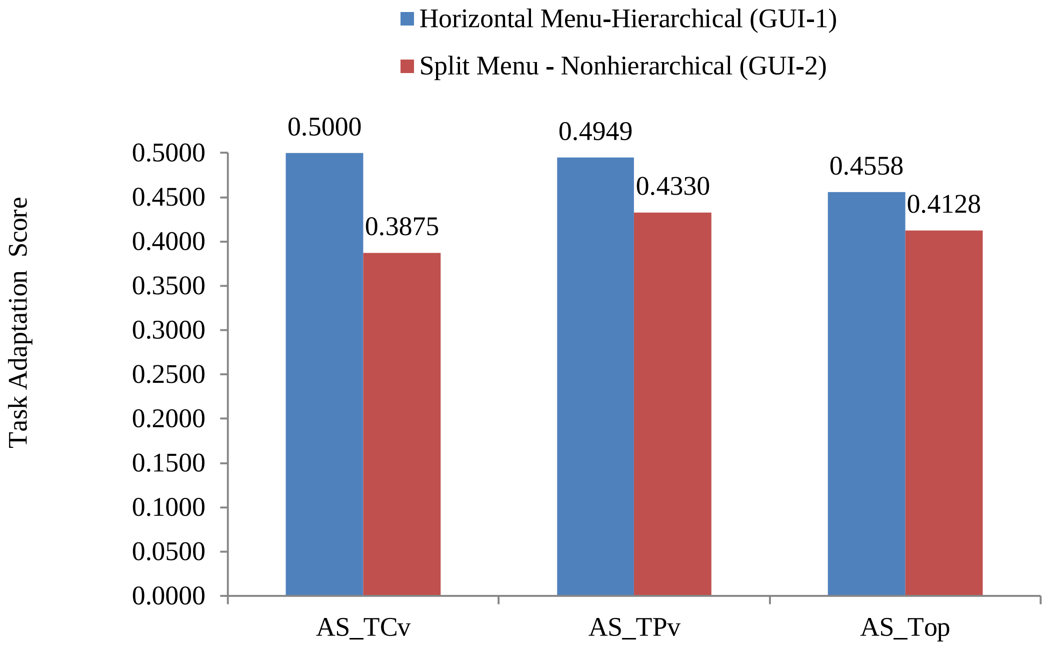


Figure 4.14 Task adaptation scores (Group-A)

From the figures we may conclude that task adaptation scores do not show significant variations across GUIs. The navigation designs of the interfaces do not influence the task adaptations between the learning tests. Therefore adapting to various learning tests of the same type remains consistent across user interfaces. Therefore task adaptations are related to either task or learner characteristics instead of user interface.

We verified the significance of differences in task adaptations between GUI-1 and GUI2 by performing the paired-samples t-tests. The conclusions from these tests are presented below.

Effect of GUI on Task Adaptations in Chapters Visited

There was no significant difference found in TAS_TCv between GUI-1 (M=0.3188, SD=0.2338) and GUI-2 (M=0.3101, SD=0.2507); [t(81)=0.2471, p=0.8054] in group-K. Same was the case with participants of group-C where no significant difference was observed in TAS_TCv between GUI-1 (M=0.3568, SD=0.2766) and GUI-2 (M=0.3623, SD=00.3470); [t(103)=-.146, p=0.884]. In application oriented learning also no significant difference in TAS_TCv between GUI-1 (M=0.4581, SD=0.3374) and GUI-2 (M=0.4689, SD=0.3780); [t(95)=-.229, p=0.819] was found.

Effect of GUI on Task Adaptations in Page Visited

We observed similar results for task adaptations in page visits also. No significant difference in TAS_TPv between GUI-1 (M=0.3487, SD=0.2283) and GUI-2 (M=0.3408, SD=0.2360) ; [t(84)=0.2184, p=0.8276] was observed in group-K. Also in group-C, there was no significant difference in TAS_TPv between GUI-1 (M=0.3860, SD=0.2694) and GUI-2 (M=0.3727, SD=0.2678); [t(104)=0.373, p=0.710]. The same trend was observed in application oriented learning having no significant difference in TAS_TPv between GUI-1 (M=0.5021, SD=0.3080) and GUI-2 (M=0.4902, SD=0.3226); [t(95)=0.293, p=0.770].

Effect of GUI on Task Adaptations in Total Operations

There was no significant difference in task adaptations in total operations (TAS_Top) between GUI-1 (M=0.3667, SD=0.2240) and GUI-2 (M=0.3675, SD=0.2253); [t(84)=-0.0219, p=0.9826] for participants of group-K. Similarly in group-C the participants exhibited no significant difference in TAS_Top between GUI-1 (M=0.3543, SD=0.2585) and GUI-2 (M=0.3723, SD=0.2131); [t(105)=-.544, p=0.588]. This was repeated in application oriented learning group also where there was no significant difference in TAS_Top between GUI-1 (M=0.4703, SD=0.2827) and GUI-2 (M=0.4592, SD=0.2929); [t(95)=0.282, p=0.779].

It was observed that the interface designs, which are under study, did not influence the task adaptations scores for GUI-1 and GUI-2 in all the three sample groups.

Correlations

We computed the correlation coefficients independently for GUI-1 and GUI-2 between task adaptation scores, e-learning self-efficacy (ELSE), prior knowledge of subjects, the sum of the learning test scores, PEOU, PU and PTLD of the GUI.

Relationships in GUI-1

In group-K significant correlations were found between PTLD and TAS_TCv [r(85)=0.300, p=.005] as well as TAS_TPv [r(85)=.271, p=.012]. The learner's e-learning self efficacy (ELSE) was correlated with perceived ease-of-use [r(85)=.233, p=.032] and learning test scores [r(85)=.334 , p=.002].

Therefore, in knowledge oriented learning, task adaptations reflect the perceived task load. Self efficacy influences the parameters of the perceived user interface designs.

In group-C PTLD was inversely correlated to PU [r(106)=-.264, p=.006] and PEOU [r(106)=-.221, p=.023]. It suggests that, higher the PEOU or PU lower will be the PTLD of an interface.

In group-A prior knowledge was inversely correlated to TAS_TCv [r(96)=-.228, p=.026] and TAS_TPv [r(96)=-.257, p=.012]. It was observed that ELSE is also inversely correlated to TAS_TPv [r(96)=-.280, p=.006]. Adaptations in Top were significantly correlated with prior knowledge [r(96)=-.271,p=.008], self-efficacy [r(96)=-.271, p=.008] and PEOU [r(96)=-.212,p=.038]. Learning test scores had several influential factors like prior knowledge in chemistry [r(96)=.277, p=.006], maths [r(96)=.270, p=.008], self-efficacy [r(96)=.307, p=.002] and perceived task load [r(96)=-.227, p=.026].

Therefore, in application oriented learning, higher subject knowledge reduces the adaptations while a high e-learning self efficacy reduces the adaptations in page referencing.

Correlation figures show no relationship between adaptation scores and learning test scores in hierarchical horizontal menu (GUI-1).

Relationships in GUI-2

In group-K task adaptations in page visits (TAS_TPv) were found to be correlated with prior knowledge [r(85)=.238, p=.038]. Higher e-learning self-efficacy reduced task adaptations of chapter visits (TAS_TCv) [r(85)=-.270, p=.014]. The adaptations in total operations were correlated to perceived usefulness [r(85)=.218, p=.045]. E-learning self-efficacy and perceived task load affected the learning test scores [r(85)=.296, p=.006 and r(85)=-.236, p=.03].

It may be noted that in knowledge oriented learning, prior topic knowledge affects page visits. Higher self-efficacy and perceived usefulness reduces the adaptations. The learning outcome is influenced by perceived task load.

In group-C, e-learning self- efficacy affected the participant's perceived ease-of-use [r(85)=.311, p=.001]. Perceived task load was inversely correlated to perceived ease-of-use [r(106)=-.363, p< .001] and perceived usefulness [r(106)=-.314, p=.001].

We can conclude that, in comprehension oriented learning e-learning efficacy (ELSE) and perceived ease-of-use play an important role. Higher ELSE increases the PEOU of the learning context and helps in reducing the perceived task load.

In group-A the e-learning self- efficacy was inversely correlated to the perceived task load [r(96)=-.278, p=.006]. The learning outcome was influenced by prior knowledge in chemistry [r(96)=.288,p=.004], prior knowledge of maths [r(96)=.212, p=.038], self-efficacy [r(96)=.222,p=.029] and perceived task load [r(96)= -.340,p=.001].

The above results indicate that, in application oriented learning, the learning outcome is significantly influenced by the characteristics of the learner, such as self- efficacy and prior knowledge.

4.7. Validation of Hypothesis H1, H3

In this thesis, we have formulated six hypotheses (section 1.4, chapter 1). The validation of the hypotheses, from the results of the study on user's adaptations, which are presented in this chapter, are discussed next.

H1: Learning task complexity has significant effect on user adaptations

The effect of learning task complexity (K, C, A) on user adaptations was investigated by comparing adaptation scores across the three learning groups K, C and A. To find the significance of differences in group adaptation scores between these groups, one way ANOVA tests were conducted.

Effect of Task Complexity on Adaptations in Beliefs

ANOVA results show that the difference in AS_PEOU in knowledge, comprehension and application groups is not statistically significant; [F (2, 284)=2.855, p=.059]. AS_PU also does not show an effect of task complexity [F (2, 284)=.584, p=.558]. The same is repeated for AS_PTLD where the difference in knowledge, comprehension and application group is not statistically significant; [F (2, 284)=2.201, p=.113].

Therefore *hypothesis H1* is not supported for adaptations in beliefs across user interfaces.

Effect of Task Complexity on Adaptations in Navigational Behavior

Adaptation scores of navigational attributes AS_TNav and AS_TPv show insignificant difference between knowledge, comprehension and application groups. [$F(2, 284)=1.514$, $p=.222$ and $F(2, 284)=2.729$, $p=.067$ respectively].

However the difference of AS_PNav and AS_Top between the three sample groups K,C and A is statistically significant [$F(2, 284)=6.126$, $p=.002$ and $F(2, 284)=3.515$, $p=.031$].

We conclude that *hypothesis H1* is supported for adaptations in page commands (PNav) and total operations (Top) across user interfaces. Adaptations in topic commands and pages visited are not significantly affected by task complexity.

Effect of Task Complexity on Adaptations in Learning Efficiencies

ANOVA results show that adaptations in learning efficiencies are significantly affected by task complexity. Results of ANOVA tests show that AS_LF [$F(2,284)=4.794$, $p=.009$], AS_IE [$F(2,284)=2.836$, $p=.049$], AS_CE [$F(2,284)=4.149$, $p=.017$] and AS_PE [$F(2,284)=3.566$, $p=.030$] are significantly different between the three sample groups K, C and A.

The ANOVA results validate *hypothesis H1* for learning efficiencies across user interfaces.

Effect of Task Complexity on Task Adaptations

In GUI-1, the task adaptation scores TAS_TCv, TAS_TPv and TAS_Top show significant difference between knowledge, comprehension and application groups [$F(2, 282)=5.654$, $p=.004$, $F(2, 283)=8.039$, $p<.001$ and $F(2, 284)=5.934$, $p=.003$ respectively].

In GUI-2, the task adaptation scores TAS_TCv, TAS_TPv and TAS_Top show significant difference between knowledge, comprehension and application groups [F(2, 281)=5.230, p=.006, F (2, 284)=7.482, p=.001 and F (2,284)=4.197, p=.016 respectively].

Table 4.14 shows the summary of hypothesis testing of H1

Table 4.14 Summary of hypothesis H1 testing

No.	Adaptations	Hypothesis H1
1	AS_PEOU	Not supported
2	AS_PU	Not supported
3	AS_PTLD	Not supported
4	AS_TNav	Not supported
5	AS_PNav	Supported
6	AS_TPv	Not supported
7	AS_Top	Supported
8	AS_LF	Supported
9	AS_IE	Supported
10	AS_CE	Supported
11	AS_PE	Supported
12	TAS_TCv	Supported
13	TAS_TPv	Supported
14	TAS_Top	Supported

From the overall results of the ANOVA we may conclude that *hypothesis H1* was partially supported.

H3: Navigation design has significant effect on user adaptations

Effect of navigation design (GUI-1 and GUI-2) on adaptations in beliefs (section 4.2), navigational behavior (section 4.3), learning efficiencies (section 4.3) and task adaptations (section 4.5) has already been shown along with the results of respective t-tests.

In the summary, we may conclude that the *hypothesis H3* is well supported for beliefs, navigational behavior and learning efficiencies. *Hypothesis H3* is not supported for leaning outcome and task adaptations.

4.8. Conclusions

From analysis of the data, we conclude that a change in user interface causes adaptation in learner's PEOU and PU. Non-hierarchical split menu has significantly higher PEOU and PU. Comprehension and application based tests increase the intrinsic cognitive load on learner and can diminish the impact of PEOU and PU of interface design on the learner. Non-hierarchical split menu design is more beneficial during knowledge based tests.

Learners exhibit more adaptations in navigational behavior as compared to adaptations in beliefs when a change occurs in the user interface used. A non-hierarchical split menu is more efficient in e-learning navigation. Learners require higher page referencing when they shift from non-hierarchical to hierarchical navigation.

We found that the UI design does not influence learner's learning outcome. It implies that the learners adapt to difficult interfaces while learning. However, UI designs influence learning efficiencies. Interaction efficiency of a UI will matter only when the learning situation demands high page referencing, like in the knowledge based tests.

Task adaptations do not change in response to change in user interface and also do not influence the learning outcome.

Summary: *In this chapter we presented the data analysis of the study on user's adaptations. The effects of navigation designs on learners' adaptations in beliefs, navigations, learning efficiency and tasks were analyzed. Hypotheses were tested and useful conclusions were obtained that are summarized at the end. The next chapter presents data analysis of the study on user adaptivity. Computations and validations of the new adaptivity measure are presented. Effects of task complexity and navigation designs are studied.*

Chapter 5

Data Analysis of the Study on User Adaptivity

Chapter 5

Data Analysis of the Study on User Adaptivity

This chapter presents the data collection and analysis of part B of the experiment i.e. study of user's adaptivity. In this chapter, the proposed measure 'user adaptivity score (UAS)' is described in detail. This is followed by the representation and analysis of data collected on adaptivity tests. The effect of user interface design and learning task complexity on user's adaptivity scores are analyzed. Hypotheses relating to user' adaptivity is validated. The proposed adaptivity measure is validated using power curve fitting equations.

5.1. Introduction

In the previous chapter, we analyzed the data collected on user's adaptations. As part B of the same experiment, we studied how learners familiarize with an e-learning interface in repetitive trials. We conducted adaptivity tests for this purpose with the same participants. In this chapter, we will present the data collection and analysis of these adaptivity tests to study user's adaptivity. The objective of this part of the experiment was to validate whether learning task complexity and navigation design have significant effect on user adaptivity (hypothesis H2,H4), whether e-learning self efficacy has significant effect on user adaptivity (H5) and whether user adaptivity has significant effect on learning outcome (H6).

In order to compare user interfaces based on user's ability to gain expertise, we propose a new measure in this thesis. The proposed measure is described next.

5.2. The Measure of User's Adaptivity Score (UAS)

User adaptivity score measures performance improvement capability of user, adapting to a new interface in n trials of repetitive tasks. The improvement in interaction performance in comparison to the previous trial is considered as *positive benefit*. Decrease in performance from previous trial is considered as *negative benefit*. If the performance remains same it is considered as *neutral benefit*. In the current study, the repetitive task (adaptation test-AT) is a set of pre-defined instructions that the user has to execute in a sequence on the particular interface. The instructions in the set are chosen such, that all functionalities of the interface are covered.

The two dimensions of user adaptivity to interface have been integrated. The first dimension is the time *performance index* (P_t) which computes how close the user is in performance to the time taken by the expert user in completing the repetitive task. It is computed as follows:

$$\textbf{Time performance index}(\mathbf{P_t}) = \frac{\textbf{Predicted optimum time for task completion } (\mathbf{T_{opt}})}{\textbf{Actual time taken to accomplish the task } (\mathbf{T_{act}})} \qquad \textbf{(5.1)}$$

The second dimension is the *effort performance index* (P_c) which computes how close the user is in performance with respect to the effort required by the expert user in completing the repetitive task. It is computed as follows:

$$\textbf{Effort performance index}(\mathbf{P_c}) = \frac{\textbf{Predicted optimum clicks required for task completion } (\mathbf{C_{opt}})}{\textbf{Actual clicks operated for the task } (\mathbf{C_{act}})} \qquad \textbf{(5.2)}$$

To measure the user's skill level in the ith trial, we have developed the integrated performance (P_i) criteria as product of P_t and P_c.

$$\mathbf{P_i = P_{t_i} \times P_{c_i}} \quad [0, 1] \qquad \textbf{(5.3)}$$

Performance index against trial of a typical user is depicted in figure 5.1 for illustration. For an adapting user, it is expected that the performance index should keep on improving in successive trials.

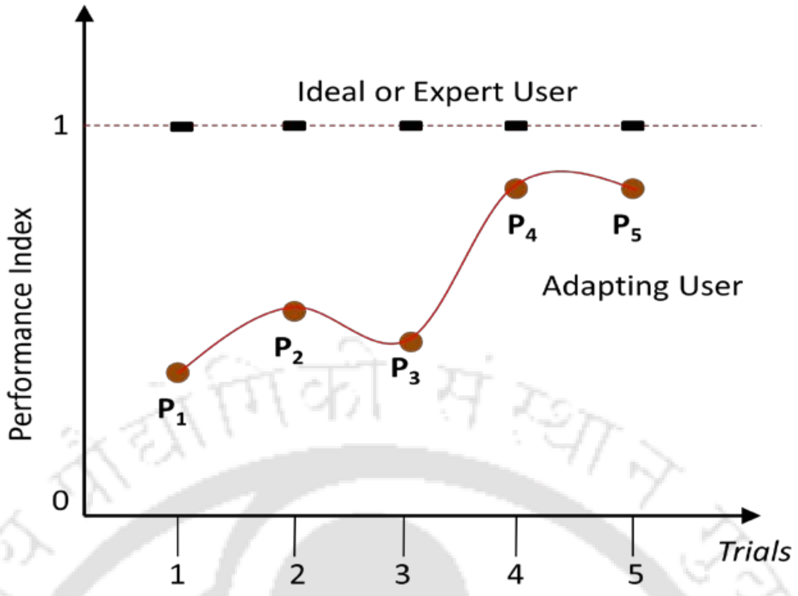


Figure 5.1 Performance curve of a typical user

The performance benefit gain is defined as follows:

Let p_i and p_{i-1} be the performance in i^{th} and $(i-1)^{th}$ trial respectively.

