An Investigation into the Cognitive Effects of Instructional Interface Visualisations

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Abstract

An investigation is conducted into the cognitive effects of using different computer based instructions media in acquisition of specific novel human skills. With recent rapid advances in computing and multimedia instructional delivery, several contemporary research have focussed on the best practices for training and learning delivered via computer based multimedia simulations. More often than not, the aim has been cost minimisation through an optimisation of the instructional delivery process for efficient knowledge acquisition. The outcome of such research effort in general have been largely divergent and inconclusive.

The work reported in this thesis utilises a dual prong methodology to provide a novel perspective on the moderating effects of computer based instructional visualisations with a focus on the interaction of interface dynamism with target knowledge domains and trainee cognitive characteristics. The first part of the methodology involves a series of empirical experiments that incrementally measures/compares the cognitive benefits of different levels of instructional interface dynamism for efficient task representation and post-acquisition skilled performance. The first of these experiments utilised a mechanical disassembly task to investigate novel acquisition of procedural motor skills by comparing task comprehension and performance. The other experiments expanded the initial findings to other knowledge domains as well as controlled for potential confounding variables. The integral outcome of these experiments helped to define a novel framework for describing multimodal perception of different computer based instruction types and its moderating effect on post-learning task performance.

A parallel computational cognitive modelling effort provided the complementary methodology to investigate cognitive processing associated with different instructional interfaces at a lower level of detail than possible through empirical observations. Novel circumventions of some existing limitations of the selected ACT-R 6.0 cognitive modelling architecture were proposed to achieve the precision required. The ACT-R modifications afforded

the representation of human motor movements at an atomic level of detail and with a constant velocity profile as opposed to what is possible with the default manual module. Additional extensions to ACT-R 6.0 also allowed accurate representation of the noise inherent in the recall of spatial locations from declarative memory. The method used for this representation is potentially extendable for application to 3-D spatial representation in ACT-R. These novel propositions are piloted in a proof-of-concept effort followed by application to a more complete, naturally occurring task sequence. The modelling methodology is validated with established human data of skilled task performances.

The combination of empirical observations and detailed cognitive modelling afforded novel insights to the hitherto controversial findings on the cognitive benefits of different multimodal instructional presentations. The outcome has implications for training research and development involving computer based simulations.

Keywords: cognitive modelling, instructional design, interface dynamism, cognitive psychology, cognitive architectures, computer based training.

"I can do all things through Christ which strengtheneth me."
(Philipians 4:13, KJV)

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Chapter 1

Introduction

1.1 Overview

Salomon (1994) tells the story of a seeing person describing the colour red to a blind person as "warm and soft". The blind person replies "Oh, it is like velvet, isn't it? So why don't you call it velvet?" This story captures the essence of abstract representation of our natural environment and the attendant inadequacy of representation media in general. Symbolic systems are used extensively to represent aspects of the natural world such as written text, spoken languages, graphic images, videos and Braille letterings. However, no single symbolic system can be generalised adequately to represent all knowledge domains. More often than not, symbolic systems have narrow information foci and extending them beyond such primary confines of focus can lead to distorted communication and misapplication.

Recent and rapid advances in computing and information technologies have made multimedia symbolic representation systems easier to create and apply to training and instructional delivery. The advent of modern, powerful computing devices affords rapid development of rich instructional interfaces that leverage on multimedia components like videos, pictures, text and animations to describe the target knowledge or skill to be acquired in the training process. Such multimedia instructions can also be applied at minimal cost and with relative safety especially in training scenarios where immersion in actual operational environment is not feasible during training such as in fire-fighting or emergency response to nuclear disasters. Consequently, computer based instructional delivery have become quite attractive and almost ubiquitous to the extent that it is now an acceptable alternative standard to well established training methods in some fields such as Advanced Cardiac Life Support (ACLS) component of medical training (Platz, Liteplo, Hurwitz & Hwang, 2011). However, it is arguable that the advances in computing technologies that have made such symbolic representation systems possible have not been matched by commensurate advances in its adaptation to fit the psychological characteristics of the intended human trainees.

Substantive contemporary research efforts have focussed on the optimisation of knowledge acquisition via computer based multimedia instructional delivery with inconclusive findings. Of particular relevance to the work reported in this thesis is the aspect that investigates the cognitive effects and comparative benefits of different levels of dynamic visualisation components of computer based multimedia instructional delivery. Dynamism of instructional visualisations refers to the time-dependent changes of the visuo-spatial objects in the interface that can portray continuously varying concepts and processes in the target knowledge domain of training. Previous related research has compared the cognitive effects and knowledge transfer benefit of dynamic versus static visualisation content of instructional interfaces with largely inconclusive findings. A meta-analysis of some of these studies identified several variables that may moderate knowledge acquisition through such interface components including the target knowledge domain and the cognitive characteristics or *abilities* of the learner (Höffler & Leutner, 2007). The inconsistent and divergent findings of related research effort on the topic may therefore be due to insufficient separation and control for the individual effect of these moderating variables and the subsequent integration of their effects. There has also been little empirical work to further validate the moderating roles of these variables and how they could be integrated with the learner's cognitive characteristics to optimise knowledge acquisition and transferability through computer based multimedia instructions.

In view of this, a series of progressive and independent studies was conducted to investigate the cognitive benefits of dynamic versus static instructional visualisations and their effects on post-learning task performance. The focus is on the moderating effect specific to the target knowledge domain with particular reference to the acquisition of novel procedural skills while controlling for all other potentially confounding variables. Furthermore, a dual-prong methodology is utilised, which include novel paradigms for low-level investigation of the atomic cognitive processes involved in the skill acquisition process as opposed to the high-level approach of contemporary related studies. The methodology involves a series of empirical experiments conducted in parallel with cognitive computational modelling that leverages the power of well-established cognitive architectural frameworks. The computational modelling aspect also include substantial extension to the base cognitive architecture to overcome some of the problems hitherto associated with the modelling of complex human procedural skill acquisition and execution. The scope of the empirical and computational modelling work is described further in Section 1.5 of this chapter.

1.2 Research Objectives

The aims of the research reported in this thesis are as follows:

- To investigate the cognitive effects of different levels of dynamic visualisation components of computer based instructional interfaces in the acquisition of novel procedural knowledge.
- To identify the cognitive mechanisms that support the acquisition of novel procedural knowledge and their effects on post-learning task performance.
- To conduct empirical investigations with human participants for validating the cognitive roles of different instructional interface visualisations in the acquisition and transfer of skilled procedural knowledge.
- To develop cognitive architecture-based computational models of human procedural knowledge acquisition via computer based instructions, which fits with empirical data.

- To contribute to Human Computer Interaction knowledge of the cognitive effects and roles of different levels of dynamic visualisation components of instructions using an interdisciplinary methodology.

1.3 Research Design and Methodology

The research methodology is a parallel combination of empirical observations and cognitive computational modelling as depicted in Figure 1.1 below. The series of empirical experiments afforded incremental measurements of post-learning performance effects of using different levels of dynamic instructional visualisations in acquiring novel procedural skills/knowledge. The general design of these experiments is shown in Figure 1.2.

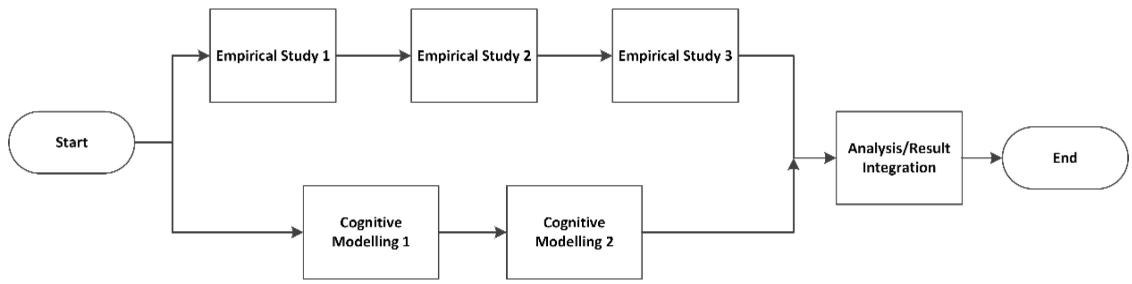


Figure 1.1 Overview of Research Methodology

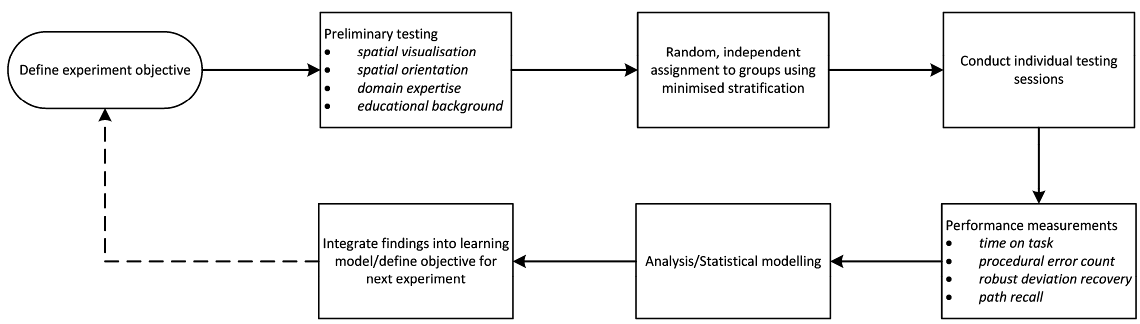


Figure 1.2 General Design of Experiments

Independent comparisons of instructional interfaces with different visualisations contents were made under controlled laboratory conditions. The cognitive effects of these learning formats were based on the analysis of post-learning performance metrics of task execution such as time on task, number of errors made and robust recovery from deviations to ideal task execution sequence. The first experiment focused on the acquisition of novel procedural motor skills by knowledge domain novices and used a mechanical disassembly task to compare task comprehension and performance while controlling for selected extraneous factors. The results provided some novel insight into the cognitive roles of different instructional visualisations but were not conclusive enough to generalise to a wider learning context, which includes skill acquisition in other related knowledge domain. Subsequently, a second experiment was conducted that focused on novel skill acquisition in the related but different knowledge domain of spatial navigation. The third experiment in the series returned the focus to the acquisition of novel procedural motor skills but controlled for domain expertise.

The net result of the series of empirical experiments was the definition of a hybrid cognitive model for multimodal acquisition of procedural knowledge in the context of computer based multimedia instructions. The model accounted for high level performance metrics of learners that acquired a novel procedural knowledge through instructional interfaces with different levels of dynamic visualisation contents. However, it abstracted much of the details of low level cognitive processing associated with the perception of such visualisations, their integration with retrievals from long term declarative memory and the intertwined role of the integral mental task representation in subsequent, observable post-learning task performance. To investigate these low level details, the hybrid cognitive learning model was formalised through a series of computational modelling effort within the framework of a modern cognitive architecture. The general design of computational modelling effort is shown in Figure 1.3 and a complete description of the methodology is provided in Chapter 6 of this thesis. A novel approach was utilised to circumvent the present limitations of the selected cognitive architecture for modelling complex human motor actions. This novel paradigm was successfully piloted in the first, proof of concept computational modelling effort by applying it to a single step of an entire task sequence. In the second, follow-up work, the cognitive modelling method was extended to more natural and complete task sequences with equally impressive outcomes.

The back-to-back paradigm of empirical observations and integrated cognitive computational modelling afforded a novel insight to the controversial cognitive role of different levels of dynamic visualisations in multimedia instructional delivery. It combines traditional methods of inquisition with powerful but relatively modern cognitive computational modelling approaches to produce a generic framework for multimodal acquisition of novel procedural knowledge, which has implications for education, research and training involving computer based training simulations.

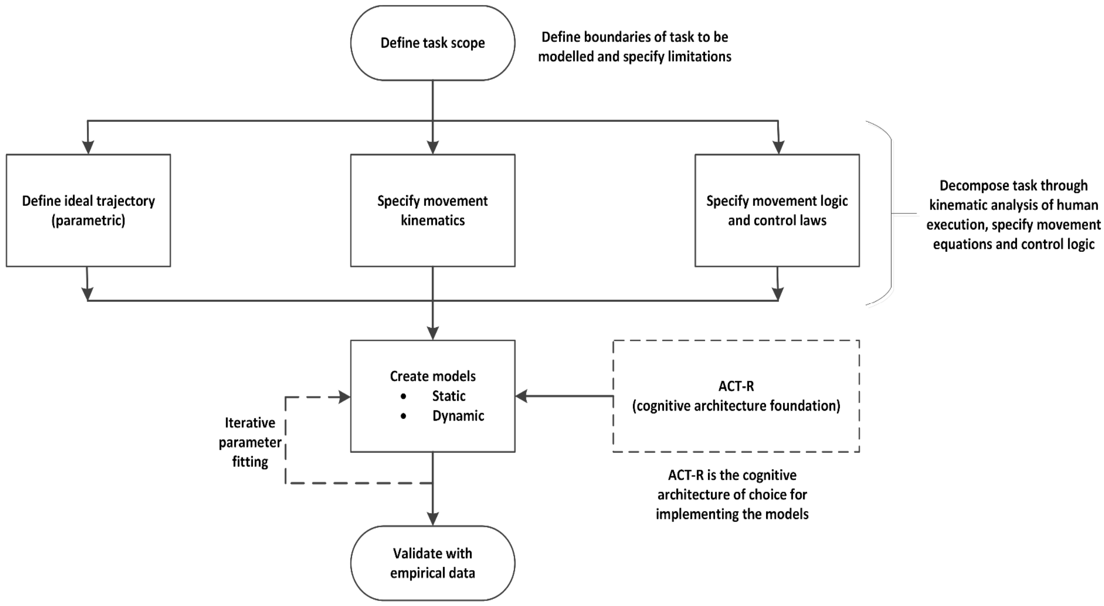


Figure 1.3 Generic cognitive modelling methodology

1.4 Research Contributions

The research reported in this thesis address the computer science aspect of a long-standing psychology question – What are the cognitive effects of instructional interface visualisations and the implications for optimizing computer based learning tools? This question is the subject of several contemporary studies as will be highlighted in the course of the report. The current research makes novel contributions to the existing body of knowledge by integrating methods across selected disciplines to approach the problem. Extensions were made to the definition of the range of interface visualisations and the notion of an 'interactive' interface was clarified to resolve the hitherto diverse and conflicting results of related previous studies. Additionally, the research methodology utilises the increasingly acceptable technique of computational cognitive modelling to conduct detailed examination of the cognitive processes that underlie overt behaviour in interaction with different instructional interface visualisations. To achieve this, novel extensions of the base framework of the selected cognitive modelling architecture are defined. This afforded the modelling of complex human cognition and associated performance than would otherwise have been possible with the original definition of the cognitive modelling architecture. Furthermore, the novel extensions defined hints at possible approaches for extending the base architecture to modelling problems in extra dimensions than originally specified. More details of these novel contributions of the thesis would be highlighted in the subsequent chapters and a list of the associated journal/conference publications is contained in Appendix A of this report.

1.5 Scope of the Report

Chapter 1 provides an overview of the work presented in this thesis. The fine detail commences in Chapter 2 with a critical review of selected research literature on the human skill acquisition process and its dependence on external symbolic knowledge representations using visualisations and artefacts. The literature review examines the human cognitive architecture from the interdisciplinary perspective of psychology, neurophysiology and cognitive computational modelling with a view to eliciting the constraints it imposes on different knowledge acquisition scenarios. A thorough understanding of the learning constraints imposed by the limitations of the human cognitive architecture is fundamental to subsequent evaluation of more modern research on the cognitive benefits or otherwise of different instructional presentation formats. The literature review also serves the purpose of clearly defining the focus of this research work and how its novel contributions fit into the current body of knowledge especially the computer science aspects of interactive learning via computer based simulations.

The empirical studies are reported in Chapters 3, 4 and 5. The first experiment reported in Chapter 3 was conducted to provide the initial framework for evaluating novel skill acquisition through instructional interfaces with different visualisations but equivalent information content. It replicates certain aspects of previous related research but extends such to include additional levels of dynamic visualisations in the comparison. Furthermore, certain extraneous moderating variables as identified from relevant research literature were controlled to develop the initial framework of a hybrid cognitive learning model for the acquisition of novel procedural knowledge via computer based training simulators. The experiment reported in Chapter 4 extends the hybrid cognitive learning model to novel skill acquisition in a different but related procedural knowledge domain. The objective is to extend the generalisability of the hybrid cognitive learning model for novel procedural knowledge acquisition. In Chapter 5, the cognitive learning model is examined further for the effect of previous knowledge or domain expertise on novel procedural knowledge acquisition with interesting results. The findings of the experiment reported in Chapter 5 have implications for rapid retraining/rerolling of domain experts to accommodate new technologies or changes to workplace processes.

The design and implementation of the cognitive computational models are described in a series of 2 experiments reported in Chapter 6. Experiment 1 details the design and implementation of the initial proof-of-concept of the modelling approach. It describes the selection of a limited range of task execution sequence for modelling as well as the rationale for the choice of the implementation cognitive modelling architecture. It further details the novel extensions made to the base cognitive modelling architecture to enable implementation of low-level cognitive processes that drive high-level, observable post-learning human task performance in procedural knowledge acquisition. The mathematical foundations of the developed models are also reported. Experiment 2 extends the novel computational modelling paradigm piloted in Experiment 1 to a more complete and natural sequential task execution. The objective is to highlight the flexibility and extensibility of our approach to modelling a wider range of more complex and natural human task performance. The results of the computational modelling experiments reported in Chapter 6 were evaluated against equivalent human empirical data from previous research.

Chapter 7 provides a general discussion that fits together the findings of the different stages of this research effort. It provides a coherent overview of the results, addresses the research questions and discusses the implications for curriculum development and training simulation design. Chapter 7 also discusses the limitations of the research and concludes the thesis with suggestions for possible future research on the subject of knowledge acquisition and the cognitive benefits associated with different levels of dynamism in instructional visualisations.

Chapter 2

Selective Literature Review

2.1 Overview

The cognitive role of symbolic multimedia representations in learning has generated intense research interest over time. This chapter reviews selected extant research literature relevant to the cognitive effects of different visualisation components in the instruction interface in a knowledge domain specific context.

The acquisition of novel knowledge from instructional media involves a series of cognitive processes. External stimuli are perceived through different modalities such as visual, verbal or somatosensory. The input percept undergoes processing, which may involve selective filtering, task features' mapping, task specific knowledge retrieval, knowledge integration and transfer to post-learning task performance. Central to these processes is the learner's cognitive architecture consisting of sensory units, information pathways, storage and processing mechanisms. Various approaches and theoretical frameworks for human cognitive architecture will be reviewed in this chapter, which would highlight its well-accepted limitations and the adaptations to overcome these limitations.

Contemporary theories of knowledge acquisition from symbolic multimedia representations are also reviewed. The discussion is focussed on how these theories are grounded in the reference framework of human cognitive architecture and the restrictions imposed on learning. The chapter further reviews the implications of these theories on opposing instruction design paradigms of the cognitive effects of different visualisations in the instruction interface. A meta-analytical review of these opposing arguments reveals that several variables moderate knowledge acquisition from multimedia representations including the knowledge domain and the cognitive characteristics of the learner. A hybrid cognitive learning model is proposed from different approaches to studying human cognitive architecture as the basis of further experiments to investigate the cognitive effects of the instructional visualisations within the context of other moderating factors.

2.2 Learning and Human Cognitive Architectures

The question 'what is learning?' has driven scientific research for centuries resulting in distinctive but complementary perspectives of the subject. The process through which humans perceive, process, acquire and transfer knowledge/skill is complex. A well-accepted view adopted in this thesis is that learning is a process that engages the learner in sense making activities that are shaped by previous knowledge (Greeno, Collins, & Resnick, 1996). Therefore, a complete understanding of the learning process requires a prerequisite examination of the human cognitive architecture that supports it. The human mind has been shown to exhibit the contrasting characteristics of an apparently unlimited storage capacity but a disproportionate limitation for attention and real-time information processing (Atkinson & Shiffrin, 1968).

There are two well accepted approaches to the supportive role of cognitive architectures in perception, cognition and behaviour – behaviourist and cognitivist. The behaviourist approach describes cognition from the perspective of stimuli perception and behavioural responses (Paivio, 1986). The target knowledge of a learning process is represented as partial simulations of sensory, motor and introspective states that are stored distributively in modality specific brain areas as active simulations of the perceived states (Barsalou, Niedenthal, Barbey & Rupert, 2003a). The alternative cognitivist view is based on an information-processing model in which information is abstracted from input stimuli and internally processed in a format independent of the source modality. Section 2.3. of this chapter describes the knowledge representation distinction of these alternate paradigms in greater detail. This section focuses on only the more widely accepted cognitivist, information-processing approach and its implication for learning.

The problem of learning is largely an explanation of why only a selective subset is retained from the complete set of input percepts. Broadbent (1958) proposed a filter theory to explain this phenomenon. The theory suggested that a filtering operation is performed on sensory percepts prior to entering the cognitive processing system. This filtering is an adaptive response to prevent overloading and to optimise the function of the limited capacity cognitive processing system. Broadbent's model, as depicted in Figure 2.1, makes a clear distinction between the 'source' of the stimuli and the 'channel' of information processing. A source presents stimuli from different spatial locations, which may be incompatible. The channel however is a result of the filtering process and presents a coherent set of events with some common characteristics, which are batched together for subsequent processing.

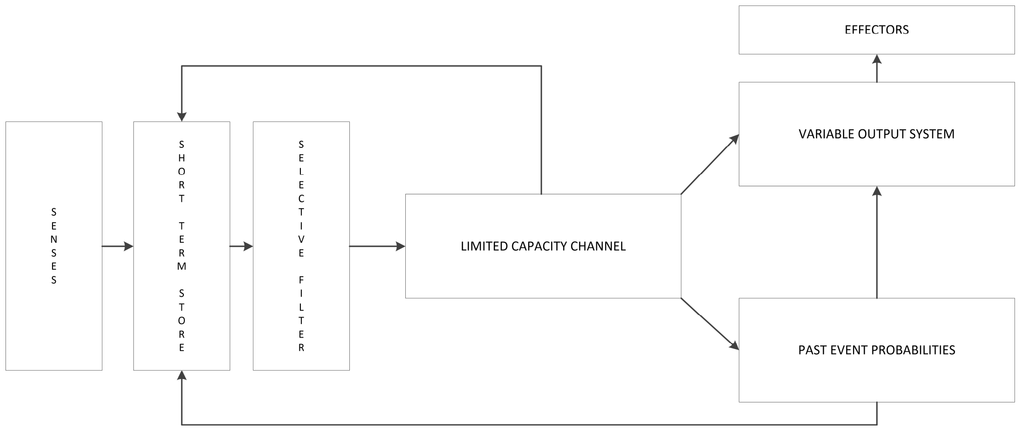


Figure 2.1 Broadbent's information-flow model of human cognitive architecture (Broadbent, 1958, pp 299)

Atkinson and Shiffrin (1968) extended Broadbent's model to include the memory structures and integrated processes that support post-perception cognition. Their model is also premised on the information processing paradigm and included permanent, functional structures and fixed processes, which are selectively controllable (see Figure 2.2). More importantly, Atkinson and Shiffrin's model specifies separate structures of the cognitive system and describes a 3-component framework that includes the sensory register, short term memory (STM) and long term memory (LTM). External stimuli are selectively forwarded to the STM where they are integrated with additional information retrieved from the LTM. The STM therefore functions as a Working Memory (WM) that holds current task specific information relevant to performance. The WM is further characterised by a severe limitation to retain information without rehearsal. This concept of a WM that integrates selective external stimuli and prior information retrieved from the LTM is one of the most powerful features of Atkinson and Shiffrin's model. It provides powerful insights into the general workings of the human memory system and particularly succeeded in highlighting the constraints of attention.

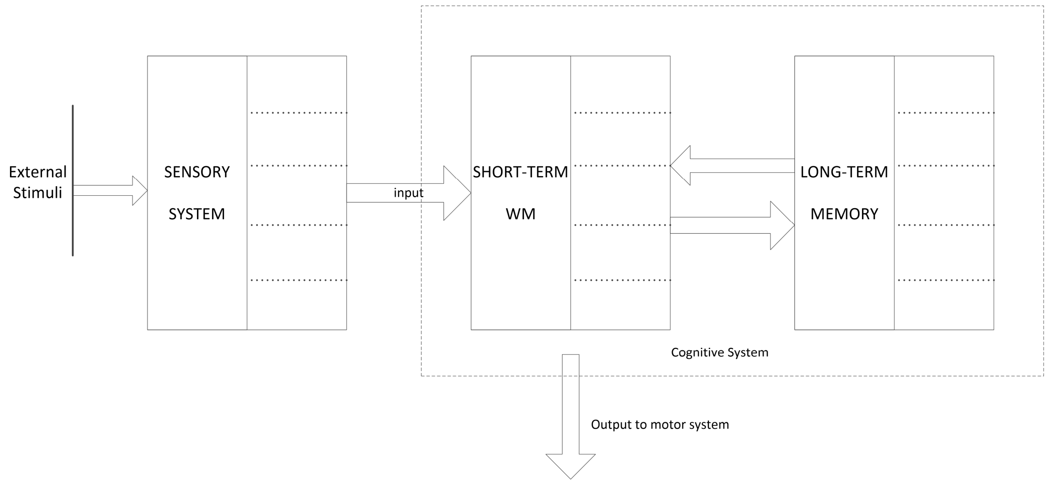


Figure 2.2 Atkinson and Shiffrin's model of human cognitive architecture (Atkinson & Shiffrin, 1968)

It is arguable however that the model left open some important questions like the exact nature of information flow between the structures, how the flow is controlled, the differential processing of various stimuli and the internal processes and structures that helps to overcome the apparent limitations of the WM. Further research effort were therefore focused on the detailed structure of the WM and how it encodes information for fast retrieval to moderate performance. Chase and Simon, (1973) proposed that the WM consists of chunks that are indexed by a discrimination net, which affords rapid categorisation of domain specific percept. The WM is also central to Holding (1985) SEEK (Search, Evaluation, Knowledge) theory, in which it stores explored concept or maintains an index of recent actions. Ericsson and Kintsch (1995) suggested that the capacity of the WM may be larger than traditionally proposed. Their Long Term Working Memory (LT-WM) theory describes a more involved role of the LTM in the maintenance of task-relevant information for performance. Additionally, abstracted information from external stimuli are thought to be encoded in a hierarchical structure of patterns and schemas. These are subsequently retrievable through a fan effect that affords rapid spreading activations across the stored schema.

In a radical departure from the unitary storage perspective, Baddeley and Hitch (1974) proposed a 3-component model of the WM, which processes perceived stimuli through separate cognitive channels. The model, as depicted in Figure 2.3,

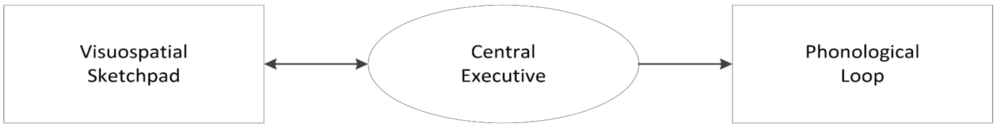


Figure 2.3 Baddeley and Hitch's 3-component model of WM

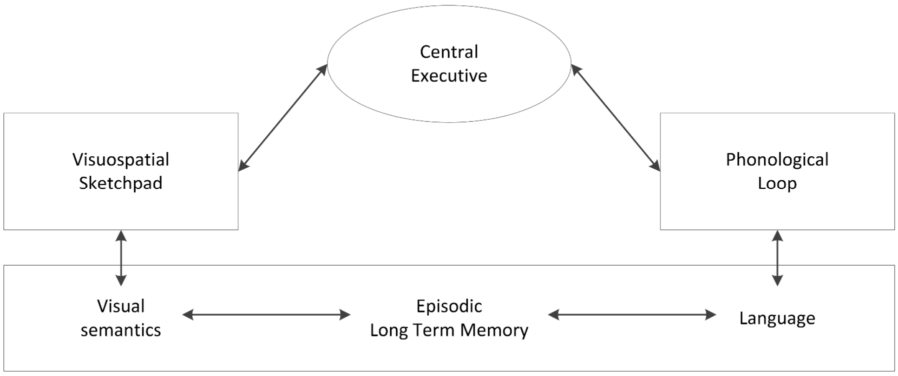


Figure 2.4 An extension of Baddeley & Hitch's model of WM, which includes an episodic buffer (Baddeley, 2000)

has separate processing channels for verbal-phonological and visual-spatial percept. It also includes a central executive module for control and manipulation of all cognitive processes through an attention mechanism. The phonological loop and visual-spatial modules therefore act as slave systems to the central executive. Baddeley & Hitch's multicomponent model has been widely accepted. It is consistent with Card, Moran and Newell's, (1983) human processor model and Paivio's, (1986) dual coding theory. It's specification of a dual processing channel however does not cover the full spectrum of possible sensory percept available to the learner. Although the auditory and visual channels account for a large part of the external percept spectrum, it may be argued that the human learner is quite capable of considerable cognitive processing and learning from other modalities such as olfactory, somatosensory and gustatory. Baddeley (1981) also highlighted this limitation of the multicomponent model and suggested that the two slave systems were only initial specifications of several other possible subsidiary systems of the WM. Baddeley (2000) later extended this model to include an episodic buffer, which provides an interface between the two slave systems (see Figure 2.4). The buffer also supports the integration of information abstracted from multi-dimensional external percept with retrievals from the LTM. The central executive utilises the episodic buffer through selective attention mechanism to model the external environment as well as generate novel cognitive representations that facilitates problem solving and skilled task execution.

In this thesis, Baddeley's extended WM model provides the baseline theoretical framework for the role of human cognitive architecture in learning from instructional interfaces with different visualisation components. The episodic buffer is hypothesised to support the integration of multisensory data with retrievals from LTM to aid task comprehension and the transfer of novel knowledge/skills. Several aspects of this process however are not fully understood. For instance, questions remain as to how the integrated data consisting of multisensory information and declarative knowledge retrievals are encoded during cognitive processing? Is the task comprehension and subsequent performance moderated by factors such as the knowledge domain, learner's individual abilities and/or the type of visualisations employed? Can knowledge/skill transfer be optimised in the learning process through more efficient instructional visualisations combinations that exploits their effects on the cognitive processing? To answer these questions, it is imperative to have a sound understanding of how mental task representations are internally hosted during cognitive processing associated with learning and subsequently referenced in post-learning task performance. The fidelity of the multidimensional encoding of task related information integrated with declarative knowledge retrievals is critical to task comprehension and skill transfer in the learning process. It appears therefore that manipulating the sensory percept through instructional design techniques that optimises the type of visualisations content would moderate the skill acquisition/knowledge transfer possible in a learning episode. The next section of this chapter explores the different approaches to knowledge representation in cognitive processing associated with learning. In a later section, contemporary divergent findings on the cognitive roles of different instructional visualisations in knowledge acquisition are reviewed. The theoretical frameworks of these findings is also discussed and a hybrid knowledge representation model is used to argue for a moderating effect of the knowledge domain. The experimental work to investigate this proposal is presented in later chapters of the thesis.

2.3 Knowledge Representation in Skills Acquisition

The concept of 'representation' is concerned with how one entity may stand in place of another. It therefore recognises the separation of the 'represented' from the 'representing' entities and defines the relationship between them (Johnson, 1992). In the research literature, two broad theoretical perspectives have defined the nature of knowledge representation in human cognition and performance. The first is a behaviourist approach, which emphasizes the synergy between perception and observable behaviour otherwise characterised as the stimulus-response view (Paivio, 1986). This paradigm is also referred to as 'embodied cognition' and it argues that human bodily states, such as postures and arm movements, are central to information processing and knowledge representation in cognition. Therefore, knowledge is viewed as modality-dependent partial simulations of sensory, motor and introspective states that are distributively stored in modality specific brain areas as active simulations of the perceived state. Embodied cognition approaches skip the intermediate stimuli representation and processing, focussing on only its perception and overt response behaviour. For example, Bargh, Chen and Burrows, (1996) conducted a study in which participants were requested to form sentences from a list of short, control words that are presented visually. Certain words were included in the list as primers such as 'gray', 'bingo' or 'florida' to connote elderliness. They observed that after the experiment, the primed participants took a relatively longer time to walk to the elevator than others even though there was no suggestion that this was an assessed part of the procedure. This suggested that the processing of the word(s) associated with a social condition (the state of being elderly) induced a relatively bodily effect of moving slowly in the critical participants. Winkielman, Berridge and Wilbarger, (2005) also found that when participants are subliminally primed with angry or happy faces while being prompted to select the gender of visually presented faces, those that viewed happy faces were prone to drinking more of a flavoured drink that was offered after the experiment. These studies suggest that behaviour may be the automatic resultant of perceived stimuli, which may be subliminal and therefore not represented by some form of conscious internal abstraction.

Embodied states have also been shown to induce higher cognitive activities and affective states in a reverse process. Wells and Petty, (1980) had people nod their heads vertically or shake it horizontally to test the effectiveness of a set of headphones while listening to agreeable or disagreeable subliminal audio messages. At the end of the experiment session, nodding participants were found to agree more with the message, irrespective of its original content and despite the fact that the nodding action was meant to test the usability of the headset only. A corresponding disagreement effect was observed in the head-shaking participants. Furthermore, the intensity of nodding or shaking was found to correlate with the agreeableness or otherwise of the audio messages. In summary, the modality dependent view or embodied cognition emphasizes the association of the stimulus and overt response rather than an intermediate abstraction of knowledge to explain cognition. Modal re-enactment of perceptual, action and retrospective states are considered central to skill acquisition and task performance rather than symbolic amodal knowledge representation. Perception, cognition and action are therefore viewed as tightly coupled processes that are mutually dependent and skilled task performance is driven by modality-specific, cognitive level re-enactments of original percepts and not by abstract semantic representations that are amodal (Barsalou et al., 2003a; Barsalou Simmons, Barbey & Wilson, 2003b; Jonides, Lacey & Nee, 2005).

The alternative paradigm is modality-independent knowledge representation in which cognition is underpinned by the abstraction and internalisation of information extracted from external stimuli. This approach is rooted in the information-processing framework of the human mind. Learning, skill acquisition and task performance are therefore driven by cognitive processes that involve the active creation and interaction with mental task models that are amodal, semantic abstractions of the input stimuli (Anderson, Qin, Jung & Carter, 2007). The acquisition of novel knowledge or skill is preceded by the creation of an internal mental representation of the perceived problem state and its solution sequence. Subsequent task performance is then achieved by active reference to this internal, abstract representation for every stage of the solution execution. This view aligns well with Fitts and Posner, (1967) three-level description of skill acquisition as depicted in Figure 2.5. Novel skill acquisition progresses through three stages – cognitive, associative and automatic. Each level is characterized by progressively effortless task performance and reducing reliance on the mental task model.

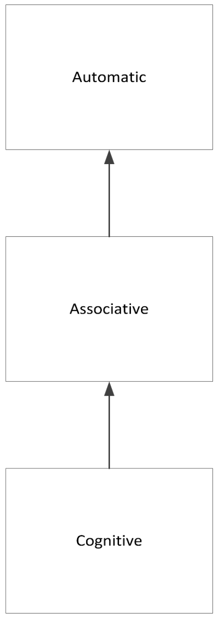


Figure 2.5 A depiction of Fitts and Posner's (1967) model of skill acquisition

Rasmussen's (1982) skill-, rule- and knowledge-based (SRK) model of human error and Logan's (1988) instance theory of automatisation also specify information abstraction as part of the cognitive processes associated with skill acquisition and mental task models that drive post-acquisition performance.

The modality-dependent and modality-independent paradigms present diametrically opposed views of the role of knowledge representation in learning associated cognitive processes. Both approaches have been argued for using brain imaging data. For example, Jonides, Lacey and Nee, (2005) have cited neural imaging analysis data from Wager and Smith, (2003) to argue for an association between perceptual mechanisms that encode external stimuli and structures that store representations of such stimuli in the WM. Conversely, the posterior parietal cortex has been implicated in the hosting of abstract knowledge representation that integrates visual and motor signals from external stimuli independently of their input modality (Gold & Shadlen, 2007; Freedman & Assad, 2011). More importantly however, other studies have advocated that knowledge representation may not simply be associated with input modality but moderated by other variables. Schumacher, Faust and Magnuson (1996) found that certain brain regions are sensitive to the content of the stimuli (e.g. verbal information) but insensitive to the modality of the input (visual or auditory presentation). Anderson et al., (2007) also proposed a mixed model where different brain regions were associated with various levels of cognitive processing along the modality specific vs abstract representation spectrum. In that study, perceptual brain structures were observed to respond in a modality-specific manner, lateral cortical regions exhibited hybrid functions of central as well as content-related processing while the functions of the caudate and cingulate areas appears to be completely independent of modality or content.

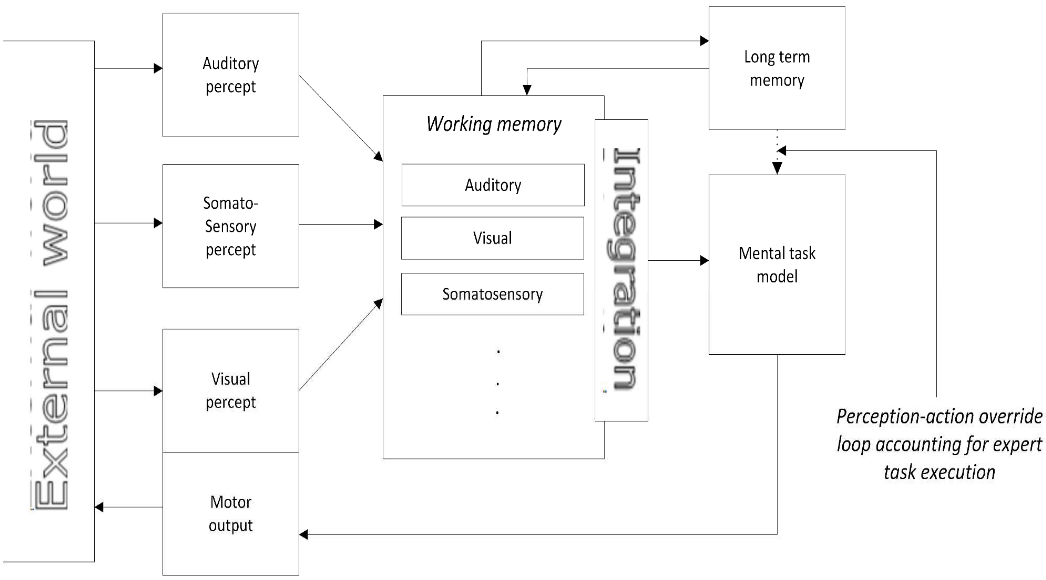


Figure 2.6 A proposed hybrid cognitive model for learning and skill acquisition

Consistent with this, a novel hybrid knowledge representation approach is proposed in this thesis that combines aspects of the embodied cognition and amodal representation paradigms. This model, as shown in Figure 2.6, suggest that an abstract mental referent is created as part of the cognitive processes in novel skill acquisition and subsequent task execution is achieved by reference to this mental model. However, the perceptual-action loop is eventually able to override this mental model in skilled performance and modify behaviour in accordance with unfolding execution and unexpected circumstances. This allows for accurate (due to a mental representation) but robust (due to overriding perception-action processes) learning and task execution. The hybrid model suggested in this thesis is consistent with modality-dependent and modality independent theoretical frameworks of novel skill acquisition such as Barsalou et al., (2003a) embodied cognition model, Fitts and Posner's (1968) three-level model, Rasmussen's (1982) SRK model, and Logan's (1988) instance theory of automatisation. The focus of this thesis however is on the differential cognitive processing of various stimuli content types that are perceived through the same modality. This will be achieved through the reverse application of the proposed hybrid model to investigate the effect of equivalent dynamic versus static instructional visualisations on the fidelity of the integral mental task referent, and measured through empirical observations of post-learning task performance.

2.4 Theories of Multimedia Representations in Skills Acquisition

Several contemporary learning theories have highlighted the central role of instructional content and mental task models in knowledge/skill acquisition. For example, Sweller's, (1988) cognitive load theory (CLT) utilises an information-processing view of human cognition to describe learning and skill acquisition in the context of 'cognitive loads' or difficulty imposed on the cognitive system in the skill acquisition process. The CLT describes a schematisation process through which relative information is organised in human memory in a tree-like structure or schema. By following the branches of the tree or tracking the nodes of the schema, humans are able to store and retrieve larger amounts of information than would otherwise be possible given the identified limited capacity of WM. This tree-like structure has also been used to explain the strategic thought processes of chess players (see e.g. Chi, Glaser & Rees 1982 to provide an exemplar reference). Sweller (1994, 2005) further suggested that schema formation is enhanced by continuous practice/re-experience of stimuli until automation is achieved where information retrieval from the LTM allows the WM to be bypassed. However, the speed of schema creation and achieving automation is influenced by the 'cognitive load' of target knowledge. Three forms of this cognitive load were identified; the first is intrinsic cognitive load, which describes the fixed, inherent difficulty of the acquirable knowledge or skill and represents the basic minimum load to overcome for cognition to occur. The second is extraneous load, which is defined as the load imposed by the instructional medium through which the knowledge is delivered and is therefore subject to instructional design. It is extrinsic to the target knowledge and constitutes a controllable barrier to knowledge acquisition. The final form is germane load, which is defined as the generative processing of instruction and the construction of new knowledge schemas to facilitate progressive expertise in task performance. The germane load is therefore associated directly with schema construction and task comprehension characteristic of expertise. In a more recent revision of the CLT, the germane load is no longer considered to be an independent source of cognitive load. It is redefined as the WM capacity required to process the element interactivity that constitutes intrinsic cognitive load. It is therefore dependent on the intrinsic cognitive load and contends with extraneous cognitive load for WM resources (Sweller, 2010). The CLT assumes that cognitive loads are additive and their summation should not exceed the WM capacity for effective learning to occur. Germane and extraneous cognitive loads interact with available WM capacity to determine the effectiveness of instructions. The intrinsic cognitive load is not subject to manipulation but may be presented incrementally through properly designed instructions that adapts to the expertise level of the learner. More importantly for this thesis, the CLT specifies certain principles that moderate learning and skill acquisition (Sweller, Ayres, & Kalyuga, 2011). One of these is the borrowing and reorganising principle, which suggests that learning is primarily achieved through borrowing existing schemas from other people's knowledge for example by mimicking, reading or listening to them. The borrowed schemas undergo reorganisation, which may result in random changes, prior to integration with the learner's declarative knowledge. The alternative and secondary method for learning is specified in another principle – randomness as genesis for problem solving. This principle advocates that where source knowledge does not exist, the learner must generate new knowledge by randomly generating procedures to solve a problem and testing each for effectiveness. The randomness associated with generating novel solutions or reorganising perceived information imposes cognitive loads on limited WM resources. Once knowledge schemas are formed in LTM however, its subsequent retrievals to facilitate task performance imposes minimal WM cost as compared to organising external percept from the senses. Using the same argument, well designed and organised instructions may facilitate efficient transfer to the LTM. Therefore, for learners with no prior knowledge, the incoming percept must be well organised to achieve optimal skill acquisition. Knowledge that is well organised prior to presentation is more effective as it bypasses the need to generate organisational structure and facilitates efficient transfer to the LTM through the creation of more effective mental task models. The CLT has influenced instructional design for several years by suggesting that instructions that balance the cognitive load for the learner through the minimisation of extraneous load and the maximisation of germane load within the boundaries of the WM capacity will optimise learning. However, the CLT has some shortcomings. For instance, it has not been able to account for the apparent variability of task difficulty for different expertise levels. Contrary to its assumption of fixed intrinsic load, further research has shown that task difficulty does not remain constant for different levels of expertise and that expertise is transferrable across related tasks (Schnotz & Kurschner 2007).