If $p_i > p_{i-1}$, then benefit is positive and performance benefit gain $\Delta_i = \frac{p_i + p_{i-1}}{2}$ **(5.4)**

If $p_i = p_{i-1}$, then benefit is neutral and performance benefit gain $\Delta_i = p_i$ **(5.5)**

If $p_i < p_{i-1}$, then benefit is negative and performance benefit gain $\Delta_i = 0$ **(5.6)**

where i=trial number

The optimal time for completion (T_{opt}) and optimal clicks required (C_{opt}) for the repetitive task is computed using Key-stroke Level Model [37] which reflects behavior of an expert user. The performance index (P_i) for an expert user will be 1 in each trial. For N trials accumulated performance benefit of an expert adapting user would be $\sum_{i=2}^{N} \Delta_i$ or N-1. Finally, the benefit-based user adaptivity score is computed as:

$$\text{User Adaptivity Score (UAS)} = \frac{\text{Performance benefits gained by actual user}}{\text{Optimal benifits gained by the expert user}}$$

$$\textbf{User Adaptivity Score (UAS)} = \frac{\sum_{i=2}^{N} \Delta_i}{N-1} \qquad (5.7)$$

User adaptivity therefore measures the user's degree of expertise achieved in familiarizing to an interface.

We conducted total 5 trials of adaptivity tests on the participants for GUI-1 and GUI-2. The participants became familiarized with the interfaces while solving the learning tests. The participant's performance on adaptivity tests and computation of user adaptivity scores for GUI-1 and GUI-2 for all the three sample groups (K, C and A) are presented in the next section.

5.3. Computing User Adaptivity

We designed a separate repetitive task for measuring adaptivity. We developed a PHP program called *adaptivity tool* to log learner's performance on this repetitive task in terms of completion time and the effort or number of clicks required. We computed the values T_{opt} and C_{opt} in Eqns. (5.1) and (5.2) for the repetitive task using the Key-stroke Level Model of task analysis (section 3.4.4, chapter 3). The values T_{act} and C_{act} in Eqns. (5.1) and (5.2) for each trial of adaptivity test for a participant were obtained from the operation log. We computed P_t, P_c and P_i for each trial for each participant and then computed the user adaptivity score using Eqn. (5.7).

Figures 5.2-5.7 show performance curves of P_t and P_c against trial for GUI-1 and GUI-2. The graph indicates the group's mean values of P_t and P_c for each trial. In figure 5.2, the trial number T1 to T5 is shown on X axis and performance index P_t and P_c is shown on Y axis. Same is repeated for figures 5.3-5.7.

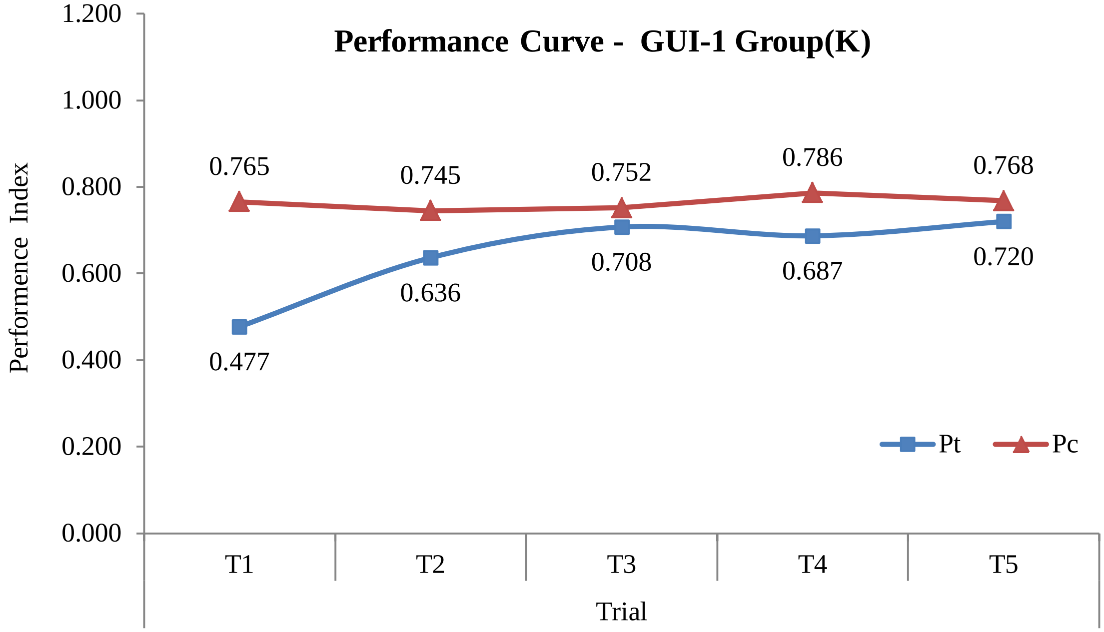


Figure 5.2 Performance curve of P_t and P_c for GUI-1 in group (K)

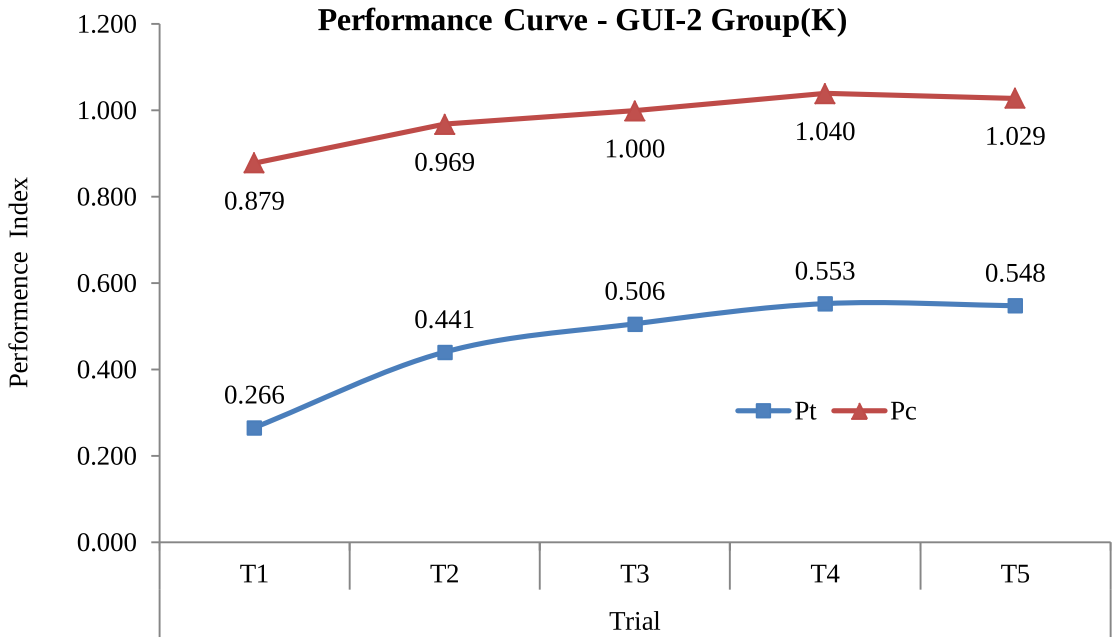


Figure 5.3 Performance curve of P_t and P_c for GUI-2 in group (K)

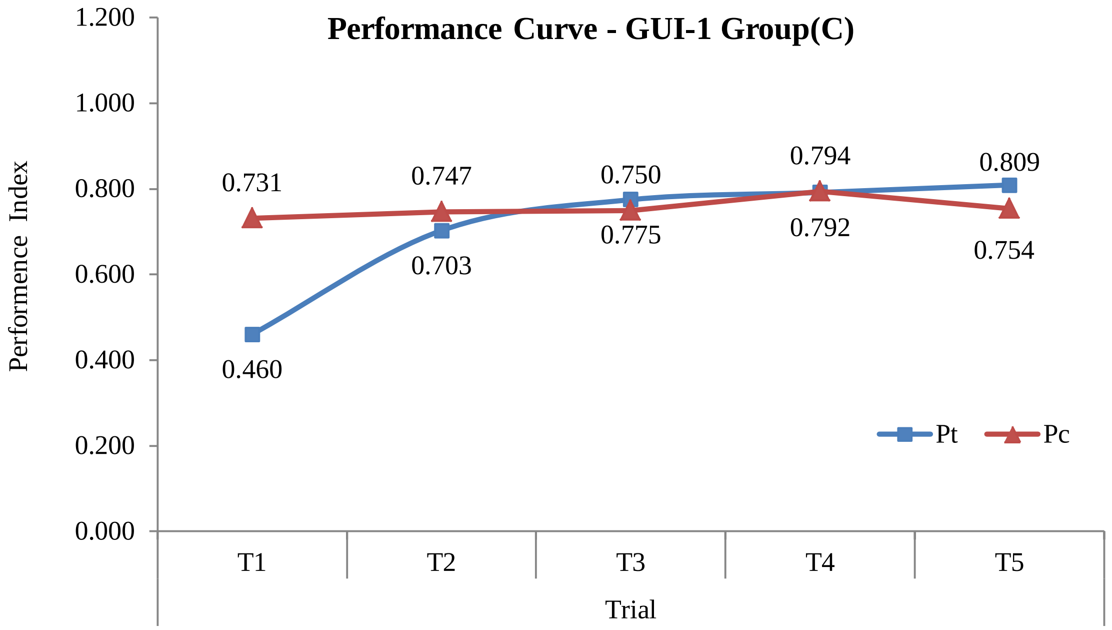


Figure 5.4 Performance curve of P_t and P_c for GUI-1 in group (C)

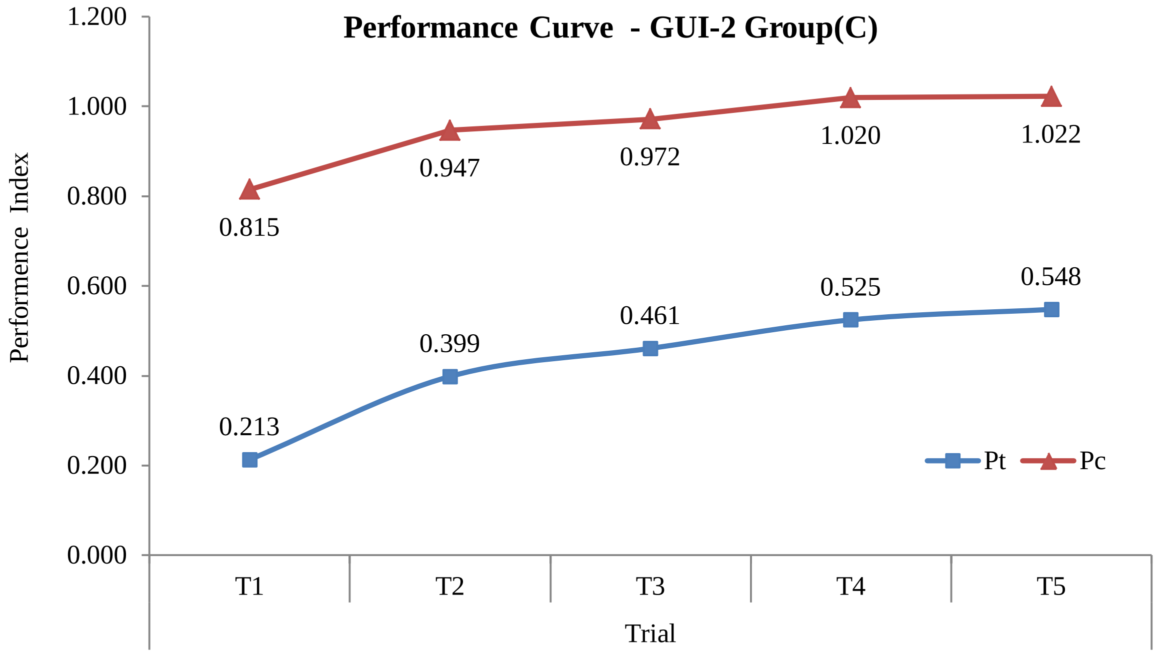


Figure 5.5 Performance curve of P_t and P_c for GUI-2 in group (C)

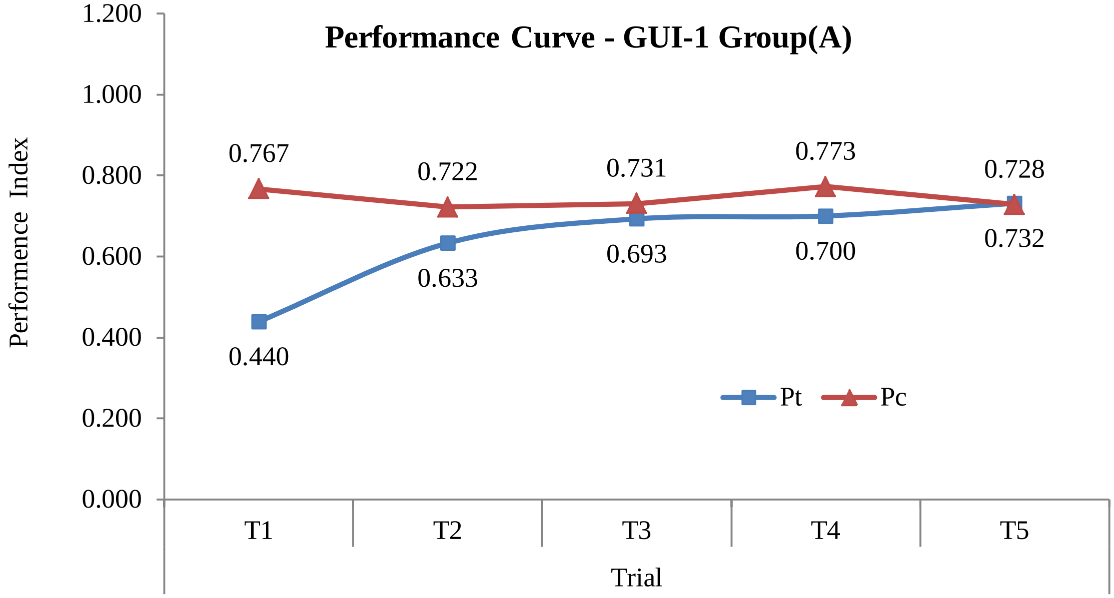


Figure 5.6 Performance curve of P_t and P_c for GUI-1 in group (A)

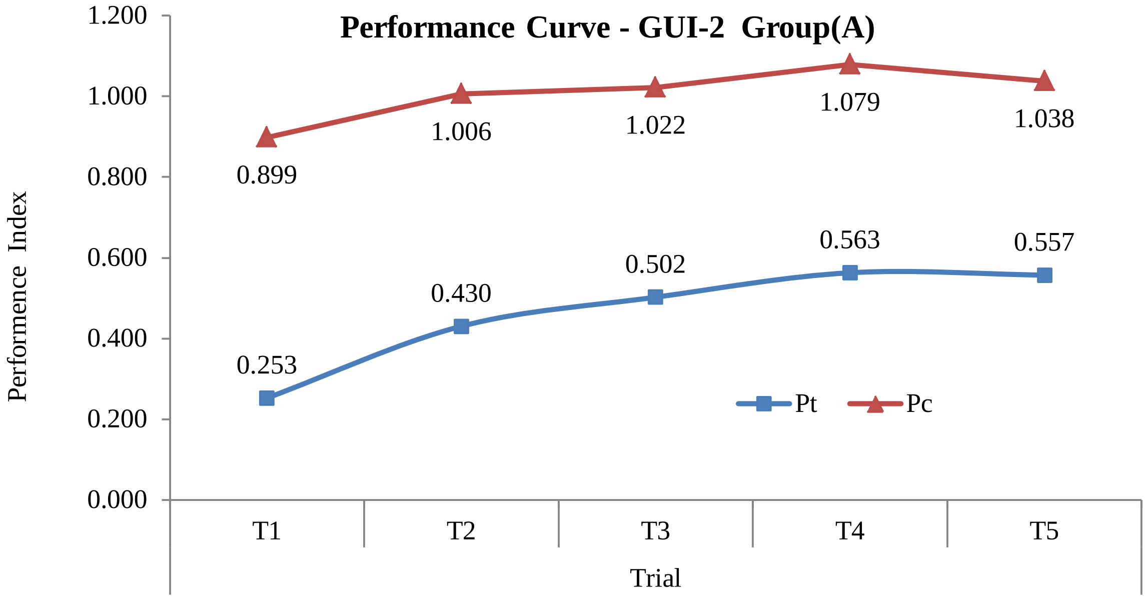


Figure 5.7 Performance curve of P_t and P_c for GUI-2 in group (A)

Analysis of Effort Performance Index Curves (P_c)

Figures 5.2-5.7 show that performance index on GUI-2 for the 5th (last) trial of adaptivity test is 1.0287, 1.0225 and 1.0382 for group K, C and A respectively as against 0.768, 0.7539 and 0.7282 on GUI-1 in group K, C and A respectively. We may therefore conclude that participants gain higher degree of expertise in interaction effort on GUI-2 as compared to GUI-1. The shape of the P_c curve for GUI-2 shows a steady rise in each trial. This reflects accumulation of performance benefits or knowledge of the interface and therefore indicates an adapting behavior of the participant. Against this in case of GUI-1, performance benefits are being lost due to ups and downs in the shape of the P_c curve which shows a non-adapting behavior of the participant.

We may conclude that participants need more practice to complete tasks in minimum efforts using hierarchical horizontal menu as compared to non-hierarchical split menu interface.

Analysis of Time Performance Index Curves (P_t)

We observe that in time performance (P_t), participants using GUI-1 perform better compared to participants using GUI-2. Time performance index in 5th (last) trial is 0.7201, 0.8091 and 0.7317 for GUI-1 in group K, C and A respectively as compared to 0.5483, 0.5479 and 0.5571 for GUI-2 in group K, C and A respectively. For both the GUIs the shape of the P_t curve shows a steady rise in successive trials indicating adapting behavior of the participants.

It may be noted that user's need more practice to increase their speed of tasks using non-hierarchical split menu interface as compared to hierarchical horizontal menu interface.

We computed integrated performance index of i^{th} trial P_i, as the product of effort performance index P_{Ci} and time performance index P_{ti} (Eqn. 5.3). Figures 5.8-5.13 show average integrated performance index P_i of the group against trial, for GUI-1 and GUI-2 in sample groups K, C and A respectively. In figure 5.8, the X axis shows the trial number T1 to T5 and Y axis shows integrated performance index P_i. Same is repeated for figures 5.9-5.13.