Mayer's, (2005) Cognitive Theory of Multimedia Learning (CTML, see Figure 2.7) is another contemporary skill acquisition reference framework that is premised on the limited WM capacity of the human information-processing cognitive paradigm. The theory makes three basic assumptions in describing the cognitive processing associated with skill acquisition from multimedia instructions including text, static pictures and dynamic animations. The first is that auditory and visual stimuli are processed through separate channels. Secondly, the channels have limited processing capacity and thirdly, that humans engage in active learning by selectively organising inputs from the separate processing channels and integrating these with prior knowledge at a later stage of cognitive processing. These assumptions are consistent with the dual coding theory (Paivio, 1986) and Baddeley and Hitch's model of the WM (Baddeley & Hitch, 1974; Baddeley, 2000).

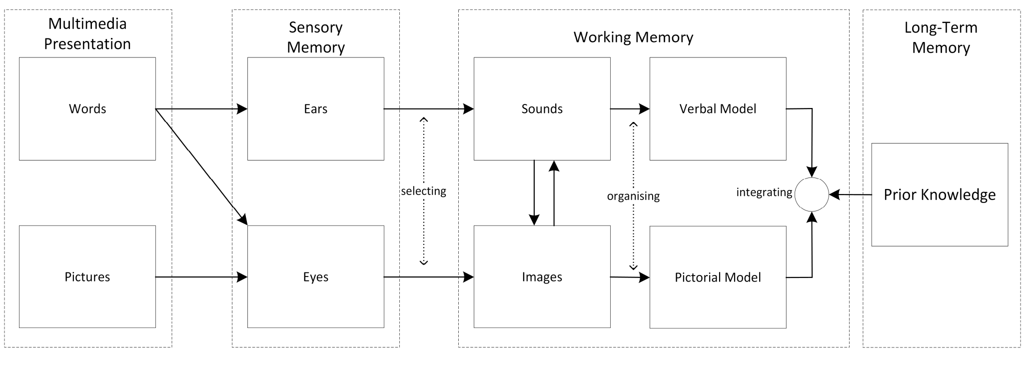


Figure 2.7 Mayer's Cognitive Theory of Multimedia Learning model (Mayer, 2005)

The CTML further specifies five cognitive processes associated with multimedia learning: the selection of words for the verbal channel, the selection of images for the visual channel, the organisation of selected words into a verbal model and selected images into a pictorial model and lastly the integration of verbal and/or pictorial models with prior knowledge retrieved from the LTM. The CTML provides a powerful explanation of the cognitive processes involved in novel skill acquisition. It is consistent with previous models of memory and learning such as Atkinson and Shiffrin's (1968) model, the CLT (Sweller, 1988) and Schnotz & Kurschner's (2007) extension of the CLT to accommodate different levels of task difficulty and skill transferability associated with expertise.

The CTML however has a potential fundamental flaw that limits its applicability for investigating the moderating effects of instructional content dynamism. It assumes that in the generation of the pictorial model from viewing an animation, the relevant segments of the dynamic stimuli are compressed into visual images and held in visual memory as snapshots. This is premised on the assumption of a limited processing capacity of the channel, which would otherwise be overwhelmed in attempting to process all parts of the animation. This thesis argues however that a dynamic construct that captures the intrinsic transitions portrayed by the dynamic stimuli (video, animation or interactive) is also integrated into the final mental task representation. The hybrid cognitive learning model proposed in this thesis (see Figure 2.4) is consistent with the selective processing of input stimuli and subsequent integration with retrievals of prior knowledge. However, it extends to include the transitions construct intrinsic to dynamic visualisations only in the final mental task model. This results in a more complete representation of the task by dynamic visualisations over their static equivalent and affords enhanced post learning task performance in specific knowledge domains. This thesis argues therefore for a novel construct of an intrinsic quality of instructional components to capture and enhance the transfer of transitory, coordinating information necessary for the skilled performance of procedural tasks. By implication, dynamic visualisations content of instructions such as videos or animations may afford an enhanced capacity to capture and transfer the coordinating transitory information that is intrinsic to the expert performance of selected skilled procedural tasks than possible with static images. This is consistent with the conclusions of a meta-analysis of 26 previous related studies by Höffler and Leutner, (2007, 2011). Höffler and Leutner's meta-analysis describes several factors that may moderate the effectiveness of different instructional visualisation components. Pertinent to the objective of this thesis, they suggested that the relative effectiveness of dynamic versus static instructional visualisation contents may be dependent, amongst other factors, on the target knowledge domain with three specifications – declarative, problem-solving and procedural. Premised on this, the hybrid cognitive learning model proposed in this thesis is applied to investigate the cognitive effects of instructional dynamism with emphasis on the acquisition of procedural knowledge. The thesis presents a series of experiments that explores this proposition in the context of different procedural knowledge domains including the acquisition of motor and spatial navigation skills. Furthermore, a computational modelling approach is utilised to provide a novel perspective on the intertwined role of cognitively processed dynamic vs static stimuli in post-learning performance of procedural tasks. The computational modelling approach is framed in the context of the Adaptive Control of Thought – Rational (ACT-R) cognitive architecture framework. The theoretical framework and architectural infrastructure of ACT-R is discussed in the next section.

2.5 Computational Modelling in Cognitive Architectures

Computational modelling with cognitive architectures is increasingly becoming a methodology of choice for many human factors studies. Cognitive architectures are general frameworks that afford computational modelling of human behaviour and cognitive performance. Some examples of widely accepted cognitive architectures include EPIC (Kieras & Meyer, 1997), SOAR (Laird, Newell & Rosenbloom, 1987) and ACT-R (Anderson, Bothell, Byrne, Douglass, Lebiere, & Qin, 2004; Anderson, 2005). These frameworks capture the capabilities and limitations of human cognitive and behavioural performance including perception, memory and motor processes. By specifying these limitations and capabilities, cognitive architectures afford the implementation of computational behavioural models that are psychologically valid and compares well with actual human performance.

In the work reported in this thesis, a computational methodology is used to model the cognitive effects of instructional components dynamism on knowledge domain dependent skill acquisition. The method afforded a low-level observation of atomic cognitive processes that define skill acquisition and drive post-learning task performance. Furthermore, it provides cognitive modelling data that was validated against empirical human data to have a fuller understanding of the moderating effects of dynamic versus static instructional visualisations.

The ACT-R architecture (version 6.0) was selected for the modelling effort because of its advanced and modular implementation, which is easily extensible. ACT-R is a theory of human cognition, which extends an original Human Associative Memory (HAM) theory (see Anderson & Bower, 1973, 1974). ACT-R modifies the HAM theory by assuming a distinctive and basic categorisation of knowledge structures into declarative and procedural (Anderson et al., 2004). Declarative knowledge is composed of logical units or chunks that encode facts such as 1+3=4 or target object 'a' is at Cartesian coordinate (4, 10) in a reference plane. Procedural knowledge on the other hand consists of condition-action rules that manipulate declarative knowledge and external percept. These rules, otherwise referred to as productions, specify some set of conditions which when fulfilled, triggers an appropriate action which could be the creation/modification of knowledge chunks and/or the execution of other task performance actions. The ACT-R theory is implemented as a hybrid cognitive architecture based on a symbolic central production system influenced by massively parallel subsymbolic processes, which are represented by a set of mathematical equations (Taatgen & Anderson, 2002; Anderson, 2005). The symbolic aspect consists of a set of modules for processing different kinds of information, which are interfaced through the central production system by their matching buffers. The modules operate in parallel through internal subsymbolic processes and communicate through the information deposited in their buffers. The central production system coordinates the behaviour of these modules by recognizing patterns in their buffers and making requested changes.

An overview of the ACT-R 6.0 architecture is shown in Figure 2.8 with production system as the core, which drives central executive functions and interactions between the other structures. The exact number of modules is not specified by the architecture but some core modules have been implemented that affords the modelling of a wide range of human cognition and performance. The critical aspects of the architecture that are pertinent to the modelling work in this thesis are the perceptual-motor system (vision, audio, motor and vocal modules), goal system, declarative knowledge mechanism and the procedural system. The perceptual-motor system allows the architecture to interact with the external world. Much of the modules of the perceptual-motor system are based on original aspects of the EPIC cognitive architecture (Meyer & Kieras, 1997) and the Human Processor Model (Card, Moran & Newell, 1983).

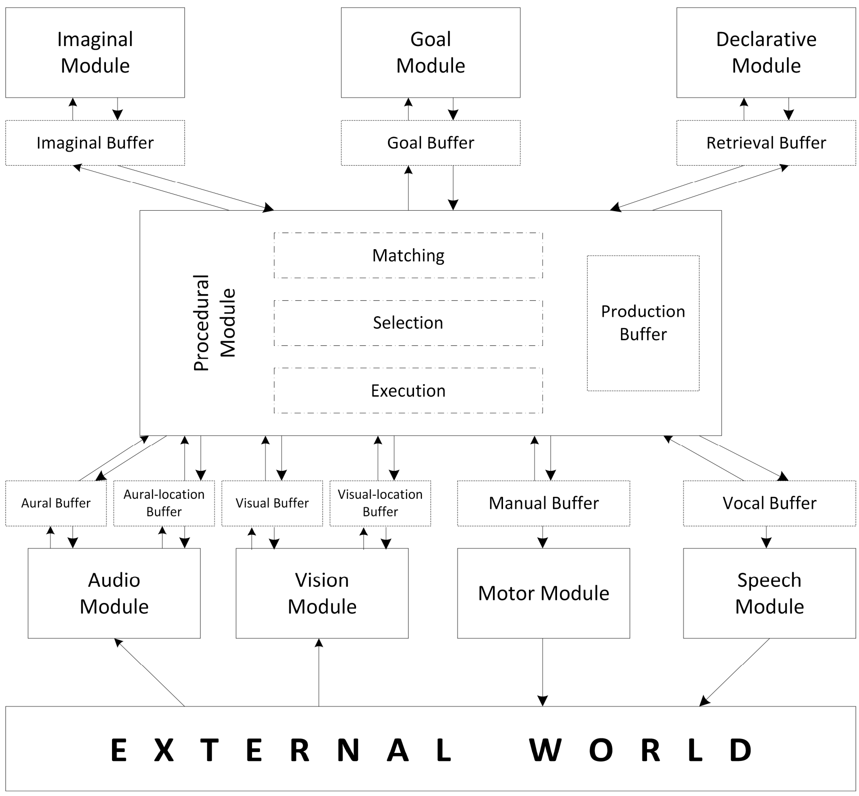


Figure 2.8 An overview of ACT-R (adapted from Anderson et al., 2004)

The vision and motor modules are of particular relevance to the modelling of the moderating effect of instructional dynamism as investigated in this thesis. The vision module implements two subsystems – visual-location and visual buffers – that define the 'where' and 'what' respectively of perceived visual stimuli. The visual-location buffer model pre-attentive visual processing (Treisman & Gelade, 1980) through chunks that represent the location of a perceived object in the visual field. The visual buffer provides the mechanism that attends to these visual-locations and encodes the perceived objects. The motor module essentially functions as the architecture's limbs by affording the execution of rudimentary motor actions to perform tasks and interact with the external world. Motor performance is decomposed into a hierarchical structure that specifies categories of all possible movements. The motor module further controls movement timings through fine specification of its distinct internal states in the cognition cycle. The execution time for simple movements are specified as internal module constants while that for more complex movements are calculated based on Fitts's Law as (ACT-R 6.0 Reference Manual, pp 297):

$$T = b\log_2(\frac{D}{W} + 0.5) \qquad - \quad 2.1$$

where T = movement time in seconds
b = a motor action type parameter
D = distance moved to a specified end target
W = width of the target

The goal system allows the ACT-R architecture to maintain task specific states that keeps track of intentions to control behaviour towards achieving an objective. It affords modelling of the human ability to select a specific course of action from a range of alternatives and align thought processes in the absence of supportive external percepts. Closely linked to the goal module is the imaginal module, which maintains context-relative information during task performance.

The declarative module is perhaps the most developed aspect of the ACT-R architecture. It specifies the declarative knowledge structure and the associated mechanisms for input of external percept and retrieval of prior knowledge from the LTM. Declarative facts are represented by units of chunk, which may be added or retrieved from the LTM. The addition and retrieval of knowledge chunks is controlled by subsymbolic processes specified by a set of equations. One of these is the chunk activation equation, which defines the procedure for chunk retrievals (Anderson et al., 2004):

$$A_i = B_i + \sum_j W_j S_{ji} \qquad - \quad 2.2$$

where B_i = base level activation of chunk i
W_j = attentional weight of element j
S_{ji} = strength of association from element j to chunk i

All the chunks in the declarative memory are assigned activation levels, which reflect their past utility and relevance to the current task context. The activation level of the chunk determines its likelihood and latency of retrieval in each cognitive cycle. Only chunks with activations above a specified threshold may be eligible for retrieval. The activation equation is extensible to accommodate various task contexts that may be encountered in modelling cognition. This extensibility is particularly crucial for the computational modelling work reported in this thesis. It afforded a novel extension of the architecture to capture atomic spatial locations for representing movement trajectories in post-learning motor execution. Further details of the extensions made to the activation equation in this thesis are provided in the cognitive modelling experiments reported in Chapter 6. The declarative module further specifies several other mechanisms that provide context-relative knowledge manipulation in task performance such as strength of association between memory chunks (Pirolli & Anderson, 1985), practice effect (Anderson, Fincham & Douglass, 1999) and retrieved content similarities/error modelling (Lebiere, Anderson & Reder, 1994; Taatgen, Lebiere & Anderson, 2006).

The procedural system provides central executive control and integrates the distributive processing that occurs in the other modules to achieve coherent cognition. It interacts with the other modules by detecting and matching patterns that appear in their buffers through specified condition-action rules to drive cognitive processing and task performance. The condition-action rules are referred to as productions and only one rule (production) may be selected for execution from all the matches during each cognition cycle. Cognition in ACT-R is therefore a hybrid phenomenon where distributive parallel processes in the other modules are moderated by serial, executive functions of the procedural system. The production selection process is noisy as a number of productions may match the selection criteria. The determination of which production is eventually selected for execution is controlled by their utility values. The utility value of a production is defined as:

$$U_i = P_i G - C_i \qquad \text{- 2.3}$$

where P_i = probability of production i achieving a goal
G = current goal value
C_i = cost of achieving the goal through production i

A modeller usually specifies the productions that drive cognition and performance in the domain being modelled. However, ACT-R's procedural system also defines a production compilation process through which new productions may be created online by running models to simulate learning and expertise (Taatgen & Lee, 2003).

ACT-R is a complex theory of the human mind complemented by a computational architecture that affords modelling to investigate and predict cognition and performance. The functions of the separate modules present a hybrid paradigm that supports both the perception-action behaviourist as well as the abstracted processing cognitivist perspective of human cognition. For instance, the audio and vision module function as purely perceptual systems while the motor and speech modules are dedicated for the processing of motor and vocal outputs respectively. Other modules however, such as the imaginal, goal and procedural modules, exhibit processing that is completely abstracted away from input or output modalities (Anderson et al., 2007)

This thesis applies the ACT-R 6.0 framework to investigate the low-level details of the moderating effect of instructional dynamism on skill acquisition and performance in specific knowledge domains. The manual modules of the base ACT-R 6.0 architecture are capable of executing rudimentary movements only and cannot be readily applied to simulate the atomic movements of fine skill execution that is being investigated. A novel methodology is therefore utilised that leverages on the extensibility of the architecture to overcome this limitation. The details of this methodology are discussed further in Chapter 6.

2.6 Summary

The limitation of the human cognitive architecture for real time processing of large amounts of information is well established in literature. Different theoretical perspectives, ranging from behaviourist stimulus response to cognitivist abstract processing, have been proposed on how the cognitive architecture adapts to overcome this limitation in the acquisition of novel knowledge/skill.

Learning models based on these theoretical frameworks have informed different approaches to investigating the cognitive effects of various instructional compositions. For instance, the CTML have suggested that different channels exist for processing various input stimuli from multimedia instructions in skill acquisition. Other models have emphasized a modality dependent perspective that is devoid of information abstraction. The emerging accepted view is that of an integral process that integrates external percept from instructions with declarative retrieval of prior knowledge to effect task comprehension and drive post-learning task performance. The effect of extraneous moderating factors, such as instructional component dynamism and modalities of perception, on skill uptake and transferability however remains controversial. Meta-analytical reviews of the different perspectives have suggested a knowledge domain dependent role of multimedia instructions that comprises dynamic and static visualisations. This thesis proposes a hybrid cognitive learning model for a novel approach to investigating the moderating effects of instructional interface dynamism. A series of experiments were conducted to validate this model. The first experiment that applies it to the acquisition of novel procedural motor skills is presented in the next chapter. Subsequent chapters present further experiments that examine other factors such as the variation of the primary knowledge domain, individual learner abilities and prior knowledge/expertise. A computational modelling technique is also employed for detailed investigation of the interaction of instructional dynamism, task comprehension and skill transferability as measured by post learning task performance.

Chapter 3

Experiment 1 – Acquisition of Novel Procedural Motor Skills

3.1 Overview

The work presented in this chapter investigates the divergent findings in the current literature on the cognitive effects of different levels of dynamic visualisation contents in instruction. An important area of contemporary research with such divergent conclusions is the comparative benefit of dynamic visualisation components of Computer Based Training (CBT)/simulator interfaces like videos, animations or user controllable objects as compared to static presentation formats that use e.g. diagrams and text. The experiment in this chapter applies the novel hybrid cognitive learning model proposed in Chapter 2 to empirically compare the effectiveness of instructions with different visualisation contents. It further argues for an intrinsic quality of instructional format construct that makes dynamic visualisations more suitable for skill acquisition and transferability in specific knowledge domains. The hypotheses made to drive the experiment are clearly stated in a later section.

3.2 Dynamic versus Static Components of Instruction

Dynamic visualisations are visual-spatial representations capable of portraying not only training artefacts, but also underlying processes such as changes in positions and trajectories of the artefacts whilst performing a skilled task. Static visualisations can also portray visual-spatial orientations but have limitations especially for processes involving continuous changes in artefact orientations such as those typical in manipulative skills like component disassembly in engineering training.

Using the framework of cognitive load theory (CLT), Mayer, Hegarty, Mayer and Campbell (2005) compared the learning outcomes of animation-based instructions with those using a series of static pictures that convey equivalent information and suggested that static media enable deeper learning than animation can afford because of reduced extraneous cognitive loads and more germane processing. As highlighted in the review in Chapter 2, the CLT assumes that three different types of cognitive load are interacting in learning from instructions – extraneous, intrinsic and germane cognitive loads (Sweller, 2005, 2010). As a general rule therefore, an optimal instructional design paradigm will minimise extraneous cognitive load, maximise germane generative processing but have no effect on the intrinsic component. The effect of learner's prior knowledge was further investigated with static visualisations and found to be more effective than dynamic alternative for low-knowledge learners. No differences in format effectiveness were found for high knowledge learners (Mayer et al, 2005; Kalyuga, 2008). Schnotz and Rasch (2005) extends this argument to propose a negative effect for high-knowledge learners because dynamic visualisations are thought to inappropriately facilitate learning in a task by reducing germane cognitive processing instead of extraneous cognitive loads. Kalyuga (2011) suggested that dynamic visualisations are not more efficient than static components of instruction because of their transience effect. Dynamic visualisations by nature present transitory and continuous information. The processing demands required to hold previous information in memory to be integrated with later information as they are presented in the dynamic stream may therefore overwhelm WM resources quickly. In contrast, static components, such as diagrams or pictures, afford more permanence of information, which may be revisited and therefore releases the learner from having to retain otherwise large amounts of information in WM during processing. Other studies have also argued that static instructional visualisations encourage the active creation of mental task models (Tversky, Morrisson & Bertrancourt, 2002; Hegarty, Kriz, & Cate, 2003) and enhances task comprehension through mental rotation and manipulation (Hegarty, 2004, 2005).

Interestingly, contrasting findings have been reported in yet other studies that suggest a benefit of dynamic instructional visualisations over statics in certain contexts. For instance, Wong, Marcus, Ayres, Smith, Cooper, Paas and Sweller (2009) have proposed a different paradigm to comparing the effectiveness of dynamic versus static instructional visualisations using the framework of the CLT. They suggest a distinction between biologically primary and secondary knowledge (see Geary, 2005; 2007) and argue that the CLT applies to the acquisition of biological secondary knowledge only. Wong et al. (2009) defined biologically secondary knowledge as that which is acquired through conscious, effortful processing in WM as against biological primary knowledge, which humans have evolved to acquire easily and automatically. Dynamic visualisations may therefore be beneficial in aiding the acquisition of biologically secondary knowledge such as human movement-based tasks because it utilises a human movement WM processor to support the creation of more accurate mental task models. In a series of experiments, Ayres, Marcus, Chan & Qian (2009) presented empirical evidence to suggest that the transiency of dynamic visualisations makes them more effective than static in specific learning contexts such as the acquisition of motor skills. This effect was attributed to the possible existence of a human mirror-neuron system that facilitates knowledge acquisition through mimicry (Rizzolatti, 2005). In a more recent study, Wong, Leahy, Marcus and Sweller (2012) extends the argument on the transiency effect to propose that transient dynamic instructional visualisations may impose overwhelming cognitive loads only when presented in very long segments. Paradoxically, the permanence benefit attributable to static visualisations is only evident in long presentation segments, which may also overwhelm WM capacity in specific circumstances such as when forward and backward referencing is limited by learning time. The appropriate segmentation of dynamic instruction visualisations would therefore overcome the transiency effect and make them more effective than equivalent static visualisations for knowledge acquisition. The benefit of dynamic instructional visualisations over static have also been attributed to its realism (Höffler, & Leutner, 2007), degree of afforded user control (Schwan & Riempp, 2004), its use in an observational learning context (Van Gog, Paas, Marcus, Ayres, & Sweller, 2009) and interestingly, when carefully integrated with static visualisations (Arguel & Jamet, 2009).

In spite of the contrasting findings, a developing convergence is that the effectiveness of different visualisations is dependent on the learning context. In the meta-analysis of 76 studies, Höffler and Leutner (2007) highlighted several moderator variables that may impact the effectiveness of different instructional visualisations. Of particular relevance to the experiment reported in this chapter, the meta-analysis suggests that dynamic visualisations are significantly superior to statics in a 'representational' context as opposed to 'decorational'. Furthermore and more importantly, the meta-analysis identifies the type of acquired knowledge as a moderator variable of instructional visualisations' effectiveness and defines three different knowledge domains – declarative, problem-solving and procedural-motor. This chapter therefore argues, on the basis of this categorisation, for an alternative approach to the comparison of the benefit of dynamic over static visualisations with particular focus on the procedural-motor knowledge domain. The definition of the knowledge domain is a crucial step for investigating the effectiveness of visualisation components of instructions. The divergent view of the reviewed studies on the effectiveness of the various instructional formats may be due to the fact that separate categories of learning processes are being described. One is the learning of cognitive tasks (declarative knowledge) that requires little or no physical manifestation of a skill to demonstrate that such knowledge has in fact been acquired (Yang, Andre & Greenbowe, 2003; Mayer et.al., 2005; Cohen & Hegarty, 2007). The post learning phase tests of skill acquisition in such studies are usually achieved by questions designed to measure speed and accuracy of recall as well as to predict or interpret states of the systems being studied. Another category involves the learning of manipulative, procedural actions or skilled motor movement to execute some complex task (Schwan & Riempp, 2004; Arguel & Jamet, 2009; Ayres et al., 2009). With respect to this second category, it is suggested that a more accurate determination of the effectiveness of the instructional format would be a test of the ability to execute the actual motor (or procedural) tasks post-learning, such as through performance measurements of assembly/disassembly. The speed and accuracy of the assembly/disassembly of physical components in such instances would provide a more valid basis for assessing the comparative advantages of different instructional formats for learning the motor skills. Furthermore, the dynamic visualisation content of the various instructional interfaces should imply an attribute of the interface to provide abstract representation of the target motor skill set during the learning process rather than varying the rate of information delivery as proposed in some of the reviewed studies.

Höffler and Leutner's (2007) meta-analysis found the largest beneficial effect size of dynamic visualisations in the acquisition of procedural-motor knowledge. The meta-analysis however restricted the definition of dynamic instructional visualisations to animations and videos only. The experiment reported in this chapter is focussed on the acquisition of procedural skill in the motor knowledge domain. However, it extends the definition of dynamic visualisations to include interactive simulations in a virtual environment. Additionally, it utilises performance measurements of actual task execution to evaluate the effectiveness of different instructional formats for learning a procedural motor skill. Previous studies have also indicated an interaction between instructional interface dynamism and the learner's previous knowledge/experience as well as spatial abilities (Yang, Andre & Greenbowe, 2003; Cohen & Hegarty, 2007; Hegarty & Kriz, 2007). Spatial visualisation ability, in this context, is defined as the "processes of apprehending, encoding, and mentally manipulating spatial forms" (Carroll, 1993). The reported experiment controls for prior knowledge and spatial ability through focussing on novel skill acquisition by novice learners and using a minimised stratification technique for the random assignment of the learners (Conlon, & Anderson, 1990). The approach is also consistent with the conceptualisation of a separate and distinct WM motor processor for the processing of biologically primary knowledge (Wong et al., 2009). It however extends this concept to investigate the independence of the learner's spatial abilities from the interaction between dynamic instructions and motor skills acquisition.

The reference cognitive framework for this experiment is the hybrid cognitive learning model proposed in Chapter 2 (see Figure 2.4). It combines behaviourist and cognitivist perspectives of cognition to define the role of the abstract mental referent that is created in the acquisition of a novel procedural skill. The experiment however focusses on the initial stages of novice trainees learning a procedural skill, which is characterised by the generation of an abstract task referent that drives execution.

3.3 Aims

The experiment was conducted to answer the research question: Are instructional interfaces that afford dynamic information, such as video and interactive, more effective than static pictures/diagrams in learning motor skills by novice trainees? The hypotheses are as follows:

Null Hypotheses

H_{00} Instructions with more dynamic visualisation contents would have no effect on the post-learning performance time of a procedural motor skill by the novice learner as compared to those with equivalent static visualisation alternatives.

H_{01} Instructions with more dynamic visualisation contents would have no effect on the post-learning performance accuracy of a procedural motor skill by the novice learner as compared to those with equivalent static visualisation alternatives.

H_{02} The interaction of instructional interface dynamism and post-learning performance of a procedural motor skill would be dependent on the novice learner's spatial visualisation ability.

Alternate/Positive Hypotheses

H_{11} Instructions with more dynamic visualisation contents would yield faster post-learning performance of a procedural motor skill by the novice learner than those with equivalent static visualisation alternatives.

H_{12} Instructions with more dynamic visualisation contents would yield more accurate post-learning performance of a procedural motor skill by the novice learner than those with equivalent static visualisation alternatives.

H_{13} The interaction of instructional interface dynamism and post-learning performance of a procedural motor skill would be independent of the novice learner's spatial visualisation ability.

3.4 Method

3.4.1 Design

A between-groups experimental design was used to compare the performances of three different groups of participants while carrying out a post-learning phase disassembly/assembly task. First, participants completed the Paper Folding Test (Ekstrom, French, Harman, & Dermen, 1976) to measure their spatial visualisation abilities. The spatial visualisation ability scores are used as a covariate in later analysis of the data to control for any confounding effect on the task performance measures. Participants were then randomly assigned based on gender and spatial visualisation abilities minimisation stratifiers (Conlon, & Anderson, 1990) to the three levels of the instructional interface type independent variable - *static*, *video* and *interactive*. The dependent variable was performance with dependent measures being total task execution time (in seconds) and task execution accuracy (number of errors). The total task execution time refers to the time taken by each participant to complete the disassembly/assembly task after exposure to a particular instructional interface to learn that task. It was regarded as a valid measure of the quality of the instructional interface consistent with the approaches of previous related research (Ayres et al., 2009; Wong et al., 2009). The quality and effectiveness of the instructional interface to engender motor skills was also evaluated by the accuracy of task execution after exposure to the training interface. This was reflected in the number of errors observed by each participant and counted during the later analysis of the video footage of task execution.

3.4.2 Participants

Ninety-one aircraft maintenance engineering trainees (3 women and 88 men, between the ages of 16 and 40 years, M = 23.5, SD = 4.5) were paid N500.00 (equivalent to about £2.50) for voluntary participation in the experiment. All participants were new recruits on the Aircraft Engineering Technology Diploma programme at the Air Force Institute of Technology (AFIT), Kaduna, Nigeria. They had at least the West African Examination Council Certificate (WAEC)[1] and were classified as novices with no prior engineering practice experience. Local ethical rules based on the British Psychological Society (BPS)[2] guidelines were complied with to ensure safety and wellbeing of all participants.

3.4.3 Materials

Participants disassembled a specially devised LEGO™ truck model, replaced a specified component, and reassembled the model after exposure to the instructional interface for learning the task. The truck model provides a good representation of

[1] www.waecnigeria.org
[2] http://www.bps.org.uk/what-we-do/ethics-standards/ethics-standards

typical motor tasks encountered in engineering maintenance and was also equally novel to all the participants as evident through a pre-test questionnaire (see below). The model truck measures 20x20x9 cm and 22 sequential procedural steps were required to execute the required task. The instructions were delivered on a Toshiba Portege M800 running under Windows 7 Professional and connected to an external 17" HP L1950g monitor, a standard keyboard and a PS2 optical mouse. Video footage of participant's execution of task was captured using minoHD Flip Model F460 video camera and transferred to the laptop hard drive for later analysis.

A pre-test questionnaire asked participants to report their names, age, gender, academic qualifications and any previous experience with LEGO or similar models. Similarly, a post-test questionnaire was used to capture the participant's assessment of the training interface. It consists of five questions asking the participants to rate on a scale ranging from 1 (Very easy) to 5 (Difficult) how easy, responsive, confusing, helpful or interesting they thought the training interface was. Samples of the pre- and post-test questionnaires along with the experiment's briefing sheet/consent form are included in Appendix B of this thesis.

With regards to the Paper Folding Test (Ekstrom et al., 1976), the test taker is asked to imagine that a piece of paper is folded and a hole punched through it. The requirement is to choose from a set of possible choices, which figure will show the result when the paper is unfolded. The licence granted by the Educational Testing Service (ETS)[3] to the author for the use of this test is included in Appendix B.

The instructions for the *static* group were delivered as a Microsoft PowerPoint 2007 presentation consisting of 13 slides. The first and second slides contained general information on the task requirements while the remaining 11 slides presented pictures of sequential procedural steps required for executing the disassembly task. Two pictures were presented for each step of the procedure with the first/upper picture showing the state of the model before and the second/lower picture showing the state after the execution of the instruction for that particular procedural step. The instruction for each procedural step is included as text contiguous to the pictures on the same slide. Visual cues were used to identify the component of interest at each procedural step and controls were provided for forward and backward navigation of the slide sequence. The assembly instructions are a reverse

[3] www.ets.org

presentation of the 11 disassembly slides with the upper and lower pictures switched. Additionally, the participant is instructed to 'attach' the components as opposed to 'detach' in the disassembly instructions. A sample screenshot for the *static* instructions interface is shown in Figure 3.1.

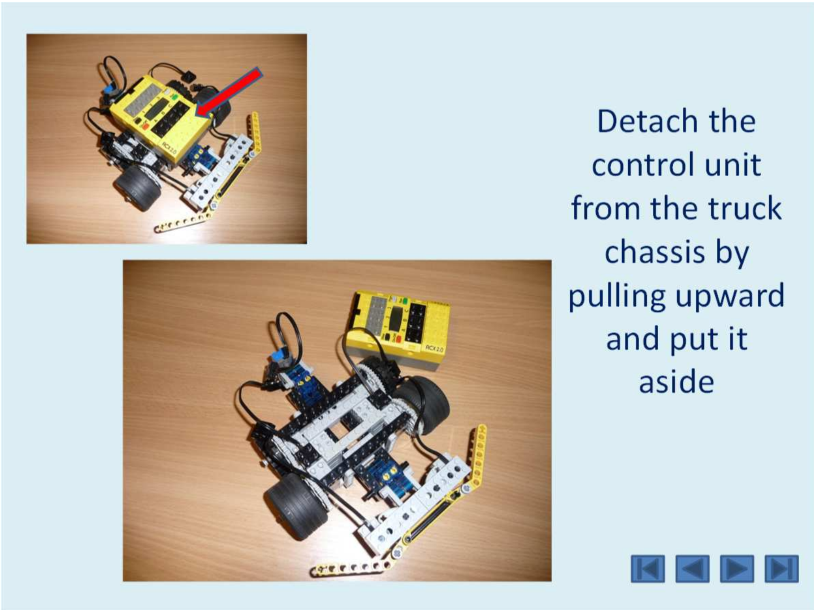


Figure 3.1 Sample screenshot of the *static* instructions interface

The *video*-based instructions were also presented as a Microsoft PowerPoint 2007 slide show similar to the *static* instructions with the exception that all the static step-wise pictures were replaced with equivalent short video clips. The video clips were created by recording the execution of the entire disassembly/assembly process in a studio equipped with apparatus to ensure evenly distributed lighting. The process was repeatedly recorded until a skilfully executed, error-free footage was obtained. The video was then broken down into 22 short clips showing single procedural steps of the process using Windows Live Movie Maker 2009. The clips are on average 22 seconds long with the longest at 49 seconds and the shortest 4 seconds. Each clip was then presented as individual PowerPoint slides arranged in the sequence for executing the task. The instruction for each procedural step is included as text contiguous to the video clip on the same slide. The participant is able to navigate forward or backward through the slide sequence as well as repeat the playback of the clip in each slide. A sample screenshot for the *video* instructions interface is shown in Figure 3.2.

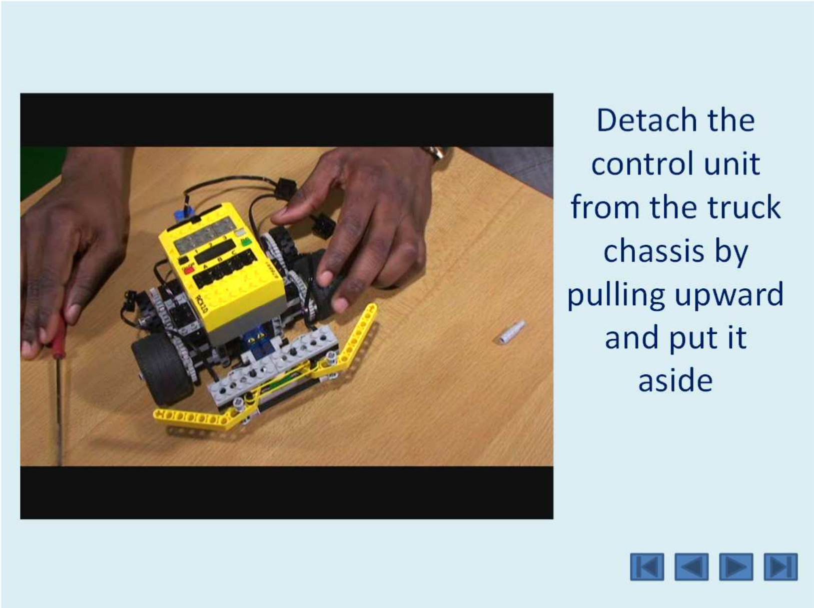


Figure 3.2 Sample screenshot of the *video* instructions interface

The instructions for the third group were presented via an *interactive* interface that allowed the participants to manipulate virtual components of the model in a simulation of the disassembly/assembly task using the mouse. A high definition video of the process similar to that used by the *video*-based group was rendered as a sequence of static pictures using Adobe Photoshop™ CS4 Extended. A Java program was then written to stitch together the rendered sequence of static pictures and produce simulated movement of each individual component using the mouse press and drag feature. The instruction for each procedural step is included as contiguous text that was presented as soon as the previous step is completed. Participants were also able to repeat the simulation and the virtual components were designed to detach/attach along the same trajectories as applicable for their equivalent physical truck component. A sample screenshot for the *interactive* instructions interface is shown in Figure 3.3.

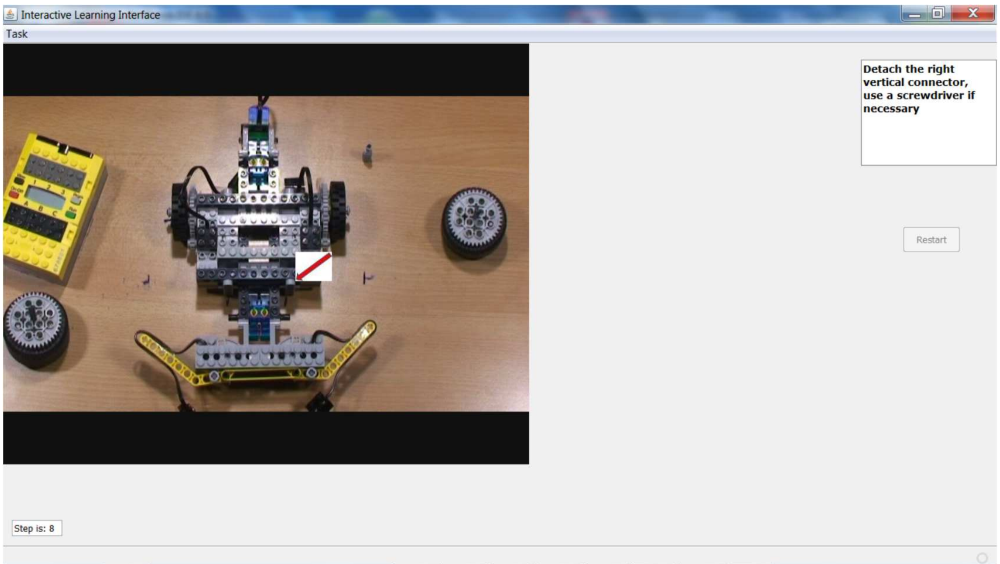


Figure 3-3 Sample screenshot of the *interactive* instructions interface

3.4.4 Procedure

All the participants were assembled in a hall and given general information about the experiment. After obtaining informed consent, they completed the pre-test questionnaire and three participants were excluded from further participation at this stage because they reported prior experience with LEGO models. Next, participants completed the Paper Folding Test (Ekstrom et al., 1976) and were randomly assigned to the three experimental groups. Subsequent participation was in individual sessions based on the instructional interface grouping but utilising a similar procedure across the groups. First, the participant is given some practice in manipulating the instructional interface using a separate but similar example interface. The example interface shows the disassembly/assembly of a pen and was designed in the same format as the experimental group instructional interface. After becoming familiar with the interface and its controls, the participant is allowed access to the actual instructional interface to learn the disassembly/assembly process without interference. The participant was allowed up to 10 minutes for this learning phase and could indicate readiness to commence the testing phase (disassembly/assembly of the physical truck model) at any time or would be asked to do so when the time allowed is up. It is important to note that none of the participants exceeded the allowed learning time nor were able to see the physical truck model during the learning phase. Furthermore, participant no longer had access to the instructional interface once the testing phase has commenced. Participants were allowed a maximum of 15 minutes to complete the testing phase and their performance was recorded in high definition video for later analysis. Determination of the timing of the learning and testing phases was based on the outcome of prior pilot experiment sessions as well as on the approaches adopted in previous related studies (see Ayres, et al., 2009; Imhof, Scheiter, & Gerjets, 2011). The participant then completed a post-test questionnaire to report how the instructional interface they were exposed to aided their subsequent task performance.

3.4.5 Data Capture

Performance time and accuracy for each participant were scored by analysing captured video data. Video data were analysed by 3 independent reviewers and discrepancies in the scores were resolved through consensus. Only the first 11 procedural steps constituting the disassembly of the model were analysed. The reassembly portion (steps 12 - 22) was not analysed as many of the participants (about 40%) failed to proceed substantially beyond the 11th procedural step. Data from 7 participants were also omitted from the final analysis for the following reasons; 1 due to video equipment failure, and 6 for failure to comply with the required procedure. Task time was measured in seconds starting from the detachment of the first component and ending with the successful removal of the last component. In 20 instances, the time spent to retrieve components accidentally dropped on the floor during the procedure was discounted from the total task time. With respect to task accuracy, every deviation from the procedural sequence outlined in the instruction was counted as an error. However, all other occurrences that are not linked to the task sequence, such as accidentally dropping components on the floor were not counted as errors.

3.5 Results

The data was summarised and means and standard deviations for task performance times, error counts and spatial visualisation ability scores of the *static*, *video* and *interactive* instruction groups are shown in Table 3.1. The data was analysed using SPSS™ version 17 and the statistical modelling outputs are presented in Appendix B. A Kolmogorov-Smirnov test of normality showed that the task performance time and error measures were not normally distributed ($p < .05$ in both measures). As a result, non-parametric tests were used as tests of differences for both measures. The observed distribution of task performance measures is consistent with previous related studies (see Ayres et al. 2009; Wong et al. 2009). Alpha level was set at .05 and Kruskal-Wallis tests revealed statistically significant differences in task performance times, $\chi 2$ (2, 81) = 8.03, $p < .05$ and error counts $\chi 2$ (2, 81) = 23.3, $p < .01$ across the three instructional groups. The *static* group recorded the highest median score for task performance times (Md = 123) and error counts (Md = 5). The median score for task performance times (Mdt) and error counts (Mda) of the other groups are: video (Mdt = 97, Mda = .5), interactive (Mdt = 94, Mda = 1).

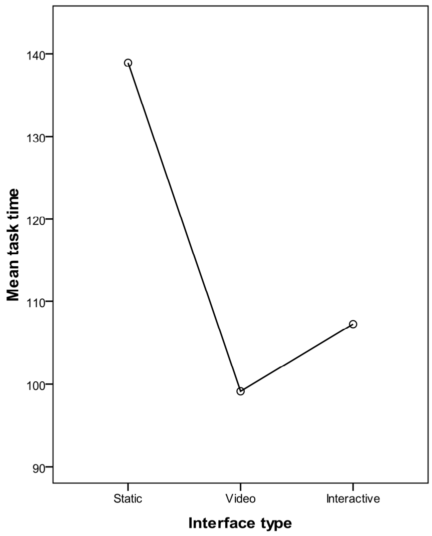
	Instructional interface group								
	Static			Video			Interactive		
	N	M	SD	N	M	SD	N	M	SD
Task time *(s)*	26	138.92	55.44	28	99.14	31.08	27	107.26	44.19
Task errors	26	4.88	3.15	28	1.21	1.40	27	1.52	1.40
Test scores	26	7.27	2.51	28	7.61	2.70	27	8.59	3.64

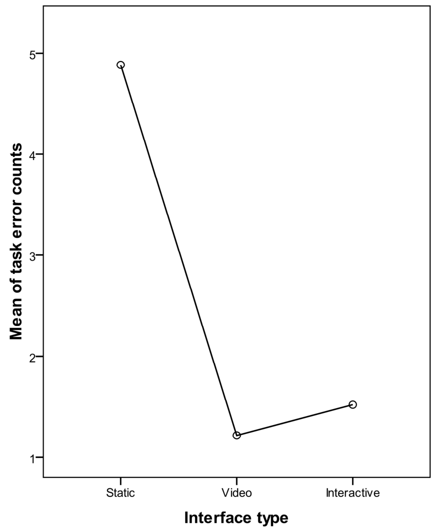
Table 3.1 Means and standard deviations for the instruction groups

After a Bonferroni adjustment, the alpha level was set at .025 and post-hoc Mann-Whitney U tests indicated that the *static* group took significantly more time to complete the task than the *video* ($Z = -2.62$, $p < .025$, $r = .29$) and *interactive* groups ($Z = -2.25$, $p < .025$, $r = .25$). Additional Mann-Whitney U tests also indicated that the *static* group were significantly less accurate in the task performance than the *video* ($Z = -4.35$, $p < .025$, $r = .48$) and *interactive* groups ($Z = -3.9$, $p < .025$, $r = .43$). There were no statistically significant differences between the task performance times ($Z = -.34$, $p > .025$) and error counts ($Z = -.93$, $p > .025$) of the video and interactive groups.

The spatial visualisation ability scores were normally distributed (Kolmogorov-Smirnov $p > .05$). A one-way between groups ANOVA, with instructional interface type as the independent variable, revealed no statistically significant difference, $F (2, 78) = 1.41$, $p > .05$, in the spatial ability scores of the groups. Two one-way between groups ANCOVAs were further conducted with the spatial visualisation ability scores as covariate to check for confounding effects of the participant's spatial abilities. The independent variable remained instructional interface type while dependent variables were task performance time and error count respectively. Preliminary checks were conducted to ensure that the covariate met the assumptions of the procedure. Following adjustment for spatial ability scores in the first ANCOVA, there was a significant difference in task performance times $F (1, 77) = 5.52$, $p < .01$, partial eta squared = .13. There was no significant effect of spatial visualisation ability scores on the task performance times $F (1, 77) = 3.42$, $p > .05$, partial eta squared = .04. Similarly, after adjusting for spatial visualisation ability scores in the second ANCOVA, there was a significant difference in task performance error counts $F (1, 77) = 23.24$, $p < .01$, partial eta squared = .38. There was no significant effect of spatial visualisation ability scores on the task performance error counts $F (1, 77) = 1.19$, $p > .05$, partial eta squared = .02.

As depicted in Figure 3.4, the *video* and *interactive* groups were 40% and 30% faster than the *static* group while Figure 3.5 further shows that the two groups (*video* and *interactive*) were 303% and 221% more accurate than the *static* group respectively. Correlations between self-reported assessment of the training interface and the instructional interface type are shown in Table 3.2. There were no significant correlations between the self-reported measures and the instructional interface type. These measures were therefore excluded from subsequent analysis. Overall, these results provide evidence to support the alternate hypothesis that more dynamically complete information (such as video and interactive) will yield significantly higher rates of skill acquisition when learning a novel motor task.





Figures 3.4 & 3.5 Mean task time and error count for the instructional groups

	1	2	3	4	5
1. Ease of use	-	-	-	-	-
2. Responsiveness	.116	-	-	-	-
3. Degree of confusion	-.174	-.119	-	-	-
4. Helpful interaction	.190	.207	-.135	-	-
5. Interesting interface	.036	.194	.048	.105	-
6. Interface type	-.063	.085	-.049	.041	.021

(N = 81)

Column Headings

1. Ease of use
2. Responsiveness
3. Degree of confusion
4. Helpful interaction
5. Interesting interface
6. Interface type

Table 3.2 Self-reported interface assessment and instructions group correlations

3.6 Discussion

The experiment investigated the interaction between procedural motor skill acquisition and the dynamism of interface visualisations by comparing the post-learning task performances of three groups of participants. It was proposed that the training interfaces that contain dynamic information showing the continuous stages of execution of the target motor skill would yield faster task performance times and fewer errors than other static interfaces independent of the learner's cognitive abilities. The results of the experiment provide initial evidence to support this view as participants that learned the tasks via interfaces with more dynamic informational content (video and interactive) performed significantly faster and more accurately than other participants that use the interface lacking such information (static). Null hypotheses H_{00} and H_{01} were therefore rejected and the alternate hypotheses H_{11} and H_{12} were accepted. Arguably, the results also suggest that the *video* and *interactive* groups were able to construct a more accurate and complete mental representation of the task than the *static* group, which subsequently aided their better performance. They may have been able to do this because they had a richer set of input stimuli including transitory and dynamic movements involved in manipulating the device components to achieve the motor task. These results are consistent with the findings of Höffler and Leutner (2007) and Ayres et al. (2009) that realistic animations portraying procedural motor knowledge are more effective than statics for learning procedural tasks. However, while the experiment replicated these findings, it further extended the definition of dynamic interfaces to include interactive interfaces that are directly manipulated by the participants. It was observed that such interactive interfaces were equally effective because they afford procedural motor knowledge and the dynamic information related to the movement of the device components.

The procedural task executed in the experiment involves a series of carefully coordinated psychomotor movements to achieve the overall disassembly task. In the context of procedural learning, Smith and Ragan (2005) have defined procedures as "… series of steps initiated in response to a particular class of circumstances, to reach a specified goal" (p. 205). More importantly, Smith and Ragan (2005) also observed that psychomotor actions have a cognitive element and involves the integration of muscular movements with a procedural rule. This "rule-governed aspect of motor skill performance" provides the sequencing control required for skilled task execution (Gagné, 1985; Gagné, Briggs, & Wager, 1992, p. 93). It is arguable therefore that the extent to which the instructional interface is able to support the creation of accurate mental task models in the acquisition of novel procedural motor skills, may be directly related to the dynamic, procedural-motor information that is intrinsic to the interface. This intrinsic procedural-motor information content of the training interface reflects the qualitative association between the target motor skill and the interface. It may define the capacity of the instruction delivery format to capture the motor coordinating information intrinsic to the execution of skilled procedural motor tasks such as the manipulation of mechanical components and devices. It may also affect novel motor skill acquisition by enabling a more accurate construction of the mental task model, which drives subsequent task performance. Using a related argument, Van Gog et al. (2009) have suggested that the mirror neuron system might help explain why instructions with dynamic visualisation content are more effective than statics for learning human motor tasks. The experiment results provide indirect support of this view although it did not attempt to address it specifically. The focus has been on using a simple human motor task only whereas a dual approach that includes a non-human motor task, such as motor action in monkeys, will be more appropriate to investigate the mirror neuron paradigm (see Rizzolatti, 2005).

The concept that an intrinsic quality of the training medium is associated with the target skill set presents an intriguing insight into the supportive role of interface visualisation especially with respect to the cognitive characteristics of the trainee. Establishing this concept however will require the definition of this quality, which the experiment results do not provide. A more precise methodology that can examine the detailed cognitive processes involved in constructing the abstract task representations as well as how this drives subsequent performance would be required. Further experiments would also be required to investigate the intrinsic supportive role of the interface visualisation in a different knowledge domain from procedural motor skill acquisition. This proposed associative construct is developed further in Chapter 6 of this thesis through computational modelling techniques using the ACT-R cognitive architecture (see Anderson et al., 2004; Anderson, 2005). The cognitive computational modelling effort is focussed on decompiling the intertwined role of stimuli perception, declarative recall and motor control that is evident in the post-learning task performances. Prior to this however, the cognitive role of the associative construct is explored further in experiments that investigate other knowledge domains and learner characteristics. These experiments are presented in the next 2 chapters of the thesis.

Interestingly, the results of the current experiment do not show statistically significant interaction between spatial visualisation ability and subsequent task performance measures. This is in contrast to the view expressed by Cohen and Hegarty (2007) and Hegarty and Kriz (2007). It is suggested that the redefinition of the cognitive role of abstract mental task representations as described in the introductory section of this chapter has given a clearer picture of the effect of spatial abilities especially with reference to novice learners. Hypothesis H_{02} was therefore rejected and hypotheses H_{13} accepted. Additionally, Smith and Ragan (2005) have proposed that in order to demonstrate procedural learning, the learner must be able to apply hypothetical mental models or 'productions' of thought through the recognition, recollection and application of a procedure. Therefore, 'knowing' the steps of a procedure is not enough but a demonstration of the knowledge is required through the actual application of it. Consistent with this, it may be argued that using the actual execution of motor tasks to assess the post-learning effectiveness of the instructional interface is more appropriate for measuring skill acquisition than using probing questions, which are designed to infer implicit behavioural changes.

3.7 Limitations of the Results

It was argued that the interaction between instructional interface dynamism and skill acquisition may be knowledge-domain dependent. This experiment however is limited to computer based skill acquisition in the procedural-motor knowledge domain only. In particular, it focusses on procedural motor skill acquisition by novice aircraft engineering trainees. More studies involving other skill acquisition/knowledge domains as well as more heterogeneous learner groups would be required to generalise the results. Such studies are the subject of further experiments that were conducted and reported in the next 2 chapters of the thesis. Additionally, it is arguable that constraining access to the instructional interface during actual task execution is counterintuitive and reduces the overall impact of the experiment methodology approach. This constraint is however acceptable as it is consistent with the methodology adopted in previous relevant studies that were reviewed. Moreover, the objective of the experiment was to investigate the cognitive effect of different levels of instructional dynamism on early stage post-learning performance only. The experiment design was further guided by an additional objective of contributing to the extant literature through an extension of the definition of dynamic interface visualisations to include those that afford interactive manipulation of virtual components in the learning context.

3.8 Conclusion

In conclusion, this experiment has arguably provided evidence for a motor associative factor of an instructional interface, which supports procedural motor skill acquisition. The results show that learning novel procedural skills from dynamic interfaces with intrinsic motor information content may be more effective than using static interfaces irrespective of the learner's cognitive abilities. The learner's cognitive abilities, in this context, refer to the spatial visualisation abilities as measured by the Paper Folding Test and used as a covariate in the statistical analysis. The results however are limited by a focus on the acquisition of procedural-motor knowledge by novices only. Consequently, a further experiment was conducted to investigate the interaction of instruction interface dynamism with post-learning task performance in the different knowledge domain of spatial navigation skills. This experiment is reported in Chapter 4.

Chapter 4

Experiment 2 – Acquisition of Novel Spatial Navigation Skills

4.1 Overview

The work reported in this chapter extends the findings of the previous experiment to investigate the cognitive effect of dynamic versus static instructional visualisations in a different domain of procedural skill acquisition. Experiment 1 reported in Chapter 3 argued that the cognitive benefit of dynamic over static instructional visualisations for learning novel skills may be domain-specific and independent of the learner's spatial visualisation ability. Experiment 2 reported in this chapter extends these findings through empirical investigations to the different domain of the acquisition of novel spatial navigation skills.

4.2 Mental Representations in Domain-specific Cognitive Task Processing

The representational theory of mind proposes that our experiences and activities are underpinned by mental representations (Chandrasekaran, Banerjee, Kurup, & Lele, 2011). The exact nature of these representations is still subject to debate but a widely received view is that of the mental imagery theory (Kosslyn & Pomerantz, 1977; Pylyshyn, 2002; Kosslyn, 2005; Kosslyn, Shephard, & Thompson, 2007). Importantly, the mental imagery theory distinguishes between perception and mental imagery. Perceptual representations require external stimuli, but mental imagery refers to representations that exists or persists in the absence or after the removal of the stimuli. The mental imagery theory is particularly well developed with respect to visual perception and visual mental imagery. A core component of the theory is the retinotopical similarity in the neuro-architecture for visual perception and visual mental imagery, which has also been established in other related neuroscience research (Tootell, Silverman, Switkes, & De Valois, 1982; Fox, Mintun, Raichle, Miezin, Allman, & Van Essen, 1986; Fox, Miezin, Allman, Van Essen, & Raichle, 1987; Yang, Heeger, & Seidemann, 2007). In the mental imagery theory, this neuro-architectural similarity is defined through the visual buffer component. During visual perception, the visual buffer is thought to encode the object (shape, texture and colour) and spatial properties of the stimulus. Visual mental imagery however is the result of an 'unpacking' process through which a mental representation akin to the original visual stimulus is sequentially reconstructed in the visual buffer. An attention-shifting mechanism evident in visual perception is also active in visual mental imagery through which retrievals from long-term memory are sequentially integrated for the reconstruction of the mental image (Kosslyn, 2005).

This thesis proposed a hybrid cognitive learning model in Chapter 2 (see Figure 2.6), which is consistent with the mental imagery theory and integrates modal and amodal paradigms of the cognitive processing that underpins the acquisition of novel procedural skills. This model suggests that an abstract mental referent is created as part of the cognitive processing involved in procedural skill acquisitions. The model further emphasizes the active referential role of this mental representation in subsequent task performances especially at the early novice learner stages. More importantly though, the model extends the mental imagery theory with the addition of a third motion component to the visual buffer to explain the comparative benefit of dynamic instructional visualisations over static components in the acquisition of such procedural skills. Dynamic visualisations afford stimuli that can intrinsically encode transitory information inherent in the external percept. This intrinsic information is encoded through the motion component of the expanded visual buffer as well as in long-term memory. The additional information encoded through the motion component arguably improves the fidelity of the subsequent mental referent resultant of the 'unpacking' process in sequential mental imagery reconstruction, thus accounting for improved task performances associated with the dynamic instructional components. Experiment 1 reported in Chapter 3 of this thesis provides initial evidence for the cognitive benefit of the intrinsic transitory information afforded by dynamic visualisations over equivalent static alternatives. The experiment reported however was limited to investigating novel procedural skill acquisition in the motor knowledge domain only. Experiment 2 reported in this chapter extends the investigation by applying the proposed hybrid cognitive learning model to novel learning in another procedural knowledge domain namely, spatial navigation.

4.3 Sequential Representations in Spatial Navigation

Traditionally, spatial navigation planning has been defined as a multi-level problem solving process (Timpf, & Kuhn, 2003; Zhang, 2008; Holscher, Tenbrink, & Wiener, 2011). The relevant cognitive level components of this process include perceptual scanning, knowledge-based retrievals and memory-based decisions (Reitter & Lebiere, 2010). In viewing spatial navigation as a sequential process, the memory-based decision making process is considered as the core of the model depicted in Figure 4.1.

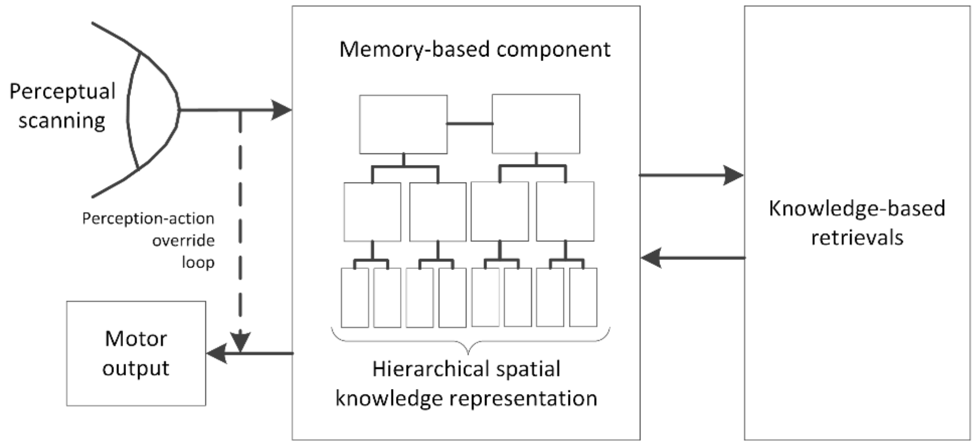


Figure 4.1 A model of cognitive processing components of spatial navigation

Visually perceived information is integrated with knowledge-based retrievals in this core component to determine executive actions in the resolution of navigational problems. From a cognitive architecture perspective, spatial knowledge representations have been modelled with different abstract structures including algebraic framework (Banerjee, & Chandrasekaran, 2010), multi-dimensional arrays (Glasgow, 1998; Lathrop, & Laird, 2007) and multi-layered hierarchies of spatial/object properties (Kosslyn, 2005). Conceptually however, acquired spatial knowledge is thought to exist either as survey way-planning or sequential route representations (Thorndyke & Hayes-Roth, 1982; McNamara & Shelton, 2003). The survey representation is an allocentric, map-like view of spatially laid out landmarks organised within a common reference system. The route representation on the other hand is egocentric and consists of sequentially organised spatial locations encoded along with respective action objects, which are executed in support of a navigational task.

Within the context of the acquisition of novel spatial navigation skills, previous studies have established an association between the initial learning perspective and spatial knowledge representations. The effect of this association on subsequent navigation performance is however still subject to debate (see Denis, 2008; Shelton & McNamara, 2004; Pazzaglia & Taylor, 2007). The acquisition of novel navigation skills may be viewed as a sequential process in general, where spatial knowledge representations of the task environment are developed incrementally as the learner interacts with the instructions. This sequential view of spatial knowledge acquisition is consistent with the neuroscience research of brain structures that support navigation performance. For instance, the posterior parietal cortex has been implicated in the sequential integration of visual and motor signals for navigation task decision-making (Gold, & Shadlen, 2007; Andersen, & Cui, 2009; Freedman, & Assad, 2011). More importantly, empirical evidence has further suggested that the acquisition of spatial navigation knowledge is cognitively sequential (Nitz, 2006; Harvey, Coen, & Tank, 2012). This may imply therefore that external factors such as the composition of task instructions will have an effect on the construction of mental spatial representations and post-learning navigation performance. Other factors that have been shown to affect navigational performance include the learner's age (Moffat, Elkins & Resnick, 2006; Rogers, Sindone III and Moffat 2012), gender (Dabbs, Chang, Strong & Milun, 1998; Coluccia & Louse, 2004), spatial abilities (Pazzaglia & DeBeni, 2006; Meneghetti, DeBeni, Pazzaglia & Gyselinck, 2011) and the nature and characteristics of the task environments (Moffat, Hampson & Hatzipantelis, 1998; Waller, 2000; Richardson, Powers & Bousquet, 2011).

4.4 Experiment Objectives

The experiment was conducted to investigate the effect of dynamic visualisation components of instruction versus equivalent static alternatives on novel post-learning navigation performance using a virtual environment. A virtual navigation environment was chosen because it is flexible and can be readily manipulated to capture the dynamics of survey (static) vs route-oriented spatial knowledge acquisition. Available technology also affords the creation of virtual environments with high levels of presence, which can promote natural behaviour that are evident in real world navigation tasks. The following hypotheses were stated:

Null Hypotheses

H_{00} Equivalent dynamic or static visualisation components of an instructional interface would result in equal comprehension and post-learning performance of a novel spatial navigation task.

H_{01} The interaction of instructional interface dynamism and post-learning performance of a novel spatial navigation task would be dependent on the novice learner's spatial orientation ability.

Alternate/Positive Hypotheses

H_{11} Dynamic visualisation components of an instructional interface would support the creation of more complete and efficient mental models of a novel spatial navigation task than equivalent static visualisation alternatives.

H_{12} The cognitive benefit of more efficient mental models of a novel spatial navigation task afforded by dynamic visualisation components of the instruction interface over equivalent static alternatives is due to an intrinsic motion attribute of the dynamic visualisations.

H_{13} The more efficient mental models afforded by dynamic visualisation components of the instructional interface over equivalent static alternatives would yield faster post-learning performance of a novel spatial navigation task.

H_{14} The more efficient mental models afforded by dynamic visualisation components of the instructional interface over equivalent static alternatives would yield more accurate post-learning performance of a novel spatial navigation task.

H_{15} The more efficient mental models afforded by dynamic visualisation components of the instructional interface over equivalent static alternatives would yield more robust post-learning performance of a novel spatial navigation task (i.e. faster recovery from errors or deviations to the optimal route).

H_{16} The interaction of instructional interface dynamism and post-learning performance of a novel spatial navigation task would be independent of the novice learner's spatial orientation ability.

4.5 Method

4.5.1 Design

A 2 x 3 mixed factorial design was used to compare the post-learning navigation performances of groups of learners. The between-groups factor contrasts the performances of the groups by manipulating the dynamic visualisations content of the instructional interface. There were two levels of the intervention – static and dynamic. These levels refer to the different interface visualisations used for presenting equivalent spatial information for learning an optimal route though a virtual environment. The within-group factor was designed to compensate for the effect of task complexity, which was identified as a possible covariate from a pilot run of the experiment. Three levels of the navigation tasks in a novel virtual environment were designed to be performed in the order of increasing complexity. The first level was designed to be simple as navigational performance at that level is arguably still subject to the effect of learning to control movements in the novel virtual environment. The third level navigation task on the other hand was quite complex as it was designed to overwhelm participant's cognitive processing resources. Extended analysis was therefore limited to the performance on the level two task only, which was designed to be of medium complexity and less subject to the participant's unfamiliarity with the virtual environment and movement controls. The within-group aspect also extends the investigation to observe an expected convergence of performance due to the practice effect.

The dependent variable was navigational performance measured by the travel path length and time, route completion rate and route retrieval robustness. The path length is defined as the total distance travelled while navigating a designated optimal route through the virtual navigation environment. The path time is the corresponding navigational time measured in seconds. Travel path length and time have been identified as valid navigation performance measures in previous related research (Richardson et al., 2011). The route completion rate is the mean count of all successfully completed navigation trials along the optimal route expressed as a percentage of the total trials performed by each experimental group. The efficiency of route error recovery (i.e. route retrieval robustness) is the ratio of the furthest point reached along the optimal route to its total length. It assesses the depth of the participant's spatial knowledge representation of the optimal route as acquired from interacting with the instruction. It's also a measure of the participant's robust navigational performance, which reflects the efficiency of recovery from deviations along the optimal route. All the performance measures were bounded by a specified time limit. Furthermore, the effect of the learner's spatial orientation ability and prior video gaming experience on the performance measures were controlled.

4.5.2 Participants

Sixty students at Robert Gordon University (42 males, 18 females, mean age = 24.25, SD = 1.06) were paid £10.00 each for voluntary participation in the experiment. Local ethics rules as well as the BPS guidelines were complied with to ensure the well-being of all participants.

4.5.3 Materials

4.5.3.1 Virtual Navigation Environment

Three levels of a virtual maze environment were created for navigation with an increasing order of complexity; Level One – Easy, Level Two – Medium and Level Three – Hard. The mazes were designed and implemented with the MazeSuite application (Ayaz, Shewokis, Curtin, Izzetoglu, Izzetoglu, & Onaral, 2011). Each maze was designed to have one optimal navigation route from a start point to a marked end point. The optimal routes are divided into curved and straight-line segments bounded by the start, turning and end points. There are 11, 24 and 39 straight line segments in maze levels one, two and three respectively. Additionally, the levels two and three mazes have one and two curved segments respectively. Movement in the mazes is controlled by a Cyborg FLY 5 joystick. Translations are executed by pushing the joystick forward or pulling it backward. Turnings/rotational movements are executed by pushing the joystick left or right during translations or while stationary. The virtual mazes are presented to the participant on an HP Compaq 8200 Elite SFF running under Windows 7 Enterprise 64-bit. The PC is connected to an HP L1950g 19" LCD monitor that affords 110^0 horizontal and 58^0 vertical field of view of the virtual navigation environment. A separate console comprising a similar monitor and associated keyboard/mouse were connected to the PC for the experiment procedural control. A screenshot of the view while navigating part of the level two maze is shown in Figure 4.2.

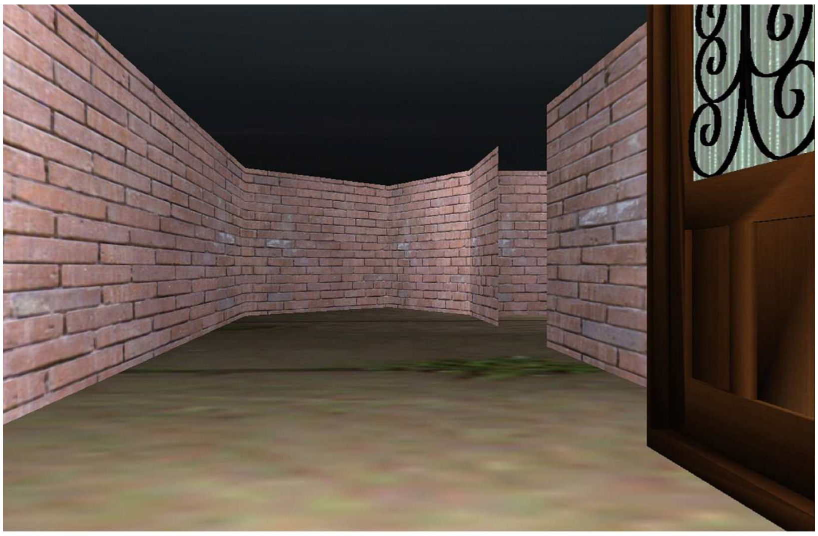


Figure 4.2 Sample screenshot of the virtual navigation environment

4.5.3.2 Navigation Instructions

The two levels of navigation instructions – static and dynamic – are presented through a macro-enabled Microsoft PowerPoint 2007 slideshow consisting of 15 slides. Slides 1 – 4, 7, 10, 13, and 15 provide textual instructions for general guidance. Slides 6, 9, and 12 are blank spacer slides for procedural control of the experiment while the different navigational instructions are presented interchangeably through slides 8, 11, and 14. The corresponding practice instructions for the different learner groups are presented on slide five. The instruction for the static group is a line map of the maze showing the walls as black lines against a white background and the optimal route as a green trace. The direction of movement along the optimal route is indicated by start and endpoint labels as well as directional arrows at the segment boundaries. Star-shaped links are inserted at all segment boundaries along the optimal route. Placing the mouse pointer over these links activates macro modules that display an egocentric view of the maze environment as the corresponding segment boundary is approached. The egocentric views are displayed in an embedded 240 x 300 pixels window placed closed to the corresponding boundary segment on the same slide. The displayed image and embedded window position are automatically updated as the mouse pointer is moved to other segment boundary links either in sequential or random order. The map also shows the location of reference landmarks such as static objects or parts of the maze walls with a different colour/texture from the immediate surrounding walls. A screenshot of the static instructions interface for the level two maze, which includes the embedded in-maze view window, is shown in Figure 4.3.

The dynamic group instruction on the other hand is an animation showing a single navigational run through the respective maze levels along the optimal route. The animation is superimposed on the lower left corner with a dynamically updated map showing a trace synchronised with the current location in the maze. The superimposed map however neither shows the location of the reference landmarks nor the direction of movement at segment boundaries, which have to be acquired as the animation is played. The participant may pause, rewind or fast-forward the playback of the animation as required. A screenshot of the dynamic instructions interface for the level two maze is shown in Figure 4.4.

4.5.3.3 Questionnaires

The pre-test questionnaire captures the participant's age, gender, dominant hand used and any disability (specifically dyslexia, epilepsy and related photo-sensitivity). Participants were further asked to report any previous video game playing experience, the period of the experience and the frequency of play at start, peak and current game play experience. A sample of the pre-test questionnaire is included in Appendix C. The post-test participant's self-assessment of performance is reported on five scales of the NASA Task Load Index (TLX)[4]. The physical demand scale of the NASA TLX was excluded from the assessment as the physical effort required for the navigation task is considered negligible and irrelevant for subsequent analysis.

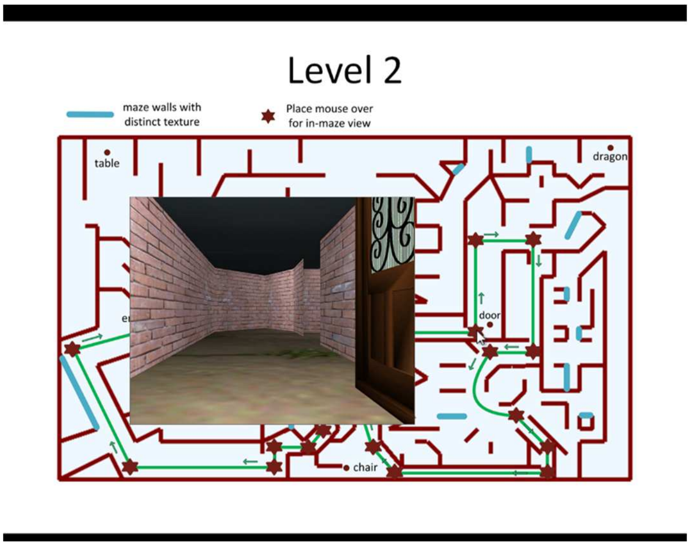


Figure 4.3 Sample screenshot of the static instructions interface

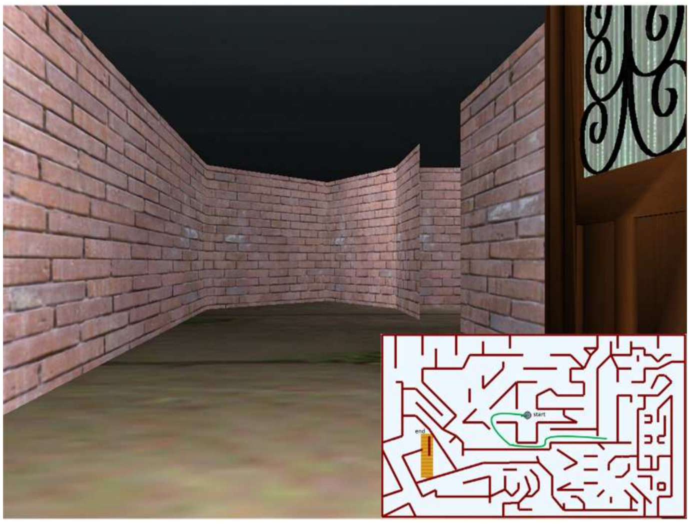


Figure 4-.4 Sample screenshot of the dynamic instructions interface

[4] http://humansystems.arc.nasa.gov/groups/TLX/ (accessed 15 February 2013)

4.5.3.4 Card Rotations Test

The card rotations test (Ekstrom et al., 1976; associated ETS licence is included in Appendix C) was used to measure participant's spatial orientation ability as a potential confounding covariate. It is a two-part test of 10 problems each. For each problem, the test taker is asked to compare a uniquely shaped card with eight other cards of different orientations and required to determine if the first card can be made to look like each of the subsequent eight cards. The uniquely shaped card may be mentally rotated for comparison but cannot be flipped or reshaped.

4.5.4 Procedure

Participants were randomly assigned to either of the two instruction-based learner groups – static or dynamic. The experiment was conducted in individual sessions of 90 minutes on the average. The participant completes the pre-test questionnaire followed by the timed card rotations test. Thereafter, the participant interacts with instruction type specific to his/her learner group seated in front of the monitor. Interaction with the instruction and task execution was sequenced into seven phases as follows – practice, level one instruction, level one task execution (three trials), level two instruction, level two task execution (three trials), level three instruction, level three task execution (two trials). The activities involved in each of these phases are described below.

In the practice phase, the participant is allowed up to five minutes to view sample instructions corresponding to their experimental group and practice controlling movements through the virtual maze environment using the joystick. The practice phase ends when the participant indicates readiness to proceed or automatically, if the allowed time expires. No relevant performance data except the actual practice time were recorded for this phase.

The details of the instruction presentation and task execution phases for the 3 maze levels are similar except for differences in the times allowed for learning and task execution as well as the number of task trials. Maximum learning times of 5, 8, and 15 minutes and task execution times of 4, 7 and 10 minutes were allowed for maze levels one, two, and three respectively. Furthermore in the task execution phases, participants executed three trials each of maze levels one and two and two trials of maze level three. The participant may choose to proceed from the instruction/learning phase to the task execution phase at any time before the expiration of the learning time allowed or would be automatically switched to the task execution phase if the learning time expires. The participant controlled pacing through the instruction slide sequence without interference except for when the experimenter is requested to terminate the learning/instruction phase early and/or load the task execution environment.

Participants' navigational performance was automatically recorded by the MazeSuite application as separate files for each trial run. Each participant's overall performance data was therefore recorded in 8 separate files for subsequent analysis. Lastly, the participant completes the NASA TLX to end the session.

4.5.5 Data Capture and Analysis

Navigational performance dependent measures of travel path length, time, route completion rate and route retrieval robustness were extracted by using the MazeSuite application to analyse the performance files recorded for each participant. The path length was expressed in maze units and path time in seconds. The computed route retrieval robustness ratios were sorted by quarter percentiles into very low, low, normal and high categories based on the static and dynamic instruction groups.

Participant's spatial orientation ability and video game playing experience were further analysed as potential navigation performance confounding variables. The spatial orientation ability was measured by the score achieved on the card rotations test. The video game playing experience is expressed as a composite score calculated from the participant's self-reported amount of game play (how long they've been playing), frequency of play at start (how often they played when they started), frequency of play at peak (how often they played when they were playing the most) and frequency of current game play. Different weights were assigned to these variables in the calculation of the composite score to reflect their relevance to performance on the current virtual navigational task. Data from four participants that reported no previous gaming experience (two each from the static and dynamic groups) were excluded from this analysis in particular. Participant's gender was not analysed as a covariate because of difficulties associated with the recruitment of volunteers for the experiment. The analysis of the data was particularly labour intensive due to the large number of extensively detailed observations afforded by the MazeSuite application. The complete analysis of each participant's performance files took about 90 minutes on average.

4.6 Results

The data was summarised and means and standard deviations of the travel path length (in maze units), path time (seconds), spatial orientation ability scores and composite video gaming experience scores for the static and dynamic groups are shown in Table 4.1.

	Instructional interface					
	Static			Dynamic		
	N	M	SD	N	M	SD
Path Length - Level 1 Trial 1	31	117.26	50.61	29	73.33	4.42
Path Length - Level 1 Trial 2	31	86.37	28.08	29	71.94	2.32
Path Length - Level 1 Trial 3	31	71.76	1.82	29	71.75	2.41
Path Length - Level 2 Trial 1	31	347.17	175.27	29	171.65	97.70
Path Length - Level 2 Trial 2	31	287.00	195.49	29	143.83	66.58
Path Length - Level 2 Trial 3	31	240.46	148.18	29	109.55	6.83
Path Length - Level 3 Trial 1	31	482.09	162.67	29	466.33	234.77
Path Length - Level 3 Trial 2	31	553.70	247.02	29	399.48	220.48
Path Time - Level 1 Trial 1	31	50.55	20.76	29	34.83	10.92
Path Time - Level 1 Trial 2	31	29.34	6.53	29	29.27	8.48
Path Time - Level 1 Trial 3	31	26.13	5.45	29	26.96	5.24
Path Time - Level 2 Trial 1	31	299.91	148.43	29	167.40	135.19
Path Time - Level 2 Trial 2	31	248.15	163.28	29	156.56	154.10
Path Time - Level 2 Trial 3	31	197.67	155.41	29	68.44	26.88
Path Time - Level 3 Trial 1	31	454.54	171.63	29	415.78	211.39
Path Time - Level 3 Trial 2	31	432.95	186.98	29	344.25	228.72
Spatial Ability Score	31	86.45	28.61	29	97.00	37.97
Video Gaming Score	29	11.16	4.50	27	12.81	4.32

Table 4.1 Means and standard deviation for navigation performance measures, spatial ability and video gaming experience

The data was analysed using SPSS™ version 17 and the statistical modelling outputs are presented in Appendix C. Large standard deviations were observed in some of the performance measures especially for the more complex upper task levels. A Kolmogorov-Smirnov test of normality however showed that the performance measures were normally distributed ($p > .05$ for all measures). As a result, parametric tests of differences were used for the analysis. Multivariate analysis of variance (MANOVA) using the Wilks lambda was performed to test for instructional group performance differences in path length and time across all trials. The results of the MANOVAs are shown in Table 4.2.

	Multivariate tests				Between-subject effects			
	F(2, 57)	*p*	Wilks Lambda	Partial eta squared		F(1, 58)	*p*	Partial eta squared
Level 1 Trial 1	11.67	.00*	.71	.29	*length*	21.66	.00**	.27
					time	13.19	.00**	.19
Level 1 Trial 2	3.92	.03*	.88	.12	*length*	7.60	.01**	.11
					time	.00	.97	.00
Level 1 Trial 3	.24	.79	.99	.00	*length*	.00	.98	.00
					time	.36	.55	.01
Level 2 Trial 1	11.08	.00*	.72	.28	*length*	22.52	.00**	.28
					time	13.01	.00**	.18
Level 2 Trial 2	7.00	.00*	.80	.20	*length*	14.02	.00**	.20
					time	4.98	.03	.08
Level 2 Trial 3	11.16	.00*	.72	.28	*length*	22.57	.00**	.28
					time	19.49	.00**	.25
Level 3 Trial 1	.44	.65	.99	.02	*length*	.09	.76	.00
					time	.61	.44	.01
Level 3 Trial 2	3.44	.03*	.89	.11	*length*	6.48	.01**	.10
					time	2.72	.10	.05

* alpha = .05

** alpha = .03

Table 4.2 Multivariate analysis of variance results for navigation performance measures across all maze levels

The dynamic group had statistically significant better performance on all navigational measures than the static group except for on the third trial of the level one maze and on the first trial of the level three maze. The alpha level was set at .03 after Bonferroni adjustment and follow-up univariate comparisons revealed that the dynamic group had better performance on all dependant measures except for the path time of the second trials of the level one and three mazes respectively. The plots in Figures 4.5 and 4.6 show the variations in the mean path length and time of the level two maze trials.

Two sets of multivariate analysis of covariance (MANCOVAS) were conducted on the level two maze trials with spatial orientation ability and video game experience as covariates respectively. Preliminary checks for linearity, homogeneity of variance-covariance matrices and multicollinearity were satisfactory. The results of the MANCOVAs are shown in Table 4.3. Following adjustment for the spatial orientation ability scores in the first set of MANCOVAs, there were statistically significant differences in the navigational performance of the two instruction groups across all trials of the level two maze. There were also statistically significant differences in performance measures attributable to the spatial orientation ability except for on the third trial of the level two maze. After Bonferroni adjustment, univariate comparisons show that the dynamic group had better performances on all the dependant performance measures except for the path time of the second trial of the level two maze. The effects of the spatial orientation ability however were only significant for the path times.

Similarly, after adjusting for the video gaming experience in the second set of MANCOVAs, there were statistically significant differences in the navigational performance of the two instruction groups across all trials of the level two maze. There was a statistically significant effect of the video gaming experience on the dependent performance measures in only the first trial of the level two maze. Following Bonferroni adjustment, univariate comparisons show that the dynamic group had better performances on all the dependent performance measures except for the path time of the second trial of the level two maze. The effect of the video gaming experience was however significant for only the path time.