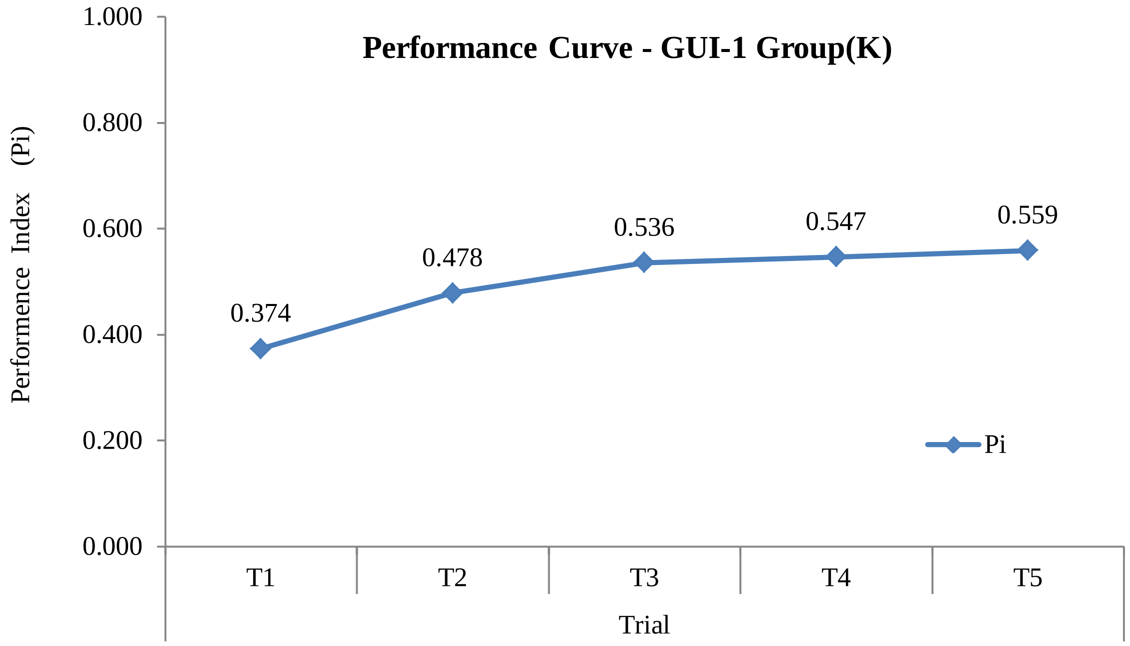


Figure 5.8 Performance curve of P_i for GUI-1 in group (K)

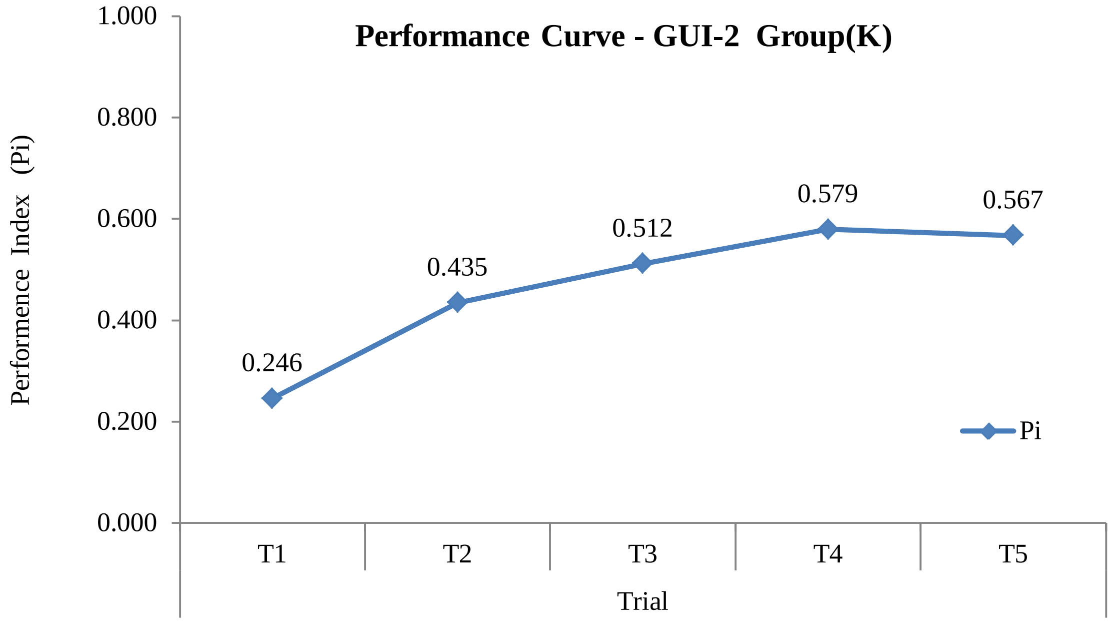


Figure 5.9 Performance curve of P_i for GUI-2 in group (K)

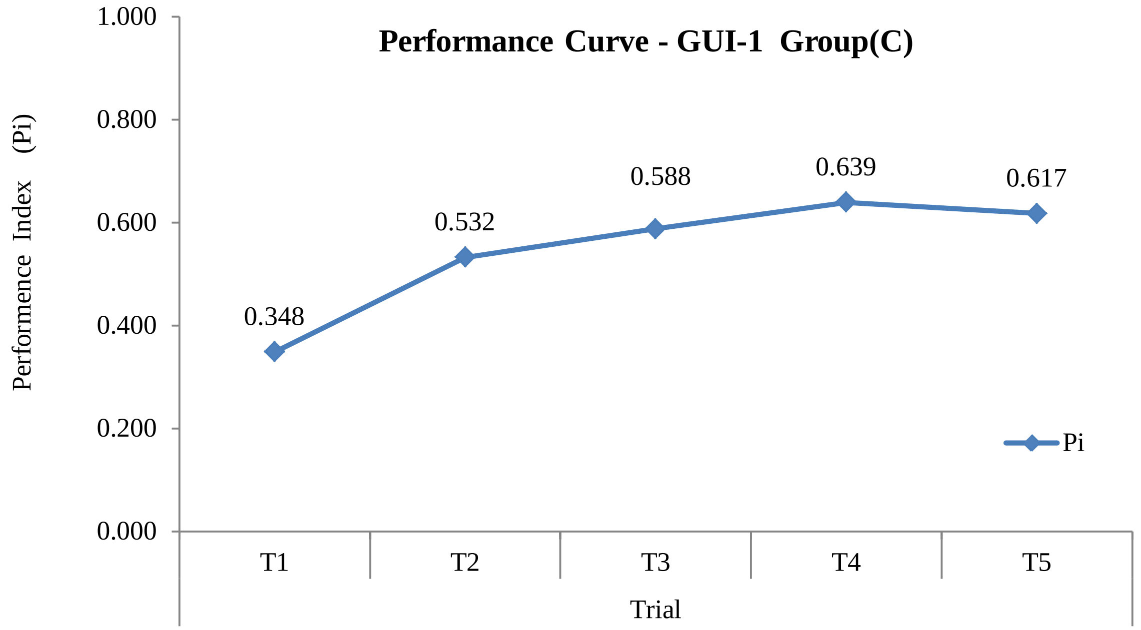


Figure 5.10 Performance curve of P_i for GUI-1 in group (C)

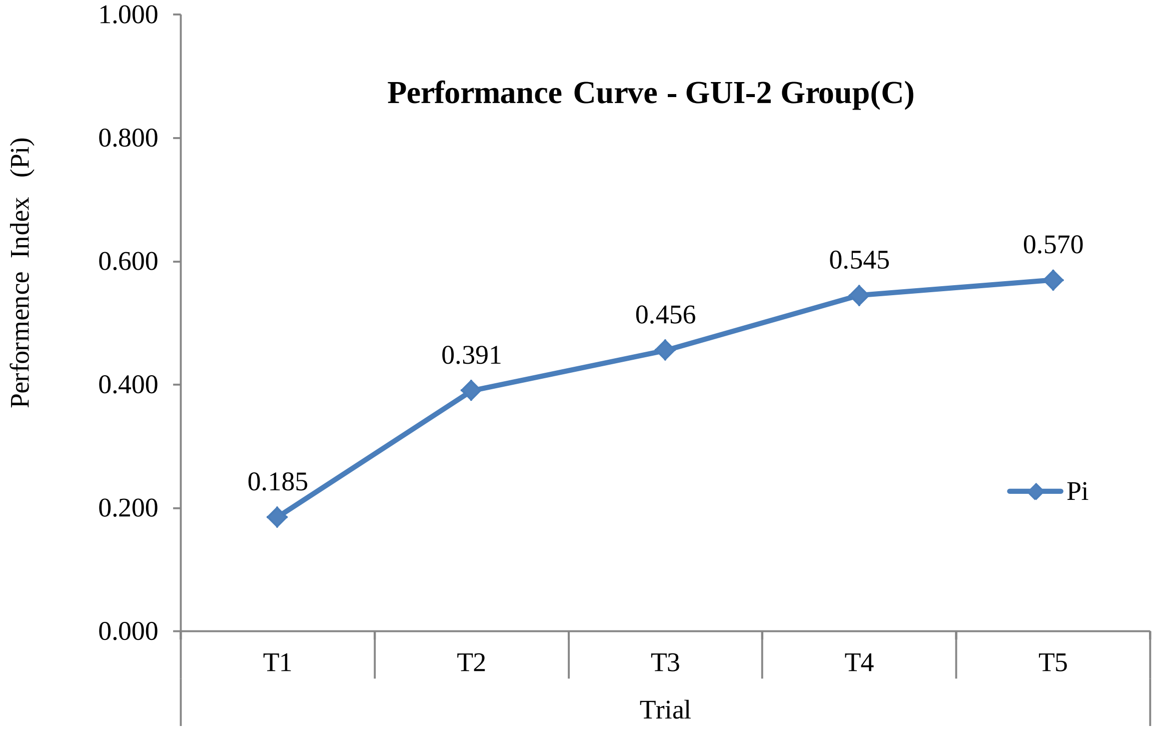


Figure 5.11 Performance curve of P_i for GUI-2 in group (C)

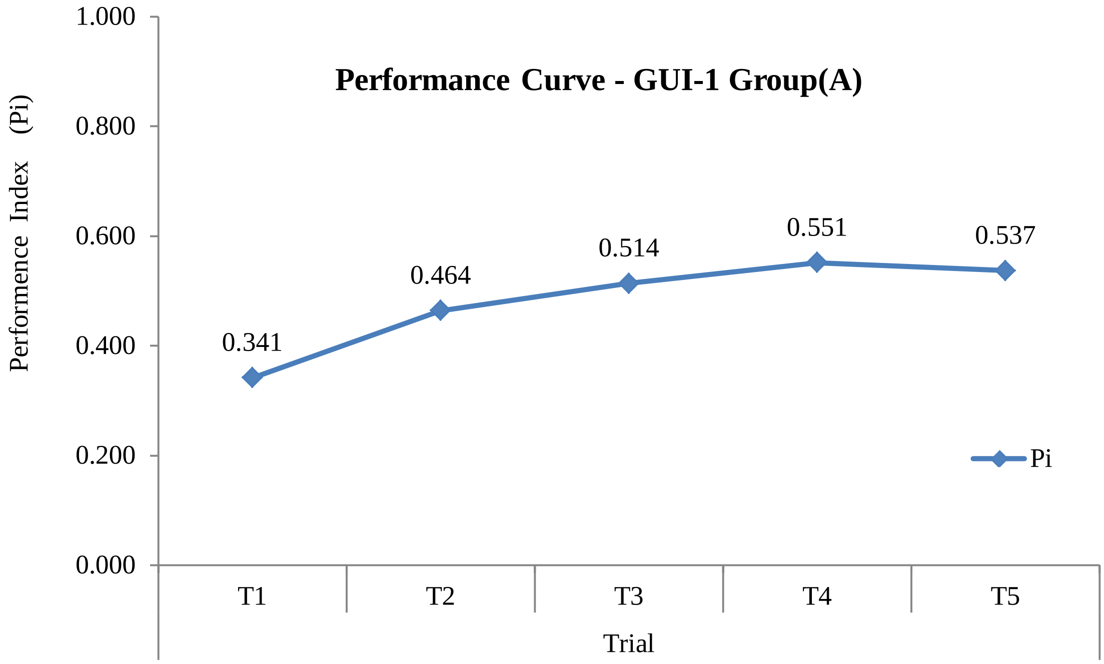


Figure 5.12 Performance curve of P_i for GUI-1 in group (A)

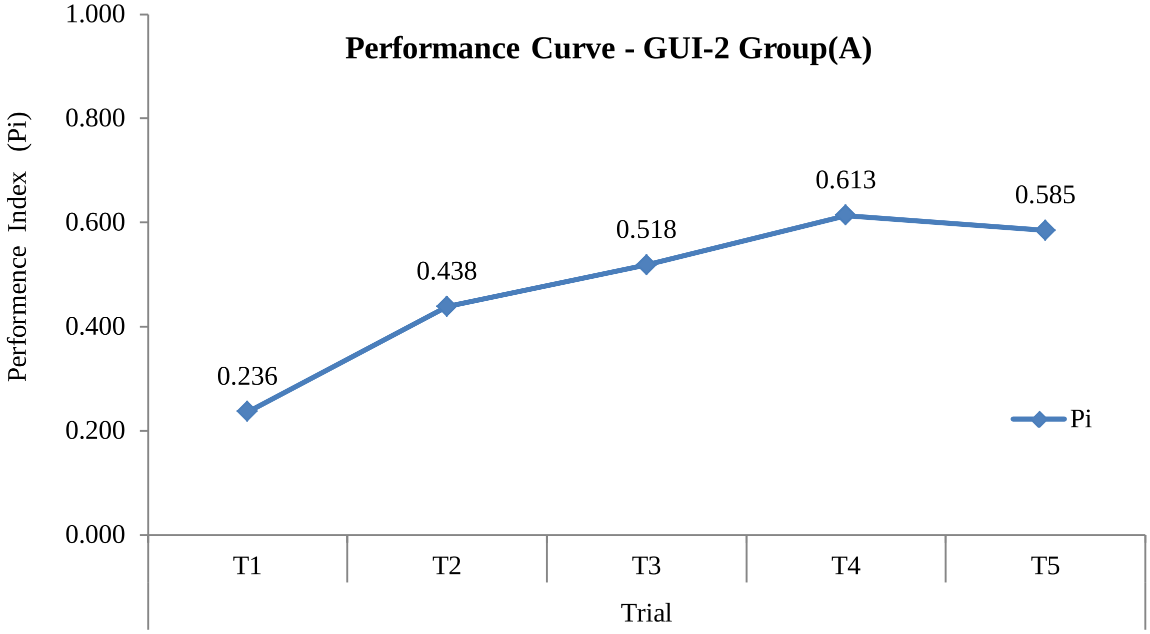


Figure 5.13 Performance curves of P_i for GUI-2 in group (A)

Analysis of Integrated Performance Index Curves (P_i)

Figures 5.8-5.13 show that after 5 trials, participants using GUI-1 and GUI-2 both attain similar degrees of expertise in adaptivity test, in all the three sample groups K, C and A. The performance index of the 5th (last) trial for GUI-1 is 0.5591, 0.6174 and 0.5367 for group K, C and A respectively and for GUI-2 it is 0.5673, 0.5698 and 0.5848 respectively. However, we observe that the performance improvement rate on GUI-2 is greater as compared to GUI-1 indicating a higher capability of adaptivity.

From the graphs of Pi it can be concluded that user's adaptivity is similar for hierarchical horizontal menu interface and non-hierarchical split menu interface.

We used PHP program to compute the positive, neutral and negative benefits and corresponding performance gains in each trial of adaptivity test for each individual using Eqns. (5.4), (5.5) and (5.6). Total benefits accumulated by all participants of the group during the adaptation period (5 trials) on GUI-1 and GUI-2 in sample groups K, C and A are shown in table 5.1.

Table 5.1 Performance benefits in adaptation period

Performance Benefits In 5 Trials **User Interface**		**Number of negative benefits**	**Number of positive benefits**	**Performance Accumulated**	**Mean Adaptivity**
Group-K (N=85)	GUI-1	127	213	105.36	0.3099
	GUI-2	102	238	111.05	0.3266
Group-C (N=106)	GUI-1	139	285	155.1	0.3658
	GUI-2	109	315	134.49	0.3172
Group-A (N=96)	GUI-1	133	251	120.9226	0.3149
	GUI-2	106	278	133.0456	0.3465

The first column of table 5.1 represents group with sample size. The second column is the user interface, followed by the number of negative benefits and then positive benefits. Total performance accumulated by the entire group is shown next and average user adaptivity score of the group in represented in the last column.

Data of table 5.1 indicates that, users using GUI-2 accumulate less negative benefits and more positive benefits compared to GUI-1. However, the performance gain accumulated from these benefits is almost same for GUI-1 and GUI-2. This is because in complex interfaces learning is difficult (performance gains are low) and forgetting is easy (performance losses are heavy), while in simpler interfaces learning is easy (performance gains are high) and forgetting is difficult (performance losses are low).

Adaptivity tests show that consistency in performance improvement is better in non-hierarchical split menu interface compared to hierarchical horizontal menu interface.

We normalized the performance benefit values in table 5.1 with the sample size. The normalized values are shown in figure 5.14 for all the three sample groups.

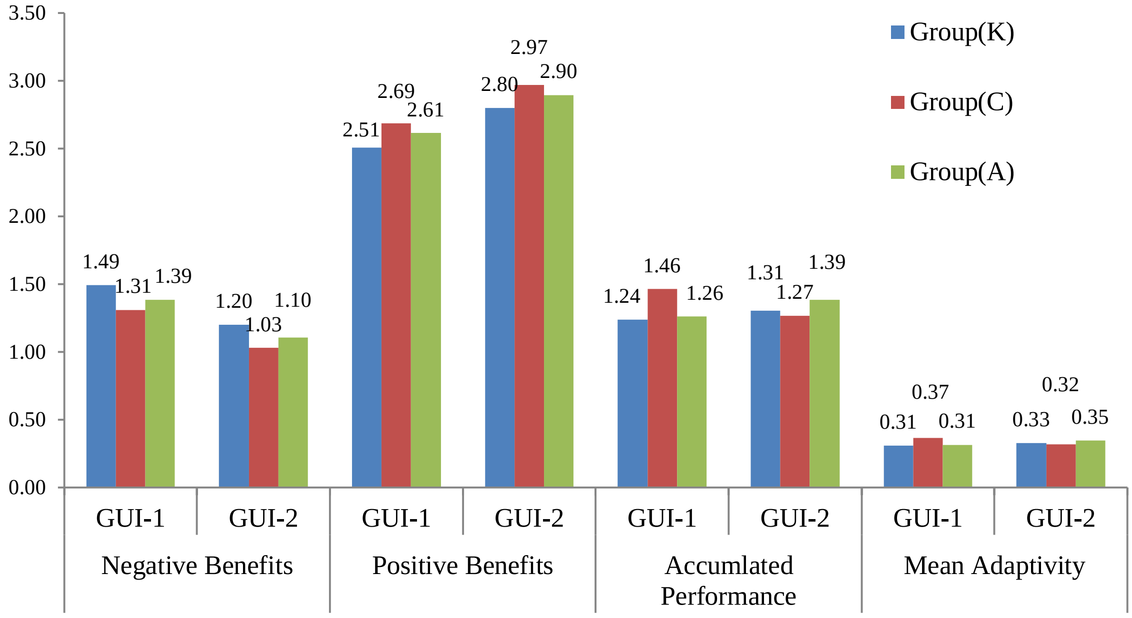


Figure 5.14 Normalized performance benefits across GUIs in adaptation period

Figure 5.14 shows that, on GUI-1, participants of group-C accumulate higher benefits and gain more expertise of interface as compared to the other learning groups. We do not observe this difference in groups on GUI-2.

This implies that the type of learning tasks which are practiced on simple hierarchical horizontal menu interface influences adaptivity, however for complex non-hierarchical split menu interface the learning task type which is practiced does not influence adaptivity.

We computed user adaptivity scores (UAS) using Eqn. (5.7) for GUI-1 and GUI-2 of each participant. Group's mean UAS in percentage for both GUIs are shown in figure 5.15.