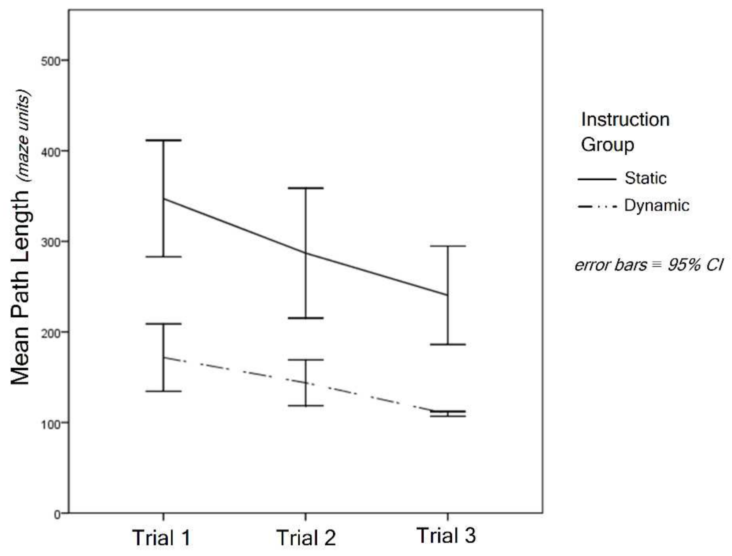


Figure 4.5 Mean path length plot for the level 2 maze task

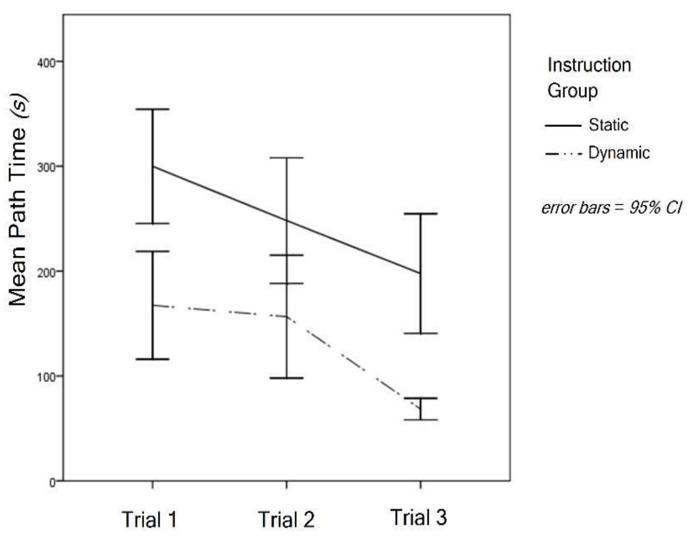


Figure 4.6 Mean path time for the level 2 maze task

Task	Effect	Multivariate tests				Between-subject effects			
		F[a]	*p*	Pillai's Trace	Partial eta squared	Performance measure	F[a]	*p*	Partial eta squared
Level 2 Trial 1	*Instruction*	10.15	.00*	.27	.27	*length*	20.49	.00**	.26
						time	11.05	.00**	.16
	Spatial Ability	4.33	.02*	.13	.13	*length*	1.03	.31	.02
						time	6.32	.02*	.10
Level 2 Trial 2	*Instruction*	6.33	.00*	.18	.18	*length*	12.33	.00**	.18
						time	3.47	.07	.08
	Spatial Ability	6.05	.00*	.18	.18	*length*	1.77	.19	.03
						time	10.73	.00**	.16
Level 2 Trial 3	*Instruction*	9.99	.00*	.26	.26	*length*	20.21	.00**	.26
						time	17.27	.00**	.23
	Spatial Ability	1.77	.18	.06	.06	*length*	3.18	.08	.05
						time	3.55	.07	.06
Level 2 Trial 1	*Instruction*	10.01	.00*	.28	.28	*length*	20.12	.00**	.28
						time	10.03	.00**	.16
	Gaming Score	4.95	.01*	.16	.16	*length*	.40	.53	.00
						time	5.72	.02**	.10
Level 2 Trial 2	*Instruction*	5.71	.01*	.18	.18	*length*	11.40	.00**	.18
						time	4.07	.04	.07
	Gaming Score	2.80	.07	.10	.10	*length*	.34	.56	.00
						time	4.24	.04	.07
Level 2 Trial 3	*Instruction*	9.60	.00*	.27	.27	*length*	19.39	.00**	.27
						time	16.76	.00**	.24
	Gaming Score	.79	.46	.03	.03	*length*	1.16	.29	.02
						time	1.59	.21	.03

[a] $F(2,56)$ for Spatial Orientation Ability Covariate (*n=60*)

[a] $F(2,52)$ for Video Gaming Experience Covariate (*n=56*)

* alpha = .05

** alpha = .03

Table 4.3 Multivariate analysis of covariance results for level 2 maze trials

Task	Chi-square (Yates continuity)	*p*	phi
Level 2 Trial 1	7.57	.01*	-.39
Level 2 Trial 2	4.68	.03*	-.31
Level 2 Trial 3	6.12	.01*	-.36

* alpha = .05

df = 1; n = 60

Table 4.4 Chi-square test results for instruction groups vs route completion rate

Task	Chi-square	*df*	*p*	Cramer's V
Level 2 Trial 1	9.91	3	.02*	.41
Level 2 Trial 2	9.84	3	.02*	.41
Level 2 Trial 3	7.97	2	.02*	.36

* alpha = .05

n = 60

Table 4.5 Chi-square results for instruction groups vs route retrieval robustness

The results of two sets of Chi-square tests for independence between the instruction groups /route completion rate and the instruction groups/route retrieval robustness for the level two maze trials are shown in Tables 4.4 and 4.5 respectively. There were significant associations between instruction groups and the route completion rates as well as the route retrieval robustness. As shown in figures 4.7 and 4.8, the dynamic group had higher route completion rate and retrieval robustness than the static group across all trials of the level two maze.

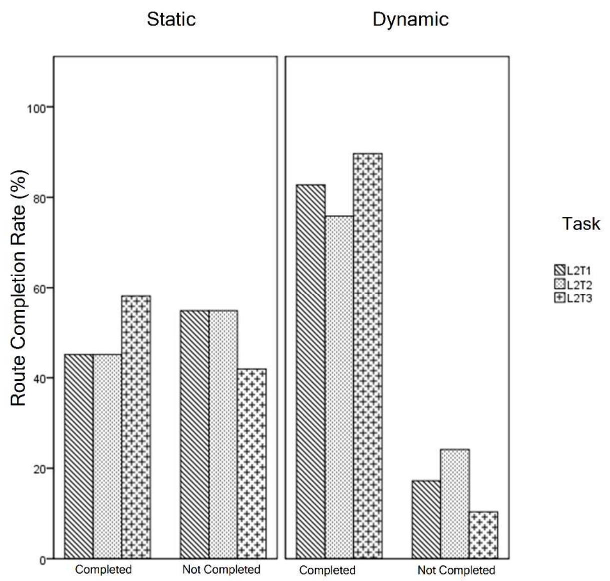


Figure 4.7 Bar chart of the route completion rates for the level 2 maze trials

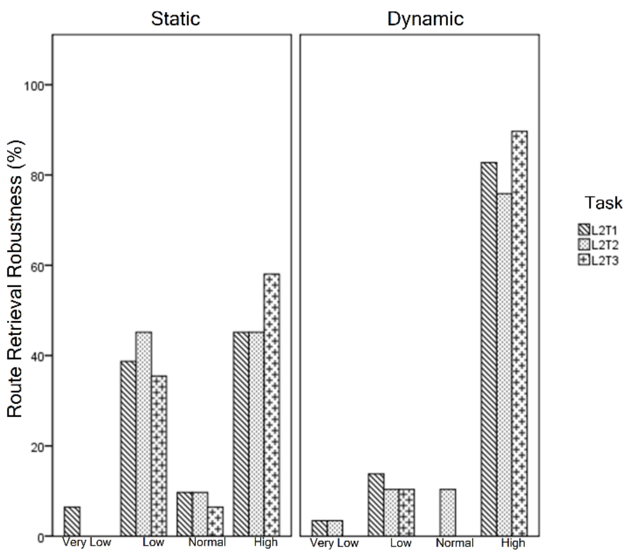


Figure 4.8 Bar chart of the route retrieval robustness measures
for the level 2 maze trials

4.7 Discussion

4.7.1 Dynamic Visualisations and Procedural Skills Acquisition

A mixed design of between and within group comparisons was used to investigate the effect of dynamic visualisation components of instruction on the acquisition of spatial navigational skills. The post-learning performance of two groups of participants navigating three levels of a virtual maze environment was subsequently compared. It was expected that the dynamic instruction group would yield better navigational performance than the static instruction group after controlling for the effects of potential confounding variables. Furthermore, a within-trial improvement as well as a convergence of performance measures between the groups due to a practice effect was expected. The results provide evidence that the dynamic group had significantly better navigational performance in general than the static group on the measures of travel path length and time. The dynamic group's significantly better performance was particularly consistent across all trials of the level two maze, which was designed to be of medium complexity and protected from the adverse effects of the participant still adjusting to the virtual task environment. The route completion rate and retrieval robustness measures were also consistently better for the dynamic group than the static. In the lower complexity level one maze, a faster convergence in performance measures was observed across all trials in both groups. In the highly complex level three maze however, performance convergence was less consistent and a significant difference in the compared groups was only observed on a later (2nd) trial. Taken together, this may suggest an interaction between task complexity, practice effect and instructional dynamism. However, the results do not provide conclusive evidence for this interaction and further studies will be required to replicate and explore this further.

It is argued that the dynamic group may have recorded better navigational performance because they had a more complete and efficient mental representation of the learned task, which included a motion variable component. The extension of the base mental representation to include additional transition information and the motion relative spatial locations of features in the virtual task environment may account for the subsequent improvement in post-learning performance. This is consistent with the core concept of the mental imagery theory that distinguishes between perception inputs and mental imagery (Kosslyn, 2005). The current experiment results however extend the visual buffer structure of the mental imagery theory with the addition of a motion processor for more efficient mental representations of procedural tasks. This is consistent with the proposition of a motor processor to explain improved motor performance attributable to dynamic presentations (Wong et al., 2009) and the explanation of learning effects by the motor-neuron system proposed by Van Gog et al. (2009). The results provide novel evidence for these associations by showing how intrinsic instructional dynamism may activate cognitive motion-variable dependent processes in the acquisition of procedural skills. Additionally, the result is also consistent with the hybrid cognitive learning processing model proposed in Chapter 2 of this thesis and validates the assumption that dynamic instructional components possess an intrinsic quality for more efficient transfer of domain-dependent procedural skills. Based on these results, Null hypothesis H_{00} was rejected and alternate hypotheses H_{11}, H_{12}, H_{13} and H_{14} were accepted.

4.7.2 Effects of Spatial Abilities and Video Gaming Experience

Spatial orientation abilities and video gaming experience has been shown to affect human navigational performance (Meneghetti et al., 2011; Richardson et al., 2011). The effect of video gaming experience in particular is more evident in the navigation of virtual environment like the mazes used in this study. In the analysis of the current experiment, the level two maze trials were selected for extended investigation, which includes controlling for the effect of the participant's spatial ability and video gaming experience. Interestingly the results, while consistent with previous findings, show a significant effect of the participant's spatial orientation ability in the path time measures of the first two trials only, which disappears on the third trial. Similarly, the effect of the video gaming experience was significant for the path time measures in the first trial only with performance quickly converging on subsequent trials. This suggest that the participant's spatial ability and video gaming experience may only account for improvements in time-dependent cognitive processing of visual stimuli and not for memory retrieval dependent processes that support travel path computations. The path length measure of navigational performance is particularly dependent on efficient memory retrieval processes of stored spatial knowledge for travel path computations. In contrast to spatial orientation ability and video gaming experience, the effect of the instructional dynamism was consistently significant for the path length measure across all trials. This may be due to the formation of a more complete and effective spatial knowledge representation afforded by the instructional dynamism, which supports more efficient memory retrievals for path computation. Null hypothesis H_{01} was therefore rejected and the alternate hypothesis H_{16} was accepted. The robustness of navigational performance as measured by the route retrieval robustness rate was consistently higher for the dynamic group than the static group across all trials of the level 2 maze. The alternate hypothesis H_{15} was therefore accepted as the findings suggest that the more efficient mental task representations of the dynamic group afforded faster recovery to temporary disruptions in spatial orientation during navigation. The beneficial effect of spatial orientation and video gaming experience however were confined to the cognitive processing of perceived external stimuli and reflects only in the travel time measures. Furthermore, the effect of these confounding factors converges faster than for the instructional dynamism, which may suggest a higher susceptibility to the practice effect.

4.8 Limitations

The results have limitations for generalisation as the spatial navigation performance effects of some potential confounding variables, such as the participant's age and gender, were not controlled. This was due to constraints imposed by the experiment recruitment process. However, the potential confounding effects of these variables were minimised through random assignment of the participants to the compared groups based on the minimisation stratifiers of age and gender.

The results are further limited in accounting for the detailed effect of spatial orientation ability and video gaming experience. Although the findings provide evidence suggesting a benefit of the spatial orientation ability and video gaming experience for process level perception operations only, these can only provide partial explanations and remains inconclusive. More comprehensive studies, which may include eye tracking methodology, would be required to conduct further investigations to establish this finding. The eye-tracking data may afford detailed investigation of the salient aspects of the compared interfaces and attention profile that support improved task performances.

The use of a virtual task environment may also restrict the generalisation of the results to navigational tasks in the real world. However, the virtual environment was utilised consistently across the compared groups. Furthermore the effect of prior video gaming experience, which has been shown to be particularly confounding for task performance in virtual environments, was also controlled.

4.9 Conclusion and Further Work

In conclusion, this study provides evidence for a motion variable component of instructional interfaces, which is associated with improved transfer of novel procedural motor skills consistent with the hybrid cognitive learning model proposed in Chapter 2. The current experiment extends that model beyond the motor knowledge domain through empirical investigations in a related but separate domain of the acquisition of novel spatial navigational skills. It was found that the benefit of dynamic instructions for the acquisition of novel spatial navigation skills persists after controlling for extraneous factors like task complexity, spatial orientation ability and video gaming experience.

The results are limited in explaining the effect of other established factors like age and gender because of constraints of the recruitment process. It also provides limited evidence for a process level beneficial effect of spatial orientation ability and video gaming experience in the acquisition of spatial navigational skills. More comprehensive studies using eye tracking methodology were suggested to investigate this association. The findings of the current experiment are not conclusive on the subject of the beneficial effect of instructional dynamism in general. They provide further evidence of an association between instructional composition and target knowledge domain for novice learners. An important question remains unanswered – what is the cognitive benefit of dynamic versus static instructional visualisation components for domain experts learning a novel procedural skill. This question is addressed in the next experiment reported in Chapter 5.

Chapter 5

Experiment 3 – Domain Expertise in Procedural Skills Acquisition

5.1. Overview

Chapter 3 of this thesis reports an experiment that demonstrates that dynamic visualisation components of instructional interfaces may be more cognitively beneficial than equivalent static alternatives for the acquisition of procedural motor skills by domain novices. This effect was attributed to an intrinsic quality of the dynamic visualisations that affords the portrayal of transitory information, which is critical to the comprehension and acquisition of the target skill. The cognitive benefit of dynamic visualisations over equivalent statics was also found in Experiment 2 reported in Chapter 4, which investigated novel acquisition in the different knowledge domain of spatial navigation. The participants of this latter experiment were also novices with respect to the target knowledge domain. These 2 experiments combined provide evidence for an interaction of instructional interface dynamism with novel skill acquisition/performance of domain novices, which is associated with an intrinsic quality of the visualisations to facilitate the creation of more accurate mental task models. The current chapter reports further work to answer the next logical question – would the cognitive benefit of dynamic instructional interface visualisations over equivalent statics persist for domain expert learners of a novel intra-domain procedure? Essentially, this question seeks to find the cognitive effects of intra-domain transferability of expertise and how this interacts with dynamic versus static interface components in skill acquisition and post-learning task performance. The experiment conducted to investigate this question is reported.

5.2 Domain Expertise and Novel Skills Acquisition

Expertise has been defined as characterised by maximal adaptations to representative tasks within a domain (Ericsson, 2004; Gegenfurtner & Seppänen, 2013). The domain specificity of expertise however is not generally accepted. For instance, Ericsson (2008) argues that expertise is essentially reproducibly superior task performance in a knowledge domain citing several examples of reference domains including chess, typing, athletics and medical surgery. Expertise in a specific domain is evident by consistently superior *ad hoc* performance without advanced preparation. Thus an expert athlete may be expected to be ready for competition at any time even if a race is delayed. Similarly, an expert medical doctor would be expected to respond adequately to a roadside accident patient as well as to scheduled patient appointments in the clinic. This view emphasizes the domain specificity of expertise and its characterisation by readiness to perform at any given time with relatively little preparation (Ericsson & Smith, 1991). The domain specific perspective generally infer a well-structured knowledge base of experts engendered by prolonged exposure, practice and experience with the domain. This facilitates automatic task execution and decision making but also an inflexible transferability to novel inter-domain tasks due to the rigidifying effect of long practice (Mayer & Wittrock, 1996; Feltovich, Spiro & Coulson, 1997).

An alternative approach to expertise defines it as not domain specific but comprising knowledge components that is generalizable across novel and unfamiliar tasks. This connotes a blurred inter-domain boundary and the structural similarity of tasks in different knowledge domains affords an optimal adaptation channel through which the transfer of expert strategies may occur (Barnett & Koslowski, 2002; Schwartz, Bransford & Sears, 2005). Interestingly, this perspective also emphasizes the core importance of extensive practice to the development of expertise consistent with this aspect of the domain specific approach to expertise. The growth trajectories of the 2 core factors of the optimal adaptation channel – innovation and efficiency – is thought to develop and improve over time and practice as well (Schwartz et al., 2005 pp 38-39).

In an attempt to reconcile the different approaches to the domain specificity of expertise, Gegenfurtner and Seppänen, (2013) proposed 3 broad aspects of transfer evident in expert performance. The first is the transfer of domain-general skills, which suggests that continuous practice in a knowledge domain facilitates the development of general heuristics or a repertoire of strategies that may be applied in other structurally similar task environments. The second aspect is the transfer of domain-specific skills where continuous practice facilitates intra-domain transfer to novel tasks only. Domain specific adjustment may be evident to accommodate the novel tasks. The third aspect describes transfer of domain-specific skills in context only. This is characterised by continuous practice in a domain, which facilitates the development of superior performance but it is relatively difficult to transfer expertise to novel inter- or intra-domain tasks. Irrespective of the diverse approaches to the domain specificity of expertise, the notion that expertise is developed through extensive practice of domain representative tasks is consistent. This factor is core to the selection of participants for the experiment reported in this chapter. Expertise from a cognitive science perspective, is defined at the micro-cognition level and refers to cognitive processes such as memory capacity and performance. Domain experts possess knowledge structures that afford competent, skilled and controlled task execution as compared to novices. Experts are able to think more qualitatively and process larger amount of information at a given moment with respect to a specific task (Farrington-Darby & Wilson, 2006).

The experiments reported in Chapters 3 and 4 of this thesis provide evidence for an interaction between the instructional interface visualisations and the cognitive processing associated with task comprehension and post-learning performance by domain novices. This effect was attributed to the intrinsic, transitory element of the dynamic interface visualisations that facilitates a more complete mental task representation and skill transferability than using equivalent static visualisations. Furthermore, the interaction was found to be independent of the novice learner's spatial ability. Would the cognitive benefit associated with dynamic interface visualisations facilitate more efficient mental representation and task performance in domain experts acquiring a novel intra-domain skill? This question was investigated in the current experiment reported. There have been very few previous studies of the moderating effect of domain expertise on the interaction of interface dynamism and mental task representations/skill acquisition. The existing studies more often than not do not distinguish sufficiently between domain expertise and individual cognitive characteristics such as spatial visualisation or orientation abilities. This has led to inconsistent findings that are not applicable in the general context. For instance, Boucheix and Schneider (2009) conducted 2 experiments to compare the cognitive effects of static versus dynamic interface visualisations on the comprehension of a dynamic mechanical system by domain experts versus novices. They concluded that dynamic interface visualisations may be beneficial for domain novices but are incompatible and ineffective for the experts when compared with using equivalent static interface visualisations. This conclusion however is arguably flawed because of the assumption that lower spatial ability equates to lower prior experience or expertise in a mechanical knowledge domain. Spatial ability has been defined as an individual capacity to perceive forms, shapes and positions of objects in a visual field, create mental representations of these forms, shapes and positions and mentally manipulate the resulting representations (Carrol, 1993). Spatial ability comprises several sub-factors including spatial visualisation, spatial relations, perceptual speed, closure speed and flexibility of closure (See Carrol, 1993 for a full review). Domain expertise however, as discussed in the early part of this section, is associated with "consistently superior performance on a specialised set of representative tasks for the domain" (Gegenfurtner, Lehtinen & Saljo, 2011). Domain expertise therefore is separate and distinct from an individual cognitive characteristic such as spatial ability. Domain expertise is developed through extensive experience and performance of tasks in the reference domain. An investigation of the moderating effect of domain expertise on novel skill acquisition through simulations with dynamic versus static interface visualisations would require a more stringent methodology that counterbalances the factor of spatial ability to discount for its confounding effect. The intrinsic loads imposed by interface visualisations have also been found to interact with domain expertise (Spanjers, Wouters, Van Gog & Van Merriënboer, 2011). In that study, the intrinsic load was manipulated by using segmented versus continuous animation interfaces to investigate a problem-solving domain. The results are however limited as the comparison did not include the cognitive effects of static visualisation components. Furthermore, the participants involved were neither complete novices nor full experts with respect to the domain of measurement, which further reduces the generalisability of the results.

Extending from the findings of Experiments 1 & 2 of this thesis (Chapters 3 & 4), it is arguable that the skill acquirable in a specific learning episode using dynamic versus static interface visualisations is dependent on 3 variables: the nature of the information to be perceived (e.g. motor actions, spatial navigation, abstract mathematical concepts etc), the medium of presentation (dynamic versus static interface visualisations) and the restrictions of the cognitive processing system. The interactions of these 3 variables are depicted in Figure 5.1.

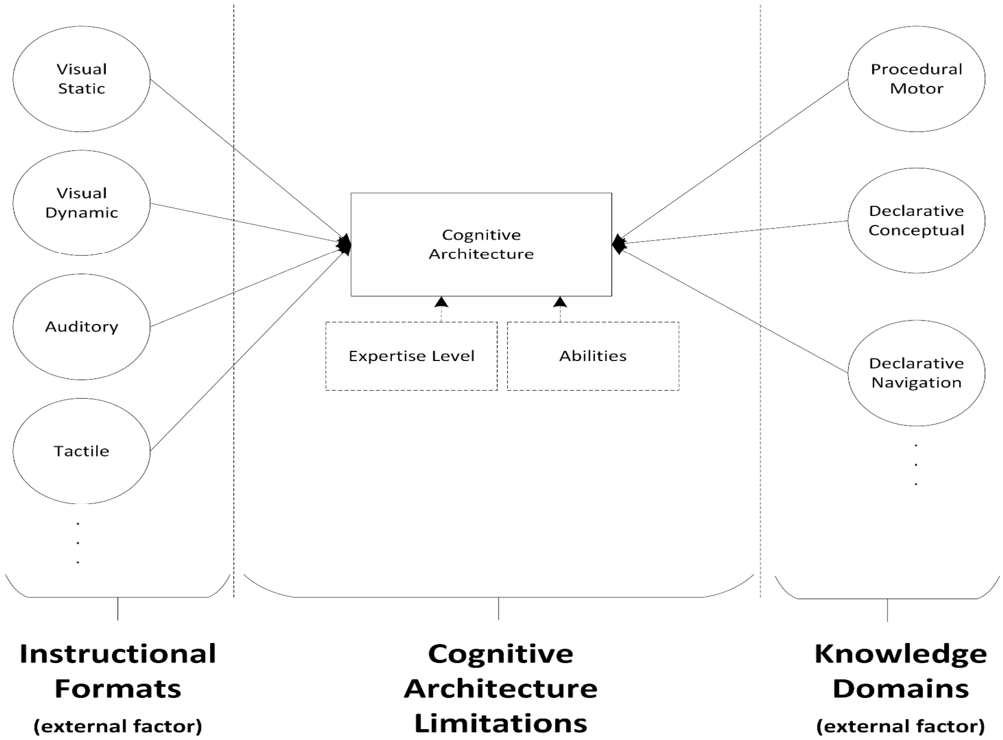


Figure 5.1 Components of the integral learning process

The limitations of the cognitive processing system are well established in literature and were extensively discussed in Chapter 2 of this thesis. Domain expertise may moderate cognitive processing limitations as experts have more developed domain knowledge schemas, which imposes less processing cost on WM (Spanjers et al., 2011). Domain expertise however, may not completely eliminate the restrictions of limited WM resources. As depicted in the hybrid cognitive model (Figure 2.6), the restrictions of the cognitive architecture could prevent expert learners from accessing the WM bypass loop for the acquisition of novel intra-domain skills. The integral effect of the 3 variables depicted in Figure 5.1 therefore should define an association between the instructional interface visualisations and the target knowledge domain. This association would be independent of the domain expertise to the extent that the current learning task is novel. With respect to the domain of procedural motor skills acquisition specifically, Experiment 1 reported in Chapter 3 argues that an intrinsic transitory information attribute of dynamic interface visualisations makes them more effective for supporting associated cognitive processing than equivalent static alternatives. This is consistent with the concept of a specialised 'movement processor' component of WM (Wong et al, 2009). The experiment reported in this chapter extends this finding to investigate the moderating effect of domain expertise on the acquisition of novel intra-domain procedural motor skills. The following hypotheses are stated:

Null Hypotheses

H_{00} Comparison of equivalent dynamic versus static interface visualisations would yield no significant differences in the acquisition of a novel procedural motor skill by domain experts.

H_{01} The moderating effect of dynamic versus static interface visualisations on the post-learning performance of a novel procedural motor skill would be dependent on the spatial visualisation ability of domain expert learners.

Alternate/Positive Hypotheses

H_{11} The intrinsic transitory information attribute of dynamic interface visualisations would facilitate the creation of a more efficient mental task model in the acquisition of a novel procedural motor skill by domain expert learners than possible with equivalent static visualisations.

H_{12} The cognitive benefit of more efficient mental models afforded by dynamic interface visualisations over equivalent static alternatives would yield faster post-learning performance of a novel procedural motor task irrespective of prior domain knowledge/expertise.

H_{13} The cognitive benefit of more efficient mental models afforded by dynamic interface visualisations over equivalent static alternatives would yield more accurate post-learning performance of a novel procedural motor task irrespective of prior domain knowledge/expertise.

H_{14} The interaction of interface dynamism and post-learning performance of a novel procedural motor task would be independent of domain expertise and the learner's spatial visualisation ability.

5.3 Method

5.3.1 Design

The experiment design is the same as described in Section 3.4.1.

5.3.2 Participants

Twenty-four aircraft maintenance engineering experts (all males, from 31-55years old, M = 44, SD = 5.5) were paid £5.00 for voluntary participation in the experiment. All participants had at least 12 years (and up to 35 years) of professional aircraft maintenance engineering at the 401 Aircraft Maintenance Depot (ACMD) of the Nigerian Air Force, Lagos, Nigeria. BPS ethical guidelines were complied with to ensure the wellbeing of all participants.

5.3.3 Materials

The same LEGO™ truck model, computer system, monitor, video camera, questionnaire, paper folding test, and instructional materials as described in Section 3.4.3 were used for the experiment.

5.3.4 Procedure

Participants performed the same disassembly/assembly task described in Section 3.4.4 with the exception that all phases of the experiment were conducted in individual sessions. The familiarisation phase was up to 5 minutes and was not recorded. Based on the outcome of the pre-test questionnaire, 4 participants were excluded from continuing because they reported previous experience with models similar to the truck model in use.

5.3.5 Analysis

Captured video data were analysed to extract performance time and accuracy similar to the procedure described in Section 3.4.5. Discrepancies in the scores were resolved through consensus by 3 independent reviewers. However, the entire 22 procedural steps of the disassembly/assembly process were analysed as against only the first 11 steps analysed in Section 3.4.5. No participant's data was excluded from the final analysis.

5.4 Results

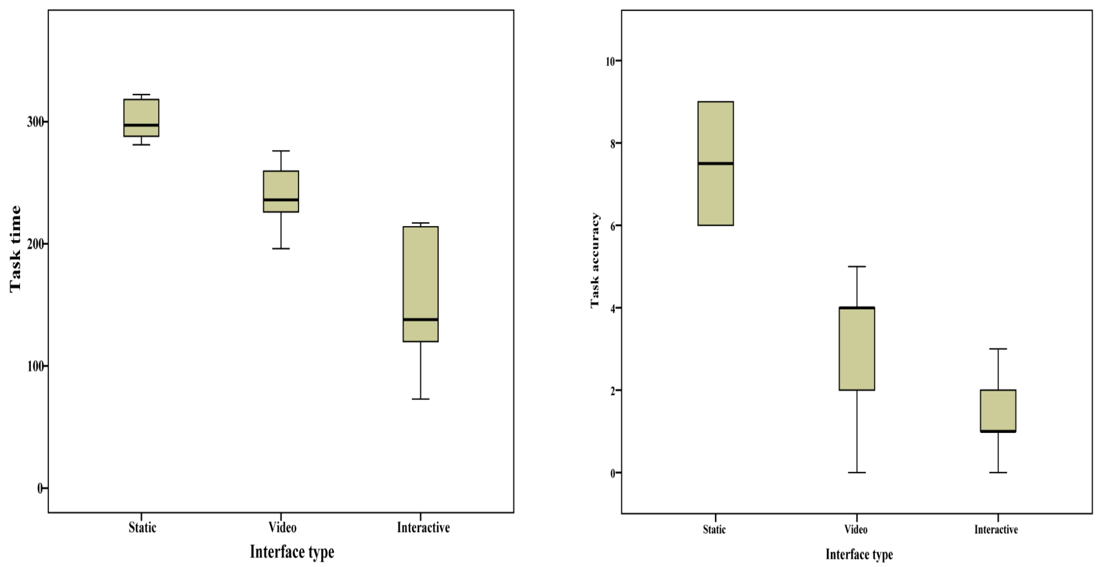
The data was analysed using SPSS™ version 17 and the statistical modelling outputs are presented in Appendix D. Table 5.1 shows the mean task performance time and error count as well as standard deviations for the static (*S-group*), video (*V-group*) and interactive *(I-group*) groups respectively. A one-way between-groups ANOVA was conducted to explore the effect of instruction interface type on task performance. There was a statistically significant difference in the task performance time ($F\ (2,\ 17) = 19.59,\ p<.05$) and accuracy ($F\ (2,\ 17) = 35.65,\ p<.05$) for the three instructional groups. The effect size, calculated using eta squared, was .70 and .81 for task time and accuracy respectively.

	Instruction interface group								
	S-group			V-group			I-group		
	N	M	SD	N	M	SD	N	M	SD
Task time *(s)*	7	322.14	59.30	7	239.86	28.12	6	150.00	56.05
Task errors	7	7.71	1.38	7	3.00	1.73	6	1.33	1.03
Test score	7	7.00	1.00	7	6.14	.90	6	7.00	.63

Table 5.1 Means and standard deviations for the compared groups

Post-hoc comparisons using Tukey HSD test indicated that the mean task time for the *S-group* (M = 322.14, SD = 59.30) was significantly different from the *V-group* (M = 239.86, SD = 28.12, p = .02) as well as the *I-group* (M = 150.00, SD = 56.10, p = .00). There was also a significant difference between the mean task time for the *V-group* and *I-group* (p = .01). Similarly, Tukey HSD further reveals significant differences between the mean error count for the *S-group* (M = 7.71, SD = 1.38) and the *V-group* (M = 3.00, SD = 1.73, p = .00) as well as the *I-group* (M = 1.33, SD = 1.03, p = .00). However, the differences between the mean error count for the *V-group* and *I-group* did not reach statistical significance (p = .12).

Two one-way between groups ANCOVAs were further conducted with spatial ability test scores as covariate. The dependent variables were task performance times and error counts respectively and preliminary checks confirmed the underlying assumptions of the homogeneity of variances were not violated ($F(2, 17) = .74$, $p > .05$ and $F(2, 17) = 1.48$, $p > .05$ respectively). After adjusting for spatial ability in the first ANCOVA, a significant difference remained in task performance times ($F(2, 16) = 18.53$, $p < .01$, partial eta squared=.67). There was no significant effect of spatial ability on task performance times ($F(1, 16) = .08$, $p > .05$, partial eta squared=.01). Similarly, adjusting for spatial ability in the second ANCOVA still showed a significant difference in task performance error counts ($F(2, 16) = 32.76$, $p < .01$, partial eta squared=.81) and no significant effect of spatial ability on the error counts ($F(1, 16) = .04$, $p > .05$, partial eta squared=.00). A graphical analysis of task performance measures is presented in Figures 5.2 and 5.3 depicting the significant effect of the dynamic contents of the instructional interfaces. Overall, the *V-group* and *I-group* were 34% and 115% faster and 157% and 480% more accurate than the *S-group* respectively.



Figures 5.2 & 5.3 Plots of task time and accuracy across interface types

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5.5 Discussion

The experiment investigated the cognitive benefit of dynamic interface visualisations over static in the acquisition of a novel intra-domain procedural motor skill and the moderating effect of prior domain knowledge/expertise. The cognitive effect of dynamic versus static interface visualisations have been earlier found to be independent of the domain novice learner's spatial visualisation ability and this could be extendable to the domain expert in the context of novel skill acquisition. This hypothesis was tested in this experiment. By controlling for the effect of other variables such as the learner's spatial visualisation ability and interface information equivalency, it was observed that domain experts, training to acquire a novel intra-domain skill, recorded significantly better measures of actual task performance after interacting with dynamic compared to static interface visualisations. The results suggest that irrespective of previous domain knowledge, trainees in the *V* and *I groups* were able to generate a more accurate and complete mental representation of novel procedural motor skills than those in the *S-group*, which accounts for their significantly higher task performance measures. Null hypothesis H_{00} was therefore rejected and the alternate hypotheses H_{11}, H_{12} and H_{13} were accepted.

The experiment methodology carefully controlled for the confounding effect of the spatial visualisation ability of the participants through stratified randomisation. This ensured counterbalanced distribution of the participants to the compared groups to compensate for individual spatial abilities and afforded a more direct observation of the effect of domain prior experience or expertise. Null hypothesis H_{01} was rejected and the alternate H_{14} was accepted. The test knowledge domain was the acquisition of procedural motor skills, which is related to the participant's expertise as they all had several years of aircraft maintenance engineering experience. In contrast to the conclusions of Boucheix and Schneider (2009), dynamic interface visualisations, such as videos and interactive re-enactment of the novel skill to be acquired, were found to yield faster and more accurate post-learning performance measures of the target skills. This provides evidence that dynamic interface visualisations affords more complete representations of novel procedural motor skills and facilitates the creation of more efficient mental task models than equivalent static alternatives. The creation of more efficient mental task models by the dynamic visualisations may be due to the intrinsic encoding of the transitory information that links the different stages of the disassembly/assembly task thus translating to better comprehension and post-learning task performance. The individual cognitive characteristics of the participants, such as spatial visualisation abilities, could not be a moderating factor as proposed by Boucheix and Schneider (2009) as it had been compensated for through the current experiment's randomisation methodology. The results are also consistent with Spanjers' et al. (2011) proposal for an interaction between the intrinsic cognitive load imposed by interface visualisations and domain expertise. It is arguable however that the current results extends the Spanjers' et al (2011) initial comparisons to include static versus dynamic interface visualisations. This afforded a fuller understanding of the cognitive effects of interface dynamism than possible through the comparison of segmented versus continuous dynamic visualisations as implemented in Spanjers et al. (2011) study. Furthermore, the participants in the current experiment are fully experts in the test reference domain having acquired several years of experience as aircraft maintenance engineers. This field of expertise is especially characterised by manual dexterity and excellent eye-hand coordination to perform continuously varying motor manipulations similar to the disassembly/assembly task that was used in the current experiment. The participants in Spanjers et al. (2011) however could neither be classified as full experts nor complete novices, which limits the generalizability of their findings.

Consistent with the Cognitive Load Theory (CLT), the dynamic interface visualisation arguably imposed less extraneous cognitive load on the participants irrespective of their prior domain expertise because the current acquisition task was novel. This implies that the beneficial cognitive association of certain instructional modalities over others for domain-specific skill acquisition may be independent of prior domain knowledge or expertise to the extent that the skill to be acquired is novel. With respect to the current experiment's reference domain of procedural motor skill acquisition, this argument aligns well with Wong et al. (2009, 2012) suggestion of a distinct 'motor processor' that is dedicated to the efficient processing of dynamic visual stimuli. Furthermore, some previous studies as discussed in Chapter 2 have argued that static interface visualisations encourages 'mental simulation', which in turn enhances germane processing and skill transferability. Detailed video analysis of this experiment's data however revealed that the *S-group* had problem in particular with component manipulation that involves rotational movements during the disassembly/assembly task performance. Additionally, task comprehension and performance of this group did not improve despite the exclusive use of pointers and other visual cues to identify components of interest in the static instructions. A possible explanation might be that there exists a minimal threshold for step-wise procedural gaps in the instructions beyond which 'mental simulation' becomes impossible for the average learner to comprehend irrespective of prior domain experience or expertise when the tasks are novel. Beyond this threshold, schema formation processes, as described by the CLT, break down and participants resort to an ineffective stochastic approach to continuing with the disassembly just as observed with domain novices in Experiment 1 (Chapter 3). The range of tasks involved however do not afford direct comparison of the performance measures of the domain novices against the experts. The domain novices as reported in Chapter 3 were largely unable to proceed beyond the disassembly phase while all the expert participants in the current experiment completed the disassembly and assembly phases of the task. Further studies that use progressively reduced step-wise procedural gaps may be required therefore to establish and measure the minimal threshold required for static interface visualisations to facilitate 'mental simulation' of procedural motor skills/performance.

5.6 Limitations

Experiment 3 reported in this chapter was limited to the narrow domain of the acquisition of novel procedural motor knowledge by domain experts. The use of expert aircraft engineers as participants may suggest an interaction of the user's experience/cognitive characteristics with task performance measures. However, this was controlled for by using a task that is novel to all the participants and excluding those reporting a previous experience with the same or similar models as the experiment's. The procedural task was also well structured and required a finite sequence of logical steps thereby reducing the probability of selective performance criteria interference with participants' previous knowledge or cognitive capabilities. It is arguable that the instructional interface for the *I-group* afforded a higher level of user interactivity than the *S* and *V-groups*, which could have moderated the results of the study. The focus however was on the dynamic instructional content, which is the ability of the video and interactive interfaces to utilise visuospatial representations for portraying the entire range of transitory states involved in the skilled movements as against the fixed visuospatial representations afforded by the static instructions. Additionally, controls were embedded in all the instructional interfaces to allow replay, rewind or forward skip of each/entire instructional step(s) and minimise the effect of user controllability. A further limitation is the relatively low sample sizes but the size of the observed effect is large enough to justify the significant findings. However, subsequent evaluative studies should include more participants as well as retention and repeated performance measurements for a more robust assessment of the association of instructional format with knowledge domain. Future comprehensive studies should also explore inter-domain persistence or otherwise of the associative effects. Such further studies may include the use of eye tracking methodology to investigate differences at the process level (cognitive and perceptual) in addition to the higher level performance measures (latencies and errors), which have been the focus of this study.

5.7 Conclusion

In conclusion, the findings of the experiment reported in this chapter have indicated a possible association between instruction and the acquisition of novel domain knowledge. Some previous studies have also shown similar results especially for the domain novice. The current study however extends to control for the effect of the learner's previous knowledge by comparing the post-learning performance measures of aircraft engineering experts in a novel procedural task that is related to their domain of expertise. Significantly shorter time-on-task and fewer errors were observed for users of instructional interfaces with dynamic visualisations as opposed to those that used interfaces with static visualisations. This observation continues to hold even after discounting for the possible effects of the learner's spatial abilities and portrays an intra-domain persistence of the beneficial association of dynamic instructions and procedural motor knowledge, which is independent of the learner's expertise or cognitive abilities.

Chapter 6

Experiments 4 & 5 – Computational Cognitive Modelling of Procedural Skills Acquisition

6.1 Overview

The experiments discussed so far in this thesis have investigated the cognitive effect of interface visualisations for procedural skill acquisitions using human participants. The findings of these experiments are often deductions based on empirical observations of human participants' post-learning task performance measures, which provides an indication of the underlying cognitive processes that support the overt behaviour. The objective of the thesis research however includes facilitation of the development of intelligent computer assisted training simulators that exploit the interaction between interface visualisations and procedural skills acquisition rate to optimise training time and cost. Arguably, such an objective may not be achieved through inferences from empirical human participant data alone. Formal techniques for quantitative measurements would be required as the foundation infrastructure for the eventual development of a framework to support rapid simulation development and training curriculum integration. The quantitative measurements may be afforded by a computational cognitive modelling methodology that apply the empirical evidence of the previous experiments to formal, psychologically valid models of human learning and task performance. The field of cognitive computational modelling is becoming increasingly relevant to cognitive science and HCI research in general. In this chapter, 2 experiments are reported that uses a modern computational cognitive modelling methodology to investigate the cognitive effects of dynamic versus static visualisations in the interface and how this moderates procedural skill acquisition in simulator based training. Novel computational cognitive modelling techniques are proposed to overcome some of the well-established limitations of modern cognitive modelling architectures for accurate simulation of detailed human motor actions. The experiments reported validates these novel modelling techniques in a two-step approach. The first (Experiment 4) is an initial proof-of-concept for the novel modelling techniques. The follow-up Experiment 5 then applies these techniques to a more complex human motor skills acquisition and task performance scenario, which is consistent with typical procedural skills training. The result of Experiment 4 are validated against equivalent human data from Experiment 1 reported in Chapter 3. Similarly, the results of Experiment 5 are validated against data sourced from the authors of a published related study. The rationale for using external data to validate Experiment 5's results is to increase the generalizability of the novel modelling methodology as will be expatiated in the following sections of this chapter.

6.2 Modelling Skills Acquisition in a Cognitive Architecture

As noted in Section 2.5 of this thesis, computational modelling with cognitive architectures is increasingly becoming a methodology of choice for many human factors studies. Examples of cognitive architectures for human behaviour and performance modelling include EPIC (Kieras & Meyer, 1997), SOAR (Laird et al., 1987) and ACT-R (Anderson et al., 2004; Anderson, 2005). These frameworks afford the implementation of computational behavioural models that are psychologically valid. The recent upsurge in the use of these architectures may be due to their increasing sophistication as well as the recognition of the interdisciplinary relevance of human factors in task performances. Comprehensive cognitive modelling architectures have also enabled an integrated theoretical approach to human factors research as opposed to the traditional paradigms that tend to explain separate aspects of human cognition only. The need for such a comprehensive theoretical framework of cognition has long been recognised in cognitive science as expressed succinctly by Newell, (1990. pp. 17–18):

> "If a theory covers only one part or component, it flirts with trouble from the start. It goes without saying that there are dissociations, independencies, impenetrabilities, and modularities. These all help to break the web of each bit of behaviour being shaped by an unlimited set of antecedents. So they are

important to understand and help to make that theory simple enough to use. But they don't remove the necessity of a theory that provides the total picture and explains the role of the parts and why they exist."

Despite the increasing success of applying computational cognitive modelling to several traditional human factors problems however, the available cognitive architectures still lack functionalities for modelling more complex task performance scenarios such as the acquisition and performance of skilled and continuous human motor action. Existing cognitive architectures, such as ACT-R, have only rudimentary capabilities for modelling motor performance. As such, they are not readily capable of modelling the fine movements involved in skilled human motor performance, because such tasks are difficult. The modelling task is further compounded by the seemingly infinite degrees of movements possible in skilled motor performance coupled with the human ability to execute the required movement almost effortlessly (Viviani & Flash, 1995). Computational modelling using a cognitive architecture has been applied to a wide range of human behavioural tasks in general but there are relatively few previous studies that have modelled human motor skill acquisition and performance in low-level detail. Modelling this category of knowledge domains not only involves the integration of percepts to create mental task representations but also specifying in detail the intertwined role of these mental models and the cognitive processes that decompile them in moderating subsequent task performance. An example of a relevant research effort is Kieras, Meyer, Ballas and Lauber's (2000) computational modelling of Martin-Emerson and Wikens', (1992) manual motor tracking and choice responses in latency tasks using the EPIC architecture. In more recent work, Salvucci, (2006) modelled automobile driving tasks using the ACT-R architecture. By leveraging the Embodied cognition, Task and Artefact (ETA) framework, Salvucci decomposed the driving task to a set of basic tasks (control, monitoring and decision making) that are subsequently integrated to accomplish the overall driving task. In particular, the control component captures all the motor actions that are associated with safe navigation during driving including manipulative lateral (steering) and longitudinal control (acceleration and braking). Salvucci's implementation of these actions were however high-level and did not include the detailed integration of the mental task representation with the atomic motor processes. For instance, Salvucci simulated lateral control by integrating feedback from a 2-point shifting visual attention model into a specified control equation that determines the degree of steering correction required to maintain safe navigation. There was no specification however of the detailed cognitive processes, which is integrated with low-level motor actions to effect the steering control. As such, Salvucci's driver model did not account for the moderating role of mental task representations on the continuous motor control actions that effect the steering. Furthermore, Salvucci's model does not account for how these mental representations were acquired in the first instance or the effect, if any, of different acquisition paradigms on subsequent motor performance.