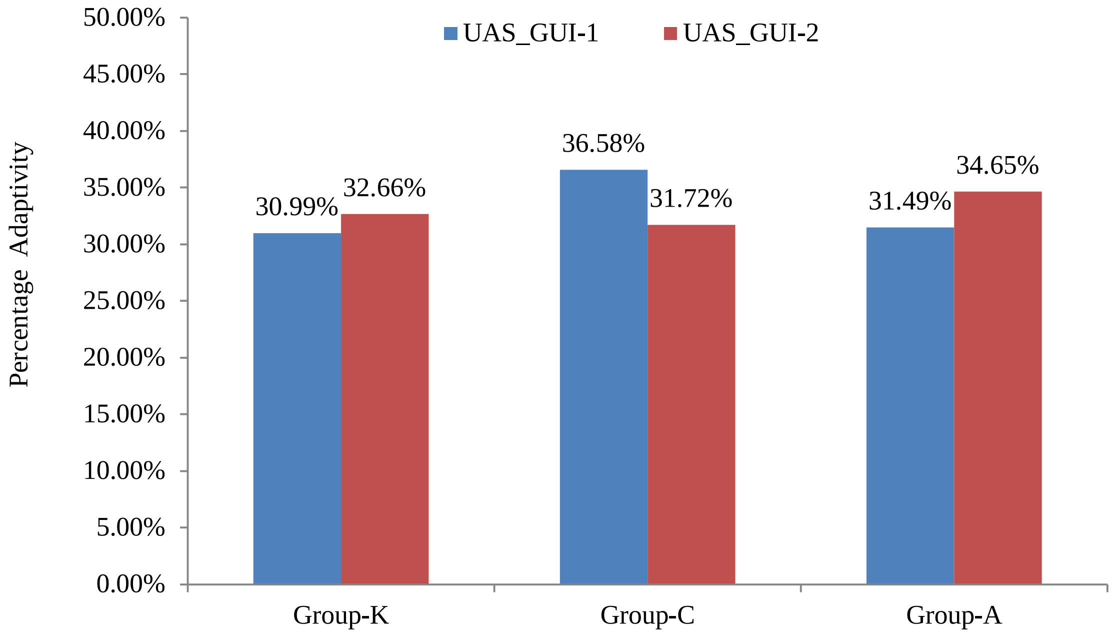


Figure 5.15 Group mean of user adaptivity scores (UAS)

Figure 5.15 indicates an overall adaptivity of 30%-35% is attained in 5 trials. We also observe that participants have similar adaptivity scores on GUI-1 and GUI-2.

We observe that on hierarchical horizontal menu interface, user's adaptivity is influenced by complexity of the learning tasks executed on it. Adaptivity on non-hierarchical split menu interface is insensitive to the complexity of learning tasks carried out on them.

5.4. Validation of Hypothesis H2, H4, H5, H6

In this thesis, we have formulated six hypotheses (section 1.4, chapter 1). Two of those (H1, H3) were based on the data of part A of the experiment, discussed in chapter 4. The validations of remaining hypotheses based on the results of user's adaptivity tests are discussed next.

H2: Learning task complexity has significant effect on user adaptivity

Since the effect of learning task complexity was to be compared between three independent groups (K, C, A), a one way ANOVA test was performed on adaptivity scores to test the significance of the differences between the three groups.

For GUI-1, the difference in adaptivity scores was found statistically significant across the three sample groups [*F*(2,284)=7.329, *p*=.001]. A Tukey post-hoc test revealed that the adaptivity scores were significantly lower for knowledge group-K (M=0.309868873, SD=0.0971748873, *p*=.002) and application group-A (M=.314902660, SD=.1067182933, *p*=.005) as compared to the comprehension group-C (M=.365793209, SD=.1316718665). There was no significant difference in adaptivity scores of knowledge and application group (*p*=.953).

For GUI-2, the difference in adaptivity scores for knowledge (M=0.326604621, SD=0.1058358378), comprehension (M=0.317199114, SD=0.1301646090) and application (M=0.346473052, SD=0.1147443554) groups was not statistically significant [*F*(2, 284)=1.587, *p* = .206].

It can be concluded that adaptivity to hierarchical horizontal menu interface is sensitive to complexity of learning tasks while adaptivity to non-hierarchical split menu interface is unaffected by learners tasks.

Therefore *hypothesis H2* is supported for hierarchical horizontal menu interface where the effect of user interface design on user adaptivity is mediated by learning task complexity.

H4: Navigation design has significant effect on user adaptivity

Paired samples t-tests were performed to find the significance of the differences in adaptivity scores between the two GUIs. Results show that, in a knowledge based test group-K, the difference in adaptivity scores of GUI-1 (M=0.30986887, SD=0.097174887) and GUI-2 (M=0.32660462, SD=0.105835838) is not significant [t(84)=-1.269, p=0.208]. However, user adaptivity scores were found to be significantly higher for GUI-1 (M=0.3658, SD=0.1317) as compared to scores for GUI-2 (M=0.3172, SD=0.1302) [t(105)=3.474, p=0.001, d=0.37, r=0.182] for the participants of group-C. In case of an application based test group-A, results were exactly the opposite. User adaptivity scores were significantly higher for GUI-2 (M=0.3465, SD=0.1147) than GUI-1 (M=0.3149, SD= 0.1067) [t(95)=-2.218, p=0.029, d=0.285, r=0.14].

Results of part A of the experiment which were discussed in chapter 4, show that participants navigate with overviewing style during comprehension based tests. Therefore, users familiarize themselves in using only high level features of the interface. Users do not get opportunity to learn the next level features. So, many advanced features of the interface remain unused. This affects their performance in adaptivity test since in this test they are supposed to use every feature of the interface. Hence, the user adaptivity scores on the simplistic GUI-1 are significantly higher than scores on the complex GUI-2 for group-C.

Since application based tests require deep processing (more page level activity), it is observed that while learning, users become familiar to the next level of features in the interfaces. We have also concluded earlier that GUI-2 supports deep processing better than GUI-1. That is why, it is observed that learners adapt quickly to GUI-2 as compared to GUI-1 during application based tests.

Overall we can infer that knowledge based learning leads to achieving same level of skills in hierarchical and non-hierarchical split menu interfaces. On the other hand, the skill levels achieved in hierarchical and non-hierarchical split menu interfaces is different during comprehension and application based learning.

Therefore, *hypothesis H4* is supported for user adaptivity during comprehension and application oriented learning. It is not supported for knowledge based learning group.

H5 : E-learning self efficacy has significant effect on user adaptivity score

E-leaning self-efficacy measures individual's confidence in judging one's capabilities of using e-learning for designated goals. Prior to adaptivity tests learner's e-learning self-efficacy was measured using a 24 item questionnaire (Appendix A1). To find the relationship between user adaptivity scores (UAS) and learner's e-learning self-efficacy (ELSE), we did a correlation analysis. Result showed that a significant correlation exists between e-learning self-efficacy (ELSE) and user adaptivity scores (UAS) of GUI-1 ($r=0.375$, $p<.001$) and GUI-2 ($r=.362$, $p<.001$) during comprehension oriented learning.

This implies that learner's e-learning capabilities and confidence affects his ability to adapt to learning interfaces in comprehension based learning.

Hypothesis H5 was therefore partially supported only for comprehension based learning.

H6 : User adaptivity has significant effect on learning outcome

In chapter 4, we had concluded that user interface designs do not affect learning outcomes. It was observed that learners adapted and performed equally well on both GUIs. However, since the learning tests given were time bound, we thought that user interface skill level or user adaptivity of learner might affect his test scores. In order to investigate, we did a correlation analysis between user adaptivity scores (UAS) and learning outcome (LO). Significant correlation was found between learning outcome (LO) and user adaptivity scores of GUI-1 ($r=0.270$, $p=.005$) and GUI-2 ($r=0.222$, $p=.022$) again for the comprehension based test group-C only.

This shows that the ability to adapt to learning interfaces affect learner's test performance during application oriented learning.

Hypothesis H6 was partially supported only for comprehension based learning.

We modeled the adaptation process of 5 trials by generating performance curve equation, using the power law. The equation parameters were correlated with adaptivity scores for validation. The complete validation process is described next.

5.5. Validating User Adaptivity

We hypothesize that the performance during repetitive trials can be modeled by a negative power function of learning, which is known as the Power Law of Practice (PLP). The law states that the performance time of a task can be described by a power function of practice. Therefore, for each new trial, the task time should reduce according to this power function.

We define *performance error* E, as the difference between expert performance (i.e. 1) and user performance P giving E= 1-P. We plotted the performance error E verses trials in Microsoft Excel generating the error curves. According to PLP, error curve should fit to a power function. We used Excel to auto-generate power fitting curve equations.

Figures 5.16-5.21 show group mean values of error E verses trial i.e. error curve and power fitting equations for both GUIs in all the three sample groups K, C and A. In figure 5.16, the X axis shows the trial number T1 to T5 and Y axis shows mean error E of the group. Same is repeated for figures 5.17-5.21.

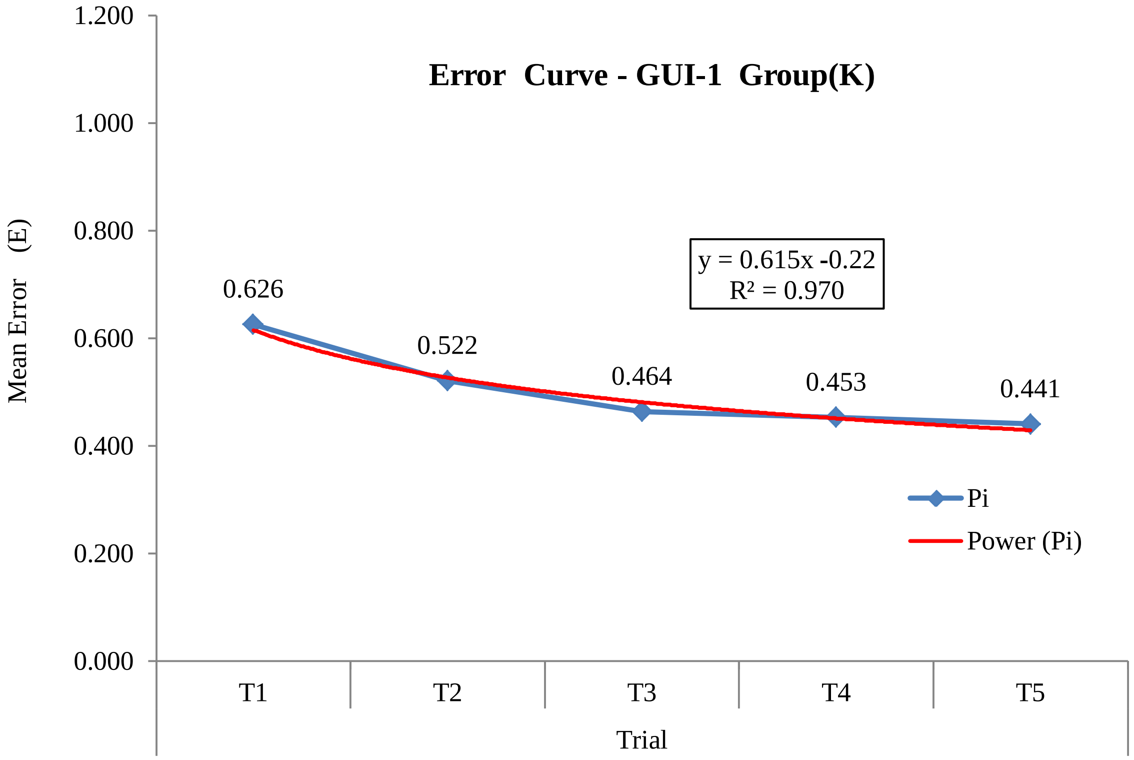


Figure 5.16 Power fitting of error curve for GUI-1 in group (K)

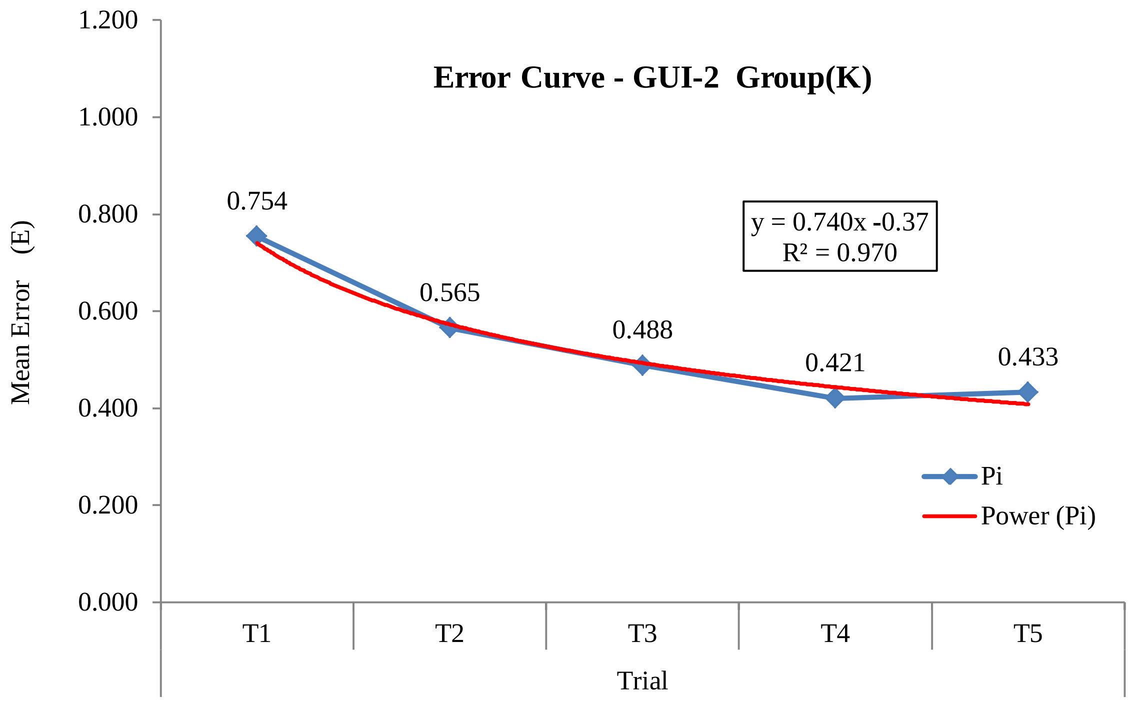


Figure 5.17 Power fitting of error curve for GUI-2 in group (K)

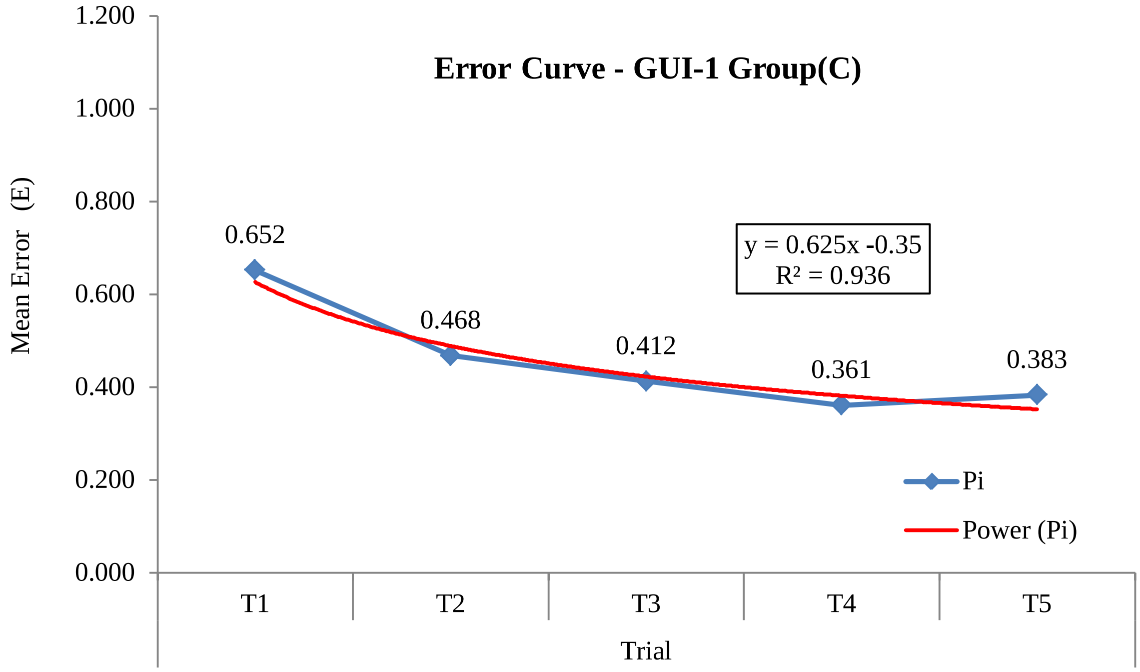


Figure 5.18 Power fitting of error curve for GUI-1 in group (C)

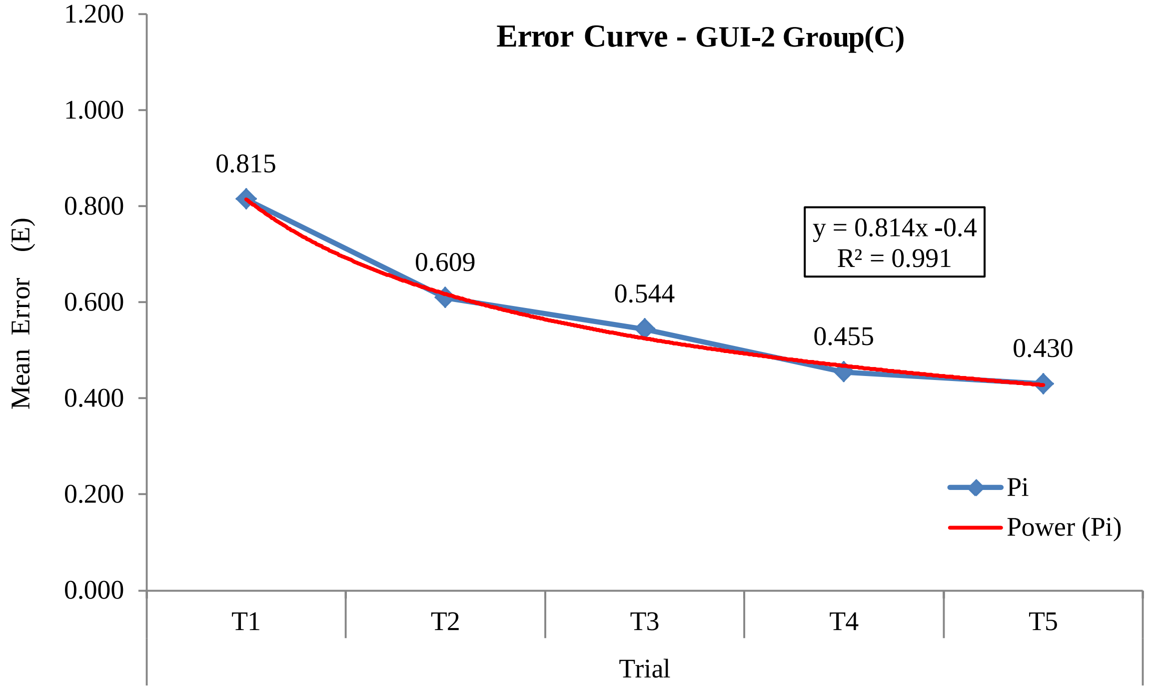


Figure 5.19 Power fitting of error curve for GUI-2 in group (C)