In even more recent work, Byrne, O'Malley, Gallagher, Purkayastha, Howie and Huegel, (2010) modelled the fine manual control involved in a motor task. The task involved controlling a coupled disk configuration to hit two targets at the ends of a linear trajectory as described in Huegel, Celik, Israr and O'Malley, (2009). Byrne et al., (2010) made three key modifications to the base ACT-R cognitive modelling architecture to achieve the atomic manual control required for the smooth movements involved in the task. First, they increased the update rate of motor output location from 50ms to 3ms. Secondly, they modified the velocity profile of the movement using the 'minimum jerk' paradigm of Hogan, (1984) and lastly, they utilised ACT-R's imaginal module to present intermediate virtual target markers to the motor module along the movement trajectory. These modifications enabled the modelling of the smoother, continuous movements involved in the task than can be afforded by the base ACT-R cognitive architecture. However, Byrne et al.'s, (2010) model does not account for the prior acquisition of cognitive mental task representations nor its intertwined role in subsequent post-learning motor control/performance. Most notably, their model uses the imaginal module for intermediate virtual target locations along the trajectory but does not specify how these intermediate locations are initially acquired or determined. This is very crucial for trajectory validation processes that are evident in post-learning task performance of acquired motor skills especially in mechanical component manipulation for assembly/disassembly.

Experiment 1 reported in Chapter 3 of this thesis argues that learners create cognitive mental task representations in the acquisition of motor skills and these representations are implicated in the subsequent post-learning performance of such motor tasks. Furthermore, it was observed that dynamic instructional visualisations afford the creation of more accurate mental task representations and arguably lead to better post-learning task performance than equivalent static visualisations. This cognitive benefit of dynamic instructional visualisations over static equivalents was shown to be dependent on the knowledge-domain (Höffler & Leutner, 2007) and independent of the learner's expertise and spatial abilities. In this chapter, a novel sequence-of-points computational modelling approach is proposed to investigate this low level intertwining of cognitive processing and executive motor actions that drives the post-learning task performance in a motor knowledge domain. Similar to Byrne et al., (2010), certain aspects of the ACT-R cognitive architecture were modified for the modelling purposes. The methodology adopted however differentiates between mental task representations acquired from dynamic versus static instructional visualisations. It further specifies a detailed validation process for intermediate points along the movement trajectory that reflects the controlling role of the different cognitive mental task representations in post-learning skilled motor performance.

6.3 The ACT-R Cognitive Architecture

ACT-R 6.0 was selected as the modelling architecture for the experiments reported in this chapter. The choice was based on its advanced and modular implementation, which facilitates the novel extensions required to simulate detailed human cognitive processes that support motor actions. ACT-R, as a theory of human cognition, was extensively discussed in the selective literature review - Chapter 2. The novel modelling techniques applied in this chapter leverages the extensibility of the ACT-R architecture through extensive modifications to the motor and imaginal modules. This allows the implementation of complex protocols that translate cognitive mental task representations into smoothly executed motor movements in simulating mechanical assembly tasks. ACT-R's versatile chunk activation processes of the declarative module, especially the partial matching retrieval mechanism, was also utilised to simulate the noise inherent in smooth manipulative movements and enable robust motor performance despite the potentially infinite degrees of movement freedom possible.

6.4 Experiment 4

6.4.1 The Task

Experiment 4 modelled a subset of the task and data of Experiment 1 as reported in Chapter 3 of this thesis. The fifth stage of the 11-step disassembly process was selected for detailed analysis and computational modelling. This step involves the rotation of the chassis of the model truck used in the experiment through π (pi) radians to access a component located underneath it as depicted in Figure 6.1. It was selected for computational modelling because it highlights the differential skills acquisition rate possible via the different instructional interface types. It is also a good example of the abstract and stochastic cognitive processing that results in observable skilled motor action. Additionally, it reduces the scope of work for the initial proof of concept modelling and avoids the substantial effort that would be required to model the entire task sequence at an early stage of the work.

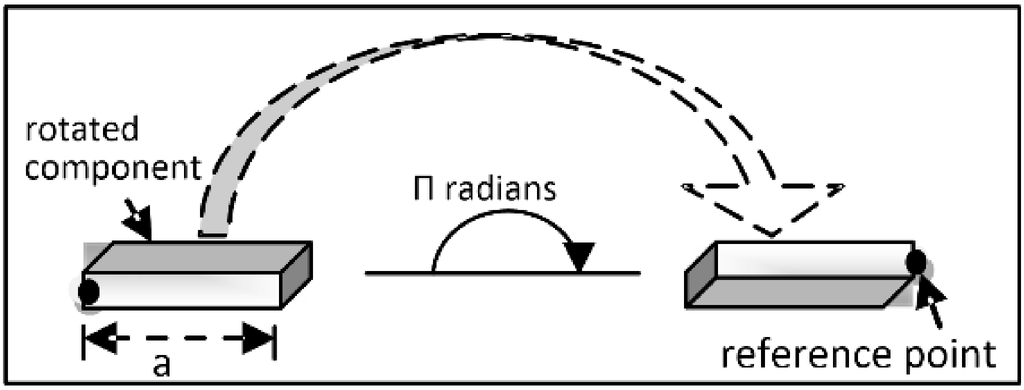

Figure 6.1 The trajectory of the manipulated model truck component

6.4.2 Movement Analysis and Strategies

A kinematic analysis (see e.g. Hamil & Knutzen, 2003) of the video data from Experiment 1 (Chapter 3) was conducted in slow motion to extract the time taken by each participant to execute the selected step of disassembly. Based on the biomechanical human movement research of Hamil and Knutzen (2003), a reference point was selected on the rotated component, as shown in Figure 6.1, to represent the sum total of manipulations and the time taken by this reference to pass through the mid and end points of the ideal semi-circular trajectory were recorded. The accuracy of the component manipulation was also recorded as an alignment of the reference point to the required path as it transits through the midpoint of the trajectory. Raw data of the kinematic analysis are detailed in Appendix E. As evident from the data, the longest time observed for completion of the rotation was 16 seconds (participants 121 & 124). A cut-off time of 17 seconds was therefore used in the computational modelling of this step as the criterion to determine successful component manipulation. As it is infinitely possible to achieve the component manipulation through stochastic processes, this cut-off time was also adopted for subsequent comparative performance analysis of data from the human participants and equivalent computational model outputs.

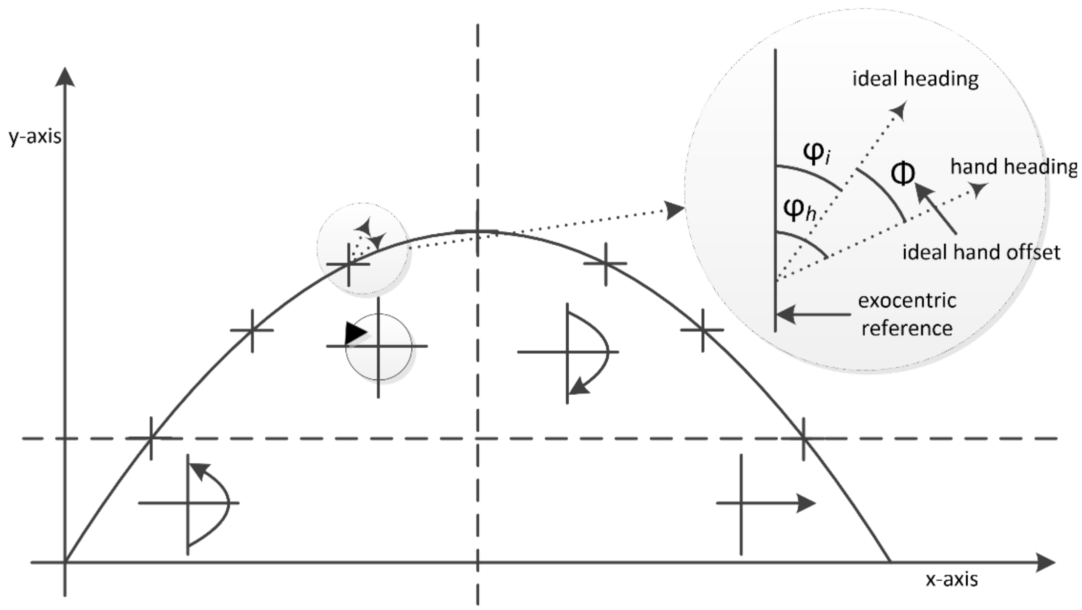

Figure 6.2 Kinematic analysis of manipulative motor movements

The kinematic analysis of the movement show that two broad strategies were at play. The first is a stochastic sequence of multidirectional movement observed mostly in the S-group participants. This group, as described in Chapter 3, were presented with only two pictures showing the initial and final states of the manipulated component. They therefore lacked declarative knowledge of all the transitory intermediate states of component manipulation. The second strategy is a combination of the first with a more directed movement along the desired trajectory aided by declarative recall. This hybrid strategy featured prominently in the improved performance of the V-group as they had acquired the declarative knowledge of the initial and final component states as well as all intermediate transitory manipulations by watching a video clip of the executed step being performed by a skilled expert. Further detailed analysis shows that different performance protocols were applied at various quadrants of the motor movement as depicted in Figure 6.2. In the early stages, there is a tendency to initiate a randomly directed movement in the general direction of the perceived end state of the manipulated component. This rapidly changes to a search space in all directions within the second quadrant where most of the failures were recorded. However, once successfully past the mid-point, subsequent movement converges rapidly to the end-point of the trajectory.

It was further observed that despite the stochasticity of the motor movements at all stages of the trajectory, participants were able to determine when a sequence of random manipulations have sufficiently deviated so as not to satisfy the possible range of configurations for the initial and end positions of the manipulated component. In such instances, they attempt correctional movements to align with the trajectory or if sufficiently deviated, the attempt instance is aborted and the disassembly task is reset to start again.

6.4.3 Modelling Continuous Motor Action - The Sequence-of-Points Technique

Two fundamental problems were posed by the computational modelling of the selected disassembly step. The first was to execute continuous motor actions required to rotate the component from the start to the end point of the semi-circular ideal trajectory. The second problem was to integrate underlying cognitive processing outputs with motor movements to align with the participant's mental task model of the task as acquired through different instructional interfaces.

For the first problem, the ACT-R 6.0 cognitive architecture includes a motor module that specifies default mechanisms for modelling a range of motor movements such as typing and mouse movements. These default mechanisms however were not suitable for the selected task modelling purposes for certain reasons. For instance the default mechanisms specify that aimed movements, such as pointing with the mouse, are executed by calculating the movement execution time based on Fitts' Law (1954) and updating the cursor location when the simulated duration has elapsed. The computations involved assume that the movement is made towards a target and requires fixed start and end cursor locations. The selected modelling task movement strategy however specifies only the start location with the end location dependent on underlying stochastic cognitive processes. To resolve this, a reference point was selected, as depicted in Figure 6.1, through which all resolved component manipulation forces act (see Hamil & Knutzen, 2003). The default ACT-R motor module was then modified to simulate the movement of this reference point as sequences of fixed magnitude, variable direction unit vectors. The start location of each unit movement vector corresponds to the end location of the previous vector. The end locations however are determined through a separate process to reflect the random output of the underlying stochastic cognitive processes. There was still a problem however as the default ACT-R motor module also assumes that aimed movements start and end with zero velocity. Additionally, the magnitude of the unit movement vectors was fixed at approximately 50ms to be consistent with previous related research (Meyer & Kieras, 1997; Salvucci & Gray, 2004). This resulted in a jerky movement profile with a very coarse output. The solution adopted was the modification of the movement velocity profile at the transitional boundaries between the unit movement vectors based on the dynamic cost optimisation approach for the mathematical modelling of human hand movements (Flash & Hogan, 1985), using the minimisation of the time integral of the square of jerk. According to Flash and Hogan, (1985), the location of a reference point at any time t along a straight line trajectory starting and ending with zero velocity is described by Equation 6.1:

$$x(t) = x_0 + (x_0 - x_f)(15\tau^4 - 6\tau^5 - 10\tau^3)$$

$$y(t) = y_0 + (y_0 - y_f)(15\tau^4 - 6\tau^5 - 10\tau^3) \qquad - \quad 6.1$$

where $\tau = t/t_f$,

x_0 and y_0 are initial hand position coordinates $(t = 0)$ and

x_f and y_f are final hand position coordinates $(t = t_f)$.

For curved point-to-point movement, the equation is redefined to include intermediate points (at times $t_1, t_2, \ldots, t_n$) inserted between the start and end positions as shown in Equation 6.2. This equation was adapted for curved point-to-point movements by using a shifting boundary technique bound by $t=0$ and $t=t_f$ across the set of movement vector transition points to accurately implement a continuous velocity profile throughout the movement trajectory. The number of unit movement vectors in a movement sequence as well as their individual directions is however stochastically dependent on the current position in the trajectory and the selected productions firing per cycle of cognitive processing. This synergistic paradigm afforded the implementation of the observed ability of the human participants to select and execute a required movement despite the seemingly infinite degrees of possible movement.

for all times $t \leq t_n$

$$x^-(\tau) = \frac{t_f^5}{720}(\mu_x(\tau_n^4(15\tau^4 - 30\tau^3) + \tau_n^3(80\tau^3 - 30\tau^4) \\ -60\tau^3\tau_n^2 + 30\tau^4\tau_n - 6\tau^5) + c_x(15\tau^4 - 10\tau^3 - 6\tau^5)) + x_0$$

$$y^-(\tau) = \frac{t_f^5}{720}(\mu_y(\tau_n^4(15\tau^4 - 30\tau^3) + \tau_n^3(80\tau^3 - 30\tau^4) \\ -60\tau^3\tau_n^2 + 30\tau^4\tau_n - 6\tau^5) + c_y(15\tau^4 - 10\tau^3 - 6\tau^5)) + y_0 \qquad - \; 6.2$$

and for all times $t \geq t_n$

$$x^+(\tau) = \frac{t_f^5}{720}(\mu_x(\tau_n^4(15\tau^4 - 30\tau^3 + 30\tau - 15) \\ +\tau_n^3(-30\tau^4 + 80\tau^3 - 60\tau^2 + 10)) + c_y(-6\tau^5 + 15\tau^4 - 10\tau^3 + 1)) + x_f \\ = x^-(\tau) + \frac{\mu_x t_f^5(\tau - \tau_n)^5}{120}$$

$$y^+(\tau) = \frac{t_f^5}{720}(\mu_y(\tau_n^4(15\tau^4 - 30\tau^3 + 30\tau - 15) \\ +\tau_n^3(-30\tau^4 + 80\tau^3 - 60\tau^2 + 10)) + c_y(-6\tau^5 + 15\tau^4 - 10\tau^3 + 1)) + y_f$$

The second problem was more important because it is linked directly to a core objective of the research, which is to investigate how the different resultant mental task models of the instructional interfaces drive post-learning motor performance. It was observed from the kinematic analysis that despite the stochasticity of the motor actions involved, participants were able to determine when a particular sequence of movements has become so inconsistent with the ideal rotation trajectory that successful manipulation of the component is no longer possible. This tacit ability suggests that participants acquire a mental model of the rotational task during learning, which moderates the subsequent task performance. Furthermore, it is significantly differentiated in the post-learning performances of the compared groups, as reported in Experiment 1 (Chapter 3), with the dynamic visualisations group recording a more robust performance than the static visualisations group. Modelling this tacit ability requires specifying a control law that translates cognitive processing outputs into corrective motor actions at an atomic level of detail. To achieve this, Fajen and Warren's (2003) dynamic model of steering and obstacle avoidance was adapted. This dynamic framework describes locomotor behaviour of goal-oriented steering in motor task performances. It consists of a system of actors and repeller components analogous to goals and obstacle in the visual field of task performance, which are represented by a set of differential equations. This dynamic model of steering was then adapted to define the limits of deviation allowable at the end of each unit movement vector execution. It also determines the mechanism for trajectory correction by specifying the magnitude of movement required to realign the trajectory of the reference point in the assembly task to enable successfully task completion. This modified control component is described by Equation 6.3:

$$\dot{\varphi}_h = -k_i(\varphi_h - \varphi_i) = k_i\Phi \qquad - \; 6.3$$

where φ_h is the direction of the heading,
φ_i is the direction of the target and
k_i is the target attractiveness factor

At the end of each unit vector execution of the movement sequence as depicted in the inset of Figure 6.2, the model determines the extent of trajectory deviation by comparing the location of the reference point with its mental task representation. The ideal component trajectory, which is defined by a separate hidden process, is used as a heuristic function to moderate this comparison. Deviation determination and the magnitude of corrective action required is controlled by setting parameters k_i and Φ, which determines attractiveness of the ideal trajectory heuristic and the actionable threshold for remedial steering respectively. The motor control law provides the mechanism to execute corrective motor actions for component manipulation only and the same magnitude of the parameters k_i and Φ were set for both the static visualisations group (*S-model*) and dynamic visualisations group (*V-model*) representations. The task performance is therefore dependent on the different mental task representations of the compared groups only.

6.4.4 ACT-R Implementation

A single representational computational model structure was developed for the compared groups of human participants (static visualisation versus dynamic visualisation groups). The main differences between the groups are in the implementation of the declarative mental task representations and how this moderates subsequent task performance. These differences and how they are integrated with task performance are detailed in the rest of this section.

A model run cycle starts the simulation of component rotation by defining the ideal trajectory as a set of parametric equations within a Cartesian reference plane:

$$x = -a\cos v \qquad y = a\sin v \qquad \text{- 6.4}$$

where a = phase shift multiplier
v = angle subtended at the centre of the trajectory

The magnitude of the unit movement vectors was also defined as:

$$d = W_x\left(\frac{\pi}{S_r}\right) \qquad \text{- 6.5}$$

where W_x = width of the ACT-R simulation window
S_r = fixed unit vector time based on previous related research (50ms)

The computed ideal trajectory is represented by a set of visual location chunks and selectively added to declarative memory through the visual module to simulate learning via dynamic or static visualisations. For the *V-model* implementation, the start, end and all intermediate visual location chunks of the ideal trajectory are added to declarative knowledge to simulate viewing a continuous presentation of the rotational movement as typical with dynamic instructions. For the *S-model* however, only the start and end visual location chunks are added to declarative knowledge thereby simulating viewing static pictures of the initial and final configurations of the rotated component respectively. Memory decay and recall difficulty associated with forgetting and random retrieval noise are handled by default ACT-R mechanisms during subsequent task execution. The randomness inherent in recall for performance was further simulated through the ACT-R 6.0 partial matching mechanism as well as through extensions of the activation equation as shown in Figure 6.3. For the x-coordinate component of the visual location chunk, partial matching was activated by defining a sim-hook function:

$$x_{similarities} = -1.0\left(\frac{abs(i_x - c_x)}{V_{diff}}\right) \quad \text{- 6.6}$$

where i_x = ideal trajectory x-coordinate
c_x = current location x-coordinate
V_{diff} = vertical distance between i_x and c_x

This equation defines a matching value for x-coordinate retrievals that range from 0 to -1 as required for ACT-R 6.0 partial matching specifications. A '0' value indicates most similarity between the current and retrieved values while a value of '-1' implies the least similarity or a complete mismatch (ACT-R 6.0 Reference Manual, pp 217).

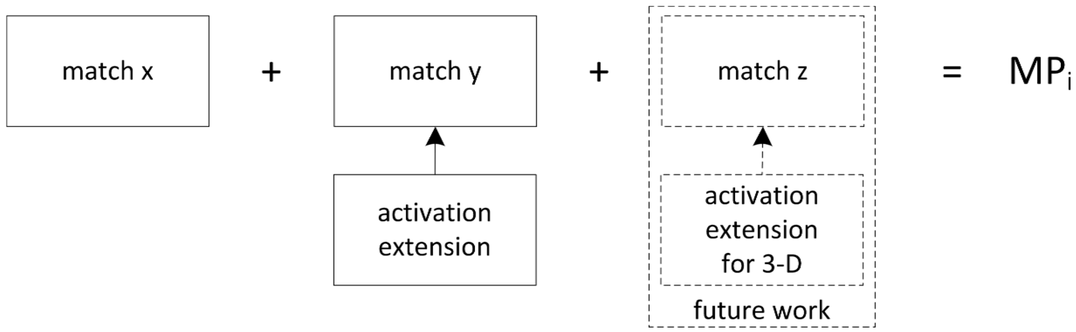

Figure 6.3 Randomised retrieval of spatial location chunks defined on ACT-R 6.0 partial matching mechanism and extensions of the activation equation

The mismatch on the y-coordinate component of the visual location chunk is defined through a novel extension of ACT-R 6.0 activation equation. The activation equation, as earlier defined in Chapter 2 (Equation 2.2), may also be expressed for a retrieved chunk *i* as (ACT-R 6.0 Reference Manual, pp 214):

$$A_i = B_i + S_i + P_i + \mathcal{E}_i \quad \text{- 6.7}$$

where B_i = base level activation
S_i = spreading activation
P_i = partial matching value
$\mathcal{E}_i$ = noise

The activation equation expressed in this form may be further extended with new terms by specifying an optional offset parameter (ACT-R 6.0 Reference Manual, pp 220). The activation offset parameter is computed through a user defined function and added to the final activation value of a chunk during retrieval processing. This powerful feature of the ACT-R 6.0 cognitive architecture afforded an extension of the activation equation to simulate a retrieval mismatch penalty for the y-coordinate of the visual location chunks with possible future extensions also for the z-coordinate in 3-D movements (see Figure 6.3). The y-coordinate activation offset for Experiment 4 models is defined by:

$$y_{offset} = -1.0\left(\frac{abs(i_y - c_y)}{H_{diff}}\right) \quad - 6.8$$

where i_y = ideal trajectory y-coordinate
c_y = current location y-coordinate
H_{diff} = horizontal distance between i_y and c_y

During a retrieval cycle, the activation value of all chunks in the model's declarative memory is computed using the activation equation supplemented with the mismatch penalties for the x and y coordinates as described above. The chunk with the highest activation value is recalled if that value is above the retrieval threshold (*rt*) parameter. The *rt* was kept at ACT-R 6.0 default value of 0.0 for all simulation runs in Experiment 4.

If a retrieval effort fails, the manipulation of the task component proceeds through random determination of spatial locations as typical of the trial-and-error approach observed in human participants. Determination of the random spatial location is implemented through ACT-R 6.0 imaginal module. It is computed as a random location within a 360° circular reference of the current location (c_x, c_y) with a radius of half the unit vector magnitude (see Equation 6.5). The direction of a randomly determined location relative to the current spatial location is independently computed and restricted by the quadrant performance protocols as outlined in Section 6.4.2 of this chapter (see Figure 6.2). The ACT-R 6.0 random module is utilised as the main randomness generator to drive the uncertainty in recalled spatial locations moderated by the performance protocol of each movement quadrant. It is a support module of ACT-R 6.0, which is designed to implement the architecture but not an integral part of the theory (ACT-R 6.0 Reference Manual, pp 24, 137). Therefore, it is not intended to model exact human behaviour.

Movement across unit vector boundaries is smoothed by a shifting boundary mechanism as specified in Section 6.4.3, Equation 6.2. Equidistant points, separated by half the magnitude of the unit movement vector, are selected on either sides of 2 adjacent vectors boundary. The reference point through which all manipulative movements act is then reset to act from the selected lower boundary point to the upper point. This affords simulation of continuous movement through each vector boundary point and avoids the limitations of ending with zero movement velocities as inherent in the default motor calculations of ACT- 6.0 based on Fitts' Law (see Equation 2.1).

The core model productions are shown in the schematic diagram in Figure 6.4. The structure of the productions algorithm is essentially the same for the *S-model* and *V-model* implementation. Differences in task performance is therefore driven by the differential implementation of model's declarative task representations as discussed above. The *S-model* starts with declarative knowledge of only the initial and final positions of the rotated component as corresponding to viewing static visualisations of these stages of the assembly. A top level goal then attempts to retrieve the next movement location for the rotated component's reference point after the start position. The retrieval fails as its declarative knowledge does not include this location and it reverts to the random location determination strategy as outlined above.

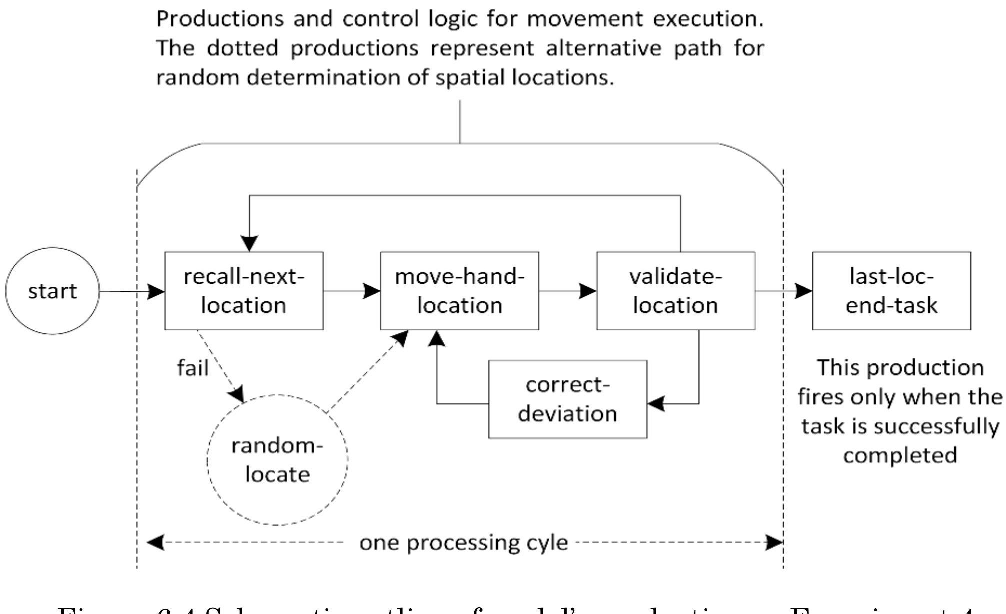

Figure 6.4 Schematic outline of model's productions – Experiment 4

When a random location is returned, the move-hand-to-location production fires to move the selected reference point to that location and simulate hand movement. The location is then validated against the model's internal representation of the task acquired during the learning phase. If the spatial location is validated, the cycle is repeated by firing subsequent productions that attempts further failed retrievals and reversion to the random location determination strategy. However, if the location is determined to have sufficiently deviated, a corrective process is activated to restrict the search space for further random location determination as described in Section 6.4.3 above. The actionable deviation threshold and search space restriction is controlled by the parameter Φ while the magnitude of the correctional movement is determined by the parameter k_l. The corrective process terminates once the trajectory deviation is reduced below the minimal threshold Φ and the model reverts back to the retrieve-fail/random-locate strategy with further location validations. The productions cycle repeats until the specified cut-off time of 17 seconds is exceeded (see Section 6.4.2 above for a determination of the cut-off criteria) or the last-loc-end-task production is fired to report a validated spatial location within a specified range of the end-position of the rotated component.

The internal task representation of the *V-model* is different from that of the *S-model* because it includes additional knowledge of the intermediate spatial locations between the start and end points of the component rotation. Its top level goal retrieval attempt is therefore more likely to be successful and the rotated component's reference point is moved directly to the retrieved spatial location. Inaccuracies in spatial location chunk retrievals are implemented through the partial matching mechanism and novel extensions of the activation equation as described above. If the retrieval is successful, a production is fired to move the hand to the recalled location followed by a validation process similar to that for the *S-model* as outlined above. If the retrieval fails, the model reverts to the random-locate strategy used by the *S-model*. The *V-model* therefore implements the hybrid strategy of task performance as determined from the kinematic analysis of the human participant's movements. A validated spatial location could trigger the correct-deviation processes to bring it within the minimum deviation threshold before another retrieval attempt is fired. The production cycle of the *V-model* is also terminated if the specified cut-off time is exceeded or when the end of the trajectory is reported.

6.4.5 Model Validation

Model strategies and performance was validated by comparative analysis with empirical test data from Experiment 1 (Chapter 3). Model and human data were analysed in the same manner to generate directly comparable and more reliable performance measures. The human data was split into Development *(n=28)* and Test *(n=59)* for analysis. The model's parameters were refined with development data and validated with the test data. Most of the ACT-R architecture parameters were kept at their default settings with the exception of the base-level constant, which was set to 5.0 to reflect the recency of acquisition of the declarative knowledge through interaction with the task instructions. The transient noise and mismatch penalty parameters were also activated with values 0.2 and 1.0 respectively. The domain-specific parameters, k_i and Φ were initially set to reasonable values and then refined for qualitative and quantitative fit to the development data. Similar final values were estimated for the two models as detailed in Table 6.1.

Parameter	Description	Value
k_i	Ideal trajectory attractiveness	1.0
Φ	Actionable deviation threshold	2.0
cut-off	Model run-time limit (seconds)	17.0

Table 6.1 Domain specific model parameters – Experiment 4

The mean task execution time and trajectory alignment rate for the human data, equivalent sample of model outputs and 500 runs of the ACT-R models are reported in Table 6.2. SPSS™ version 17 statistical modelling outputs are presented in Appendix E. The measures for 500 model runs are presented as an indication of the model behaviour over a large sample size only. Further analysis/comparisons were conducted between human data and equivalent sample of model outputs only. The model's quantitative predictions were very accurate on the performance measures of time to mid-trajectory (R^2=.98, *RMSE*=.52), end-trajectory (R^2=.98, *RMSE*=.56) and trajectory tracking (see Table 6.2). Independent-samples t-tests were further conducted for paired comparison of human and model data. The results, as detailed in

Table 6.3, replicated the significant differences observed between the *S-human* and *V-human* in the empirical data. Furthermore, no significant differences were found in within-group comparison of human and model performance measures.

Category	*n*	Mid point		End point		Trajectory (%)	
		M	*SD*	*M*	*SD*	Completed	Aligned
S-human	30	8.39	3.93	10.77	3.96	43.3	33.33
S-model	30	8.56	3.48	10.55	3.6	40.0	23.33
S-model(500)	500	9.70	3.89	10.89	3.36	43.6	40.6
V-human	29	3.28	1.75	4.93	1.73	100	100
V-model	29	3.2	.49	5.35	.7	100	100
V-model(500)	500	2.85	.44	4.8	.61	100	100

Table 6.2 Descriptive statistics for human and model performance measures – Experiment 4

Paired Categories	Time to mid-point						Time to end-point					
	t (df)	*p(two-tailed)*	*eta squared*	*mean difference*	*95% CI*		*t (df)*	*p(two-tailed)*	*eta squared*	*mean difference*	*95% CI*	
S-model V-model	5.31 (11.18)	<.01	.42	5.36	3.14	7.57	5.0 (11.35)	<.01	.39	5.19	2.89	7.49
S-human S-model	-.12 (23)	.91	<.01	-.17	-3.26	2.91	.12 (23)	.85	<.01	.30	-2.92	3.45
V-human V-model	.22 (32.38)	.83	<.01	.07	-.61	.76	-1.22 (37)	.23	<.01	-.42	-1.13	.28

Table 6.3 Comparative analysis of human and model data – Experiment 4

6.4.6 Discussion

A selected step Experiment 1 (Chapter 3) task is modelled in ACT-R 6.0 cognitive architecture by using a novel sequence-of-points technique. The computational model implements similar productions structure for the two independent groups compared – static pictures versus video task instructions. The declarative knowledge structures were however different to reflect interaction with the respective static and dynamic visualisations components of the instructional interfaces. The model's quantitative predictions on post-learning task performance were accurate and replicated the significant differences observed in the human data from the original study. This reinforces the argument that dynamic instructional visualisations may be more cognitively beneficial than static equivalents for the acquisition of procedural motor knowledge. The results are however limited as only a single step of an entire assembly sequence was modelled. A more complete comparison will include the entire assembly sequence of procedural motor tasks. This limitation is addressed in a follow-up Experiment 5 based on the sequence-of-point modelling paradigm in the ACT-R 6.0 architecture.

6.5 Experiment 5

6.5.1 The Task.

The objective of Experiment 5 was to extend the sequence-of-point modelling methodology to an entire sequence of procedural-motor task. A decision was taken to model a previously published related study instead of using data from experiments conducted in the course of the current research work. The aim is to provide a wider context for the justification of the sequence-of-point modelling methodology and extend its generalizability to independently sourced data. The experimental task of Watson, Butterfield, Curran and Craig, (2010) was therefore selected for modelling in Experiment 5. The task compares the effectiveness of dynamic and static computer multimedia instructions for learning a novel mechanical assembly task. Beyond the data reported in Watson et al. (2010), the raw experiment materials (videos and static presentations) and fine details of the procedure were also required for precise kinematic analysis. Mr Watson was therefore contacted directly and he was gracious enough to provide the requested materials as well as to grant permission for their use. Watson et al. (2010) experimental task was to assemble a device comprised of 49 separate parts as depicted in Figure 6.5 and detailed in Table 6.4. The device must be put together in a particular sequence comprising four progressive stages – central gear assembly, frame, propeller and crank arm. Participants were independently grouped by three instructional interfaces – animated video, static diagrams and text -

and completed one post-learning assembly task per day for five consecutive days. Task performance of the independent groups was compared on the factors of device assembly time and errors.

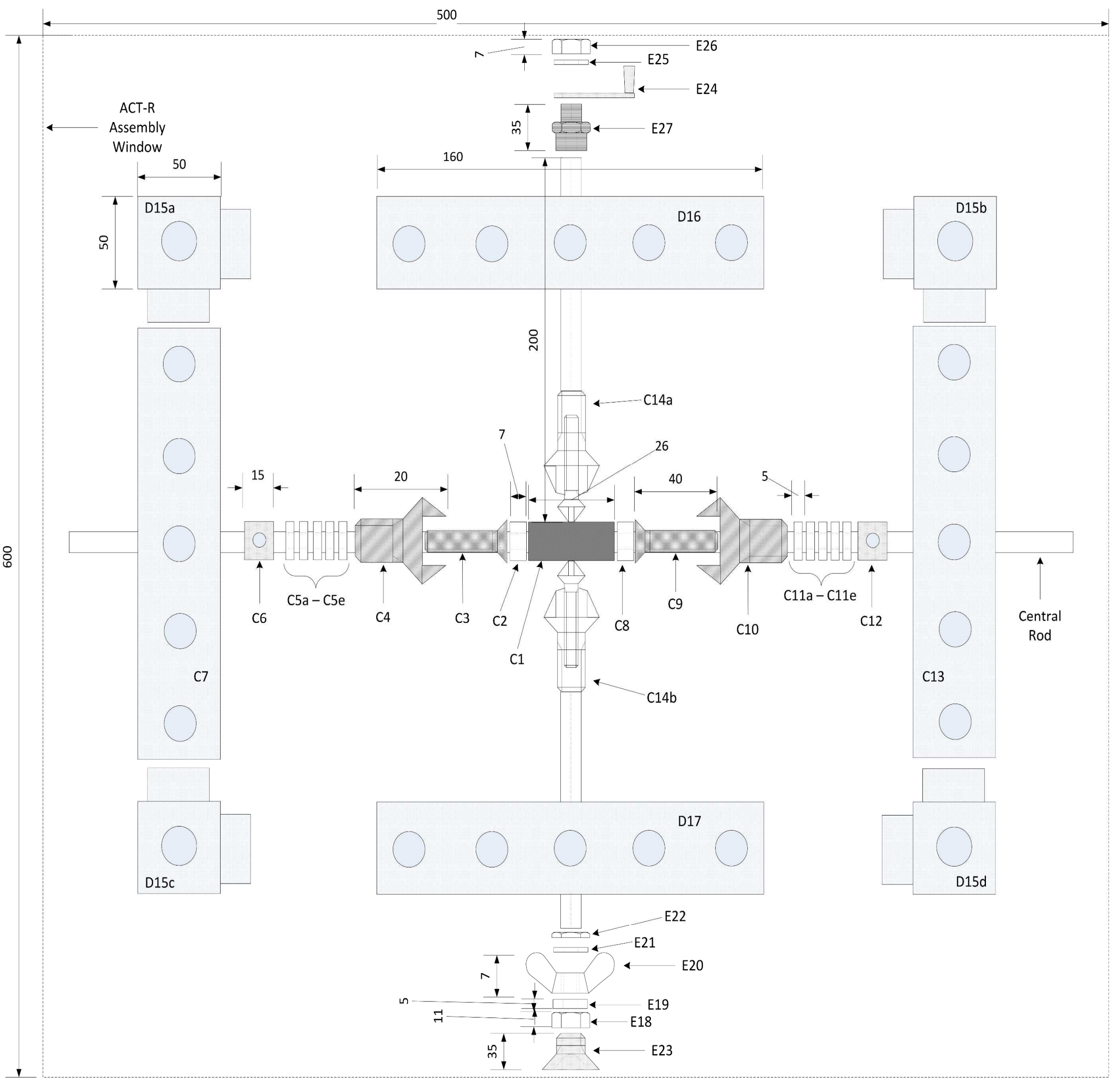

Figure 6.5 Schematic diagram of assembled device. Kinematic analysis of the numbered parts are detailed in Table 6.4

Serial	Code	Component	Thickness (units)	Start	End	Trajectory
1.	C1	Spacer Ring (on long central rod)	26	0,300	250,300	Right
2.	C2	Left Metal Washer	7	0,300	237,300	Right
3.	C3	Left Gripping Screw	40	0,300	230,300	Right
4.	C4	Left Bevelled Gear	20	0,300	230,300	Right
5.	C5a	Left Thin Washer	5	0,300	210,300	Right
6.	C5b	Left Thin Washer	5	0,300	205,300	Right
7.	C5c	Left Thin Washer	5	0,300	200,300	Right
8.	C5d	Left Thin Washer	5	0,300	195,300	Right
9.	C5e	Left Thin Washer	5	0,300	190,300	Right
10.	C6	Left Collar	15	0,300	185,300	Right
11.	C7	Left Beam	50	0,300	170,300	Right
12.	C8	Right Metal Washer	7	500,300	263,300	Left
13.	C9	Right Gripping Screw	40	500,300	270,300	Left
14.	C10	Right Bevelled Gear	20	500,300	270,300	Left
15.	C11a	Right Thin Washer	5	500,300	290,300	Left
16.	C11b	Right Thin Washer	5	500,300	295,300	Left
17.	C11c	Right Thin Washer	5	500,300	300,300	Left
18.	C11d	Right Thin Washer	5	500,300	305,300	Left
19.	C11e	Right Thin Washer	5	500,300	310,300	Left
20.	C12	Right Collar	15	500,300	315,300	Left
21.	C13	Right Beam	50	500,300	330,300	Left
22.	C14a	Upper Central Gear Assembly	200	250,0	250,300	Down
23.	C14b	Lower Central Gear Assembly	200	250,600	250,300	Up
24.	D15a	Upper Left Corner Piece	50	0,0	170,0	Right
25.	D15b	Upper Right Corner Piece	50	500,0	330,0	Left
26.	D15c	Lower Left Corner Piece	50	0,600	170,600	Right
27.	D15d	Lower Right Corner Piece	50	500,600	330,600	Left
28.	D16	Upper Beam	50	250,0	250,220	Down
29.	D17	Lower Beam	50	250,600	250,380	Up
30.	E18	Thick Washer	11	250,500	250,600	Down
31.	E19	Thin Washer	5	250,500	250,589	Down
32.	E20	Propeller	7	250,500	250,584	Down
33.	E21	Thin Washer	5	250,500	250,577	Down
34.	E22	Outer Nut	7	250,500	250,572	Down
35.	E23	Gripping Screw	35	250,565	250,465	Up
36.	E24	Crank Arm	8	250,100	250,15	Up
37.	E25	Washer	5	250,100	250,23	Up
38.	E26	Nut	7	250,100	250,28	Up
39.	E27	Part-threaded Nut	35	250,35	250,135	Up
40.	N1	Tightening Screws (not modelled)				
41.	N2	Tightening Screws (not modelled)				
42.	N3	Tightening Screws (not modelled)				
43.	N4	Tightening Screws (not modelled)				
44.	N5	Tightening Screws (not modelled)				
45.	N6	Tightening Screws (not modelled)				
46.	N7	Tightening Screws (not modelled)				
47.	N8	Tightening Screws (not modelled)				
48.	N9	Tightening Screws (not modelled)				
49.	L1	Long Central Rod	Fixed	Fixed	Fixed	Fixed

Table 6.4 Decomposition of assembly movements within a 2-D Cartesian framework

Some modifications were made to adapt the experiment for cognitive modelling. The data in the original study (Watson et al, 2010) describes the immediate post-learning performance effect on the first build as well as long term retention and performance convergence for the three compared groups over five builds. The cognitive modelling in Experiment 5 however is limited to the early stages of performance for the animated video (*dynamic* or *V-group*) and static visualisations (*static* or *S-group*) instruction groups only. The performance of the text group was not modelled as it is not relevant to the objective of the experiment. Furthermore, only the first post-learning build for the *V-group* and *S-group* were modelled as the objective was to compare the performance effect of the mental task representations afforded by the different instructional visualisations and not long term retention or performance convergence. The methodology of Watson et al. (2010) also allowed for continuous reference to the instructions during the task execution and their subsequent data analysis separated the reference time from the actual build time. In contrast, the modelling technique in this experiment assumes a single interaction with the instructions with no further references during the task execution. Lastly, due to the restrictions imposed by the 2-D visual reference framework of the ACT-R architecture, the assembly of nine components whose trajectories were orthogonal to the main plane of assembly was not modelled (see Figure 6.5 & Table 6.4).

6.5.2 Movement Analysis and Sequencing

The trajectories of the assembled components were analysed as linear movements between specific start and end points in a 2-D Cartesian reference plane (see Figure 6.5 & Table 6.4). The physical assembly components were represented as virtual objects with similar scales. The virtual reference start and end points for each assembled component were also scaled to correspond to actual manipulations of the physical model components. The trajectories were grouped into four categories based on the direction of movement from the start to the end points – right, left, up or down within the Cartesian reference framework. The virtual reference values in a 2-D space for the entire assembly task modelling is detailed in Table 6.4. The assembly starts with the central rod in place and the components are progressively attached in the order implied in Table 6.4 (component C2 to E27) until the task is completed.