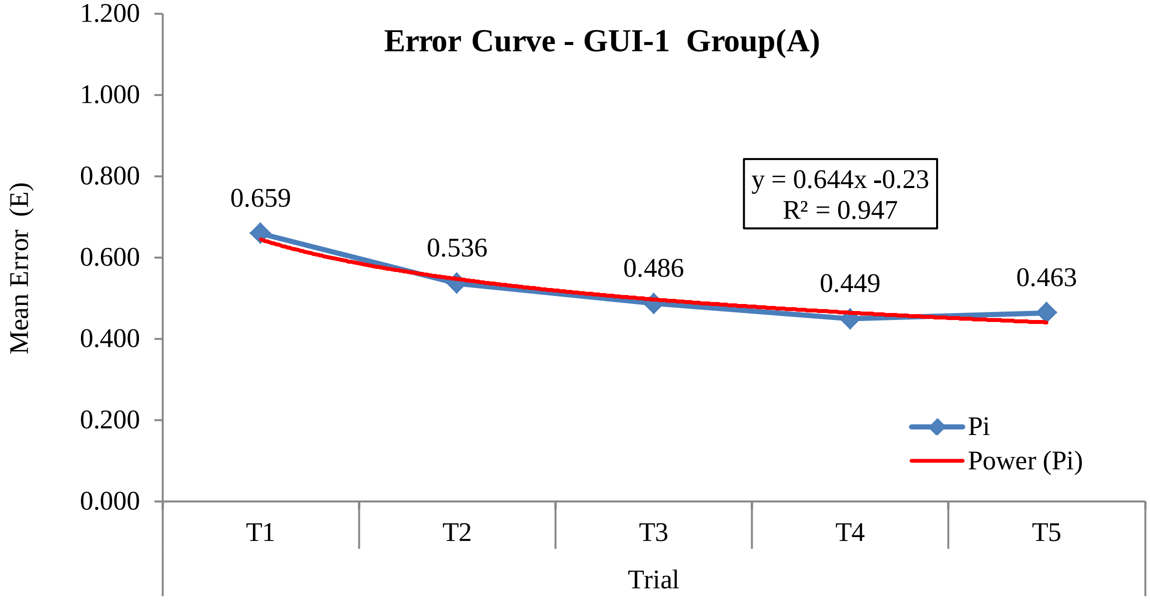


Figure 5.20 Power fitting of error curve for GUI-1 in group (A)

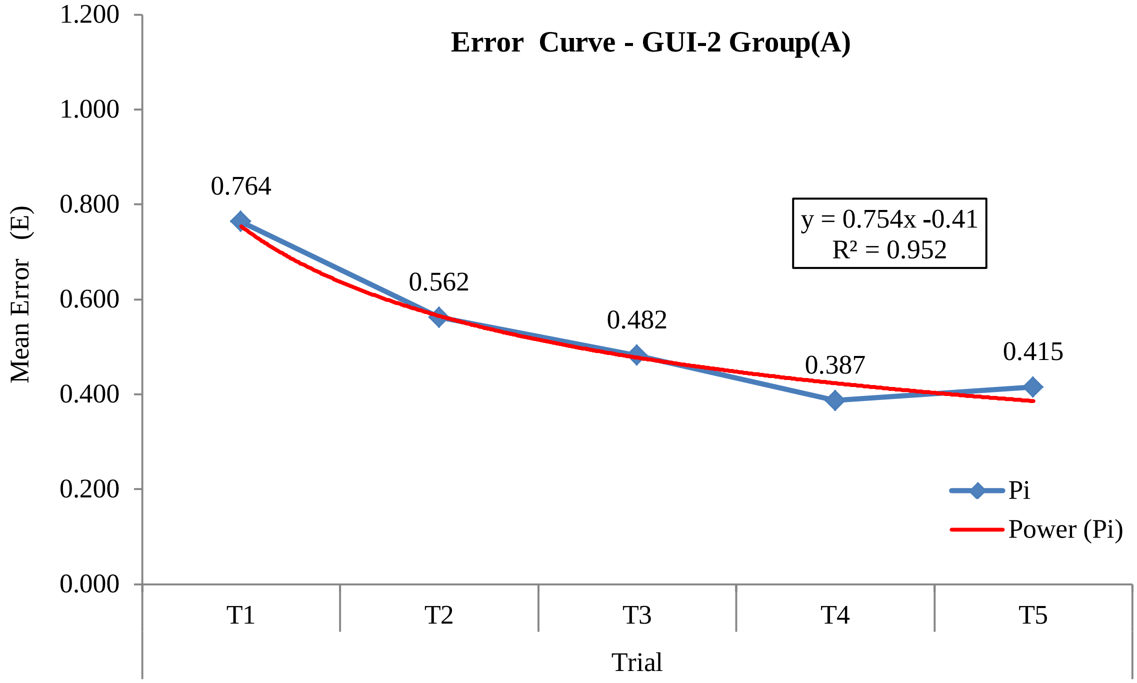


Figure 5.21 Power fitting of error curve for GUI-2 in group (A)

Table 5.2 represents power curve equation attributes for both GUIs.

Table 5.2 Power curve equation attributes

		Group-K		**Group-C**		**Group-A**		
No.	**Attribute of learning**	**GUI-1**	**GUI-2**	**GUI-1**	**GUI-2**	**GUI-1**	**GUI-2**	**Interpretation**
1	Y intercept	0.615	0.74	0.625	0.814	0.644	0.754	Initial difficulty (prior knowledge)
2	Slope	-0.22	-0.37	-0.35	-0.4	-0.23	-0.41	Learning rate (rate of knowledge gain)
3	Fit (R^2)	0.97	0.97	0.936	0.991	0.947	0.952	Extent to which power law holds good
4	Plateau arrival	Earlier	Later	Earlier	Later	Earlier	Later	Difficult to master (requires more practice or trials)

In the power fitting curve equation, y denotes error and x denotes trial number. Therefore, the coefficient of x in the equation, i.e. *Y intercepts* gives the error value for the first trial. This error is the initial difficulty faced by the user and depends on the learner's prior knowledge of the task or interface. The second row of the table 5.2 shows the exponent value of x in the equation and represents the *slope* or the learning rate. The third row represents R^2 value which is always between 0 and 1, and shows the goodness of the fit. R^2 value of 1 means the error curve perfectly fits power function or obeys PLP. The last row shows the arrival of *plateau* in the power curve which represents the point after which learning or performance improvement stops.

Data from table 5.2 shows that, users face greater initial difficulty using GUI-2 as seen from the higher values of Y intercepts (0.74, 0.814 and 0.754) as compared to Y intercepts of GUI-1 (0.615, 0.625 and 0.644). However, learners show quick adaptation to GUI-2 which is evident in higher slope values (-0.37, -0.4 and -0.41) as compared to slope values of GUI-1(-0.22, -0.35 and -0.23). High R^2 values for both the GUIs in all sample groups show that user's performance in successive trials fits well to the power law function.

Learner's distraction during adaptivity test can reflect in noisy error curves which influence curve equations. Taking cumulative error per unit (CEPU) instead of instantaneous error value in plotting the error curves, nullifies the effect of noisy error curves. CEPU considers previous error values in computing the current value and therefore reduces impact of distractions. CEPU was computed as follows:

$$\mathrm{CEPU}_n = \frac{\sum_{i=1}^{n} E_i}{n}$$

Where CEPU_n = Cumulative error per unit until the n^{th} trial

E_i = Error in performing the i^{th} trial of task

We plotted the CEPU against trial, called as experience curve. To get an idea, we will show experience curves of 3 participants on GUI-1 and 3 participants on GUI-2 of the knowledge oriented group-K only. The participants selected are from 3 different ranges of adaptivity scores in the group. Experience curves of the participants #P1, #P2 and #P3 of group-K using GUI-1 are shown in figures 5.22-5.24. User adaptivity score (UAS) of the participant is also shown in the graphs for reference.

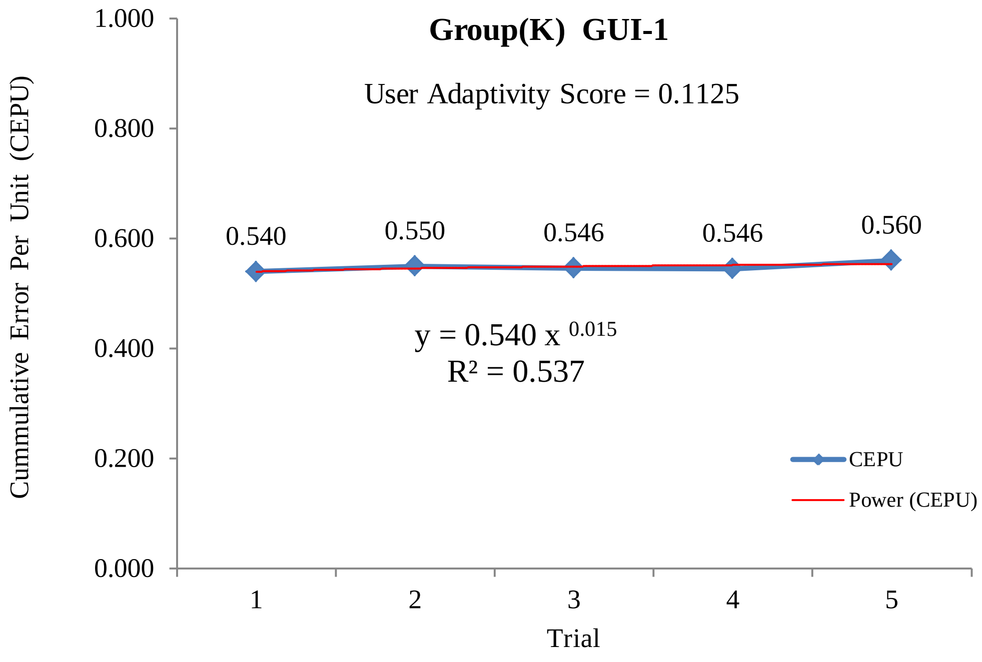


Figure 5.22 Experience curve of participant #P1 on GUI-1 (Very Low Adaptivity)

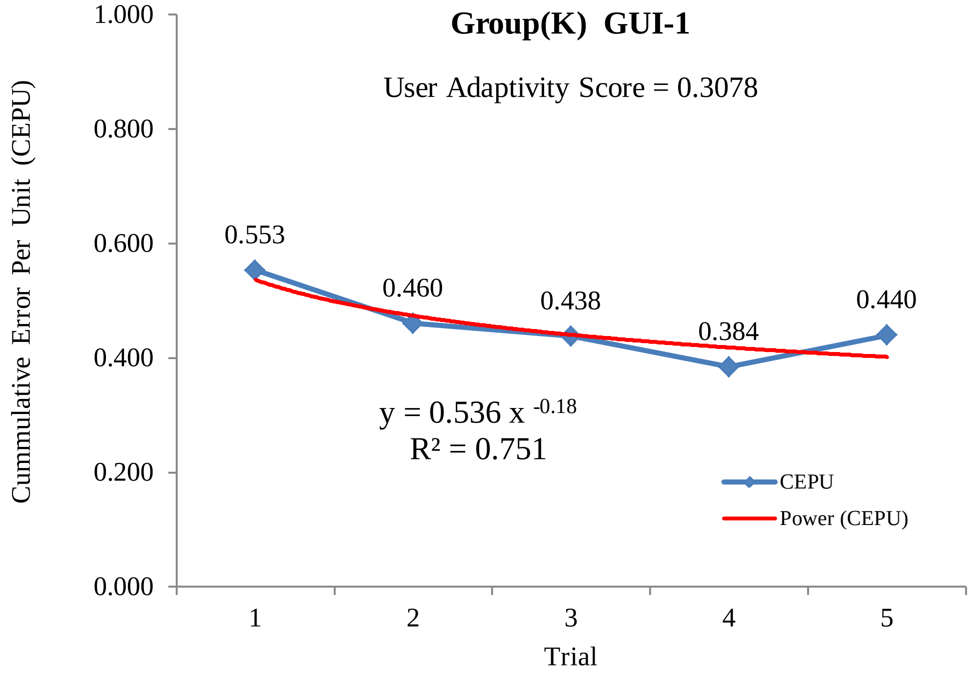


Figure 5.23 Experience curve of participant #P2 on GUI-1 (Low Adaptivity)

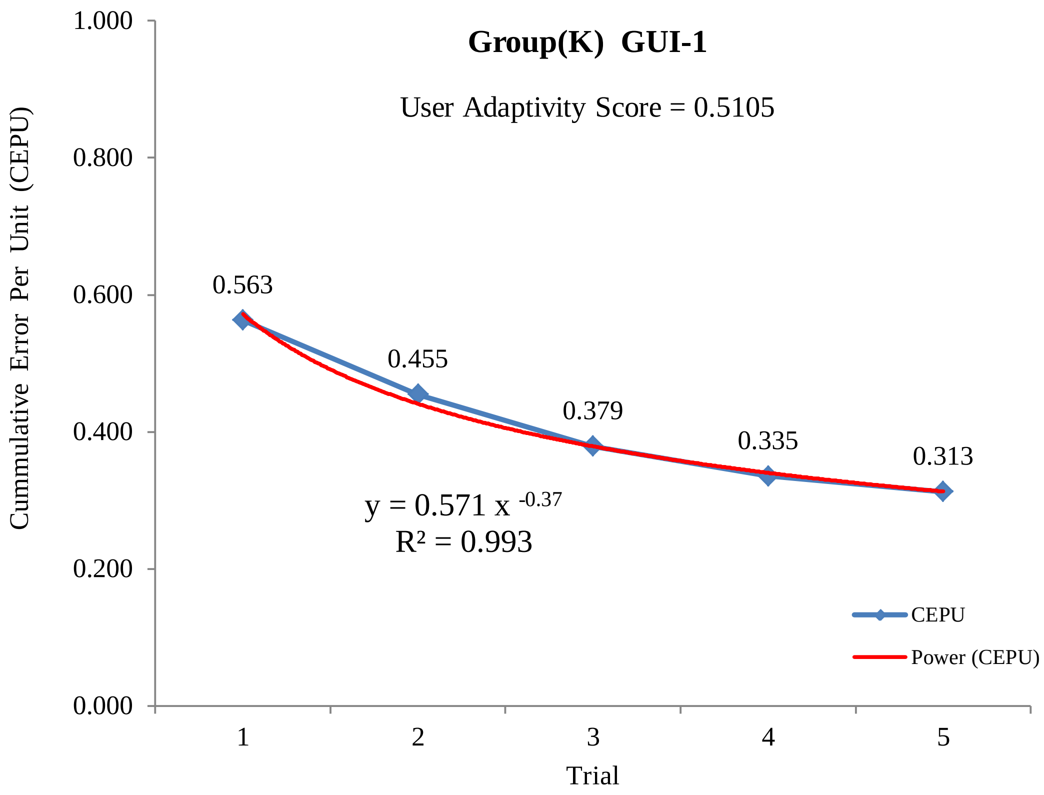


Figure 5.24 Experience curve of participant #P3 on GUI-1 (Medium Adaptivity)

Shape of the experience curve in figure 5.22 and 5.23 and the value of R^2 (goodness of fit) clearly indicate that #P1 and #P2 show non-adapting behavior. This is also evident from their low user adaptivity scores. We also observe a correlation of slope of curve (exponent of x) with the user adaptivity score. Higher value of R^2 and slope is related with higher adaptivity score reflecting an adapting user behavior. Lower value of R^2 and slope is related with lower adaptivity score reflecting a non-adapting behavior.

Similar experience curves of participants #P4, #P5 and #P6 of group-K using GUI-2 and having different ranges of adaptivity scores are shown in figures 5.25-5.27.

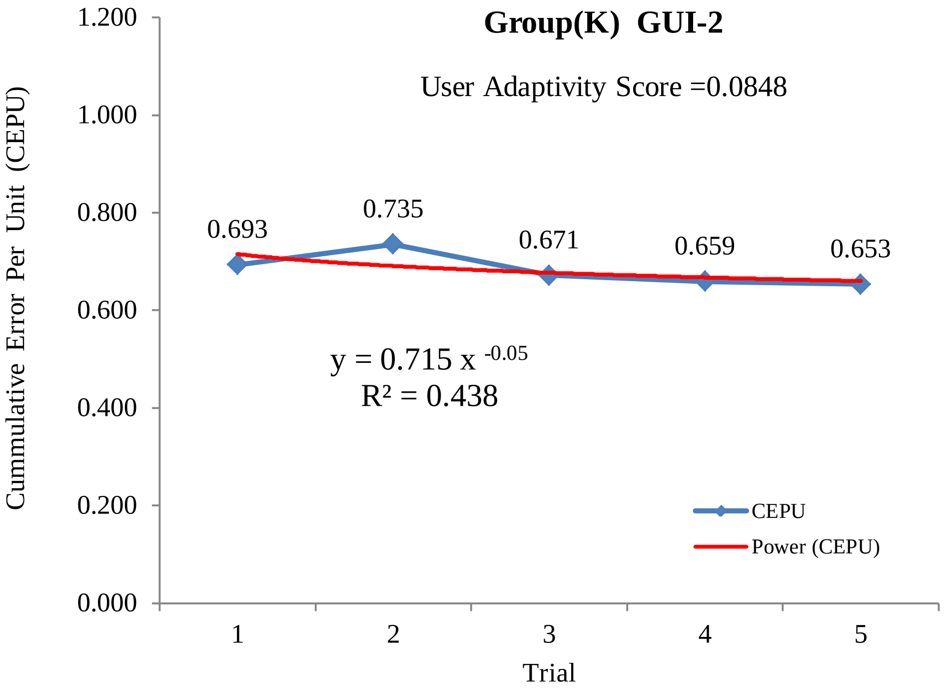


Figure 5.25 Experience curve of participant #P4 on GUI-2 (Very Low Adaptivity)

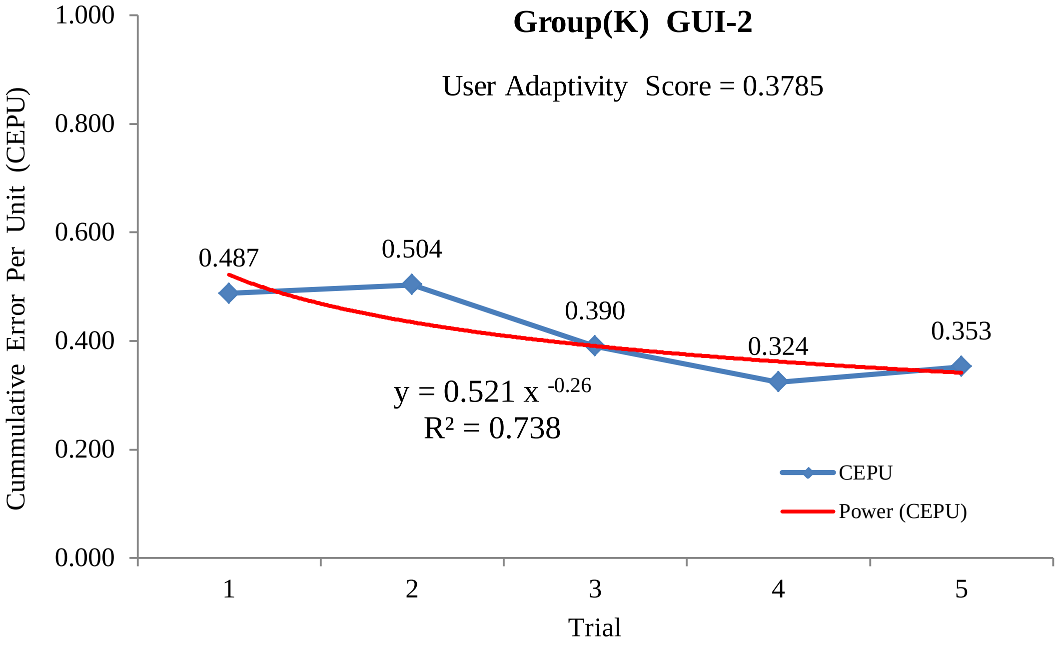


Figure 5.26 Experience curve of participant #P5 on GUI-2 (Low Adaptivity)