6.5.3 Extending the Sequence-of-points Technique

The model's production systems, as shown in Figure 6.6, is essentially the same as that for Experiment 4 with additional mechanisms to switch to the next component in the sequence or reset a failed assembly attempt. The next-component production is fired when the reference point of the component being assembled is within specified limits of its trajectory end point. A component's assembly attempt may also be reset to the start position if the movements have substantially deviated from the ideal assembly trajectory that successful coupling is no longer possible. The reset mechanism allows the model to retry the assembly of such components in the same manner as observed in the analysis of equivalent human performance data. The main differences between the representative *S-model* and *V-model* was in the declarative mental task knowledge structures as applicable in Experiment 4. The *S-model's* mental task representation includes only the start and end spatial locations of each component's assembly trajectory, which corresponds to viewing static pictures of the components in such configurations. It utilises the same retrieve-fail/random-locate strategy as its equivalent representation in Experiment 4 and uses the same control process to correct deviations to the assembly trajectory. The *V-model's* mental task representation includes knowledge of the start and end locations as well as all intermediate spatial locations of the assembly sequence corresponding to learning from dynamic instructional visualisations. It utilises the hybrid strategy as described in Experiment 4, which combines intermediate location retrieval attempts with the random-locate mechanism when retrieval fails. ACT-R's partial matching mechanism and extensions of the activation equation are also used to simulate retrieved location inaccuracies as described in Experiment 4.

6.5.4 Model Validation

The mean assembly times (in seconds) for 100 runs each of the *S-model* and *V-model* and the corresponding data from human participants (Watson et al., 2010) are shown in Table 6.5. The table also shows data for 10 runs each of the cognitive models groups (*S-model [10]* & *V-model [10]*) for direct comparison with the equivalent sample size of human participants from Watson et al. (2010) study. SPSS™ version 17 statistical modelling outputs are presented in Appendix E.

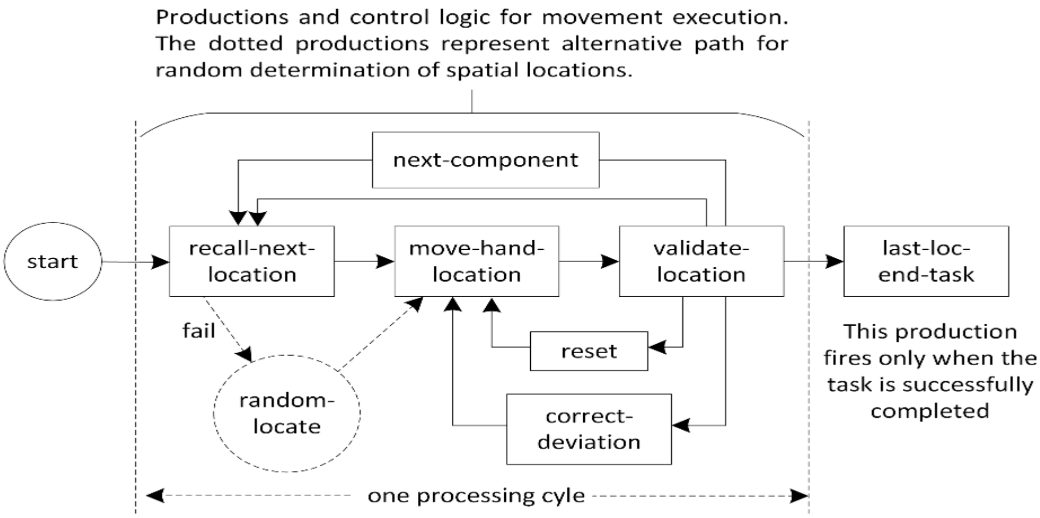

Figure 6.6 Schematic outline of model's productions – Experiment 5

Group	*n*	Central Gear		Frame		Propeller		Crank Arm/Total		Error Counts	
		M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Diagram (static)	10	-	-	-	-	-	-	710.9	329.0	7 *(total)*	
S-model [10]	10	-	-	-	-	-	-	692.2	105.9	8.6	0.8
S-model	100	524.5	30.1	620.0	32.3	650.6	32.7	682.8	33.8	84.7	13.4

Table 6.5 Descriptive statistics for human and model performance measures – Experiment 5

It is important to note here the different attributes of the human and model data and how this was treated in the comparison analysis. The human data and its corresponding 10 runs of model data does not include timings for the sub stages of the assembly. Although these timings were captured in the 100 runs of the models, the final comparison across all groups was limited to only the final build times. In the Watson et al.'s, (2010) study, the overall task performance time for the human participants were further broken down into reference time and net build time. In developing the computational models however, no references were made to the instructional interface during the assembly task execution. Model output data was therefore compared to the appropriate net build times of human data only. Additionally, the sample size for human participants (Watson et al., 2010) was small, which may account for the large deviations reported in that study. Despite this, the reported human data clearly shows the trend of learning differences and interface effectiveness between the compared groups. The Animation group (*dynamic*) recorded considerably lower deviation than the Diagram (*static*) group indicating more consistent superior performance. This decreasing trend in performance time was also replicated in the models' data. Interestingly, correspondingly large standard deviations were observed in only the *S-model [10]* and *V-model [10]* group's data with more consistent deviations recorded for the 100-runs of model data. This may imply that the larger sample size of the 100-runs model groups afforded a more consistent measurement of task performance. The *S-model [10]* and *V-model [10]* group's data were excluded from the subsequent analysis and results discussed in this thesis as the equivalent raw data of human participants from Watson et al.'s (2010) study were not provided as requested.

The ACT-R architecture and task domain parameters settings from Experiment 4 were retained with the exception that no cut-off time was set for the task. The cut-off criteria was not required as the task was to complete the entire assembly and not a sub step. The model's quantitative data was analysed with similar parametric statistical tests to those used in the original study by Watson et al., (2010). An independent samples t-test revealed that the *V-model's* mean task performance time (M = 515.5, SD = 75.0) was significantly faster than the *S-model* (M = 682.8, SD = 33.8; $t(198) = 20.4$, $p = .0$ (two-tailed)). The magnitude of the differences in the means was very large (mean difference = 167.4, 95% CI: 151.1 to 183.6, eta squared = 0.7). This is partially consistent with the results of Watson et al., (2010), which found a significant effect of instructional group on overall build times with the Animation group observed to be 28% faster than the Diagram group. Curiously however, no significant effect of the instructional group was observed for net build times. Watson et al.'s (2010) further analysis shows that only the difference between the Animation and Text instruction groups overall build times was significant (which was not modelled in this study) while that for the Animation versus Diagram group did not reach statistical significance. Only one assembly error was reported in the assembly performance of the Animation (*dynamic*) group at Build 1 while seven errors were observed for the Diagram (*static*) group. The mean error counts for the models however were much higher. An independent samples t-test revealed that the *S-model* had significantly higher mean error count (M = 84.7, SD = 13.4) than the *V-model* (M = 1.4, SD = 1.6; t(198) = 61.9, p = .0 (two-tailed)). The magnitude of the differences in the means was very large (mean difference = 83.3, 95% CI: 80.6 to 86.0, eta squared = 0.9).

6.5.5 Discussion

A computational model was developed in the ACT-R 6.0 architecture to replicate the performance of dynamic versus static groups of human participants acquiring procedural skills for a sequential assembly task (Watson et al., 2010). The model utilised the sequence-of-point technique from Experiment 4 for individual component rotation and extended this with further productions to switch to the next component in the sequence when the sub-assembly was completed. It also included additional mechanisms that simulate component manipulation retrials for failed assembly attempts. The performance of human participants that learned the assembly task through static instructional visualisations was simulated by the model's declarative knowledge that includes chunks of the start and end trajectory positions for each manipulated component (*S-model*). The declarative knowledge of the representative model for participants learning through dynamic instructional visualisations (*V-model*) however included chunks of the start and end component positions as well as all the intermediate spatial locations along the trajectory of manipulation.

In general, the model's quantitative predictions replicated the trends observed in the equivalent analysis of human data from Watson et al., (2010). However, the analysis of the model's data revealed statistically significant differences between the compared groups in contrast to the findings of Watson and his colleagues. An explanation for this could be that the methodology of Watson et al., (2010) was not powerful enough to detect statistically significant differences between the compared groups due to the low samples sizes used. Their data however clearly shows the trend of learning differences and interface effectiveness between the compared groups. In the Experiment 5 reported, the sample sizes for the model data were much larger

(100 model runs for each group), and the subsequent data analysis was powerful enough to detect significant differences in the performances of the compared groups.

6.6 General Discussion

In a series of two experiments, a novel sequence-of-points method is applied to model the acquisition and execution of skilled, procedural-motor movements in ACT-R 6.0 cognitive architecture. The first experiment of the series was essentially a proof of concept that applies the sequence-of-point approach to a selected single step of the sequential procedural task from Experiment 1 (Chapter 3). The modelled step was selected because its performance was significantly moderated by the level of dynamic visualisations components of the instructions for learning it. The second, follow-up experiment extends the modelling methodology to an entire task sequence from Watson et al. (2010) to overcome the limitation of the first experiment. Model data from both experiments were validated with equivalent empirical human data from the related studies with significantly accurate quantitative prediction outcomes.

The sequence-of-points method successfully addresses two key problems associated with modelling the acquisition of skilled human motor performance – the smooth execution of continuous movements along curved and linear trajectories and the simulation of the cognitive roles of different mental task representations in post-learning task performance. The first problem is a long-recognised constraint in computational cognitive modelling of human motor performance. Most modern cognitive architectures have only rudimentary mechanisms for simulating motor performance and the modelling of smooth continuous movement trajectories is especially difficult (Flash & Hogan, 1985; Byrne et al., 2010). The sequence-of-point method addresses this problem by decomposing continuous motor movement trajectories into unit vectors of fixed magnitude and variable direction. This approach also specifies a continuous velocity profile across the transitional boundaries of sequential unit vectors based on Flash and Hogan's (1985) dynamic cost optimisation method for the mathematical modelling of human movements. It is similar to the technique utilised in a related previous study by Byrne et al., (2010) but was restricted in that study to simple linear movements only. Additionally, Byrne et al.'s, (2010) approach relies solely on the imaginal module of the ACT-R cognitive architecture for virtual visual targets for motor movement termination. In contrast, the approach in the current experiment affords modelling of curved as well as linear motor movements by specifying different parametric equations for various segments of the trajectory. Furthermore, it specifies a separate abstract process that integrates the task declarative knowledge with the mechanisms of the imaginal module to determine spatial locations for unit movement termination. This allows flexible, robust and on-the-fly determination of movement trajectory that simulates the effect of different instructional approaches on post-learning task performance.

The second problem is more important and relates directly to the overall objective of the study, which is to investigate the integrated, intertwined role of cognitive mental task representations acquired from different levels of dynamic instructional visualisations on post-learning procedural-motor task performance. This is modelled through the specification of different declarative knowledge structures of the mental task models acquired through instructions with varying levels of dynamic visualisations component. Furthermore, the approach adopted abstracts the underlying cognitive processing and trajectory computations from the ACT-R manual module, which executes the actual motor movements. The abstraction process relies on a process control law similar to Salvucci's (2006) 2-points model for modelling lateral steering control in highway driver behaviour (see also Salvucci & Gray, 2004). Salvucci's method however does not address prior learning and acquisition of mental task models through different instructional formats and the subsequent effect of this on post-learning performance. The specification of the control law in the current experiment is a novel application of Fajen and Warren's (2003) steering model, where the ideal movement trajectory becomes the heuristic for the abstract process that integrates participant's mental task model with actual motor execution.

The sequence-of-point modelling method combines the partial matching mechanism of the ACT-R retrieval module with a novel extension of the activation equation to simulate the stochasticity of spatial location recall during the motor task execution. This afforded the fairly accurate simulation of humans' ability to select and execute a specific movement trajectory from the large degrees of freedom inherent in skilled procedural-motor performance (see e.g. Vivian & Flash, 1995). Such extensions of the ACT-R architecture could be further developed to modelling more natural 3-D spatial movements. One possible method could be the further extension of the activation equation to simulate spatial locations recall inaccuracies in a third 'z' coordinate for a 3-D reference framework. However, such an approach would require an upgrade of the visual system of the ACT-R architecture to support 3-D visual location chunks, which is not possible in the current version 6.0.

The comparative analysis of the model's data with equivalent empirical data was more consistent in Experiment 4 than in Experiment 5. The inconsistencies with human data observed in Experiment 5 could be attributed to slight differences in the methodologies adopted, sample sizes and data analysis techniques. Watson et al.'s, (2010) sample sizes were quite small (10 participants per group) and the subsequent analysis is arguably not powerful enough to elicit statistically significant differences in the performances of the independent groups. In contrast, sufficient runs of the computational models were conducted (100 runs per group), which afforded statistically significant differences to be observed in the post-learning task performance measures. In general however, the computational model's predictions were closely accurate for comparative human data in the two experiments conducted. The results provided evidence that dynamic instructional visualisations may be more effective for learning procedural-motor skills than their static equivalents. This is also consistent with the view that post-learning performance is moderated by the type of requested knowledge (Höeffler & Leutner, 2007), the level of dynamism of the instructional interface (Höeffler & Leutner, 2011) and dedicated processing of dynamic instructional percept through a separate WM motor processor construct (Wong et al., 2009).

6.7 Limitations

The computational models developed in this study were implemented in the ACT-R 6.0 cognitive architecture version. Accordingly, the simulations were constrained to the 2-D spatial reference framework of the ACT-R visual system. The corresponding human performance data however involved natural 3-D spatial movement. This limitation was minimised by integrating well established mathematical models of human movement from previous related research in the design. Additionally, only the subset of procedural-motor movements that lie in a 2-D reference framework was modelled and all other with orthogonal trajectories were excluded. An extension of the ACT-R activation equation could be a possible methodology for future work to extend the modelling to 3-D spatial movements. This would however require substantial upgrade to the visual reference system of the base ACT-R architecture.

The participant's spatial ability and domain expertise has been established as a moderating factor for post-learning procedural-motor performance by previous related research (Höeffler, 2010; Höeffler & Leutner, 2011; Gegenfurtner et al., 2011). In contrast to the corresponding human data however, the models developed did not control for this factor, which limits the generalizability of the results.

6.8 Conclusion

A novel computational modelling methodology is utilised to argue for a central cognitive role of acquired mental task representations in the post-learning performance of skilled motor tasks. The methodology distinguished mental task representations acquired from instructions with dynamic visualisation contents as opposed to those with static alternatives and demonstrated their comparative moderating effects on efficient transfer to actual motor performance. There were two components of the methodology, each addressing separate aspects of problems associated with detailed modelling of fine, human motor performance in contemporary cognitive architectures like the ACT-R 6.0. The first part is a sequence-of-point technique for the specification of task-related spatial knowledge in declarative WM. This technique is based on the application of well-accepted mathematical models to generate list structures that simulate variously acquired mental task models in the declarative knowledge module of the base cognitive architecture. These structures are later integrated with the subsequent execution of the procedural motor task to simulate differences in performance corresponding to the different initial instruction formats. The second component of the methodology is a movement control mechanism for the integration of the mental task models to actual task execution. This is implemented as a motor control law based also on established mathematical models of human motor control. The motor control law affords the translation of variously acquired mental task representations into smooth, continuous human movement in the execution of the task. It also specifies a process for simulating the stochastic but effective selection of a desired movement trajectory from an infinite range of alternatives that is inherent in human motor performance. The combination of the sequence-of-points technique and the movement control mechanism constitutes the methodology that affords the simulation of the atomic motor actions evident in skill acquisition and performance. To the best of the author's knowledge, this is a novel paradigm for the computational modelling of skilled human motor performance, which overcomes the limitation of coarse motor output inherent in the default implementation of contemporary cognitive modelling architectures such as the ACT-R 6.0.

The methodology was validated through incremental development of ACT-R 6.0 models in two experiments and the comparative analysis of the model's outputs with equivalent empirical human data from previous studies. The first experiment's model provided a proof of concept but was limited to a single step of a procedural task sequence. The second experiment's model extended the methodology to the entire task sequence to overcome this limitation. The two model's quantitative performance measures were fairly accurate and correlate significantly with the equivalent human data. This provides further evidence that dynamic instructional visualisations are more effective that their static alternatives for capturing the latent transitory information that are intrinsic and key to the efficient execution of skilled procedural motor tasks. The results are however limited as the model movements were implemented in 2-D space as opposed to the more natural 3-D human movements used in the comparative studies. This limitation is dictated by the underlying restrictions of the ACT-R 6.0 default visual module used for implementation and may be overcome in further studies by an extension of the sequence-of-point technique as we have specified. Future studies would also be required to evaluate the established effect of other performance moderating factors, such as the learner's spatial ability, which was not accounted for in the implementation of the cognitive models.

Chapter 7

General Discussion and Conclusion

7.1. Overview

The research presented in this thesis investigates the cognitive effects of different visualisations components of computer simulated instructional interfaces. The focus has been on the comparison of empirical performance measures of complex tasks/skills, which were acquired through instructional interfaces with different levels of dynamic components. The first set of experiments partially replicate and contribute to previous related studies through novel extensions of methodology. These experiments compared empirical post-learning performance data of different groups of human participants to infer the cognitive processes that support novel skills acquisition. The results also provide evidence for a novel hybrid cognitive learning model that describes the domain specific benefit of dynamic versus static visualisations components of the instructional interface. This first set of experiments was followed by another series that applied novel computational cognitive modelling techniques to examine the topic of interest. The increasingly acceptable methodology of cognitive modelling afforded psychologically valid and integrated descriptions of the underlying cognitive processes that drive overt performance of novel skills. Novel extensions to the base framework of the selected ACT-R 6.0 architecture were also described, which afford the atomic modelling of complex human skills acquisition and the integration of mental task representations with fine motor performance.

By way of summary and for convenience, the objectives of the research as stated in Chapter 1 are reproduced below and subsequently evaluated against the outcome of the work reported:

- To investigate the cognitive effects of different levels of dynamic visualisation components of computer based instructional interfaces in the acquisition of novel procedural knowledge.

- To identify the cognitive mechanisms that support the acquisition of novel procedural knowledge and their effects on post-learning task performance.
- To conduct empirical investigations with human participants for validating the cognitive roles of different instructional interface visualisations in the acquisition and transfer of skilled procedural knowledge.
- To develop cognitive architecture-based computational models of human procedural knowledge acquisition via computer based instructions, which fits with empirical data.
- To contribute to the HCI knowledge of the cognitive effects and roles of different levels of dynamic visualisation components of instructions using an interdisciplinary methodology.

The first objective – investigation of the cognitive effects of interface dynamic content – was addressed from various perspectives by all the experiments reported. The empirical experiments described in Chapters 3, 4 and 5 compare directly the cognitive effects of manipulating the dynamic visualisation contents of instructional interfaces on post-learning task performance of human participants.

The second objective is focussed on low-level description of the cognitive processes that support novel skill acquisition through different instructional interfaces. This objective was framed in the literature review of Chapter 2 culminating in the deduction of a novel hybrid cognitive learning model to describe modal and amodal perspectives of skill/knowledge acquisition. Experiment 1 reported in Chapter 3 replicates evidence supporting the concept of a specialised 'motor processor' component of WM as established in related studies. The results of Experiment 1 also show that the specialised processor component of WM is consistent with the hybrid cognitive learning model proposed in Chapter 2. The work continues by extending this concept, through the subsequent Experiment 2 reported in Chapter 4, to other procedural knowledge domain outwith motor skill acquisition. The cognitive mechanisms identified were examined in low level details by the computational cognitive models developed in the series of experiments reported in Chapter 6.

The third objective to conduct empirical investigations of novel procedural skill acquisition using human participants has been met with the experiments reported in Chapters 3, 4 and 5. A total of 180 human participants were sourced across the experiments reported in this thesis. The methodology of each experiment was varied to account for different perspective of the research question.

The fourth objective to develop psychologically valid computational models of human procedural skill acquisition via computer based simulated learning was met by the cognitive modelling effort reported in Chapter 6. A series of experiments were described that utilise the ACT-R 6.0 cognitive architecture to iteratively model and investigate the cognitive mechanisms associated with novel procedural skill acquisition and post-learning task performance. The resultant models describe in atomic details the simulation of instructions, interface components perception, differential mental task models associated with interface components and integration of mental representations in subsequent task performance. The results of the modelling effort were validated with established empirical data to provide novel insights to the underlying cognitive mechanisms that drive procedural skill acquisition and performance.

The final listed objective was to contribute to HCI knowledge regarding the cognitive benefits of instructional interface dynamism using an interdisciplinary approach. The methodology of the experiments described in the thesis integrates theories and techniques from various disciplines including neurophysiology, educational psychology, mathematical modelling, neuroscience, artificial intelligence and cognitive psychology. Relevant aspects of these disciplines were integrated together seamlessly to investigate and argue for the results that have been presented throughout the thesis.

7.2. Hypothesis Testing

In the course of the research, several hypotheses were formulated to drive the reported experiments. These hypothesis were tested and accepted or rejected based on the results of each experiment. The experiments and associated hypotheses were structured to focus on separate aspects of and incrementally address the overall research problem. To facilitate a general discussion cutting across all the reported experiments, a revised and comprehensive version of all the hypotheses is enumerated below. This summarised version integrates the separate aspects to directly address the overall research objectives:

Null Hypotheses

H_{00} Instruction interfaces with more dynamic visualisation contents would have no effect on the post-acquisition performance time of novel procedural skills/knowledge as compared to those with equivalent static visualisation alternatives.

H_{01} Instruction interfaces with more dynamic visualisation contents would have no effect on the post-acquisition performance accuracy of novel procedural skills/knowledge as compared to those with equivalent static visualisation alternatives.

H_{02} The interaction of instructional interface dynamism and post-acquisition performance of novel procedural motor skills/knowledge would be dependent on the learner's spatial abilities.

H_{03} The moderating effect, if any, of dynamic versus static interface visualisations on the post-learning performance of novel, procedural and domain specific skills/knowledge would be dependent on the prior knowledge or expertise of the learner.

Alternate/Positive Hypotheses

H_{11} Dynamic visualisation components of an instructional interface would facilitate the creation of more complete and efficient mental models of novel procedural skills/knowledge than equivalent static visualisation alternatives.

H_{12} The cognitive benefit of more efficient mental models of novel procedural skills/knowledge afforded by dynamic visualisations components of the instruction interface over equivalent static visualisation alternatives is due to an intrinsic motion attribute of the dynamic visualisations.

H_{13} The cognitive benefit of more efficient mental models afforded by dynamic visualisations components of the instruction interface over equivalent static visualisations alternatives would yield faster post-learning performance of novel procedural skills/knowledge.

H_{14} The cognitive benefit of more efficient mental models afforded by dynamic visualisation components of the instruction interface over equivalent static visualisation alternatives would yield more accurate post-learning performance of novel procedural skills/knowledge.

H_{15} The interaction of instructional interface dynamism and post-learning performance of novel procedural skills/knowledge would be independent of the learner's spatial abilities.

H_{16} The moderating effect of instructional interface dynamism and post-learning performance of novel procedural skills/knowledge would be independent of prior domain knowledge or expertise of the learner.

H_{17} The more efficient mental task models afforded by dynamic visualisation contents of the instruction interface versus equivalent static alternatives would facilitate more robust post-learning performance of novel procedural skills/knowledge.

Null hypotheses H_{00} and H_{01} were rejected as the post-learning performance time and accuracy afforded by dynamic instructional interface visualisations were found to be significantly faster and better than possible with equivalent static visualisation alternatives. This finding was consistent across the results of the experiments reported in Chapters 3, 4 and 5. The alternative hypothesis H_{13}, H_{14} and H_{17} were therefore accepted.

The spatial orientation and visualisation abilities of the participants were controlled in the experiments reported in Chapter 3, 4 and 5. However, it was highlighted in Chapter 5 that spatial ability comprises of sub factors such as spatial visualisation, spatial relations (orientation), perceptual speed, closure speed and flexibility of closure (Carrol, 1993). The null hypothesis H_{02} may therefore be rejected only to the extent controlled for in the reported experiments. In line with this, spatial orientation and visualisation abilities were found not to have significant moderating effect on the cognitive benefits of instructional interface dynamism. The alternative hypothesis H_{15} was therefore accepted.

Experiment 3 reported in Chapter 5 found a significant effect and benefit of instructional interface dynamism irrespective of prior domain knowledge or expertise to the extent that the learned skill is novel. Null hypothesis H_{03} was therefore rejected and alternate hypothesis H_{16} accepted.

The computational cognitive models developed in Chapter 6 afforded detailed investigation of the formation of mental task models from visual stimuli associated with novel learning and skill acquisition. They further modelled the integration of these mental task representations with subsequent task performance with a significant benefit observed for dynamic visualisations stimuli than equivalent static alternatives. Alternate hypotheses H_{11} and H_{12} were therefore accepted.

The acceptance/rejection of these hypotheses are further discussed in the following sections of this chapter.

7.3. A Hybrid Cognitive Model of Multimodal Perception

The multimodal perception of external stimuli and the associated cognitive processes that integrates the percept into coherent mental models were discussed in Chapter 2. The thrust of the discussion argued for a novel hybrid cognitive learning model of stimuli perception from multimodal channels as typical in a multimedia learning environment. The model further describes the modality specific and cognitive processes that underlie the behavioural responses associated with perception of different stimuli. This model was subsequently used to argue that the particular attributes of different external stimuli may yield varying utilisation levels of the cognitive processing bandwidth afforded by each modal channel. The fidelity and completeness of novel mental task representations is therefore dependent on the attributes of the percept. For example, the transitory information carrying attribute of dynamic interface visualisations have been shown in Chapter 3 to afford more complete mental representation of a motor task than possible through equivalent static visualisations. The results presented in Chapter 3 shows that the post-learning performance of a novel motor task was faster and more accurate when the instruction interface comprised of dynamic visual stimuli versus static visual stimuli. This result is consistent with Wong et al, (2009) specialised 'motor processor' view and was extended through further experiments reported in Chapter 4 to the separate procedural knowledge domain of spatial navigation. In this second experiment, a novel 'motion processor' was proposed as an extension of the visual buffer component of the mental imagery theory (Kosslyn, 2005). This motion-variable dependent processor is argued to be activated by the additional translational information inherent in the dynamic instruction interface, which portrays motion relative spatial features of the navigation space. The performance measures of navigation path length and time were therefore found to be consistently shorter and faster respectively for instances of novel spatial navigation skills acquired through interaction with dynamic instructions as opposed to static. The cognitive effect of interface dynamism was also found to be significantly different on the factors of route completion rate and robust performance.

The hybrid cognitive learning model was further applied to investigate the moderating effect of prior domain knowledge or expertise on the interaction of interface dynamism and novel procedural skills acquisition. The model, as presented in Chapter 5, was restructured to emphasize the central role of the learner's cognitive architecture in the novel skills acquisition process and how it may be moderated by domain expertise. Overall, the empirical results reported in Chapter 5 show that while domain expertise may moderate cognitive architecture limitations by affording more developed knowledge schemas, it may not completely eliminate the established restrictions of the WM. Similar to domain novices therefore, the performance of experts on novel intra-domain procedural skills were also found to be moderated by instruction interface dynamism. The intrinsic attribute of dynamic instructional interface visualisations to facilitate the creation of more accurate mental task models as opposed to static visualisations may therefore be independent of domain prior knowledge or expertise to the extent that the learning task is novel.

In general, the experiments reported in Chapters 3, 4 and 5 addressed various aspects of the hybrid cognitive learning model to show the cognitive effects of instruction interface dynamism on novel procedural skill acquisition. The experiments' methodologies also variously controlled for the potential confounding effect of extraneous variables such as the spatial visualisation, spatial orientation and prior video gaming experience.

7.4. Computational Modelling and Architectural Extensions

The computational models discussed in this thesis allow a rigorous and detailed investigation of the cognitive effects of instructional interface visualisations than possible with empirical comparisons of independent groups. As highlighted in

Chapter 6, modern cognitive modelling architectures, such as ACT-R 6.0, have become established tools for application to a range of traditional human factors problems. The strength of these methods is that they afford the implementation of psychologically valid behavioural models that facilitate quantitative investigations of human factors problems. The models developed and discussed in the series of experiments reported in Chapter 6 required novel extensions to the base framework of the selected ACT-R 6.0 cognitive modelling architecture. The extensions made enabled modelling of atomic cognitive processes associated with learning a novel procedural skill via different instructional interface visualisations and how this is further integrated with subsequent task performance. Notably, a functional decomposition technique was used to represent complex human movements with mathematically derived unit vectors. Further novel extensions were then defined for ACT-R 6.0 activation equations to enable the Cartesian representation of intermediate locations along the modelled movement trajectories.

The integration of several thousand cycles of unit movements was moderated by separately defined control logic to replicate task execution and performance measures observed in the empirical data of equivalent groups of human participants.

7.5. Main Findings

The work reported in this thesis contains several major findings, which are original contributions to the research area. These are enumerated below:

- A novel hybrid cognitive learning model is proposed to explain domain specific skill acquisition via computer based instructional simulators. The model affords comparison of different interface formats and optimisation of the cognitive benefits associated with instructional delivery.
- The proposition of an intrinsic attribute of the instructional interface that supports the presentation of transitory, domain specific information and facilitates task comprehension, development of expert mental models and performance.

- The discovery of the cognitive benefits of dynamic instructional presentations over static alternatives to facilitate novel, intra-domain skills acquisition and performance irrespective of prior domain expertise.
- The validation of these discoveries through empirical investigations of human performance and computational simulations that utilizes modern cognitive modelling methodologies.
- The proposition of a novel modelling methodology that extends the ACT-R 6.0 cognitive architecture and affords the simulation of human motor learning and performance at an atomic level of detail.
- The development of a psychologically valid computational cognitive model that simulates human interaction with dynamic versus static interface elements and the consequent effect on the performance of novel procedural task.

7.6. Limitations

Some limitations were highlighted along with the discussion of each experiment reported in this thesis. These limitations are aggregated and discussed further in this section.

The thrust of the experiments conducted was to investigate the cognitive effects of instructional interface dynamism on novel skill acquisition. In doing this, the knowledge-domain for the investigation was largely restricted to tasks that were procedural and functionally decomposable to logical sequences of sub-tasks. Although it is arguable that the investigation spanned a range of different tasks, further experiments would be required to establish the cognitive effects under observation in other non-procedural knowledge domain e.g. declarative knowledge and problem-solving knowledge.

Age and gender variables have been found in previous studies to have a moderating effect on spatial navigation performance. The restrictions imposed by the recruitment process of Experiment 2 reported in Chapter 4 however made it difficult to control for these potentially confounding variables. It was especially difficult to recruit across a wide age and gender range because the primary source of participants were university students. Voluntary participation in the experiment was sourced through advertisement posted on virtual and physical noticeboards across the Robert

Gordon University community. The methodology used however compensated for this limitation by randomly assigning available participants based on age and gender stratification to achieve a more even spread. An additional limitation of the findings in Chapter 4 is the inconclusive evidence for a process level moderating effect of spatial orientation and prior video gaming experience on spatial navigation performance. It is important to note that the potential confounding effects of prior video gaming experience on task performance in a virtual environment was controlled for in the experiment. Further investigation of this exciting finding however may benefit from the application of eye tracking methodology to correlate visual reference fields during learning with subsequent task performance. This was not pursued further in this work as it is considered tangential to the objectives of the research.

Experiment 3 reported in Chapter 5 involves a low sample size, which may arguably limit its generalisation. This was due to the problems associated with recruiting the special expertise required for participation in the experiment. It was difficult to arrange participation in the experiment around the busy schedules of the expert aircraft engineers recruited and in many instances, scheduled sessions had to be cancelled at the last minute because of emergency work requirements.

The limitations of the computational cognitive models that were developed in this work were highlighted in Chapter 6. Simulation of human motor performance in the models was restricted to a 2-D Cartesian reference plane as opposed to the more natural 3-D human movements. This limitations was imposed by the underlying restrictions of the base ACT-R 6.0 cognitive architecture framework. The default visual module and GUI device of this architecture are currently designed to implement a 2-D visual reference field. Substantial upgrade of the architecture would be required to support 3-D visual referencing and movement simulation. The models developed did not also account for the potential confounding effects of other extraneous variables such as the learner's spatial ability and prior domain knowledge.

At this point, it is important to highlight the time and effort that were required to plan, setup, conduct and analyse the experiments reported in this thesis. A lot of time was dedicated to the review of extant literature at the initial planning stages in order to search for and reference related research. Following this, the design phase of the experiments involved several test runs and iterative refinement, which were not reported directly in the thesis. These test runs were conducted mostly with participants from RGU research community and personal friends of the author and were very important for the discovery of problem areas prior to live implementation of the experiments. Some of the final experiments, like those reported in Chapters 3 and 5, were conducted outside the United Kingdom with attendant logistics issues. It took about 10 months to secure the appropriate approval from the Ministry of Defence, Nigeria to access the secure sites and participants required for the experiments. As noted previously, these participants were required in particular because of their specific skills set. The conduct of the experiment was spread over several weeks to accommodate the individual sessions ranging from about 40 minutes for the experiment reported in Chapter 3 to approximately 120 minutes for that reported in Chapter 4. The subsequent analysis of the recorded sessions took an even longer time as the data has to be extracted through an iterative process of play, stop, rewind and play. This made the data extraction process painstakingly slow but meticulous. The development of the cognitive models was also difficult because of the complexity of the ACT-R 6.0 architecture and it's novelty to the author.

Lastly, it is important to note and acknowledge the intensive revision cycles associated with each of the publication output of this research work. Each publication received inputs from anonymous peer reviews with the suggestions received in each review cycle incrementally integrated to produce the final refined experimental methods and results. The longest publication cycle took 13 months for the work reported in Chapter 3.

7.7. Future Work

The work reported in this thesis would benefit from further experiments that would use revised methodologies to address some of the limitations highlighted in the previous section. As a starting point, such future experiments could be designed to directly compare the post-learning performance of novices versus experts on the acquisition of novel, intra-domain knowledge through different instructional interfaces. The direct comparison of novice versus expert performance would yield a fresh insight into the moderating effect of domain expertise on instructional interface dynamism.

It will also be interesting to discover a threshold interface cognitive load for the moderating effect of instructional dynamism. The transitory nature of dynamically presented information imposes some cognitive load on the learner who has to keep portions of the previous frame in WM to integrate with subsequent frames for comprehension. Preliminary work by Spanjers et al., (2011) has manipulated the length of dynamic instructional visualisations to measure the cognitive benefits of segmented versus continuous presentation. Their work however did not directly compare these visualisations with other types such as static text, pictures or diagrams. A suggested methodology for further work would directly compare different instructional interface visualisations and manipulate the associated cognitive loads through gradual incrementation of the length and complexity of the visualisations.

Future experiments may also benefit from an eye-tracking methodology to investigate the salient aspects of dynamic versus static instructional interface visualisations. The eye-tracking data may support overall performance comparison by examining attention during interaction with the different instructional interfaces. It may also indicate the aspects of the instructional interface that directly support the development of expert mental task models and performance.

The computational cognitive models reported in this thesis may be developed further to account for extraneous factors, which were controlled for in the complementary empirical experiments such as spatial abilities, domain expertise and prior video gaming experience. A suggested methodology for this would be to pre-populate the declarative memory structure of the models with chunks that represent prior domain expertise or knowledge. An alternative methodology may train the models on domain related skills for a while prior to applying them to novel skills/tasks of interest. A further improvement to the cognitive modelling investigative approach would be to extend the models for representing 3-D movements as highlighted in the previous section of this chapter. This would require extensive upgrade of the base ACT-R 6.0 architecture or the selection of another appropriate modelling architecture. It may be possible however to modify the current ACT-R 6.0 architecture by defining a novel device module that extends the default visual module and GUI device for 3-D visual referencing. Other possible modifications suggested in Chapter 6 include the extension of the activation equation and partial matching mechanism of the ACT-R 6.0 architecture for 3-D spatial modelling.

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Appendices

Appendix A

List of Publications

- Akinlofa, O.R., Patrik, P.O'B. & Elyan, E. (2013). Effect of Interface Dynamism on Learning Procedural Motor Skills, *Interacting with Computers* **25**(3): 259-269.
- Akinlofa, O.R., Patrik, P.O'B. & Elyan, E. (in press). The cognitive effect of dynamic representations on procedural skill acquisitions: A computational modelling approach, *The International Journal for Human-Computer Interaction Journal*.
- Akinlofa, O.R., Patrik, P.O'B. & Elyan, E. (2013). Domain expertise and the effectiveness of dynamic simulator interfaces in the acquisition of procedural motor skills, *British Journal of Educational Technology* **44**(5): 810-820.
- Akinlofa, O.R., Patrik, P.O'B. & Elyan, E. (in press). The cognitive benefits of dynamic representations in the acquisition of spatial navigation skills, *Computers in Human Behavior*.
- Akinlofa, O.R., Patrik, P.O'B. & Elyan, E. (2012). Performance modelling of interface dynamism in motor skills acquisition, *in* N. Rußwinkel, U. Drewitz & H. van Rijn (eds), *Proceedings of the 11th International Conference on Cognitive Modeling*, Universitaetsverlag der TU Berlin, Berlin, pp. 129–130.
- Akinlofa, O.R., Patrik, P.O'B. & Elyan, E. (2012). The acquisition of spatial navigational skills from dynamic versus static visualisations, *BCS-HCI '12 Proceedings of the 26th Annual BCS Interaction Specialist Group Conference on People and Computers*, British Computer Society, Swinton, pp. 298–302.

Appendix B

Materials and Analysis Data – Experiment 1

Pre-test Questionnaire

BACKGROUND QUESTIONNAIRE

Please complete the questionnaire below by providing the required details. For questions with a scale range of response, you are required to mark 'X' in the box that corresponds to your answer. Please mark only one box. An example is provided below:

How often do you use internet banking?

- [ ] *Never*
- [ ] *Occasionally*
- [ ] *Usually*
- [x] *Mostly*
- [ ] *Always*

Information provided will be used for research experiment purposes only. Thank you.

Part A – Personal Details

1. Full Names ....

2. Age: ☐ 16 – 20 ☐ 21 – 25 ☐ 26 – 30 ☐ 31 – 35 ☐ 36 – 40 ☐ 41 – 45 ☐ 46 – 50 ☐ Above 50

3. Gender: ☐ Male ☐ Female

4. Are you a student: ☐ Yes ☐ No

4a. If yes, what are you studying?...

5. What is your highest educational qualification?
   - ☐ Primary School Certificate
   - ☐ WAEC/SSCE/NECO or equivalent
   - ☐ OND
   - ☐ HND or First Degree
   - ☐ Postgraduate Diploma or Degree

6. Please describe your academic background?
   ☐ Pure Sciences ☐ Engineering ☐ Arts ☐ Social Sciences
   ☐ Others..
   (please specify)

7. Do you have any previous experience with assembling *Lego** toys?
   ☐ Yes ☐ No

*The Lego Group is a company that manufactures toys and other children creativity materials that are assembled from small and carefully designed building blocks *(www.lego.com)*

Post-test Questionnaire

Interface Format ☐ Static ☐ Video ☐ Interactive ☐

Name...

Part B

In this section, you are presented with a question and a range of possible responses. You are required to mark 'X' through the option that most appropriately expresses your answer to the question. Please mark only one option. An example is provided below:

How often do you use Facebook to connect with your friends and family?

◯	(X)	◯	◯	◯
Very often	*Quite often*	*Usually*	*Once in a while*	*Never*

In this example, the indicated response is 'Quite often' shown by an 'X' drawn through the selected option. Now proceed to complete the questions below. Thank you.

1. How easy was it to use the instruction interface?

◯	◯	◯	◯	◯
Very easy	Quite easy	Easy	Not so easy	Difficult

2. How would you rate the responsiveness of the training interface you used?

◯	◯	◯	◯	◯
Very responsive	Quite responsive	Responsive	A little responsive	Not responsive

3. To what degree did you find the training interface you used confusing?

◯	◯	◯	◯	◯
Very confusing	Quite confusing	Confusing	A little confusing	Not confusing

4. Do you feel that your interaction with the training interface was helpful in your subsequent execution of the actual assembly of the model truck?

◯	◯	◯	◯	◯
Very helpful	Quite helpful	Helpful	A little helpful	Not helpful

5. Please rate how interesting the training interface was:

◯	◯	◯	◯	◯
Very interesting	Quite interesting	Interesting	A little interesting	Not interesting

Thank you for completing the questionnaire.

Experiment Briefing Sheet/Consent Form

Name:.. Date:.....................
(please print) (DD/MM/YYYY)

Thank you for participating in this experiment.

Data Protection

In the course of the experiment, video data will be captured for later analysis. All captured data will be used for research purposes only and will not be passed on to third parties for any other purpose. In the event of publication of the research, all data will be anonymised.

Procedure

The experiment will be conducted in three phases. In Phase One, you will answer some questions in a visualisation and spatial-orientation ability test which will last for about 5 minutes. In Phase Two, you'll be required to use one of three computer-based training interfaces to learn a mechanical task. This phase should take about 15 minutes to complete. In the final phase, you will be given a model of a mechanical device and required to carry out the task you have learnt in Phase Two. You will also be required to complete a short questionnaire. This last phase will take about 20 minutes to complete bringing the total duration of the experiment to approximately 40 minutes.

In Phase Two, you will be given some specific instructions depending on which of the 3 possible interfaces your instructions will be delivered on. This would be determined during the experiment. Although there may be several methods of executing the mechanical task in Phase Three, you are however required to adhere as much as possible to that specified through the instructions interface of Phase Two. Take note also that once you commence Phase Three, you will no longer be able to access the instructions interface.

You will be asked to commence with Phase One when ready. Good luck.

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Page 2 of 2

Statistical Modelling Outputs (SPSS™ version 17)

```
GET  FILE='E:\PhD Work\Thesis\Appendices\Chap 3\field_afit_t.sav'.
MEANS TABLES=t_time t_errors test_s BY i_face  /CELLS MEAN
COUNT STDDEV.
```

Means

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 3\field_afit_t.sav

Case Processing Summary

	Cases					
	Included		Excluded		Total	
	N	Percent	N	Percent	N	Percent
Task time * Interface type	81	100.0%	0	.0%	81	100.0%
Task errors * Interface type	81	100.0%	0	.0%	81	100.0%
Test score * Interface type	81	100.0%	0	.0%	81	100.0%

Report

Interface type		Task time	Task errors	Test score
Static	Mean	138.92	4.88	7.2692
	N	26	26	26
	Std. Deviation	55.444	3.154	2.50691
Video	Mean	99.14	1.21	7.6071
	N	28	28	28
	Std. Deviation	31.079	1.397	2.69896
Interactive	Mean	107.26	1.52	8.5926
	N	27	27	27
	Std. Deviation	44.185	1.397	3.64015
Total	Mean	114.62	2.49	7.8272
	N	81	81	81
	Std. Deviation	47.066	2.675	3.00745

NPAR TESTS /K-W=t_time t_errors BY i_face(1 3) /MISSING ANALYSIS.

NPar Tests

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 3\field_afit_t.sav

Kruskal-Wallis Test

Ranks

	Interface type	N	Mean Rank
Task time	Static	26	51.69
	Video	28	34.88
	Interactive	27	37.06
	Total	81	
Task errors	Static	26	58.75
	Video	28	30.36
	Interactive	27	34.94
	Total	81	

Test Statistics[a,b]

	Task time	Task errors
Chi-Square	8.030	23.354
df	2	2
Asymp. Sig.	.018	.000

a. Kruskal Wallis Test

b. Grouping Variable: Interface type

MEANS TABLES=t_time t_errors BY i_face /CELLS COUNT MEDIAN.

Means

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 3\field_afit_t.sav

Report

Interface type		Task time	Task errors
Static	N	26	26
	Median	123.00	5.00
Video	N	28	28
	Median	97.00	.50
Interactive	N	27	27
	Median	94.00	1.00
Total	N	81	81
	Median	107.00	2.00

NPAR TESTS /M-W= t_time t_errors BY i_face(1 2) /MISSING ANALYSIS.

NPar Tests

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 3\field_afit_t.sav

Mann-Whitney Test

Ranks

	Interface type	N	Mean Rank	Sum of Ranks
Task time	Static	26	33.33	866.50
	Video	28	22.09	618.50
	Total	54		
Task errors	Static	26	36.92	960.00
	Video	28	18.75	525.00
	Total	54		

Test Statistics[a]

	Task time	Task errors
Mann-Whitney U	212.500	119.000
Wilcoxon W	618.500	525.000
Z	-2.623	-4.350
Asymp. Sig. (2-tailed)	.009	.000

a. Grouping Variable: Interface type

NPAR TESTS /M-W= t_time t_errors BY i_face(1 3) /MISSING ANALYSIS.

NPar Tests

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 3\field_afit_t.sav

Mann-Whitney Test

Ranks

	Interface type	N	Mean Rank	Sum of Ranks
Task time	Static	26	31.87	828.50
	Interactive	27	22.31	602.50
	Total	53		
Task errors	Static	26	35.33	918.50
	Interactive	27	18.98	512.50
	Total	53		

Test Statistics[a]

	Task time	Task errors
Mann-Whitney U	224.500	134.500
Wilcoxon W	602.500	512.500
Z	-2.251	-3.895
Asymp. Sig. (2-tailed)	.024	.000

a. Grouping Variable: Interface type

NPAR TESTS /M-W= t_time t_errors BY i_face(2 3) /MISSING ANALYSIS.

NPar Tests

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 3\field_afit_t.sav

Mann-Whitney Test

Ranks

	Interface type	N	Mean Rank	Sum of Ranks
Task time	Video	28	27.29	764.00
	Interactive	27	28.74	776.00
	Total	55		
Task errors	Video	28	26.11	731.00
	Interactive	27	29.96	809.00
	Total	55		

Test Statistics[a]

	Task time	Task errors
Mann-Whitney U	358.000	325.000
Wilcoxon W	764.000	731.000
Z	-.337	-.931
Asymp. Sig. (2-tailed)	.736	.352

a. Grouping Variable: Interface type

ONEWAY test_s BY i_face /MISSING ANALYSIS.

Oneway

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 3\field_afit_t.sav

ANOVA

Test score

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	25.268	2	12.634	1.411	.250
Within Groups	698.312	78	8.953		
Total	723.580	80			

UNIANOVA t_time BY i_face WITH test_s /METHOD=SSTYPE(3) /INTERCEPT=INCLUDE /EMMEANS=TABLES(i_face) WITH(test_s=MEAN) /PRINT=ETASQ HOMOGENEITY /CRITERIA=ALPHA(.05) /DESIGN=test_s i_face.

Univariate Analysis of Variance

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 3\field_afit_t.sav

Tests of Between-Subjects Effects

Dependent Variable:Task time

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	30066.631[a]	3	10022.210	5.244	.002	.170
Intercept	193354.732	1	193354.732	101.177	.000	.568
test_s	6539.956	1	6539.956	3.422	.068	.043
i_face	21105.719	2	10552.860	5.522	.006	.125
Error	147150.504	77	1911.046			
Total	1241324.000	81				
Corrected Total	177217.136	80				

a. R Squared = .170 (Adjusted R Squared = .137)

Estimated Marginal Means

Interface type

Dependent Variable:Task time

Interface type	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Static	137.216[a]	8.623	120.045	154.386
Video	98.470[a]	8.269	82.003	114.936
Interactive	109.602[a]	8.508	92.660	126.543

a. Covariates appearing in the model are evaluated at the following values: Test score = 7.8272.

```
UNIANOVA t_errors BY i_face WITH test_s   /METHOD=SSTYPE(3)
/INTERCEPT=INCLUDE   /EMMEANS=TABLES(i_face)
WITH(test_s=MEAN)   /PRINT=ETASQ HOMOGENEITY
/CRITERIA=ALPHA(.05)   /DESIGN=test_s i_face.
```

Univariate Analysis of Variance

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 3\field_afit_t.sav

Tests of Between-Subjects Effects

Dependent Variable:Task errors

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	225.490[a]	3	75.163	16.691	.000	.394
Intercept	103.945	1	103.945	23.082	.000	.231
test_s	5.352	1	5.352	1.188	.279	.015
i_face	209.344	2	104.672	23.243	.000	.376
Error	346.757	77	4.503			
Total	1076.000	81				
Corrected Total	572.247	80				

a. R Squared = .394 (Adjusted R Squared = .370)

Estimated Marginal Means

Interface type

Dependent Variable:Task errors

Interface type	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Static	4.836[a]	.419	4.002	5.669
Video	1.195[a]	.401	.396	1.994
Interactive	1.586[a]	.413	.763	2.408

a. Covariates appearing in the model are evaluated at the following values: Test score = 7.8272.

```
CORRELATIONS   /VARIABLES=ease response confused helpful interest
i_face   /PRINT=TWOTAIL NOSIG   /MISSING=PAIRWISE.
```

Correlations

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 3\field_afit_t.sav

Correlations

		Ease of use	Responsiveness	Degree of confusion	Helpful interaction	Interesting interface	Interface type
Ease of use	Pearson Correlation	1	.116	-.174	.190	.036	-.063
	Sig. (2-tailed)		.301	.120	.089	.752	.578
	N	81	81	81	81	81	81
Responsiveness	Pearson Correlation	.116	1	-.119	.207	.194	.085
	Sig. (2-tailed)	.301		.288	.063	.082	.451
	N	81	81	81	81	81	81
Degree of confusion	Pearson Correlation	-.174	-.119	1	-.135	.048	-.049
	Sig. (2-tailed)	.120	.288		.231	.669	.666
	N	81	81	81	81	81	81
Helpful interaction	Pearson Correlation	.190	.207	-.135	1	.105	.041
	Sig. (2-tailed)	.089	.063	.231		.351	.717
	N	81	81	81	81	81	81
Interesting interface	Pearson Correlation	.036	.194	.048	.105	1	.021
	Sig. (2-tailed)	.752	.082	.669	.351		.853
	N	81	81	81	81	81	81
Interface type	Pearson Correlation	-.063	.085	-.049	.041	.021	1
	Sig. (2-tailed)	.578	.451	.666	.717	.853	
	N	81	81	81	81	81	81

Appendix C

Materials and Analysis Data – Experiment 2

Pre-test Questionnaire

BACKGROUND QUESTIONNAIRE

Please complete the questionnaire below by providing the required details. For questions with a scale range of response, you are required to mark 'X' in the box that corresponds to your answer. Please mark only one box. An example is provided below:

How often do you use internet banking?

- [ ] *Never*
- [ ] *Occasionally*
- [ ] *Usually*
- [x] *Mostly*
- [ ] *Always*

Information provided will be used for research experiment purposes only. Thank you.

1. Age: ☐ 16 – 20 ☐ 21 – 25 ☐ 26 – 30 ☐ 31 – 35 ☐ 36 – 40 ☐ 41 – 45 ☐ 46 – 50 ☐ Above 50

2. Gender: ☐ Male ☐ Female

3. Are you a student: ☐ Yes ☐ No

3a. If yes, what are you studying?..

4. What is your highest educational qualification?
   - ☐ Primary School Certificate
   - ☐ Completed Secondary School or equivalent
   - ☐ College Diploma
   - ☐ First Degree
   - ☐ Postgraduate Diploma or Degree

5. Please describe your academic background?
   ☐ Science ☐ Engineering ☐ Arts
   ☐ Others...
   (please specify)

6. Are you: ☐ Left-handed ☐ Right-handed

7. Do you have Dyslexia? ☐ Yes ☐ No

8. Do you have Epilepsy? ☐ Yes ☐ No

9. Do you have difficulty with distinguishing right and left directions? ☐ Yes ☐ No

10. Are you allergic to flashing lights or patterns streaking across a computer screen? ☐ Yes ☐ No

Additional questionnaire - Video Game Experience

1. Do you or have you ever played video games? *(either on a computer or game console)*

☐ Yes ☐ No *(skip the remaining questions if you've selected 'No')*

2. If yes, how long ago did you play your first video game?

......................(years/months)

3. On average, how often did you play video games when you first started?

☐ 1 hour per week
☐ 2 hours per week
☐ 3 hours per week
☐ 4 hours per week
☐ 5 hours per week
☐ 6 to 10 hours per week
☐ over 10 hours per week

4. On average, how often did you play video games during your peak gaming experience?

☐ 1 hour per week
☐ 2 hours per week
☐ 3 hours per week
☐ 4 hours per week
☐ 5 hours per week
☐ 6 to 10 hours per week
☐ over 10 hours per week

5. On average, how often do you play video games currently?

☐ Don't play anymore
☐ 1 hour per week
☐ 2 hours per week
☐ 3 hours per week
☐ 4 hours per week
☐ 5 hours per week
☐ 6 to 10 hours per week
☐ over 10 hours per week

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Title of Study: Spatial Navigation in a Virtual Environment.

Subjects: Students of Robert Gordon University, Aberdeen, Scotland.

Method: The study is designed to investigate the relationship between perception of different visualisations and recall in spatial navigation of a virtual environment.

The Card Rotations Test will be used to measure participants spatial orientation abilities, which will be used as a covariate in the statistical analysis of the data.

Relevance of *Kit* tests to problem(s) being studied: This study is a follow-up to an earlier experiment for which a similar ETS Licence was obtained (dated 10 January 2011). The Card Rotations Test will be used to measure spatial orientation abilities, which will be used as a co-variate in the analysis of the data to control for its effect.

Name of test(s) to be used:	Number of copies to be produced:
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1. Card Rotations Test	

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We require about 70 participants for an exciting and innocuous experiment involving perception and recall of stimuli presented on a computer monitor. All you have to do is navigate a virtual environment using a joystick and get paid £10 for a single session lasting about 1.5 hours. If interested, please click on the following link to provide your name, email and choose a convenient date/time:

http://www.doodle.com/7mdpepdxrpamte6c

For further information, contact 0600330@rgu.ac.uk.
The Cognitive Engineering Research Group Lab page is at:
http://www.comp.rgu.ac.uk/docs/is/index.html.

Statistical Modelling Outputs (SPSS™ version 17)

MEANS TABLES=e1_exLen e2_exLen e3_exLen m1_exLen m2_exLen m3_exLen h1_exLen h2_exLen e1_exTi e2_exTi e3_exTi m1_exTi m2_exTi m3_exTi h1_exTi h2_exTi sp_test comp_g BY i_face /CELLS MEAN COUNT STDDEV.

Means

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 4\spanav_data_refined.sav

Case Processing Summary

	Cases					
	Included		Excluded		Total	
	N	Percent	N	Percent	N	Percent
Extrapolated Length - Level 1 Trial 1 * Interface	60	100.0%	0	.0%	60	100.0%
Extrapolated Length - Level 1 Trial 2 * Interface	60	100.0%	0	.0%	60	100.0%
Extrapolated Length - Level 1 Trial 3 * Interface	60	100.0%	0	.0%	60	100.0%
Extrapolated Length - Level 2 Trial 1 * Interface	60	100.0%	0	.0%	60	100.0%
Extrapolated Length - Level 2 Trial 2 * Interface	60	100.0%	0	.0%	60	100.0%
Extrapolated Length - Level 2 Trial 3 * Interface	60	100.0%	0	.0%	60	100.0%
Extrapolated Length - Level 3 Trial 1 * Interface	60	100.0%	0	.0%	60	100.0%
Extrapolated Length - Level 3 Trial 2 * Interface	60	100.0%	0	.0%	60	100.0%
Extrapolated Time - Level 1 Trial 1 * Interface	60	100.0%	0	.0%	60	100.0%
Extrapolated Time - Level 1 Trial 2 * Interface	60	100.0%	0	.0%	60	100.0%

Extrapolated Time - Level 1 Trial 3 * Interface	60	100.0%	0	.0%	60	100.0%
Extrapolated Time - Level 2 Trial 1 * Interface	60	100.0%	0	.0%	60	100.0%
Extrapolated Time - Level 2 Trial 2 * Interface	60	100.0%	0	.0%	60	100.0%
Extrapolated Time - Level 2 Trial 3 * Interface	60	100.0%	0	.0%	60	100.0%
Extrapolated Time - Level 3 Trial 1 * Interface	60	100.0%	0	.0%	60	100.0%
Extrapolated Time - Level 3 Trial 2 * Interface	60	100.0%	0	.0%	60	100.0%
Spatial Ability Score * Interface	60	100.0%	0	.0%	60	100.0%
Composite Game Experience Score * Interface	56	93.3%	4	6.7%	60	100.0%

Report

	Interface					
	Static			Dynamic		
	Mean	N	Std. Deviation	Mean	N	Std. Deviation
Extrapolated Length - Level 1 Trial 1	117.2555	31	50.61344	73.3307	29	4.41955
Extrapolated Length - Level 1 Trial 2	86.3669	31	28.07779	71.9426	29	2.32021
Extrapolated Length - Level 1 Trial 3	71.7621	31	1.81527	71.7471	29	2.41037
Extrapolated Length - Level 2 Trial 1	347.1695	31	175.26877	171.6526	29	97.69529
Extrapolated Length - Level 2 Trial 2	286.9980	31	195.49470	143.8286	29	66.58368
Extrapolated Length - Level 2 Trial 3	240.4633	31	148.17982	109.5494	29	6.83176
Extrapolated Length - Level 3 Trial 1	482.0913	31	162.67236	466.3324	29	234.76856
Extrapolated Length - Level 3 Trial 2	553.6952	31	247.02139	399.4832	29	220.48337
Extrapolated Time - Level 1 Trial 1	50.5462	31	20.76339	34.8308	29	10.91746
Extrapolated Time - Level 1 Trial 2	29.3408	31	6.53210	29.2724	29	8.47787
Extrapolated Time - Level 1 Trial 3	26.1324	31	5.44877	26.9558	29	5.24088
Extrapolated Time - Level 2 Trial 1	299.9101	31	148.43136	167.4046	29	135.18974
Extrapolated Time - Level 2 Trial 2	248.1548	31	163.27688	156.5638	29	154.09549
Extrapolated Time - Level 2 Trial 3	197.6680	31	155.40625	68.4434	29	26.87754
Extrapolated Time - Level 3 Trial 1	454.5373	31	171.63365	415.7784	29	211.39424

Extrapolated Time - Level 3 Trial 2	432.9500	31	186.98362	344.2467	29	228.72027
Spatial Ability Score	86.4516	31	28.60867	97.0000	29	37.96803
Composite Game Experience Score	11.1638	29	4.49702	12.8111	27	4.32320

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/INTERCEPT=INCLUDE   /EMMEANS=TABLES(i_face)
/PRINT=ETASQ HOMOGENEITY   /CRITERIA=ALPHA(.05)
/DESIGN= i_face.
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General Linear Model

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 4\spanav_data_refined.sav

Between-Subjects Factors

		Value Label	N
Interface	1	Static	31
	2	Dynamic	29

Multivariate Tests[b]

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
Intercept	Pillai's Trace	.901	258.647[a]	2.000	57.000	.000	.901
	Wilks' Lambda	.099	258.647[a]	2.000	57.000	.000	.901
	Hotelling's Trace	9.075	258.647[a]	2.000	57.000	.000	.901
	Roy's Largest Root	9.075	258.647[a]	2.000	57.000	.000	.901
i_face	Pillai's Trace	.290	11.665[a]	2.000	57.000	.000	.290
	Wilks' Lambda	.710	11.665[a]	2.000	57.000	.000	.290
	Hotelling's Trace	.409	11.665[a]	2.000	57.000	.000	.290
	Roy's Largest Root	.409	11.665[a]	2.000	57.000	.000	.290

a. Exact statistic

b. Design: Intercept + i_face

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	Extrapolated Length - Level 1 Trial 1	28908.538[a]	1	28908.538	21.663	.000	.272
	Extrapolated Time - Level 1 Trial 1	3700.490[b]	1	3700.490	13.191	.001	.185
Intercept	Extrapolated Length - Level 1 Trial 1	544241.122	1	544241.122	407.837	.000	.875
	Extrapolated Time - Level 1 Trial 1	109217.131	1	109217.131	389.321	.000	.870
i_face	Extrapolated Length - Level 1 Trial 1	28908.538	1	28908.538	21.663	.000	.272
	Extrapolated Time - Level 1 Trial 1	3700.490	1	3700.490	13.191	.001	.185
Error	Extrapolated Length - Level 1 Trial 1	77398.532	58	1334.457			
	Extrapolated Time - Level 1 Trial 1	16270.896	58	280.533			
Total	Extrapolated Length - Level 1 Trial 1	659557.176	60				
	Extrapolated Time - Level 1 Trial 1	130655.855	60				
Corrected Total	Extrapolated Length - Level 1 Trial 1	106307.070	59				
	Extrapolated Time - Level 1 Trial 1	19971.386	59				

a. R Squared = .272 (Adjusted R Squared = .259)

b. R Squared = .185 (Adjusted R Squared = .171)

Estimated Marginal Means

Interface

Dependent Variable	Interface	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Extrapolated Length - Level 1 Trial 1	Static	117.255	6.561	104.122	130.389
	Dynamic	73.331	6.783	59.752	86.909
Extrapolated Time - Level 1 Trial 1	Static	50.546	3.008	44.525	56.568
	Dynamic	34.831	3.110	28.605	41.057

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GLM e2_exLen e2_exTi BY i_face   /METHOD=SSTYPE(3)
/INTERCEPT=INCLUDE   /EMMEANS=TABLES(i_face)
/CRITERIA=ALPHA(.05)   /DESIGN= i_face.
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General Linear Model

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 4\spanav_data_refined.sav

Between-Subjects Factors

		Value Label	N
Interface	1	Static	31
	2	Dynamic	29

Multivariate Tests[b]

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	.962	727.919[a]	2.000	57.000	.000
	Wilks' Lambda	.038	727.919[a]	2.000	57.000	.000
	Hotelling's Trace	25.541	727.919[a]	2.000	57.000	.000
	Roy's Largest Root	25.541	727.919[a]	2.000	57.000	.000
i_face	Pillai's Trace	.121	3.919[a]	2.000	57.000	.025
	Wilks' Lambda	.879	3.919[a]	2.000	57.000	.025
	Hotelling's Trace	.137	3.919[a]	2.000	57.000	.025
	Roy's Largest Root	.137	3.919[a]	2.000	57.000	.025

a. Exact statistic

b. Design: Intercept + i_face

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	Extrapolated Length - Level 1 Trial 2	3117.448[a]	1	3117.448	7.597	.008
	Extrapolated Time - Level 1 Trial 2	.070[b]	1	.070	.001	.972
Intercept	Extrapolated Length - Level 1 Trial 2	375510.969	1	375510.969	915.049	.000

	Extrapolated Time - Level 1 Trial 2	51475.268	1	51475.268	906.769	.000
i_face	Extrapolated Length - Level 1 Trial 2	3117.448	1	3117.448	7.597	.008
	Extrapolated Time - Level 1 Trial 2	.070	1	.070	.001	.972
Error	Extrapolated Length - Level 1 Trial 2	23801.611	58	410.373		
	Extrapolated Time - Level 1 Trial 2	3292.530	58	56.768		
Total	Extrapolated Length - Level 1 Trial 2	405134.702	60			
	Extrapolated Time - Level 1 Trial 2	54829.136	60			
Corrected Total	Extrapolated Length - Level 1 Trial 2	26919.059	59			
	Extrapolated Time - Level 1 Trial 2	3292.600	59			

a. R Squared = .116 (Adjusted R Squared = .101)

b. R Squared = .000 (Adjusted R Squared = -.017)

Estimated Marginal Means

Interface

Dependent Variable	Interface	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Extrapolated Length - Level 1 Trial 2	Static	86.367	3.638	79.084	93.650
	Dynamic	71.943	3.762	64.413	79.473
Extrapolated Time - Level 1 Trial 2	Static	29.341	1.353	26.632	32.050
	Dynamic	29.272	1.399	26.472	32.073

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/INTERCEPT=INCLUDE   /EMMEANS=TABLES(i_face)
/CRITERIA=ALPHA(.05)   /DESIGN= i_face.
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General Linear Model

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Between-Subjects Factors

		Value Label	N
Interface	1	Static	31
	2	Dynamic	29

Multivariate Tests[b]

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	.999	38537.070[a]	2.000	57.000	.000
	Wilks' Lambda	.001	38537.070[a]	2.000	57.000	.000
	Hotelling's Trace	1352.178	38537.070[a]	2.000	57.000	.000
	Roy's Largest Root	1352.178	38537.070[a]	2.000	57.000	.000
i_face	Pillai's Trace	.008	.238[a]	2.000	57.000	.789
	Wilks' Lambda	.992	.238[a]	2.000	57.000	.789
	Hotelling's Trace	.008	.238[a]	2.000	57.000	.789
	Roy's Largest Root	.008	.238[a]	2.000	57.000	.789

a. Exact statistic

b. Design: Intercept + i_face

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	Extrapolated Length - Level 1 Trial 3	.003[a]	1	.003	.001	.978
	Extrapolated Time - Level 1 Trial 3	10.157[b]	1	10.157	.355	.554
Intercept	Extrapolated Length - Level 1 Trial 3	308579.894	1	308579.894	68433.616	.000
	Extrapolated Time - Level 1 Trial 3	42228.347	1	42228.347	1475.677	.000

i_face	Extrapolated Length - Level 1 Trial 3	.003	1	.003	.001	.978
	Extrapolated Time - Level 1 Trial 3	10.157	1	10.157	.355	.554
Error	Extrapolated Length - Level 1 Trial 3	261.533	58	4.509		
	Extrapolated Time - Level 1 Trial 3	1659.742	58	28.616		
Total	Extrapolated Length - Level 1 Trial 3	309186.825	60			
	Extrapolated Time - Level 1 Trial 3	43901.521	60			
Corrected Total	Extrapolated Length - Level 1 Trial 3	261.536	59			
	Extrapolated Time - Level 1 Trial 3	1669.899	59			

a. R Squared = .000 (Adjusted R Squared = -.017)

b. R Squared = .006 (Adjusted R Squared = -.011)

Estimated Marginal Means

Interface

				95% Confidence Interval	
Dependent Variable	Interface	Mean	Std. Error	Lower Bound	Upper Bound
Extrapolated Length - Level 1 Trial 3	Static	71.762	.381	70.999	72.525
	Dynamic	71.747	.394	70.958	72.536
Extrapolated Time - Level 1 Trial 3	Static	26.132	.961	24.209	28.056
	Dynamic	26.956	.993	24.967	28.944

```
GLM m1_exLen m1_exTi BY i_face   /METHOD=SSTYPE(3)
/INTERCEPT=INCLUDE   /EMMEANS=TABLES(i_face)
/CRITERIA=ALPHA(.05)   /DESIGN= i_face.
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General Linear Model

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Between-Subjects Factors

		Value Label	N
Interface	1	Static	31
	2	Dynamic	29

Multivariate Tests[b]

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	.779	100.456[a]	2.000	57.000	.000
	Wilks' Lambda	.221	100.456[a]	2.000	57.000	.000
	Hotelling's Trace	3.525	100.456[a]	2.000	57.000	.000
	Roy's Largest Root	3.525	100.456[a]	2.000	57.000	.000
i_face	Pillai's Trace	.280	11.083[a]	2.000	57.000	.000
	Wilks' Lambda	.720	11.083[a]	2.000	57.000	.000
	Hotelling's Trace	.389	11.083[a]	2.000	57.000	.000
	Roy's Largest Root	.389	11.083[a]	2.000	57.000	.000

a. Exact statistic

b. Design: Intercept + i_face

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	Extrapolated Length - Level 2 Trial 1	461579.268[a]	1	461579.268	22.520	.000
	Extrapolated Time - Level 2 Trial 1	263072.761[b]	1	263072.761	13.011	.001
Intercept	Extrapolated Length - Level 2 Trial 1	4033159.180	1	4033159.180	196.770	.000
	Extrapolated Time - Level 2 Trial 1	3272105.508	1	3272105.508	161.835	.000
i_face	Extrapolated Length - Level 2 Trial 1	461579.268	1	461579.268	22.520	.000
	Extrapolated Time - Level 2 Trial 1	263072.761	1	263072.761	13.011	.001
Error	Extrapolated Length - Level 2 Trial 1	1188816.592	58	20496.838		
	Extrapolated Time - Level 2 Trial 1	1172691.533	58	20218.820		
Total	Extrapolated Length - Level 2 Trial 1	5779616.792	60			
	Extrapolated Time - Level 2 Trial 1	4773723.887	60			

Corrected Total	Extrapolated Length - Level 2 Trial 1	1650395.861	59
	Extrapolated Time - Level 2 Trial 1	1435764.294	59

a. R Squared = .280 (Adjusted R Squared = .267)

b. R Squared = .183 (Adjusted R Squared = .169)

Estimated Marginal Means

Interface

				95% Confidence Interval	
Dependent Variable	Interface	Mean	Std. Error	Lower Bound	Upper Bound
Extrapolated Length - Level 2 Trial 1	Static	347.169	25.714	295.698	398.641
	Dynamic	171.653	26.585	118.436	224.869
Extrapolated Time - Level 2 Trial 1	Static	299.910	25.539	248.789	351.031
	Dynamic	167.405	26.405	114.550	220.259

```
GLM m2_exLen m2_exTi BY i_face   /METHOD=SSTYPE(3)
/INTERCEPT=INCLUDE   /EMMEANS=TABLES(i_face)
/CRITERIA=ALPHA(.05)   /DESIGN= i_face.
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General Linear Model

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 4\spanav_data_refined.sav

Between-Subjects Factors

		Value Label	N
Interface	1	Static	31
	2	Dynamic	29

Multivariate Tests[b]

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	.700	66.507[a]	2.000	57.000	.000
	Wilks' Lambda	.300	66.507[a]	2.000	57.000	.000
	Hotelling's Trace	2.334	66.507[a]	2.000	57.000	.000

	Roy's Largest Root	2.334	66.507[a]	2.000	57.000	.000
i_face	Pillai's Trace	.197	7.000[a]	2.000	57.000	.002
	Wilks' Lambda	.803	7.000[a]	2.000	57.000	.002
	Hotelling's Trace	.246	7.000[a]	2.000	57.000	.002
	Roy's Largest Root	.246	7.000[a]	2.000	57.000	.002

a. Exact statistic

b. Design: Intercept + i_face

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	Extrapolated Length - Level 2 Trial 2	307120.688[a]	1	307120.688	14.018	.000
	Extrapolated Time - Level 2 Trial 2	125693.979[b]	1	125693.979	4.977	.030
Intercept	Extrapolated Length - Level 2 Trial 2	2781080.474	1	2781080.474	126.942	.000
	Extrapolated Time - Level 2 Trial 2	2454227.611	1	2454227.611	97.187	.000
i_face	Extrapolated Length - Level 2 Trial 2	307120.688	1	307120.688	14.018	.000
	Extrapolated Time - Level 2 Trial 2	125693.979	1	125693.979	4.977	.030
Error	Extrapolated Length - Level 2 Trial 2	1270680.132	58	21908.278		
	Extrapolated Time - Level 2 Trial 2	1464651.932	58	25252.620		
Total	Extrapolated Length - Level 2 Trial 2	4423997.654	60			
	Extrapolated Time - Level 2 Trial 2	4084511.893	60			
Corrected Total	Extrapolated Length - Level 2 Trial 2	1577800.819	59			
	Extrapolated Time - Level 2 Trial 2	1590345.911	59			

a. R Squared = .195 (Adjusted R Squared = .181)

b. R Squared = .079 (Adjusted R Squared = .063)

Estimated Marginal Means

Interface

				95% Confidence Interval	
Dependent Variable	Interface	Mean	Std. Error	Lower Bound	Upper Bound
Extrapolated Length - Level 2 Trial 2	Static	286.998	26.584	233.784	340.212
	Dynamic	143.829	27.486	88.810	198.847

Extrapolated Time - Level 2 Trial 2	Static	248.155	28.541	191.023	305.286
	Dynamic	156.564	29.509	97.495	215.632

```
GLM m3_exLen m3_exTi BY i_face   /METHOD=SSTYPE(3)
/INTERCEPT=INCLUDE   /EMMEANS=TABLES(i_face)
/CRITERIA=ALPHA(.05)   /DESIGN= i_face.
```

General Linear Model

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 4\spanav_data_refined.sav

Between-Subjects Factors

		Value Label	N
Interface	1	Static	31
	2	Dynamic	29

Multivariate Tests[b]

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	.763	91.796[a]	2.000	57.000	.000
	Wilks' Lambda	.237	91.796[a]	2.000	57.000	.000
	Hotelling's Trace	3.221	91.796[a]	2.000	57.000	.000
	Roy's Largest Root	3.221	91.796[a]	2.000	57.000	.000
i_face	Pillai's Trace	.281	11.157[a]	2.000	57.000	.000
	Wilks' Lambda	.719	11.157[a]	2.000	57.000	.000
	Hotelling's Trace	.391	11.157[a]	2.000	57.000	.000
	Roy's Largest Root	.391	11.157[a]	2.000	57.000	.000

a. Exact statistic

b. Design: Intercept + i_face

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	Extrapolated Length - Level 2 Trial 3	256791.004[a]	1	256791.004	22.566	.000
	Extrapolated Time - Level 2 Trial 3	250206.597[b]	1	250206.597	19.485	.000
Intercept	Extrapolated Length - Level 2 Trial 3	1835591.752	1	1835591.752	161.304	.000
	Extrapolated Time - Level 2 Trial 3	1061048.481	1	1061048.481	82.632	.000
i_face	Extrapolated Length - Level 2 Trial 3	256791.004	1	256791.004	22.566	.000
	Extrapolated Time - Level 2 Trial 3	250206.597	1	250206.597	19.485	.000
Error	Extrapolated Length - Level 2 Trial 3	660024.590	58	11379.734		
	Extrapolated Time - Level 2 Trial 3	744760.305	58	12840.695		
Total	Extrapolated Length - Level 2 Trial 3	2800556.324	60			
	Extrapolated Time - Level 2 Trial 3	2091862.084	60			
Corrected Total	Extrapolated Length - Level 2 Trial 3	916815.594	59			
	Extrapolated Time - Level 2 Trial 3	994966.903	59			

a. R Squared = .280 (Adjusted R Squared = .268)

b. R Squared = .251 (Adjusted R Squared = .239)

Estimated Marginal Means

Interface

Dependent Variable	Interface	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Extrapolated Length - Level 2 Trial 3	Static	240.463	19.160	202.111	278.815
	Dynamic	109.549	19.809	69.897	149.202
Extrapolated Time - Level 2 Trial 3	Static	197.668	20.352	156.928	238.408
	Dynamic	68.443	21.042	26.322	110.564

```
GLM h1_exLen h1_exTi BY i_face   /METHOD=SSTYPE(3)
/INTERCEPT=INCLUDE   /EMMEANS=TABLES(i_face)
/CRITERIA=ALPHA(.05)   /DESIGN= i_face.
```

General Linear Model

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 4\spanav_data_refined.sav

Between-Subjects Factors

		Value Label	N
Interface	1	Static	31
	2	Dynamic	29

Multivariate Tests[b]

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	.861	176.035[a]	2.000	57.000	.000
	Wilks' Lambda	.139	176.035[a]	2.000	57.000	.000
	Hotelling's Trace	6.177	176.035[a]	2.000	57.000	.000
	Roy's Largest Root	6.177	176.035[a]	2.000	57.000	.000
i_face	Pillai's Trace	.015	.442[a]	2.000	57.000	.645
	Wilks' Lambda	.985	.442[a]	2.000	57.000	.645
	Hotelling's Trace	.016	.442[a]	2.000	57.000	.645
	Roy's Largest Root	.016	.442[a]	2.000	57.000	.645

a. Exact statistic

b. Design: Intercept + i_face

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	Extrapolated Length - Level 3 Trial 1	3720.974[a]	1	3720.974	.092	.762
	Extrapolated Time - Level 3 Trial 1	22508.760[b]	1	22508.760	.611	.437
Intercept	Extrapolated Length - Level 3 Trial 1	1.348E7	1	1.348E7	334.472	.000
	Extrapolated Time - Level 3 Trial 1	1.135E7	1	1.135E7	308.314	.000
i_face	Extrapolated Length - Level 3 Trial 1	3720.974	1	3720.974	.092	.762
	Extrapolated Time - Level 3 Trial 1	22508.760	1	22508.760	.611	.437
Error	Extrapolated Length - Level 3 Trial 1	2337124.687	58	40295.253		
	Extrapolated Time - Level 3 Trial 1	2134994.003	58	36810.241		

Total	Extrapolated Length - Level 3 Trial 1	1.585E7	60
	Extrapolated Time - Level 3 Trial 1	1.355E7	60
Corrected Total	Extrapolated Length - Level 3 Trial 1	2340845.662	59
	Extrapolated Time - Level 3 Trial 1	2157502.763	59

a. R Squared = .002 (Adjusted R Squared = -.016)

b. R Squared = .010 (Adjusted R Squared = -.007)

Estimated Marginal Means

Interface

				95% Confidence Interval	
Dependent Variable	Interface	Mean	Std. Error	Lower Bound	Upper Bound
Extrapolated Length - Level 3 Trial 1	Static	482.091	36.053	409.923	554.260
	Dynamic	466.332	37.276	391.717	540.948
Extrapolated Time - Level 3 Trial 1	Static	454.537	34.459	385.560	523.515
	Dynamic	415.778	35.627	344.462	487.095

GLM h2_exLen h2_exTi BY i_face /METHOD=SSTYPE(3) /INTERCEPT=INCLUDE /EMMEANS=TABLES(i_face) /CRITERIA=ALPHA(.05) /DESIGN= i_face.

General Linear Model

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Between-Subjects Factors

		Value Label	N
Interface	1	Static	31
	2	Dynamic	29

Multivariate Tests[b]

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	.815	125.577[a]	2.000	57.000	.000
	Wilks' Lambda	.185	125.577[a]	2.000	57.000	.000

	Hotelling's Trace	4.406	125.577[a]	2.000	57.000	.000
	Roy's Largest Root	4.406	125.577[a]	2.000	57.000	.000
i_face	Pillai's Trace	.108	3.436[a]	2.000	57.000	.039
	Wilks' Lambda	.892	3.436[a]	2.000	57.000	.039
	Hotelling's Trace	.121	3.436[a]	2.000	57.000	.039
	Roy's Largest Root	.121	3.436[a]	2.000	57.000	.039

a. Exact statistic

b. Design: Intercept + i_face

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	Extrapolated Length - Level 3 Trial 2	356323.969[a]	1	356323.969	6.475	.014
	Extrapolated Time - Level 3 Trial 2	117892.935[b]	1	117892.935	2.720	.104
Intercept	Extrapolated Length - Level 3 Trial 2	1.361E7	1	1.361E7	247.375	.000
	Extrapolated Time - Level 3 Trial 2	9050452.420	1	9050452.420	208.830	.000
i_face	Extrapolated Length - Level 3 Trial 2	356323.969	1	356323.969	6.475	.014
	Extrapolated Time - Level 3 Trial 2	117892.935	1	117892.935	2.720	.104
Error	Extrapolated Length - Level 3 Trial 2	3191748.755	58	55030.151		
	Extrapolated Time - Level 3 Trial 2	2513649.236	58	43338.780		
Total	Extrapolated Length - Level 3 Trial 2	1.732E7	60			
	Extrapolated Time - Level 3 Trial 2	1.176E7	60			
Corrected Total	Extrapolated Length - Level 3 Trial 2	3548072.724	59			
	Extrapolated Time - Level 3 Trial 2	2631542.171	59			

a. R Squared = .100 (Adjusted R Squared = .085)

b. R Squared = .045 (Adjusted R Squared = .028)

Estimated Marginal Means

Interface

Dependent Variable	Interface	Mean	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
Extrapolated Length - Level 3 Trial 2	Static	553.695	42.133	469.357	638.033

	Dynamic	399.483	43.561	312.286	486.681
Extrapolated Time - Level 3 Trial 2	Static	432.950	37.390	358.105	507.795
	Dynamic	344.247	38.658	266.864	421.629

```
GLM m1_exLen m1_exTi BY i_face WITH sp_test
/METHOD=SSTYPE(3)   /INTERCEPT=INCLUDE
/EMMEANS=TABLES(i_face) WITH(sp_test=MEAN)
/CRITERIA=ALPHA(.05)   /DESIGN=sp_test i_face.
```

General Linear Model

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Between-Subjects Factors

		Value Label	N
Interface	1	Static	31
	2	Dynamic	29

Multivariate Tests[b]

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	.453	23.184[a]	2.000	56.000	.000
	Wilks' Lambda	.547	23.184[a]	2.000	56.000	.000
	Hotelling's Trace	.828	23.184[a]	2.000	56.000	.000
	Roy's Largest Root	.828	23.184[a]	2.000	56.000	.000
sp_test	Pillai's Trace	.134	4.326[a]	2.000	56.000	.018
	Wilks' Lambda	.866	4.326[a]	2.000	56.000	.018
	Hotelling's Trace	.154	4.326[a]	2.000	56.000	.018
	Roy's Largest Root	.154	4.326[a]	2.000	56.000	.018
i_face	Pillai's Trace	.266	10.145[a]	2.000	56.000	.000
	Wilks' Lambda	.734	10.145[a]	2.000	56.000	.000
	Hotelling's Trace	.362	10.145[a]	2.000	56.000	.000
	Roy's Largest Root	.362	10.145[a]	2.000	56.000	.000

a. Exact statistic

b. Design: Intercept + sp_test + i_face

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	Extrapolated Length - Level 2 Trial 1	482706.261[a]	2	241353.131	11.781	.000
	Extrapolated Time - Level 2 Trial 1	380055.248[b]	2	190027.624	10.260	.000
Intercept	Extrapolated Length - Level 2 Trial 1	664303.985	1	664303.985	32.428	.000
	Extrapolated Time - Level 2 Trial 1	870181.095	1	870181.095	46.983	.000
sp_test	Extrapolated Length - Level 2 Trial 1	21126.993	1	21126.993	1.031	.314
	Extrapolated Time - Level 2 Trial 1	116982.486	1	116982.486	6.316	.015
i_face	Extrapolated Length - Level 2 Trial 1	419693.046	1	419693.046	20.487	.000
	Extrapolated Time - Level 2 Trial 1	204596.716	1	204596.716	11.047	.002
Error	Extrapolated Length - Level 2 Trial 1	1167689.600	57	20485.782		
	Extrapolated Time - Level 2 Trial 1	1055709.046	57	18521.211		
Total	Extrapolated Length - Level 2 Trial 1	5779616.792	60			
	Extrapolated Time - Level 2 Trial 1	4773723.887	60			
Corrected Total	Extrapolated Length - Level 2 Trial 1	1650395.861	59			
	Extrapolated Time - Level 2 Trial 1	1435764.294	59			

a. R Squared = .292 (Adjusted R Squared = .268)

b. R Squared = .265 (Adjusted R Squared = .239)

Estimated Marginal Means

Interface

Dependent Variable	Interface	Mean	Std. Error	95% Confidence Interval	
				Lower Bound	Upper Bound
Extrapolated Length - Level 2 Trial 1	Static	344.261[a]	25.866	292.466	396.056
	Dynamic	174.762[a]	26.754	121.188	228.336
Extrapolated Time - Level 2 Trial 1	Static	293.066[a]	24.594	243.817	342.315
	Dynamic	174.721[a]	25.439	123.780	225.661

a. Covariates appearing in the model are evaluated at the following values: Spatial Ability Score = 91.5500.

```
GLM m2_exLen m2_exTi BY i_face WITH sp_test
/METHOD=SSTYPE(3)   /INTERCEPT=INCLUDE
/EMMEANS=TABLES(i_face) WITH(sp_test=MEAN)
/CRITERIA=ALPHA(.05)   /DESIGN=sp_test i_face.
```

General Linear Model

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Between-Subjects Factors

		Value Label	N
Interface	1	Static	31
	2	Dynamic	29

Multivariate Tests[b]

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	.442	22.162[a]	2.000	56.000	.000
	Wilks' Lambda	.558	22.162[a]	2.000	56.000	.000
	Hotelling's Trace	.792	22.162[a]	2.000	56.000	.000
	Roy's Largest Root	.792	22.162[a]	2.000	56.000	.000
sp_test	Pillai's Trace	.178	6.052[a]	2.000	56.000	.004
	Wilks' Lambda	.822	6.052[a]	2.000	56.000	.004
	Hotelling's Trace	.216	6.052[a]	2.000	56.000	.004
	Roy's Largest Root	.216	6.052[a]	2.000	56.000	.004
i_face	Pillai's Trace	.184	6.330[a]	2.000	56.000	.003
	Wilks' Lambda	.816	6.330[a]	2.000	56.000	.003
	Hotelling's Trace	.226	6.330[a]	2.000	56.000	.003
	Roy's Largest Root	.226	6.330[a]	2.000	56.000	.003

a. Exact statistic

b. Design: Intercept + sp_test + i_face

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	Extrapolated Length - Level 2 Trial 2	345281.978[a]	2	172640.989	7.984	.001
	Extrapolated Time - Level 2 Trial 2	357792.449[b]	2	178896.225	8.273	.001
Intercept	Extrapolated Length - Level 2 Trial 2	558121.850	1	558121.850	25.811	.000
	Extrapolated Time - Level 2 Trial 2	965373.440	1	965373.440	44.644	.000
sp_test	Extrapolated Length - Level 2 Trial 2	38161.290	1	38161.290	1.765	.189
	Extrapolated Time - Level 2 Trial 2	232098.470	1	232098.470	10.734	.002
i_face	Extrapolated Length - Level 2 Trial 2	266557.145	1	266557.145	12.327	.001
	Extrapolated Time - Level 2 Trial 2	74985.402	1	74985.402	3.468	.068
Error	Extrapolated Length - Level 2 Trial 2	1232518.841	57	21623.138		
	Extrapolated Time - Level 2 Trial 2	1232553.462	57	21623.745		
Total	Extrapolated Length - Level 2 Trial 2	4423997.654	60			
	Extrapolated Time - Level 2 Trial 2	4084511.893	60			
Corrected Total	Extrapolated Length - Level 2 Trial 2	1577800.819	59			
	Extrapolated Time - Level 2 Trial 2	1590345.911	59			

a. R Squared = .219 (Adjusted R Squared = .191)

b. R Squared = .225 (Adjusted R Squared = .198)

Estimated Marginal Means

Interface

Dependent Variable	Interface	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Extrapolated Length - Level 2 Trial 2	Static	283.089[a]	26.574	229.876	336.303
	Dynamic	148.007[a]	27.487	92.966	203.048
Extrapolated Time - Level 2 Trial 2	Static	238.515[a]	26.574	185.300	291.729
	Dynamic	166.869[a]	27.487	111.827	221.911

a. Covariates appearing in the model are evaluated at the following values: Spatial Ability Score = 91.5500.

```
GLM m3_exLen m3_exTi BY i_face WITH sp_test
/METHOD=SSTYPE(3)   /INTERCEPT=INCLUDE
```

/EMMEANS=TABLES(i_face) WITH(sp_test=MEAN)
/CRITERIA=ALPHA(.05) /DESIGN=sp_test i_face.