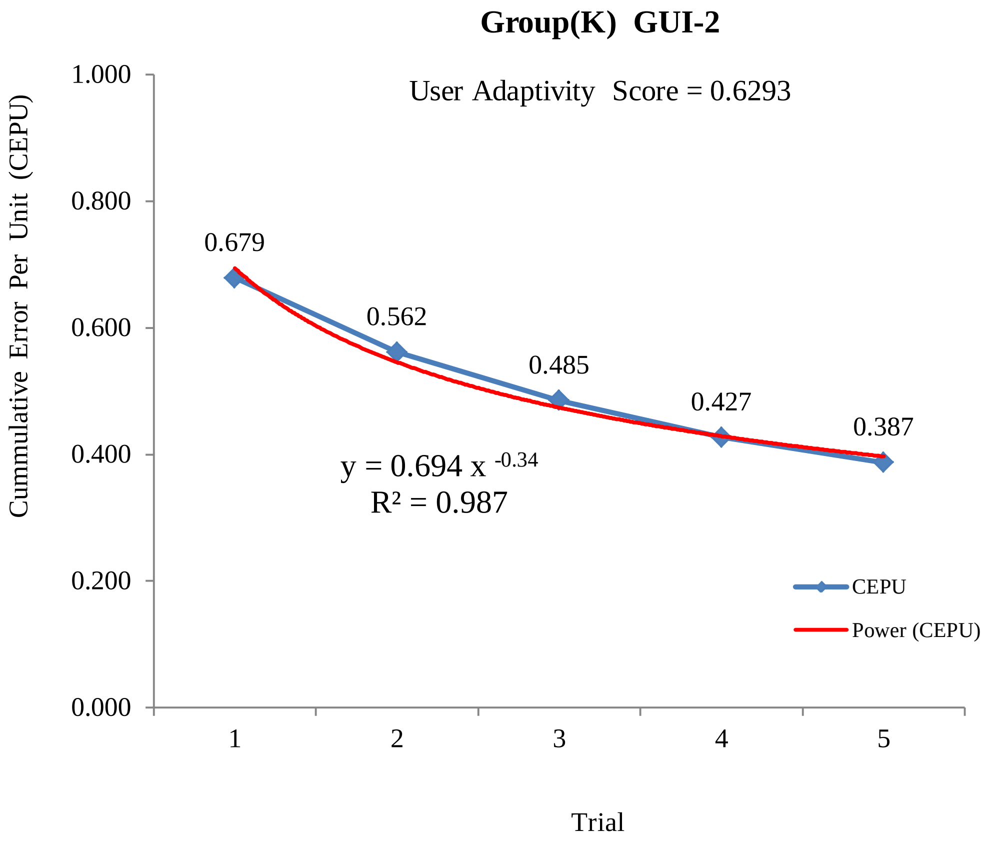


Figure 5.27 Experience curve of participant #P6 on GUI-2 (High Adaptivity)

The graphs in figures 5.25-5.27 of GUI-2 show a similar trend of increasing R^2 and learning rate with user adaptivity scores. We observed greater initial difficulty and higher learning rates for GUI-2 as compared to GUI-1 in all three sample groups K, C and A.

Therefore, though non-hierarchical split menu design has initial difficulty of learning compared to hierarchical horizontal menu design, however users gain expertise of non-hierarchical split menu design faster than hierarchical horizontal menu design. So depending on the learning period available a choice can be made between these designs.

Correlations

To strengthen the relationship between adaptivity scores and power fitting curve, we performed correlation analysis of adaptivity scores with power equation parameters (Y intercept, slope and R^2). User adaptivity scores of GUI-1 were strongly correlated with slope [r(287)=-.602, p<.001] and R^2 [r(287)=.341, p<.001]. Similarly, user adaptivity scores of GUI-2 were strongly correlated with slope [r(287)=-.619, p<.001] and R^2 [r(287)=.243, p<.001].

We can conclude that the power law of practice can be used to model user adaptivity measure. Also a strong relationship exists between slope of experience curve and adaptivity score. Therefore, user adaptivity score proves to be an integrated measure, reflecting adaptation capability or experience level.

5.6. Tracing User's Adaptation Path

To be able to understand adaptation process to a finer degree, we need to know how the user progresses on various dimensions of performance in the adaptation period. This will help in evaluating the underlined user interfaces in those perspectives. In the current study we measured adaptivity performance on two dimensions i.e. effort and time. We plotted time performance index P_t verses effort performance index P_c to trace the user's path from novice to expert on these dimensions.

Figures 5.28-5.33 show adaptation paths of groups K, C and A for both GUIs. For example the figure 5.28 shows time performance index value on X axis and corresponding effort performance index values on Y axis. The area of this graph which is on the bottom-left can be considered as novice region while the area on the top-right can be considered as expert region. Same is repeated for figures 5.29-5.33.

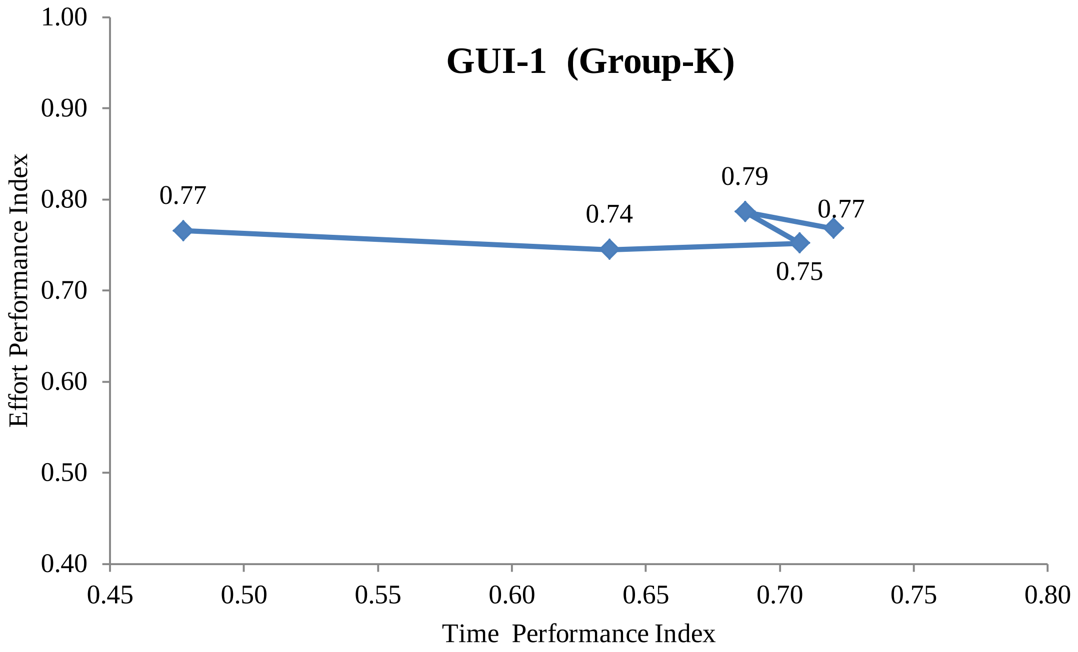


Figure 5.28 Adaptation path of group (K) participants on GUI-1

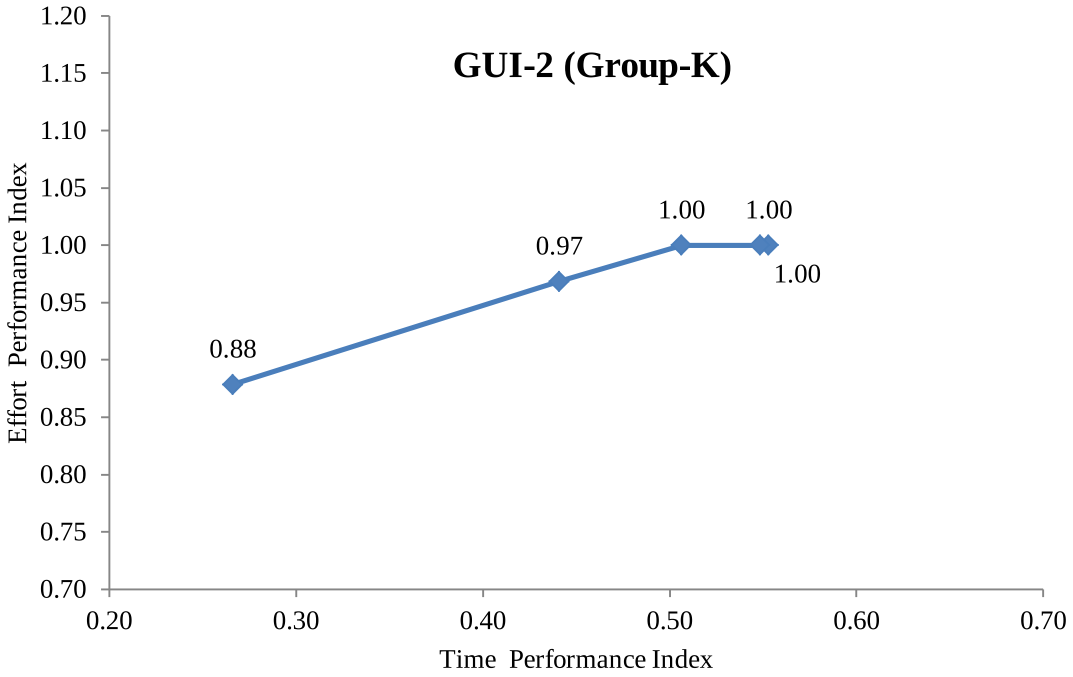


Figure 5.29 Adaptation path of group (K) participants on GUI-2

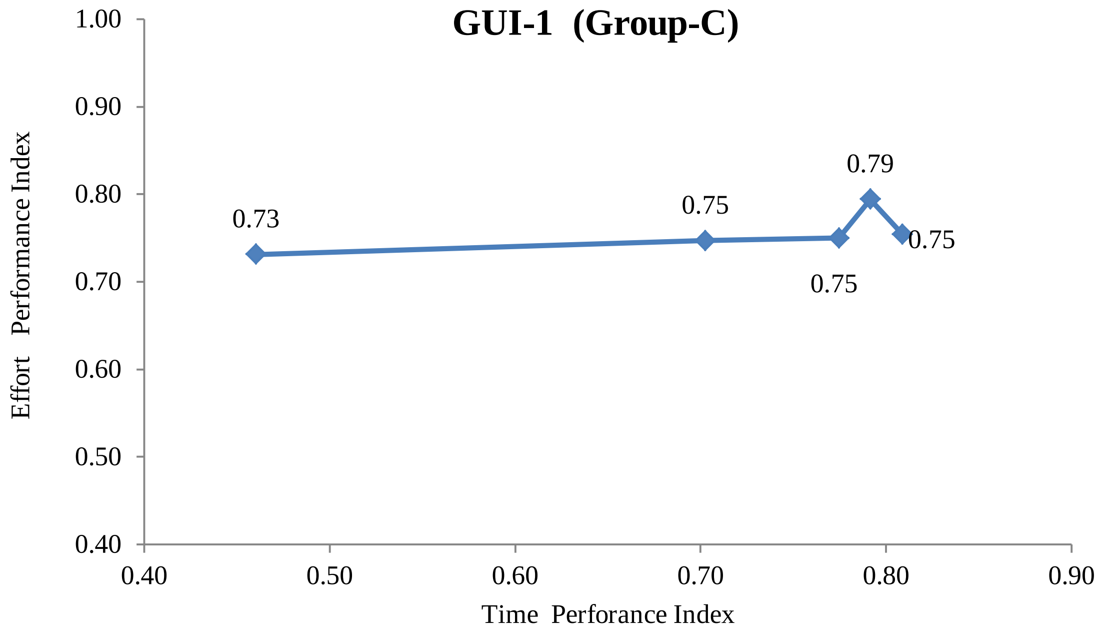


Figure 5.30 Adaptation path of group (C) participants on GUI-1

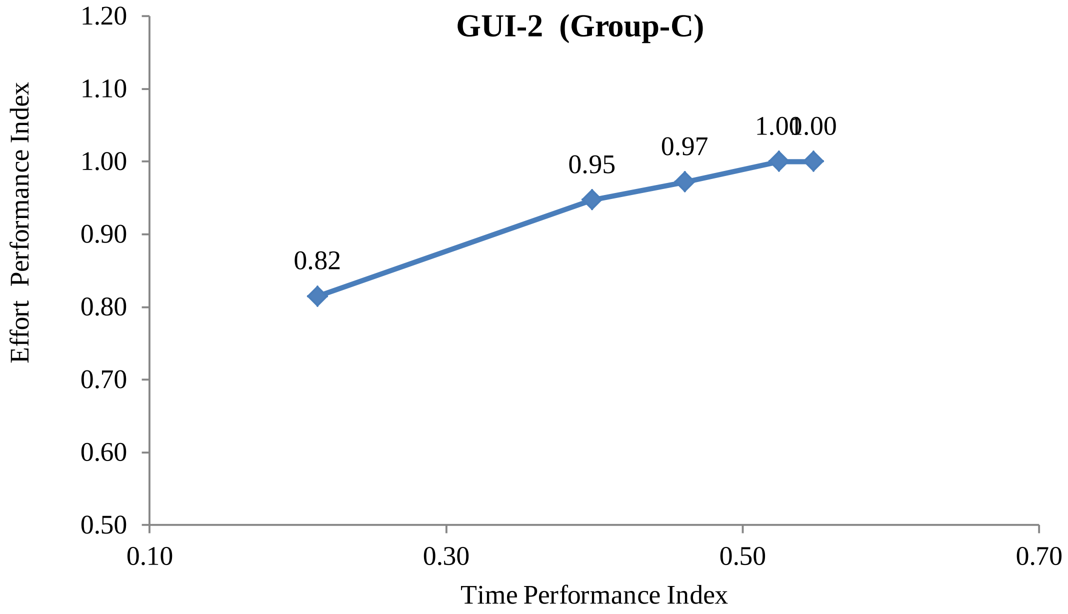


Figure 5.31 Adaptation path of group (C) participants on GUI-2

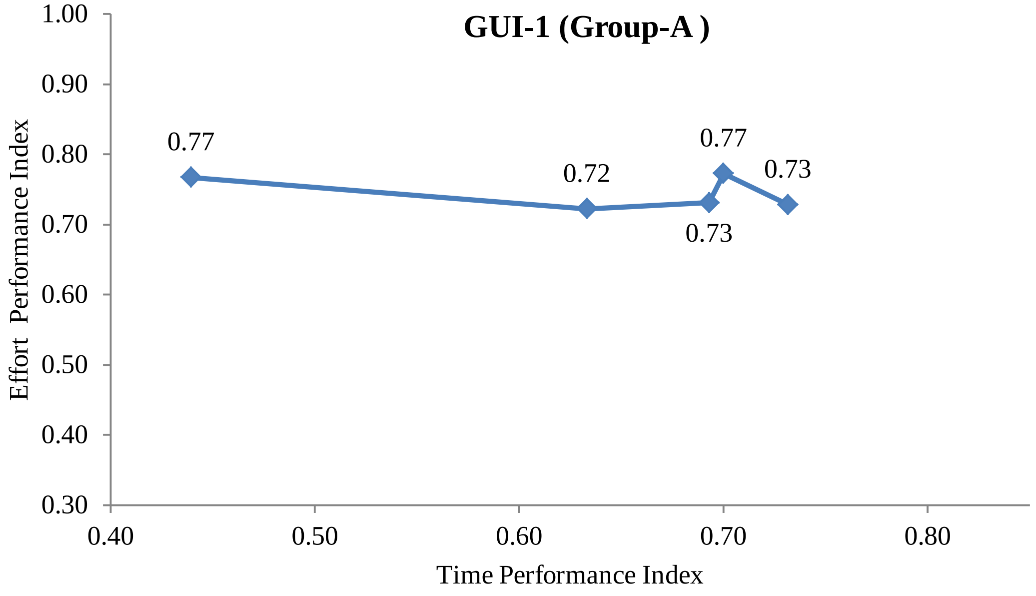


Figure 5.32 Adaptation path of group (A) participants on GUI-1

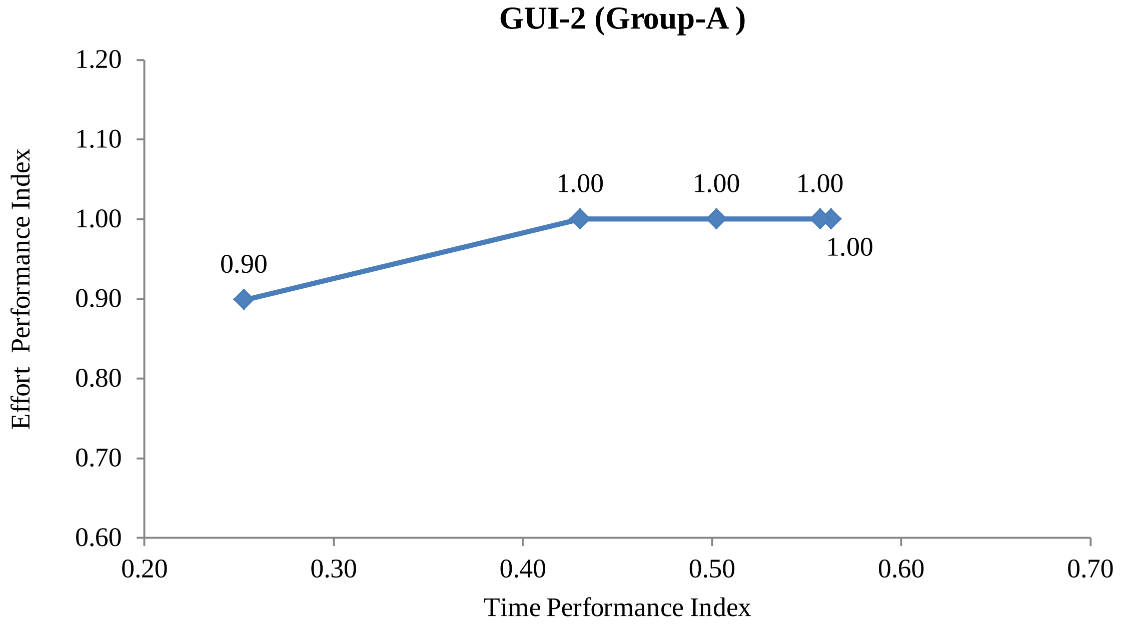


Figure 5.33 Adaptation path of group (A) participants on GUI-2

We observe that GUI-1 users show equal degrees of adaptation along both the axis. However, GUI-2 users show unequal degrees of adaptations along the same axis. We also observe that GUI-2 users reach accuracy level (P_c) of expert user but take more time. This reflects the complexity of the interface in terms of density of interactive elements, which increases reaction time. Also the adaptation path reflects a cautious behavior (slow in time) during adaptation. Therefore, by tracing the adaptation paths, we can determine to what degree the user has adapted in these two dimensions.

5.7. Conclusions

The proposed user adaptivity measure and the measuring tool proved to be very useful in computing and analyzing adaptivity in two dimensions namely time and effort. Based on the analysis, we conclude that expertise in effort can be achieved easily in the non-hierarchical split menu interface as compared to the hierarchical horizontal menu. Performance improvements shown on hierarchical horizontal menu are inconsistent as compared to non-hierarchical split menu. As far as overall adaptivity is concerned, both the navigation styles are equal.

Based on accumulation of positive (learning) and negative (forgetting) benefits for adaptivity test, we may infer that in complex interfaces, learning is difficult and forgetting is easy while in simpler interfaces, learning is easy and forgetting is difficult. Adaptivity to simple interfaces can be mediated by the type of learning task that is practiced. On the other hand, for complex interfaces, the learning task type does not influence adaptivity. Comprehension and application oriented learning creates opportunities to learn and gain expertise of interfaces as compared to knowledge oriented learning.

Based on the validity of the proposed adaptivity measure, we conclude that the user adaptivity score proves to be an integrated measure, reflecting adaptation capability and expertise level. Also, the adaptivity tool can analyze various dynamism of individual adaptivity in multiple dimensions.

Summary: *In this chapter we presented the data analysis of the user's adaptivity. User's adaptivity was analyzed on two dimensions. Time adaptation and effort adaptation. Two learning interface designs were compared on the basis of user's adaptivity scores and equations of learning curves. The hypotheses were tested and conclusions derived from the results. The next chapter will provide explanations of results obtained from the data analysis in chapter 4 and 5. Inferences based on design principles will be discussed and design guidelines will be suggested. At the end, the scope of future work will be presented.*

Chapter 6

Discussions and Conclusions

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Discussions and Conclusions

6.1. Introduction

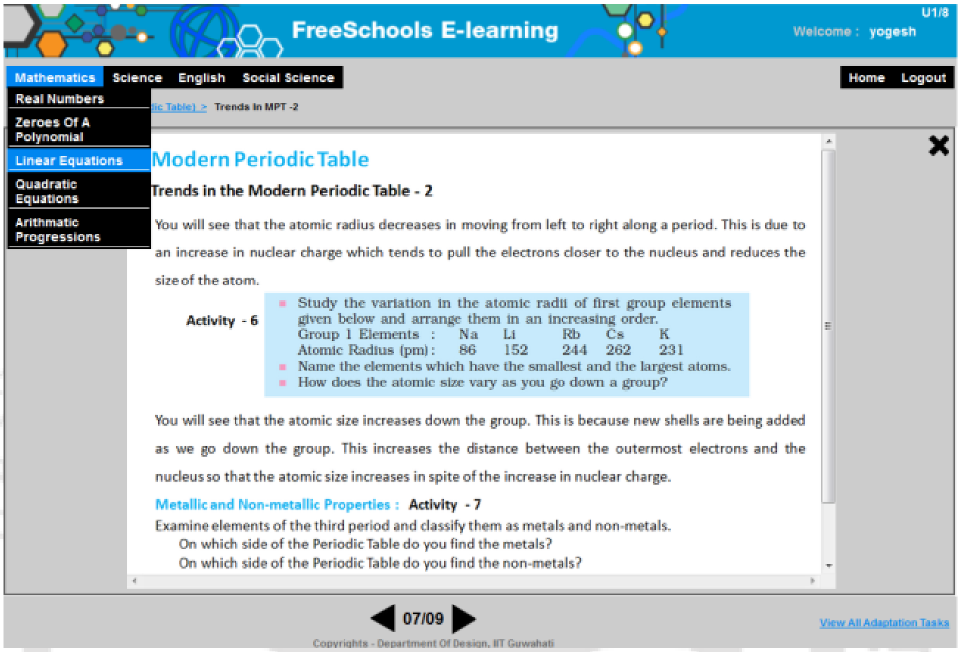
In this research, we investigated effects of changing the user interface designs and task complexities in e-learning, on the degrees of learners' adaptations. Adaptations in internal factors like PEOU, PU and PTLD and external factors like navigational behavior, learning efficiency, task-adaptations and adaptivity were studied. We proposed two measures, namely, *task adaptation score (TAS)* and *user adaptivity score (UAS)* to compare the user interface designs, which are under study. We set-up an experiment to measure adaptation and adaptivity scores of participants under situations of two types of learning interfaces and three types of learning tasks.

Six working hypotheses were formulated for testing, using empirical results. It was found that, learning task complexity had significant effect on user's adaptations in navigational behavior, learning efficiency and task adaptations (*hypothesis H1*). However, learning task complexity did not affect PEOU, PU and PTLD. Empirical results obtained showed that in hierarchical horizontal menu (GUI-1) the user' adaptivity is influenced by the learning task complexity (*hypothesis H2*), which was not found in hierarchical spilt menu interface. The two navigation designs showed a significant effect on the user' adaptations in belief, navigational behavior and learning efficiency (*hypothesis H3*). However, learners did not show change in learning outcome and task adaptations across the two GUIs. The effect of navigation designs on user's adaptivity was found to be mediated by the learning task complexity. Navigation designs had significant effect on user adaptivity during comprehension and application oriented learning (*hypothesis H4*). During knowledge oriented learning, no significant difference was found in user adaptivity between the two GUIs. It was also found that in comprehension based learning, learners' e-learning self efficacy effects their adaptivity score (*hypothesis H5*) while the adaptivity score influences the learning outcome (*hypothesis H6*).

6.2. Discussions

6.2.1. *Effect of Navigation Design*

The navigation designs of the two GUIs under study are once again shown in figure 7.1



Modern Periodic Table

Trends in the Modern Periodic Table - 2

You will see that the atomic radius decreases in moving from left to right along a period. This is due to an increase in nuclear charge which tends to pull the electrons closer to the nucleus and reduces the size of the atom.

Activity - 6

- Study the variation in the atomic radii of first group elements given below and arrange them in an increasing order.

Group 1 Elements :	Na	Li	Rb	Cs	K
Atomic Radius (pm) :	86	152	244	262	231

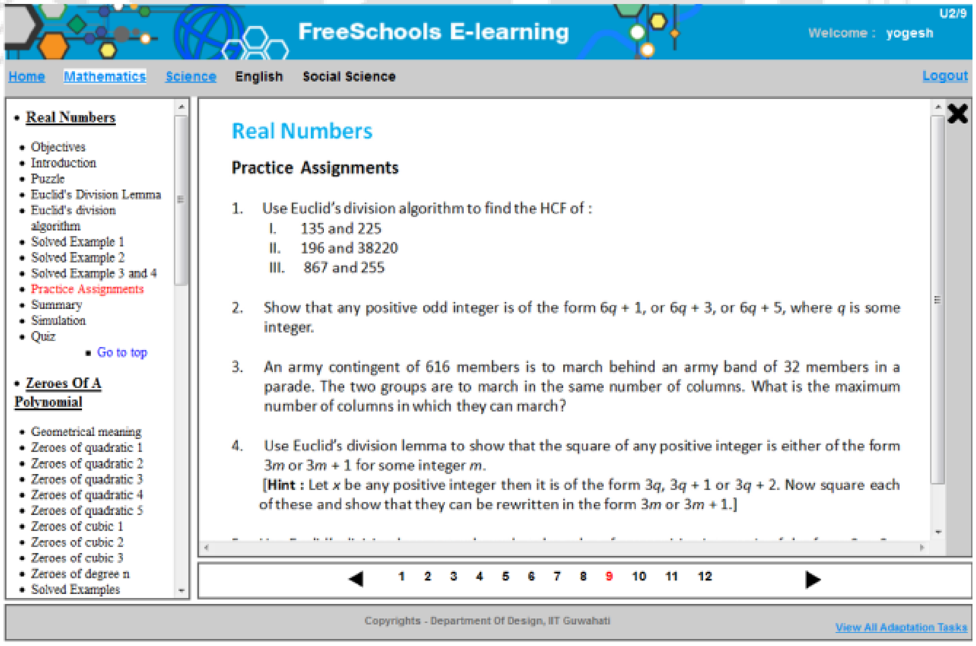
- Name the elements which have the smallest and the largest atoms.
- How does the atomic size vary as you go down a group?

You will see that the atomic size increases down the group. This is because new shells are being added as we go down the group. This increases the distance between the outermost electrons and the nucleus so that the atomic size increases in spite of the increase in nuclear charge.

Metallic and Non-metallic Properties : **Activity - 7**

Examine elements of the third period and classify them as metals and non-metals.
On which side of the Periodic Table do you find the metals?
On which side of the Periodic Table do you find the non-metals?

Figure 6.1 GUI-1



Real Numbers

Practice Assignments

1. Use Euclid's division algorithm to find the HCF of :
   I. 135 and 225
   II. 196 and 38220
   III. 867 and 255
2. Show that any positive odd integer is of the form $6q + 1$, or $6q + 3$, or $6q + 5$, where q is some integer.
3. An army contingent of 616 members is to march behind an army band of 32 members in a parade. The two groups are to march in the same number of columns. What is the maximum number of columns in which they can march?
4. Use Euclid's division lemma to show that the square of any positive integer is either of the form $3m$ or $3m + 1$ for some integer m.
   [**Hint** : Let x be any positive integer then it is of the form $3q$, $3q + 1$ or $3q + 2$. Now square each of these and show that they can be rewritten in the form $3m$ or $3m + 1$.]

Figure 6.2 GUI-2

Overall, GUI-2 showed higher perceived ease-of-use and perceived usefulness as compared to GUI-1. Higher perceived ease-of-use in GUI-2 was due to the non-hierarchical links causing less time and error in identifying learning contents. Representation of entire concept map of the course in the form of split menu enhanced the perceived usefulness of GUI-2. Participants experienced higher perceived task load (PTLD) of learning on GUI-1 as compared to GUI-2 in knowledge oriented learning. The intrinsic cognitive load of comprehension and application oriented learning being higher; it overrode the GUI design effect on the learner's PTLD. This was evident from the insignificant differences in PTLD across GUIs during comprehension and knowledge oriented learning. *Thus, non-hierarchical split menu design can benefit more in reducing perceived task load if knowledge based learning is under taken.*

Large adaptation in page commands, were observed across GUIs. GUI-1 required more navigation effort compared to GUI-2. The hyperlinked and labeled topic and sub-topic menus of GUI-2 reduced irrelevant page accesses (page commands) to a large extent. GUI-1 had sequential access of pages, going through many irrelevant pages before arriving at the relevant content page. Thus from the learners' content processing efficiency (pages visited) aspect GUI-2 was better than GUI-1. *In short, the two navigation designs, which were under study, induced significant adaptations in user's learning behavior.*

No effect was found of navigation designs of GUI-1 and GUI-2 on test scores of learners in all three sample groups. This is an important observation for inferring that the navigation designs introduced do not affect the performance. Learners adapt to interfaces while learning. Significant adaptations in learning focus were observed in all sample groups. These adaptations were highest in magnitude amongst all other adaptations. Learning focus of GUI-1 was significantly higher than that of GUI-2. GUI-1 shows deep processing at page level as compared to GUI-2, which shows higher surface processing. This is due to the reduction in page demand and random page accesses in GUI-2. Since GUI-1 requires more effort, consequently the interaction efficiency of GUI-2 was therefore significantly higher than GUI-1. However, there was no significant difference in interaction efficiency between GUIs in application oriented learning groups. *Therefore, higher the page demands greater will be the impact of interaction efficiency.*

Significant adaptations were found in click efficiency (CE) in all the sample groups. Click efficiency of GUI-2 was significantly higher than that of GUI-1. *So use of non-hierarchical split menu interface enhances operational performance efficiency*. Overall, it may lead to saving of time during goal oriented learning because less physical effort means less time. Similarly, significant adaptations were found in page efficiency (PE) for all sample groups with PE of GUI-2 being significantly higher than that of GUI-1. *This suggests that split menu not only reduces operations but also increases effectiveness of the pages read in form of high test scores.*

6.2.2. Effect of Learning Task Complexity

The difference between perceptions of GUI-1 and GUI-2 remained same across learning task complexity. There was no evidence of the effect of learning task complexity (K, C, A) on differences in perceptions across interfaces. *This shows that beliefs or perceptions about a specific user interface remain persistent and are influenced by its design and not by the complexity of learning objectives.*

For hierarchical horizontal menu (GUI-1) as well as non-hierarchical split menu (GUI-2) the page commands were significantly higher for knowledge oriented learning compared to others. Overall page command usage in decreasing order was for knowledge, comprehension and application. The knowledge oriented learning goal was to find answers to the unknown facts which required more page processing. While comprehension and application oriented learning demanded more of mental processing than page processing. The adaptations in page commands between GUIs also showed variations across task complexity. Between GUIs, adaptations in page commands were significantly lower for knowledge group compared to comprehension and application groups. This is because in addition to lower demand for page accesses in comprehension and application oriented learning, and also the inherent property of GUI-2 requiring less commands . So the difference in page commands is seen more for comprehension and application oriented learning.

Also the topic commands for hierarchical horizontal menu (GUI-1) were marginally higher for knowledge oriented learning as compared to others. Since in GUI-2 the navigation is random and focused at lower granularity of page level, there were no significant adaptations found across task complexity. Between GUIs adaptations in topic commands were similar across task complexities because the cognitive load did not affect topic level processing.

Page visits were significantly lower for application oriented learning for both GUIs because they focused on applying knowledge rather than searching knowledge. Page demands vary as per the cognitive load of task and not the navigation design. However, better navigation design can improve proportionately, the actual pages visited. Hence, between GUIs, adaptations in page visits will not be affected across task complexities.

Finally total operations done on GUI-1 and GUI-2 are significantly lower for application oriented learning as compared to other groups. So both the GUI's are equally sensitive to the shift from physical to mental load of learning tasks. Between GUIs, adaptations in total operations were significantly lower for knowledge group because of higher page demands and processing in knowledge oriented learning.

Learning performance (LO) is significantly higher for knowledge group as compared to others, for both the GUIs. This directly relates to the complexity in terms of higher learning skills required for comprehension and applications oriented learning. Since, in application oriented learning, the learning task complexity directly influences cognitive load, which is person specific. Therefore there is greater difference in performances across GUIs during application oriented learning.

Learning focus was significantly lower for knowledge group and comprehension group as compared to application group for both the GUIs. In other words knowledge and comprehension inherently requires surface processing. *Since GUI-2 supports efficient surface processing it should be preferred more during knowledge or comprehension oriented learning*. Between GUI adaptation in LF (AS_LF) was significantly higher for comprehension and application group which suggests that navigation designs influence deep processing much greater during comprehension and application based learning.

No significant effect of task complexity was observed on interaction efficiencies in both GUIs. It means that, the differences in the interaction efficiencies are attributed to interface design only, because of which, between GUIs adaptations in IE (AS_IE) also do not show significant change across different task complexities.

Task complexity did not affect operational performance efficiency (CF_C) and page performance efficiency (CF_P) in GUI-1. However in GUI-2 CF_C and CF_P were significantly lower for knowledge and comprehension group as compared to application groups. This also indirectly proves that knowledge and comprehension groups require more operations and page references as compared to application oriented learning. *So for knowledge and comprehension we may have summary pages with more than one display on one screen. While for application oriented learning a full page display with a multilevel menu is beneficial.* Application oriented learning requires higher deep processing which is in addition supported by GUI-2 features, hence, between GUI adaptations in CF_C (AS_CF_C) and CF_P (AS_CF_P) were observed higher for application oriented learning.

6.2.3. Role of Task Adaptations

No significant difference was found in task adaptation scores of chapters visited (AS_TCv), pages visited (AS_TPv) and total operations (AS_Top) between GUI-1 and GUI-2 for all three sample groups. It suggests that even though learning navigation patterns were significantly different on GUI-1 and GUI-2, the adaptations in content processing (chapters or pages) being task dependant showed no effect of interface design and therefore were similar across GUIs.

The task adaptation scores in application oriented learning were found significantly higher than the scores of knowledge and comprehension oriented learning for chapters and pages on both GUIs. This is an interesting observation showing the fact that between the task cognitive load, the variation is more for application oriented learning. During application oriented learning the test questions generated higher differences in cognitive load as compared to the knowledge or comprehension oriented learning questions. Variations in cognitive demand being more it results in larger task adaptations. *To summarize, the task adaptations reflect the cognitive load of task and are not influenced by the specific navigation designs that were studied.*

6.2.4. User Adaptivity and Interface Design

It was observed that navigation designs of interfaces induced significant differences in user adaptivity. User adaptivity on GUI-1 was significantly higher than GUI-2 for comprehension oriented learning. The user adaptivity on GUI-2 was significantly higher than GUI-1 for application oriented learning. These differences are because comprehension oriented learning requires more of surface processing and therefore the learners maximize this benefit by familiarizing efficiently to the simplistic design of GUI-1. The GUI-2 features and interactivity is not required for comprehension based learning and hence interface learning doesn’t happen. Visa versa in application oriented learning deep processing and feature rich GUI enhances learners motivation and efficiency while a simplistic design like GUI-1 hinders learning efficiency. So learners adapt more effectively to GUI-2 during application oriented learning.

Adaptivity to GUI-1 is significantly higher during comprehension oriented learning. No such significant variation is observed in adaptivity in GUI-2 across task- complexity.

In summary, during knowledge oriented learning both GUIs are good from adaptivity perspective. GUI-1 benefited adaptivity during comprehension oriented learning because adaptivity was significantly higher than knowledge group and application group, while GUI-2 benefited adaptivity during application oriented learning.

Based on the previous discussion, we recommend the following navigation design guidelines for e-learning interfaces.

6.2.5. Guidelines for E-learning Navigation Design

1. Use adaptable navigation, based on intrinsic cognitive load of learning.
2. Use hyperlinked navigation when surface processing, explorations and comparisons among the results are required like in knowledge or comprehension based learning.
3. Use sequential navigation when deeper understanding of concepts within same topics is required like in the case of application oriented learning.

4. Interaction efficiency of navigation designs will matter in situations of higher page demands of learning tasks like knowledge oriented learning. If routine tasks of learners involve heavy analysis or application of concepts then interaction efficiency will not matter.
5. Use multiple levels in navigation design to enhance surface processing efficiency which is required in knowledge and comprehension based learning
6. Use multiple views of learning contents to enhance deep processing efficiency to build germane load in application oriented learning.
7. Increase adaptivity in learning interfaces stepwise based on user' adaptivity levels.

6.3. Summary of Contributions

In this thesis, we proposed an adaptation measure *task adaptation score (TAS)* which can be used to compare interface designs and cognitive load of learning tasks. In part A of the experiment on user adaptations, we used this measure to compute adaptation scores of change caused by navigation designs of learning interfaces. Another measure, *user adaptivity score (UAS)* was proposed, to measure user's ability to gain expertise of an interface through practice. In part B of the experiment on user adaptivity, two dimensions of user adaptivity, namely, time performance index (P_t) and effort performance index (P_c), were integrated. We designed 18 learning tests based on three cognitive levels of learning objectives. A separate adaptivity testing tool was developed for measuring adaptivity. We collected data of 287 participants from 1435 response sheets. The interaction data on adaptivity was obtained for 6 learning tests and 10 trials. Based on the results obtained from the analysis of the data collected, recommendations were made in the form of guidelines for navigation design of e-learning user interfaces.

6.4. Limitations of the Research and Scope of Future Work

This thesis contributes by utilizing two new measures in studying learners' internal and external factors of adaptations in an e-learning set-up. Since the experiments were done in a controlled environment; internal validity was fairly good. The reliability of scales and the computations used was also high. However there are several avenues for future research and improvement of the methodology.

Participants

The sample group of this research was undergraduate engineering students in their early twenties. Study of adaptivity of learners of different age groups can be useful in further validating the results from the current research for more representative population.

Performance Function

The performance function developed for user's adaptivity can be further improved to include factors like errors made, features used, method used that will enrich the quality of the measure.

Expert's Performance based on KLM

The expert's performance based on key-stroke level model (KLM) on various factors may show influence of age and culture. This may affect computations of performance index in adaptivity tool. A further study of identifying age and culture specific benchmarks for expert performances is required.

Task complexity levels

Effect of additional levels of task complexities from diverse domain can be studied to investigate and model domain specific adaptation behavior.

Other Interaction Patterns

The interface designs that were studied differed only in topic and page navigation styles. A study of GUIs having more number of pedagogic features with different interaction patterns can be carried out. Adaptation scores of other tasks like search and help could be considered for future work.

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Appendices

Appendix – A1

User Adaptability To E-Learning Interfaces (UAELI)
Usability Lab , Department Of Design, Indian Institute Of Technology , Guwahati

Pre-Experiment Questionnaire Q1

Note: This questionnaire survey is solely for the purpose of research work. The research team assures you that the information provided by you will be kept confidential and used only for this research. Your participation will be a great contribution to our research and will be greatly acknowledged. Please feel free to fill in the following form.

E-LEARNING is learning/teaching (individually/collaboratively) through electronically delivered contents (computer/ internet).

PART (A) → Learner's Demography (DM) - (Please circle the correct choice)

LGUN	**Login User Name**	
DM01	Name of participant	
DM02	Institution / School	
DM03	City [State]	
DM04	Sex	• [M] Male • [F] Female
DM05	Age (in years and months)	
DM06	Education undergoing	• School • UG • PG • PhD Branch -
DM07	Education (year)	Class - • 8th • 9th • 10th **OR** Year - • 1st • 2nd • 3rd • 4th • 5th
DM08	Computer experience	• 0-2 years • 4-6 years • > 8 years • 2-4 years • 6-8 years
DM09	Do you have a personal computer with internet connectivity?	• Yes • No
DM10	How many hours (h) do you use computer during a week?	• < 1 h • 5-10h • 15-20h • >25 h • 1-5h • 10-15h • 20-25h
DM11	How many hours (h) do you use internet during a week?	• < 1 h • 5-10h • 15-20h • >25 h • 1-5h • 10-15h • 20-25h
DM12	Your ability and confidence in using computers	• poor • intermediate • experienced • advanced
DM13	Your ability and confidence in using internet.	• poor • intermediate • experienced • advanced
DM14	Your ability and confidence in e-learning	• poor • intermediate • experienced • advanced
DM15	Have you undertaken online courses or undergone computer based training? (CBT) program?	Yes / No
DM16	Rate your knowledge of mathematics	Poor ← 1 2 3 4 5 6 7 → Excellent
DM17	Rate your knowledge of chemistry	Poor ← 1 2 3 4 5 6 7 → Excellent
DM18	Rate your knowledge of HCI	Poor ← 1 2 3 4 5 6 7 → Excellent
DM19	Rate your knowledge of Design	Poor ← 1 2 3 4 5 6 7 → Excellent
DM20	Rate your knowledge of Computer/Internet	Poor ← 1 2 3 4 5 6 7 → Excellent
DM21	**Your mobile number**	
DM22	**Your e-mail addresses**	

Appendix – A1

PART (B) → E-Learning Self Efficacy (ELSE) - (Please circle the correct choice)

No	Statement	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
ELSE1	I understand terms/words relating to Internet	1	2	3	4	5
ELSE2	I have the necessary skills for using e-learning software	1	2	3	4	5
ELSE3	I can turn to an online discussion group when help is needed	1	2	3	4	5
ELSE4	I can use the Internet to gather data	1	2	3	4	5
ELSE5	I can troubleshoot Internet problems	1	2	3	4	5
ELSE6	I can usually deal with most difficulties that I encounter when learning online	1	2	3	4	5
ELSE7	I find working with computers easy	1	2	3	4	5
ELSE8	I have difficulties with most of the software applications I have tried to use*	1	2	3	4	5
ELSE9	Computers frighten me*	1	2	3	4	5
ELSE10	I enjoy working with computers	1	2	3	4	5
ELSE11	Computers make me much more productive	1	2	3	4	5
ELSE12	I am confident in my abilities to make use of computers in learning	1	2	3	4	5
ELSE13	I find it difficult to get computers to do what I want them to*	1	2	3	4	5
ELSE14	I find working with computers confusing*	1	2	3	4	5
ELSE15	I would rather that we did not have to learn how to use computers*	1	2	3	4	5
ELSE16	I usually find it easy to learn how to use a new software application	1	2	3	4	5
ELSE17	Using computers makes learning more interesting	1	2	3	4	5
ELSE18	I always seem to have problems when trying to use computers*	1	2	3	4	5
ELSE19	Some computer packages definitely make learning easier	1	2	3	4	5
ELSE20	Computer jargon baffles me*	1	2	3	4	5
ELSE21	Computers are good aids to learning	1	2	3	4	5
ELSE22	Computers help me to save a lot of time	1	2	3	4	5
ELSE23	I find working with computers very frustrating*	1	2	3	4	5
ELSE24	When using computers I worry that I might press the wrong button and damage it*	1	2	3	4	5

Appendix – A2

User Adaptivity To E-Learning Interfaces (UAELI)
Usability Lab , Department Of Design, Indian Institute Of Technology , Guwahati

Post-Experiment Questionnaire **Q2**

Note: This questionnaire survey is solely for the purpose of research work. The research team assures you that the information provided by you will be kept confidential and used only for this research. Your participation will be a great contribution to our research and will be greatly acknowledged. Please feel free to fill in the following form.

E-LEARNING is learning/teaching (individually/collaboratively) through electronically delivered contents (computer/ internet).

User Name	Group	Task Set (V1)	GUI (V2)

PART (A) → Perceived Ease-of-use (PEOU) and Usefulness (PU)

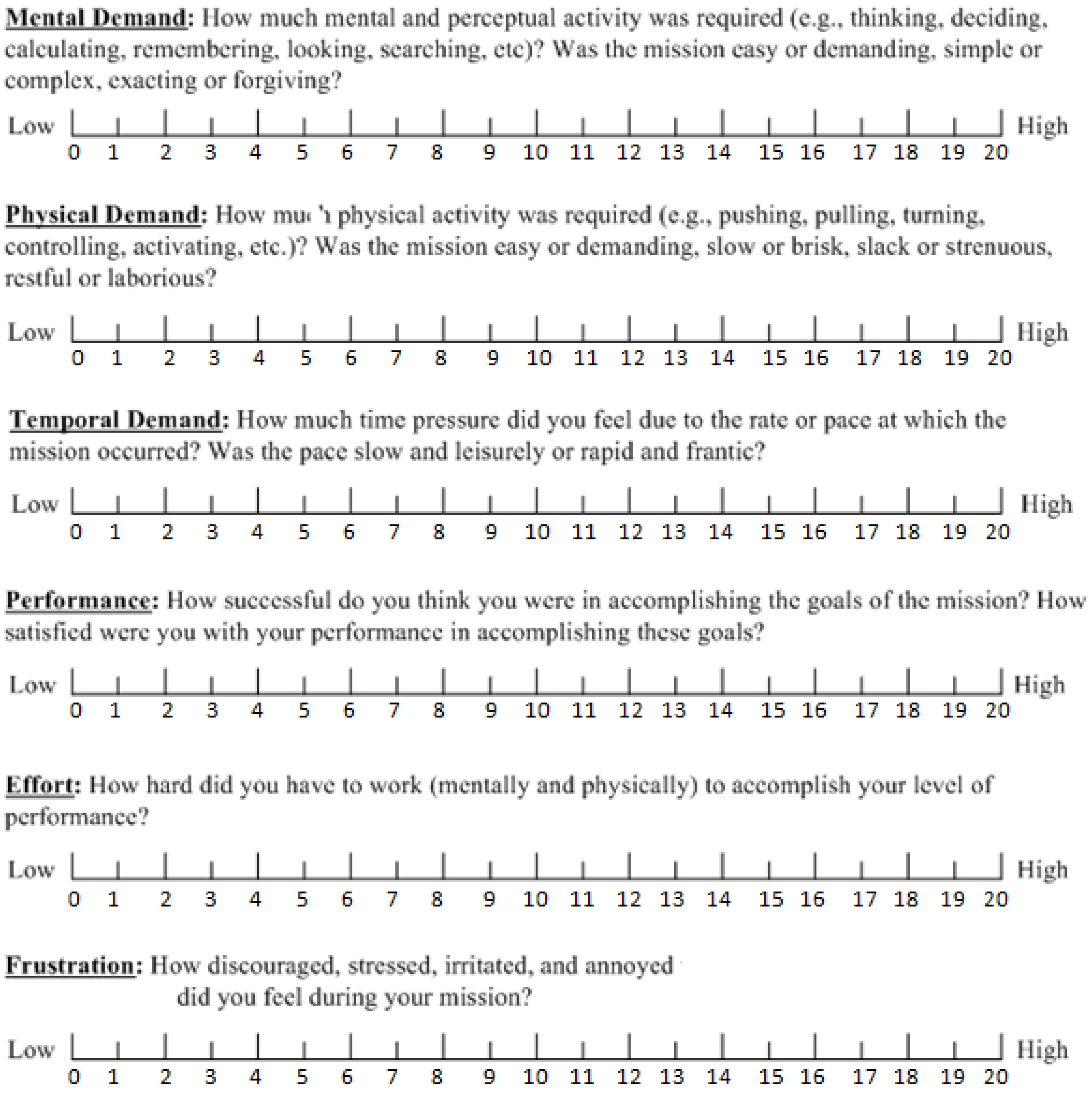
(Please circle the correct choice)

No	Statement	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
PEOU1	I find this learning interface easy to use for my studies	1	2	3	4	5	6	7
PEOU2	Learning to use this learning interface is easy for me	1	2	3	4	5	6	7
PEOU3	I find it ease with this learning interface to learn what I want to learn	1	2	3	4	5	6	7
PEOU4	This learning interface is simple and understandable to me to use for my studies	1	2	3	4	5	6	7
PEOU5	I find this learning interface very flexible in helping me for my studies	1	2	3	4	5	6	7
PEOU6	It is easy for me to become expert in using this learning interface	1	2	3	4	5	6	7
PU1	Using this learning interface will make me learn more quickly	1	2	3	4	5	6	7
PU2	Using this learning interface will make me learn more effectively (precisely)	1	2	3	4	5	6	7
PU3	Using this learning interface will improve my results	1	2	3	4	5	6	7
PU4	Using this learning interface I will learn more	1	2	3	4	5	6	7
PU5	Using this learning interface will make it easier for me to study	1	2	3	4	5	6	7
PU6	I find this learning interface very useful in studies	1	2	3	4	5	6	7

Appendix – A2

PART (B) → NASA-TLX Mental Workload Rating Scale

Please place an “X” along each scale at the point that best indicates your experience with **the learning interface**



Mental Demand: How much mental and perceptual activity was required (e.g., thinking, deciding, calculating, remembering, looking, searching, etc)? Was the mission easy or demanding, simple or complex, exacting or forgiving?

Low 0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 High

Physical Demand: How much physical activity was required (e.g., pushing, pulling, turning, controlling, activating, etc.)? Was the mission easy or demanding, slow or brisk, slack or strenuous, restful or laborious?

Low 0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 High

Temporal Demand: How much time pressure did you feel due to the rate or pace at which the mission occurred? Was the pace slow and leisurely or rapid and frantic?

Low 0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 High

Performance: How successful do you think you were in accomplishing the goals of the mission? How satisfied were you with your performance in accomplishing these goals?

Low 0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 High

Effort: How hard did you have to work (mentally and physically) to accomplish your level of performance?

Low 0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 High

Frustration: How discouraged, stressed, irritated, and annoyed did you feel during your mission?

Low 0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 High

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Compiled by: Yogesh Deshpande (PhD Scholar) Q2: Version 3.0 (Revision 0) Date: 18/12/2012

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Appendix – A3

Learning Test

Set-K1 **LT1**

1	Rational numbers are a) numbers without fraction like negative, zero and positive integers b) numbers that cannot be written as a simple fraction c) numbers that can be written as simple fraction or ratio
2	__________ takes place when magnesium ribbon is burnt a) Reaction b) Precipitation c) Oxidation d) Synthesis
3	The color of neutral litmus solution is a) pink b) yellow c) purple d) none of above
4	Which statement is correct a) Metallic oxides are acidic in nature b) Non-metallic oxides are basic in nature c) Non-Metallic oxides are acidic in nature
5	Metal with low melting points is a) mercury b) arsenic c) gallium d) sodium

Appendix – A3

Learning Test

Set-C1 LT1

1	The graph of y= mx+z is straight line which intersects x axis at a) -z/m,0 b) m/z,0 c) -m/z,0
2	Which of the following quadratic equations is in the standard form a) $2x^2 +1- 3x = 0$ b) $4x - 3x^2 + 2 = 0$ c) $2x^2 + x - 300 = 0$ d) $1 - x^2 + 300 = 0$
3	For a chemical equation to be balanced a) the total reactants on LHS should be equal to total products on RHS b) the total atomic number of LHS should be equal to RHS c) total mass on LHS should be equal to RHS d) all of the above
4	The element having 5 electrons in its valence shell will form a) single bond b) double bond c) triple bond d) quadruple bond
5	In which of the following situations, does the list of numbers involved does not make an arithmetic progression? a) Taxi fare at each km when fare is Rs. 15 for the first km and Rs. 8 for each additional km. b) The amount of money in the account every year, when Rs. 10000 is deposited at compound interest at 8% per annum. c) Cost of digging a well after every meter of digging, when it costs Rs. 150 for the first meter and rises by Rs. 50 for each subsequent meter.

Appendix – A3

Learning Test

Set-A1 LT1

1	HCF of 2832 and 240 a) 32 b) 48 c) 42
2	The balanced form of the chemical equation $Fe + H_2O \rightarrow Fe_3O_4 + H_2$ is a) $4Fe + 3H_2O \rightarrow Fe_3O_4 + 3H_2$ b) $3Fe + 4H_2O \rightarrow Fe_3O_4 + 4H_2$ c) $3Fe + 4H_2O \rightarrow 4Fe_3O_4 + 3H_2$
3	An army contingent of 616 members is to march behind an army band of 32 members in a parade. The two groups are to march in the same number of columns. What is the maximum number of columns in which they can march? a) 8 b) 10 c) 12
4	Balanced chemical equation of reaction Barium chloride + Aluminium sulphate → Barium sulphate +Aluminium chloride is a) $3Al_2(SO_4)_3 + 2BaCl_2 \longrightarrow 3AlCl_3 + 2BaSO_4$ b) $Al_2(SO_4)_3 + 3BaCl_2 \longrightarrow 2AlCl_3 + 3BaSO_4$ c) $3Al(SO_4)_3 + 3BaCl_2 \longrightarrow 3AlCl_6 + 3BaSO_4$
5	You have to pack 1300 oranges and 450 mangoes into boxes with same number in each box to be sent by post. The postal service charges Rs. 50 per box as delivery charge. The maximum number of fruits that can be packed in each box so as to keep the postal charge at minimum is a) 50 b) 90 c) 45

List of Publications

1. Deshpande, Y., Yammiyavar, P. & Bhattacharya, S. (2012 December). ‘Adaptation’ in Children - A GUI Interaction Based Task-Performance Study. In *HWID 2012 working conference on “Work Analysis and HCI”, CBS, Denmark.* **Will be published in Springer Book (Under print)**
2. Deshpande, Y., Bhattacharya, S., & Yammiyavar, P. (2012, December). A behavioral approach to modeling Indian children's ability of adopting to e-learning environment. In *Intelligent Human Computer Interaction (IHCI), 2012 4th International Conference on* (pp. 1-7). IEEE.
3. Deshpande, Y., Yammiyavar, P. & Bhattacharya, S. **(Submitted).** Modeling Beliefs in Indian Children During E-Learning Adoption. To *Journal of Information Technology and Application in Education (JITAE)*
4. Deshpande, Y., Bhattacharya, S., & Yammiyavar, P. **(Accepted).** A Study of the Impact of Task Complexity and Interface Design on E-Learning Task Adaptations. In *11th Asia Pacific Conference on Computer Human Interaction (APCHI 2013).*

Additional Publications

1. Yammiyavar, P., & Deshpande, Y. (2012, January). Usability evaluation of a virtual lab by adapting structured & unstructured techniques. In *Technology Enhanced Education (ICTEE), 2012 IEEE International Conference on* (pp. 1-10). IEEE.
2. Yammiyavar, P., & Deshpande, Y. (2012, March). Familiarity and Task Performance Relationship In the case of Children Interacting with Computers. Presented in *Symposium on Human Computer Interaction Design In Virtual Environments, DoD , IITG, India*
3. Debayan, D., Yammiyavar, P., & Deshpande, Y. (2012). Measuring Success of E-Learning Applications: A Review. In *International Conference on Electrical Engineering and Computer Science, ICEECS 2012.*

Curriculum Vitae

Yogesh Deshpande

born on October 28th , 1965, in Mumbai, India

Education

1976-1984	Preparatory Schooling in Pune, India
1984-1988	Bachelor Of Engineering, E&TC , University of Pune, India
19990-19992	Master Of Engineering, E & TC, University of Pune, India

Jobs

1992-1996	Business – Computer Training
1996-2000	Lecturer at PVG’s College Of Engineering
2000-2001	Corporate Training at SEED InfoTech Pvt. Ltd.
2001-2005	Assistant Professor, Sinhgad College Of Engineering
2005-2010	Assistant Professor, Vishwakarma Institute Of Information Technology
Since July 2010	Doctoral studies at Usability , Interaction & HCI design Lab, Department Of Design , Indian Institute Of Technology , Guwahati, India

Teaching Interests

Human Computer Interaction
Software Engineering
Object Oriented Design
Computer Organization
Software Testing

Research Interests

Human Computer Interaction
Usability Engineering
Interactive Learning Environments

Affiliations

Life Member, Indian Society For technical Education
Life Member, Computer Society Of India

Awards

National Merit Scholar Award , 1982
Rational Practitioner Award in OOAD/UML , 2000
BSI Certified Lead Auditor - ISO 9001:2000 , 2007
IT Department Best Teacher Award for year 2008-09