General Linear Model

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Between-Subjects Factors

		Value Label	N
Interface	1	Static	31
	2	Dynamic	29

Multivariate Tests[b]

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	.397	18.461[a]	2.000	56.000	.000
	Wilks' Lambda	.603	18.461[a]	2.000	56.000	.000
	Hotelling's Trace	.659	18.461[a]	2.000	56.000	.000
	Roy's Largest Root	.659	18.461[a]	2.000	56.000	.000
sp_test	Pillai's Trace	.059	1.771[a]	2.000	56.000	.179
	Wilks' Lambda	.941	1.771[a]	2.000	56.000	.179
	Hotelling's Trace	.063	1.771[a]	2.000	56.000	.179
	Roy's Largest Root	.063	1.771[a]	2.000	56.000	.179
i_face	Pillai's Trace	.263	9.991[a]	2.000	56.000	.000
	Wilks' Lambda	.737	9.991[a]	2.000	56.000	.000
	Hotelling's Trace	.357	9.991[a]	2.000	56.000	.000
	Roy's Largest Root	.357	9.991[a]	2.000	56.000	.000

a. Exact statistic

b. Design: Intercept + sp_test + i_face

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	Extrapolated Length - Level 2 Trial 3	291689.132[a]	2	145844.566	13.298	.000

	Extrapolated Time - Level 2 Trial 3	293835.661[b]	2	146917.830	11.944	.000
Intercept	Extrapolated Length - Level 2 Trial 3	401187.178	1	401187.178	36.581	.000
	Extrapolated Time - Level 2 Trial 3	296459.633	1	296459.633	24.101	.000
sp_test	Extrapolated Length - Level 2 Trial 3	34898.129	1	34898.129	3.182	.080
	Extrapolated Time - Level 2 Trial 3	43629.063	1	43629.063	3.547	.065
i_face	Extrapolated Length - Level 2 Trial 3	221653.876	1	221653.876	20.211	.000
	Extrapolated Time - Level 2 Trial 3	212385.711	1	212385.711	17.266	.000
Error	Extrapolated Length - Level 2 Trial 3	625126.462	57	10967.131		
	Extrapolated Time - Level 2 Trial 3	701131.242	57	12300.548		
Total	Extrapolated Length - Level 2 Trial 3	2800556.324	60			
	Extrapolated Time - Level 2 Trial 3	2091862.084	60			
Corrected Total	Extrapolated Length - Level 2 Trial 3	916815.594	59			
	Extrapolated Time - Level 2 Trial 3	994966.903	59			

a. R Squared = .318 (Adjusted R Squared = .294)

b. R Squared = .295 (Adjusted R Squared = .271)

Estimated Marginal Means

Interface

Dependent Variable	Interface	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Extrapolated Length - Level 2 Trial 3	Static	236.725[a]	18.925	198.828	274.623
	Dynamic	113.545[a]	19.575	74.346	152.744
Extrapolated Time - Level 2 Trial 3	Static	193.488[a]	20.043	153.353	233.624
	Dynamic	72.911[a]	20.731	31.398	114.425

a. Covariates appearing in the model are evaluated at the following values: Spatial Ability Score = 91.5500.

```
GLM m1_exLen m1_exTi BY i_face WITH comp_g
/METHOD=SSTYPE(3)   /INTERCEPT=INCLUDE
/EMMEANS=TABLES(i_face) WITH(comp_g=MEAN)
/CRITERIA=ALPHA(.05)   /DESIGN=comp_g i_face.
```

General Linear Model

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Between-Subjects Factors

		Value Label	N
Interface	1	Static	29
	2	Dynamic	27

Multivariate Tests[b]

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	.442	20.603[a]	2.000	52.000	.000
	Wilks' Lambda	.558	20.603[a]	2.000	52.000	.000
	Hotelling's Trace	.792	20.603[a]	2.000	52.000	.000
	Roy's Largest Root	.792	20.603[a]	2.000	52.000	.000
comp_g	Pillai's Trace	.160	4.946[a]	2.000	52.000	.011
	Wilks' Lambda	.840	4.946[a]	2.000	52.000	.011
	Hotelling's Trace	.190	4.946[a]	2.000	52.000	.011
	Roy's Largest Root	.190	4.946[a]	2.000	52.000	.011
i_face	Pillai's Trace	.279	10.077[a]	2.000	52.000	.000
	Wilks' Lambda	.721	10.077[a]	2.000	52.000	.000
	Hotelling's Trace	.388	10.077[a]	2.000	52.000	.000
	Roy's Largest Root	.388	10.077[a]	2.000	52.000	.000

a. Exact statistic

b. Design: Intercept + comp_g + i_face

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	Extrapolated Length - Level 2 Trial 1	466382.653[a]	2	233191.326	11.174	.000
	Extrapolated Time - Level 2 Trial 1	352673.029[b]	2	176336.515	9.623	.000
Intercept	Extrapolated Length - Level 2 Trial 1	538506.581	1	538506.581	25.805	.000
	Extrapolated Time - Level 2 Trial 1	769392.920	1	769392.920	41.986	.000
comp_g	Extrapolated Length - Level 2 Trial 1	8290.201	1	8290.201	.397	.531

	Extrapolated Time - Level 2 Trial 1	104796.006	1	104796.006	5.719	.020
i_face	Extrapolated Length - Level 2 Trial 1	419845.512	1	419845.512	20.119	.000
	Extrapolated Time - Level 2 Trial 1	183814.050	1	183814.050	10.031	.003
Error	Extrapolated Length - Level 2 Trial 1	1106015.603	53	20868.219		
	Extrapolated Time - Level 2 Trial 1	971222.506	53	18324.953		
Total	Extrapolated Length - Level 2 Trial 1	5299430.654	56			
	Extrapolated Time - Level 2 Trial 1	4221395.203	56			
Corrected Total	Extrapolated Length - Level 2 Trial 1	1572398.256	55			
	Extrapolated Time - Level 2 Trial 1	1323895.536	55			

a. R Squared = .297 (Adjusted R Squared = .270)

b. R Squared = .266 (Adjusted R Squared = .239)

Estimated Marginal Means

Interface

Dependent Variable	Interface	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Extrapolated Length - Level 2 Trial 1	Static	343.022[a]	27.057	288.751	397.292
	Dynamic	166.641[a]	28.059	110.361	222.921
Extrapolated Time - Level 2 Trial 1	Static	283.736[a]	25.355	232.880	334.592
	Dynamic	167.029[a]	26.294	114.290	219.768

a. Covariates appearing in the model are evaluated at the following values: Composite Game Experience Score = 11.9580.

```
GLM m2_exLen m2_exTi BY i_face WITH comp_g
/METHOD=SSTYPE(3)   /INTERCEPT=INCLUDE
/EMMEANS=TABLES(i_face) WITH(comp_g=MEAN)
/CRITERIA=ALPHA(.05)   /DESIGN=comp_g i_face.
```

General Linear Model

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Between-Subjects Factors

		Value Label	N
Interface	1	Static	29
	2	Dynamic	27

Multivariate Tests[b]

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	.345	13.705[a]	2.000	52.000	.000
	Wilks' Lambda	.655	13.705[a]	2.000	52.000	.000
	Hotelling's Trace	.527	13.705[a]	2.000	52.000	.000
	Roy's Largest Root	.527	13.705[a]	2.000	52.000	.000
comp_g	Pillai's Trace	.097	2.795[a]	2.000	52.000	.070
	Wilks' Lambda	.903	2.795[a]	2.000	52.000	.070
	Hotelling's Trace	.108	2.795[a]	2.000	52.000	.070
	Roy's Largest Root	.108	2.795[a]	2.000	52.000	.070
i_face	Pillai's Trace	.180	5.712[a]	2.000	52.000	.006
	Wilks' Lambda	.820	5.712[a]	2.000	52.000	.006
	Hotelling's Trace	.220	5.712[a]	2.000	52.000	.006
	Roy's Largest Root	.220	5.712[a]	2.000	52.000	.006

a. Exact statistic

b. Design: Intercept + comp_g + i_face

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	Extrapolated Length - Level 2 Trial 2	296009.360[a]	2	148004.680	6.463	.003
	Extrapolated Time - Level 2 Trial 2	238338.103[b]	2	119169.051	5.107	.009
Intercept	Extrapolated Length - Level 2 Trial 2	402665.626	1	402665.626	17.584	.000
	Extrapolated Time - Level 2 Trial 2	639279.655	1	639279.655	27.398	.000
comp_g	Extrapolated Length - Level 2 Trial 2	7795.129	1	7795.129	.340	.562
	Extrapolated Time - Level 2 Trial 2	98951.850	1	98951.850	4.241	.044
i_face	Extrapolated Length - Level 2 Trial 2	261078.098	1	261078.098	11.401	.001

	Extrapolated Time - Level 2 Trial 2	94926.969	1	94926.969	4.068	.049
Error	Extrapolated Length - Level 2 Trial 2	1213643.457	53	22898.933		
	Extrapolated Time - Level 2 Trial 2	1236659.397	53	23333.196		
Total	Extrapolated Length - Level 2 Trial 2	4203299.938	56			
	Extrapolated Time - Level 2 Trial 2	3709586.372	56			
Corrected Total	Extrapolated Length - Level 2 Trial 2	1509652.817	55			
	Extrapolated Time - Level 2 Trial 2	1474997.500	55			

a. R Squared = .196 (Adjusted R Squared = .166)

b. R Squared = .162 (Adjusted R Squared = .130)

Estimated Marginal Means

Interface

				95% Confidence Interval	
Dependent Variable	Interface	Mean	Std. Error	Lower Bound	Upper Bound
Extrapolated Length - Level 2 Trial 2	Static	286.380[a]	28.343	229.530	343.229
	Dynamic	147.291[a]	29.393	88.336	206.246
Extrapolated Time - Level 2 Trial 2	Static	240.195[a]	28.611	182.809	297.581
	Dynamic	156.326[a]	29.670	96.815	215.837

a. Covariates appearing in the model are evaluated at the following values: Composite Game Experience Score = 11.9580.

```
GLM m3_exLen m3_exTi BY i_face WITH comp_g
/METHOD=SSTYPE(3)   /INTERCEPT=INCLUDE
/EMMEANS=TABLES(i_face) WITH(comp_g=MEAN)
/CRITERIA=ALPHA(.05)   /DESIGN=comp_g i_face.
```

General Linear Model

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Between-Subjects Factors

		Value Label	N
Interface	1	Static	29
	2	Dynamic	27

Multivariate Tests[b]

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	.360	14.600[a]	2.000	52.000	.000
	Wilks' Lambda	.640	14.600[a]	2.000	52.000	.000
	Hotelling's Trace	.562	14.600[a]	2.000	52.000	.000
	Roy's Largest Root	.562	14.600[a]	2.000	52.000	.000
comp_g	Pillai's Trace	.029	.785[a]	2.000	52.000	.461
	Wilks' Lambda	.971	.785[a]	2.000	52.000	.461
	Hotelling's Trace	.030	.785[a]	2.000	52.000	.461
	Roy's Largest Root	.030	.785[a]	2.000	52.000	.461
i_face	Pillai's Trace	.270	9.599[a]	2.000	52.000	.000
	Wilks' Lambda	.730	9.599[a]	2.000	52.000	.000
	Hotelling's Trace	.369	9.599[a]	2.000	52.000	.000
	Roy's Largest Root	.369	9.599[a]	2.000	52.000	.000

a. Exact statistic

b. Design: Intercept + comp_g + i_face

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	Extrapolated Length - Level 2 Trial 3	236592.404[a]	2	118296.202	11.561	.000
	Extrapolated Time - Level 2 Trial 3	257344.263[b]	2	128672.131	10.506	.000
Intercept	Extrapolated Length - Level 2 Trial 3	290175.029	1	290175.029	28.359	.000
	Extrapolated Time - Level 2 Trial 3	212417.395	1	212417.395	17.344	.000
comp_g	Extrapolated Length - Level 2 Trial 3	11851.705	1	11851.705	1.158	.287
	Extrapolated Time - Level 2 Trial 3	19507.277	1	19507.277	1.593	.212
i_face	Extrapolated Length - Level 2 Trial 3	198411.530	1	198411.530	19.391	.000
	Extrapolated Time - Level 2 Trial 3	205268.180	1	205268.180	16.760	.000
Error	Extrapolated Length - Level 2 Trial 3	542311.354	53	10232.290		
	Extrapolated Time - Level 2 Trial 3	649104.492	53	12247.255		
Total	Extrapolated Length - Level 2 Trial 3	2469183.627	56			

	Extrapolated Time - Level 2 Trial 3	1879883.067	56
Corrected Total	Extrapolated Length - Level 2 Trial 3	778903.758	55
	Extrapolated Time - Level 2 Trial 3	906448.755	55

a. R Squared = .304 (Adjusted R Squared = .277)

b. R Squared = .284 (Adjusted R Squared = .257)

Estimated Marginal Means

Interface

				95% Confidence Interval	
Dependent Variable	Interface	Mean	Std. Error	Lower Bound	Upper Bound
Extrapolated Length - Level 2 Trial 3	Static	232.195[a]	18.947	194.193	270.197
	Dynamic	110.943[a]	19.648	71.534	150.352
Extrapolated Time - Level 2 Trial 3	Static	191.306[a]	20.728	149.730	232.882
	Dynamic	67.977[a]	21.496	24.861	111.092

a. Covariates appearing in the model are evaluated at the following values: Composite Game Experience Score = 11.9580.

```
CROSSTABS   /TABLES=m1_comp BY i_face   /FORMAT=AVALUE
TABLES   /STATISTICS=CHISQ PHI   /CELLS=COUNT ROW COLUMN
TOTAL   /COUNT ROUND CELL.
```

Crosstabs

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 4\spanav_data_refined.sav

Level 2 Trial 1 Completed * Interface Crosstabulation

			Interface		
			Static	Dynamic	Total
Level 2 Trial 1 Completed	Yes	Count	14	24	38
		% within Level 2 Trial 1 Completed	36.8%	63.2%	100.0%
		% within Interface	45.2%	82.8%	63.3%
		% of Total	23.3%	40.0%	63.3%
	No	Count	17	5	22
		% within Level 2 Trial 1 Completed	77.3%	22.7%	100.0%

	% within Interface	54.8%	17.2%	36.7%
	% of Total	28.3%	8.3%	36.7%
Total	Count	31	29	60
	% within Level 2 Trial 1 Completed	51.7%	48.3%	100.0%
	% within Interface	100.0%	100.0%	100.0%
	% of Total	51.7%	48.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	9.121[a]	1	.003		
Continuity Correction[b]	7.573	1	.006		
Likelihood Ratio	9.512	1	.002		
Fisher's Exact Test				.003	.003
Linear-by-Linear Association	8.968	1	.003		
N of Valid Cases	60				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 10.63.

b. Computed only for a 2x2 table

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	-.390	.003
	Cramer's V	.390	.003
N of Valid Cases		60	

CROSSTABS /TABLES=m2_comp BY i_face /FORMAT=AVALUE TABLES /STATISTICS=CHISQ PHI /CELLS=COUNT ROW COLUMN TOTAL /COUNT ROUND CELL.

Crosstabs

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 4\spanav_data_refined.sav

Level 2 Trial 2 Completed * Interface Crosstabulation

			Interface		
			Static	Dynamic	Total
Level 2 Trial 2 Completed	Yes	Count	14	22	36
		% within Level 2 Trial 2 Completed	38.9%	61.1%	100.0%
		% within Interface	45.2%	75.9%	60.0%
		% of Total	23.3%	36.7%	60.0%
	No	Count	17	7	24
		% within Level 2 Trial 2 Completed	70.8%	29.2%	100.0%
		% within Interface	54.8%	24.1%	40.0%
		% of Total	28.3%	11.7%	40.0%
Total		Count	31	29	60
		% within Level 2 Trial 2 Completed	51.7%	48.3%	100.0%
		% within Interface	100.0%	100.0%	100.0%
		% of Total	51.7%	48.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	5.884[a]	1	.015		
Continuity Correction[b]	4.675	1	.031		
Likelihood Ratio	6.023	1	.014		
Fisher's Exact Test				.019	.015
Linear-by-Linear Association	5.786	1	.016		
N of Valid Cases	60				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 11.60.

b. Computed only for a 2x2 table

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	-.313	.015
	Cramer's V	.313	.015

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	-.313	.015
	Cramer's V	.313	.015
N of Valid Cases		60	

CROSSTABS /TABLES=m3_comp BY i_face /FORMAT=AVALUE TABLES /STATISTICS=CHISQ PHI /CELLS=COUNT ROW COLUMN TOTAL /COUNT ROUND CELL.

Crosstabs

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 4\spanav_data_refined.sav

Level 2 Trial 3 Completed * Interface Crosstabulation

			Interface		
			Static	Dynamic	Total
Level 2 Trial 3 Completed	Yes	Count	18	26	44
		% within Level 2 Trial 3 Completed	40.9%	59.1%	100.0%
		% within Interface	58.1%	89.7%	73.3%
		% of Total	30.0%	43.3%	73.3%
	No	Count	13	3	16
		% within Level 2 Trial 3 Completed	81.3%	18.8%	100.0%
		% within Interface	41.9%	10.3%	26.7%
		% of Total	21.7%	5.0%	26.7%
Total		Count	31	29	60
		% within Level 2 Trial 3 Completed	51.7%	48.3%	100.0%
		% within Interface	100.0%	100.0%	100.0%
		% of Total	51.7%	48.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	7.646[a]	1	.006		
Continuity Correction[b]	6.116	1	.013		
Likelihood Ratio	8.134	1	.004		
Fisher's Exact Test				.008	.006
Linear-by-Linear Association	7.519	1	.006		
N of Valid Cases	60				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 7.73.

b. Computed only for a 2x2 table

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	-.357	.006
	Cramer's V	.357	.006
N of Valid Cases		60	

CROSSTABS /TABLES=m1_p_cat BY i_face /FORMAT=AVALUE TABLES /STATISTICS=CHISQ PHI /CELLS=COUNT ROW COLUMN TOTAL /COUNT ROUND CELL.

Crosstabs

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 4\spanav_data_refined.sav

Route Robustness L2T1 * Interface Crosstabulation

			Interface		
			Static	Dynamic	Total
Route Robustness L2T1	Very Low	Count	2	1	3
		% within Route Robustness L2T1	66.7%	33.3%	100.0%
		% within Interface	6.5%	3.4%	5.0%
		% of Total	3.3%	1.7%	5.0%
	Low	Count	12	4	16

		% within Route Robustness L2T1	75.0%	25.0%	100.0%
		% within Interface	38.7%	13.8%	26.7%
		% of Total	20.0%	6.7%	26.7%
	Normal	Count	3	0	3
		% within Route Robustness L2T1	100.0%	.0%	100.0%
		% within Interface	9.7%	.0%	5.0%
		% of Total	5.0%	.0%	5.0%
	High	Count	14	24	38
		% within Route Robustness L2T1	36.8%	63.2%	100.0%
		% within Interface	45.2%	82.8%	63.3%
		% of Total	23.3%	40.0%	63.3%
Total		Count	31	29	60
		% within Route Robustness L2T1	51.7%	48.3%	100.0%
		% within Interface	100.0%	100.0%	100.0%
		% of Total	51.7%	48.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	9.909[a]	3	.019
Likelihood Ratio	11.281	3	.010
Linear-by-Linear Association	6.723	1	.010
N of Valid Cases	60		

a. 4 cells (50.0%) have expected count less than 5. The minimum expected count is 1.45.

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	.406	.019
	Cramer's V	.406	.019
N of Valid Cases		60	

CROSSTABS /TABLES=m2_p_cat BY i_face /FORMAT=AVALUE TABLES /STATISTICS=CHISQ PHI /CELLS=COUNT ROW COLUMN TOTAL /COUNT ROUND CELL.

Crosstabs

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 4\spanav_data_refined.sav

Route Robustness L2T2 * Interface Crosstabulation

			Interface		
			Static	Dynamic	Total
Route Robustness L2T2	Very Low	Count	0	1	1
		% within Route Robustness L2T2	.0%	100.0%	100.0%
		% within Interface	.0%	3.4%	1.7%
		% of Total	.0%	1.7%	1.7%
	Low	Count	14	3	17
		% within Route Robustness L2T2	82.4%	17.6%	100.0%
		% within Interface	45.2%	10.3%	28.3%
		% of Total	23.3%	5.0%	28.3%
	Normal	Count	3	3	6
		% within Route Robustness L2T2	50.0%	50.0%	100.0%
		% within Interface	9.7%	10.3%	10.0%
		% of Total	5.0%	5.0%	10.0%
	High	Count	14	22	36
		% within Route Robustness L2T2	38.9%	61.1%	100.0%
		% within Interface	45.2%	75.9%	60.0%
		% of Total	23.3%	36.7%	60.0%
Total		Count	31	29	60
		% within Route Robustness L2T2	51.7%	48.3%	100.0%
		% within Interface	100.0%	100.0%	100.0%
		% of Total	51.7%	48.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	9.840[a]	3	.020
Likelihood Ratio	10.835	3	.013
Linear-by-Linear Association	5.821	1	.016
N of Valid Cases	60		

a. 4 cells (50.0%) have expected count less than 5. The minimum expected count is .48.

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	.405	.020
	Cramer's V	.405	.020
N of Valid Cases		60	

CROSSTABS /TABLES=m3_p_cat BY i_face /FORMAT=AVALUE TABLES /STATISTICS=CHISQ PHI /CELLS=COUNT ROW COLUMN TOTAL /COUNT ROUND CELL.

Crosstabs

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 4\spanav_data_refined.sav

Route Robustness L2T3 * Interface Crosstabulation

			Interface		
			Static	Dynamic	Total
Route Robustness L2T3	Low	Count	11	3	14
		% within Route Robustness L2T3	78.6%	21.4%	100.0%
		% within Interface	35.5%	10.3%	23.3%
		% of Total	18.3%	5.0%	23.3%
	Normal	Count	2	0	2
		% within Route Robustness L2T3	100.0%	.0%	100.0%

		% within Interface	6.5%	.0%	3.3%
		% of Total	3.3%	.0%	3.3%
	High	Count	18	26	44
		% within Route Robustness L2T3	40.9%	59.1%	100.0%
		% within Interface	58.1%	89.7%	73.3%
		% of Total	30.0%	43.3%	73.3%
Total		Count	31	29	60
		% within Route Robustness L2T3	51.7%	48.3%	100.0%
		% within Interface	100.0%	100.0%	100.0%
		% of Total	51.7%	48.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	7.968[a]	2	.019
Likelihood Ratio	9.028	2	.011
Linear-by-Linear Association	6.616	1	.010
N of Valid Cases	60		

a. 2 cells (33.3%) have expected count less than 5. The minimum expected count is .97.

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	.364	.019
	Cramer's V	.364	.019
N of Valid Cases		60	

Appendix D

Analysis Data – Experiment 3

GET FILE='E:\PhD Work\Thesis\Appendices\Chap 5\field_acmd.sav'. MEANS TABLES=t_time t_errors test_s BY i_face /CELLS MEAN COUNT STDDEV.

Means

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 5\field_acmd.sav

Case Processing Summary

	Cases					
	Included		Excluded		Total	
	N	Percent	N	Percent	N	Percent
Task time * Interface type	20	100.0%	0	.0%	20	100.0%
Task errors * Interface type	20	100.0%	0	.0%	20	100.0%
Test score * Interface type	20	100.0%	0	.0%	20	100.0%

Report

Interface type		Task time	Task errors	Test score
Static	Mean	322.14	7.71	7.0000
	N	7	7	7
	Std. Deviation	59.303	1.380	1.00000
Video	Mean	239.86	3.00	6.1429
	N	7	7	7
	Std. Deviation	28.121	1.732	.89974
Interactive	Mean	150.00	1.33	7.0000
	N	6	6	6
	Std. Deviation	56.054	1.033	.63246
Total	Mean	241.70	4.15	6.7000

	N	20	20	20
	Std. Deviation	85.017	3.083	.92338

ONEWAY t_time t_errors BY i_face /MISSING ANALYSIS
/POSTHOC=TUKEY ALPHA(0.05).

Oneway

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 5\field_acmd.sav

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Task time	Between Groups	95774.486	2	47887.243	19.590	.000
	Within Groups	41555.714	17	2444.454		
	Total	137330.200	19			
Task errors	Between Groups	145.788	2	72.894	35.648	.000
	Within Groups	34.762	17	2.045		
	Total	180.550	19			

Post Hoc Tests

Multiple Comparisons

Tukey HSD

Dependent Variable	(I) Interface type	(J) Interface type	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Task time	Static	Video	82.286*	26.428	.016	14.49	150.08
		Interactive	172.143*	27.507	.000	101.58	242.71
	Video	Static	-82.286*	26.428	.016	-150.08	-14.49
		Interactive	89.857*	27.507	.012	19.29	160.42
	Interactive	Static	-172.143*	27.507	.000	-242.71	-101.58
		Video	-89.857*	27.507	.012	-160.42	-19.29
Task errors	Static	Video	4.714*	.764	.000	2.75	6.68
		Interactive	6.381*	.796	.000	4.34	8.42
	Video	Static	-4.714*	.764	.000	-6.68	-2.75

		Interactive	1.667	.796	.121	-.37	3.71
	Interactive	Static	-6.381*	.796	.000	-8.42	-4.34
		Video	-1.667	.796	.121	-3.71	.37

*. The mean difference is significant at the 0.05 level.

```
UNIANOVA t_time BY i_face WITH test_s   /METHOD=SSTYPE(3)
/INTERCEPT=INCLUDE   /EMMEANS=TABLES(i_face)
WITH(test_s=MEAN)   /PRINT=ETASQ HOMOGENEITY
/CRITERIA=ALPHA(.05)   /DESIGN=test_s i_face.
```

Univariate Analysis of Variance

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 5\field_acmd.sav

Between-Subjects Factors

		Value Label	N
Interface type	1	Static	7
	2	Video	7
	3	Interactive	6

Levene's Test of Equality of Error Variances[a]

Dependent Variable:Task time

F	df1	df2	Sig.
.818	2	17	.458

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + test_s + i_face

Tests of Between-Subjects Effects

Dependent Variable:Task time

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	95994.143[a]	3	31998.048	12.386	.000	.699
Intercept	12349.999	1	12349.999	4.780	.044	.230
test_s	219.657	1	219.657	.085	.774	.005

i_face	95739.721	2	47869.860	18.529	.000	.698
Error	41336.057	16	2583.504			
Total	1305708.000	20				
Corrected Total	137330.200	19				

a. R Squared = .699 (Adjusted R Squared = .643)

Estimated Marginal Means

Interface type

Dependent Variable:Task time

			95% Confidence Interval	
Interface type	Mean	Std. Error	Lower Bound	Upper Bound
Static	320.903[a]	19.676	279.191	362.615
Video	242.160[a]	20.771	198.127	286.193
Interactive	148.760[a]	21.182	103.857	193.663

a. Covariates appearing in the model are evaluated at the following values: Test score = 6.7000.

```
UNIANOVA t_errors BY i_face WITH test_s   /METHOD=SSTYPE(3)
/INTERCEPT=INCLUDE   /EMMEANS=TABLES(i_face)
WITH(test_s=MEAN)   /PRINT=ETASQ HOMOGENEITY
/CRITERIA=ALPHA(.05)   /DESIGN=test_s i_face.
```

Univariate Analysis of Variance

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 5\field_acmd.sav

Between-Subjects Factors

		Value Label	N
Interface type	1	Static	7
	2	Video	7
	3	Interactive	6

Levene's Test of Equality of Error Variances[a]

Dependent Variable:Task errors

F	df1	df2	Sig.
1.714	2	17	.210

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + test_s + i_face

Tests of Between-Subjects Effects

Dependent Variable:Task errors

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	145.866[a]	3	48.622	22.430	.000	.808
Intercept	3.432	1	3.432	1.583	.226	.090
test_s	.078	1	.078	.036	.852	.002
i_face	142.013	2	71.007	32.756	.000	.804
Error	34.684	16	2.168			
Total	525.000	20				
Corrected Total	180.550	19				

a. R Squared = .808 (Adjusted R Squared = .772)

Estimated Marginal Means

Interface type

Dependent Variable:Task errors

			95% Confidence Interval	
Interface type	Mean	Std. Error	Lower Bound	Upper Bound
Static	7.691[a]	.570	6.483	8.899
Video	3.043[a]	.602	1.768	4.319
Interactive	1.310[a]	.614	.009	2.611

a. Covariates appearing in the model are evaluated at the following values: Test score = 6.7000.

Appendix E

Materials and Analysis Data – Experiment 4 & 5

Raw Scores – Kinematic Analysis

ID	Time to 2nd Quadrant	Time to Mid-point	Time to End-point	Interface Type	Completed Rotation
045				1	2
049	35			1	2
052	4	9	12	1	1
055				1	2
058				1	2
061				1	2
064				1	2
067		13	15	1	1
070				1	2
073		5	7	1	1
076				1	2
079	19			1	2
082	3			1	2
085				1	2
088		10	12	1	1
091				1	2
094				1	2
097	3	9	12	1	1
100		8	12	1	1
103		12	14	1	1
106	3			1	2
109		3	6	1	1
112				1	2
115		6	8	1	1
118		4	6	1	1
121	2	14	16	1	1
124	7	13	16	1	1
127	11			1	2
130	13			1	2
133		3	5	1	1
047	6	7	9	2	1
048	1	2	4	2	1
051	3	5	6	2	1
054	2	3	5	2	1
057	1	3	5	2	1
060	1	2	4	2	1
063		3	4	2	1
066		1	3	2	1
069	3	5	8	2	1
072	3	4	5	2	1
075	3	4	5	2	1
078		2	4	2	1
081	2	3	5	2	1
084		1	3	2	1
087		1	3	2	1
090		3	4	2	1
093	1	2	3	2	1
096	2	3	5	2	1
099		4	5	2	1
102		3	5	2	1
105		4	6	2	1
108		2	4	2	1
111		3	6	2	1
114	2	3	4	2	1
117		2	3	2	1
120	2	3	5	2	1
123	4	8	9	2	1
126		2	3	2	1
129	1	7	8	2	1

Statistical Modelling Outputs – Experiment 4 (SPSS™ version 17)

```
GET FILE='E:\PhD Work\Thesis\Appendices\Chap 6\combined_step_4_final.sav'. MEANS TABLES=t_mid t_end BY i_face /CELLS MEAN COUNT STDDEV.
```

Means

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 6\combined_step_4_final.sav

Case Processing Summary

	Cases					
	Included		Excluded		Total	
	N	Percent	N	Percent	N	Percent
Time to Mid-point * Interface Type	831	74.3%	287	25.7%	1118	100.0%
Time to End-point * Interface Type	801	71.6%	317	28.4%	1118	100.0%

Report

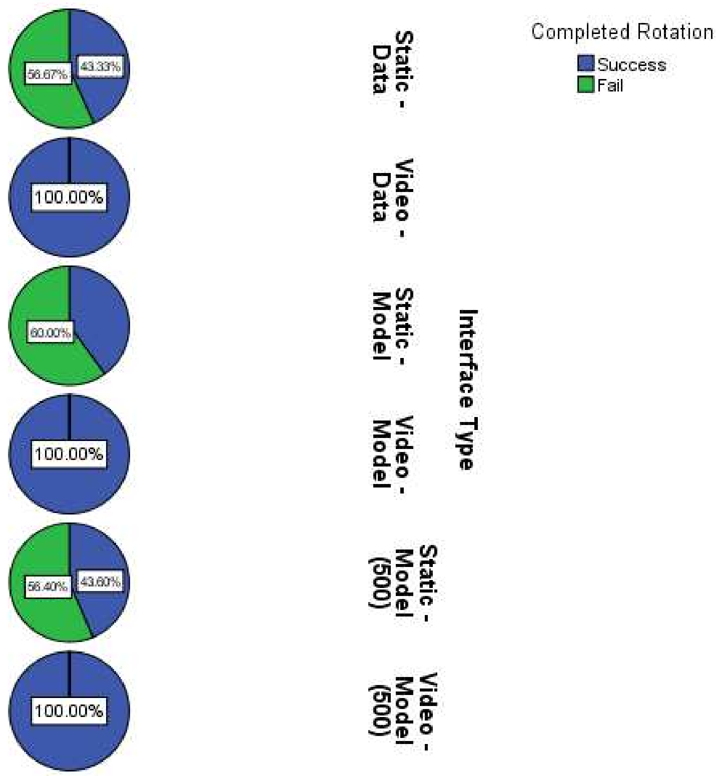
Interface Type		Time to Mid-point	Time to End-point
Static - Data	Mean	8.3846	10.8462
	N	13	13
	Std. Deviation	3.92722	3.97589
Video - Data	Mean	3.2759	4.9310
	N	29	29
	Std. Deviation	1.75044	1.73063
Static - Model	Mean	8.5583	10.5458
	N	12	12
	Std. Deviation	3.48104	3.60192
Video - Model	Mean	3.2021	5.3536
	N	29	29
	Std. Deviation	.49124	.70333
Static - Model (500)	Mean	9.6933	10.8924
	N	248	218

	Std. Deviation	3.88884	3.35665
Video - Model (500)	Mean	2.8474	4.7969
	N	500	500
	Std. Deviation	.44327	.60839
Total	Mean	5.0869	6.6652
	N	831	801
	Std. Deviation	3.88053	3.39957

```
* Chart Builder. GGRAPH   /GRAPHDATASET NAME="graphdataset" VARIABLES=i_face comp COUNT()[name="COUNT"] MISSING=LISTWISE REPORTMISSING=NO   /GRAPHSPEC SOURCE=INLINE. BEGIN GPL   SOURCE: s=userSource(id("graphdataset"))   DATA: i_face=col(source(s), name("i_face"), unit.category())   DATA: comp=col(source(s), name("comp"), unit.category())   DATA: COUNT=col(source(s), name("COUNT"))   COORD: polar.theta(startAngle(0))   GUIDE: axis(dim(1), null())   GUIDE: axis(dim(3), label("Interface Type"), opposite())   GUIDE: legend(aesthetic(aesthetic.color.interior), label("Completed Rotation"))   SCALE: linear(dim(1), dataMinimum(), dataMaximum())   SCALE: cat(dim(3), include("1", "2", "4", "5", "6", "7"))   SCALE: cat(aesthetic(aesthetic.color.interior), include("1", "2"))   ELEMENT: interval.stack(position(summary.percent(COUNT*1*i_face))), color.interior(comp)) END GPL.
```

GGraph

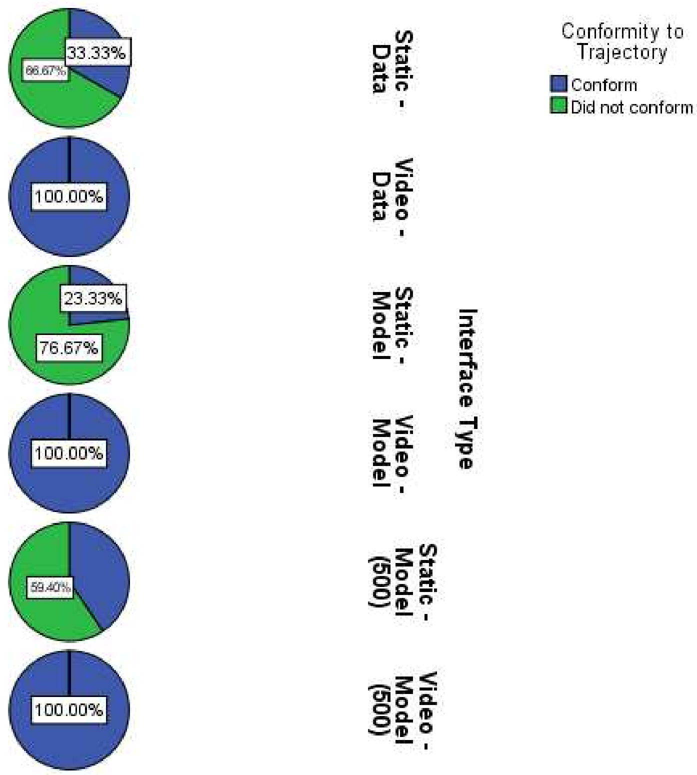
[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 6\combined_step_4_final.sav



* Chart Builder. GGRAPH /GRAPHDATASET NAME="graphdataset" VARIABLES=i_face t_conf COUNT()[name="COUNT"] MISSING=LISTWISE REPORTMISSING=NO /GRAPHSPEC SOURCE=INLINE. BEGIN GPL SOURCE: s=userSource(id("graphdataset")) DATA: i_face=col(source(s), name("i_face"), unit.category()) DATA: t_conf=col(source(s), name("t_conf"), unit.category()) DATA: COUNT=col(source(s), name("COUNT")) COORD: polar.theta(startAngle(0)) GUIDE: axis(dim(1), null()) GUIDE: axis(dim(3), label("Interface Type"), opposite()) GUIDE: legend(aesthetic(aesthetic.color.interior), label("Conformity to Trajectory")) SCALE: linear(dim(1), dataMinimum(), dataMaximum()) SCALE: cat(dim(3), include("1", "2", "4", "5", "6", "7")) SCALE: cat(aesthetic(aesthetic.color.interior), include("21", "22")) ELEMENT: interval.stack(position(summary.percent(summary.percent(COUNT*1*i_face, base.all())))), color.interior(t_conf)) END GPL.

GGraph

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 6\combined_step_4_final.sav



T-TEST GROUPS=i_face(4 5) /MISSING=ANALYSIS /VARIABLES=t_mid t_end /CRITERIA=CI(.95).

T-Test

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 6\combined_step_4_final.sav

Group Statistics

	Interface Type	N	Mean	Std. Deviation	Std. Error Mean
Time to Mid-point	Static - Model	12	8.5583	3.48104	1.00489
	Video - Model	29	3.2021	.49124	.09122
Time to End-point	Static - Model	12	10.5458	3.60192	1.03979
	Video - Model	29	5.3536	.70333	.13061

Independent Samples Test

			Time to Mid-point		Time to End-point	
			Equal variances assumed	Equal variances not assumed	Equal variances assumed	Equal variances not assumed
Levene's Test for Equality of Variances		F	46.327		40.793	
		Sig.	.000		.000	
t-test for Equality of Means		t	8.235	5.308	7.550	4.955
		df	39	11.182	39	11.349
		Sig. (2-tailed)	.000	.000	.000	.000
		Mean Difference	5.35626	5.35626	5.19228	5.19228
		Std. Error Difference	.65045	1.00902	.68773	1.04796
	95% Confidence Interval of the Difference	Lower	4.04061	3.13982	3.80123	2.89436
		Upper	6.67192	7.57271	6.58334	7.49020

```
T-TEST GROUPS=i_face(1 4)   /MISSING=ANALYSIS
/VARIABLES=t_mid t_end   /CRITERIA=CI(.95).
```

T-Test

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 6\combined_step_4_final.sav

Group Statistics

	Interface Type	N	Mean	Std. Deviation	Std. Error Mean
Time to Mid-point	Static - Data	13	8.3846	3.92722	1.08922
	Static - Model	12	8.5583	3.48104	1.00489
Time to End-point	Static - Data	13	10.8462	3.97589	1.10271
	Static - Model	12	10.5458	3.60192	1.03979

Independent Samples Test

			Time to Mid-point		Time to End-point	
			Equal variances assumed	Equal variances not assumed	Equal variances assumed	Equal variances not assumed
Levene's Test for Equality of Variances		F	.390		.459	
		Sig.	.539		.505	
t-test for Equality of Means		t	-.117	-.117	.197	.198
		df	23	22.969	23	22.995
		Sig. (2-tailed)	.908	.908	.845	.845
		Mean Difference	-.17372	-.17372	.30032	.30032
		Std. Error Difference	1.48940	1.48196	1.52187	1.51563
	95% Confidence Interval of the Difference	Lower	-3.25477	-3.23961	-2.84791	-2.83504
		Upper	2.90734	2.89217	3.44855	3.43568

T-TEST GROUPS=i_face(2 5) /MISSING=ANALYSIS
/VARIABLES=t_mid t_end /CRITERIA=CI(.95).

T-Test

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 6\combined_step_4_final.sav

Group Statistics

	Interface Type	N	Mean	Std. Deviation	Std. Error Mean
Time to Mid-point	Video - Data	29	3.2759	1.75044	.32505
	Video - Model	29	3.2021	.49124	.09122
Time to End-point	Video - Data	29	4.9310	1.73063	.32137

Group Statistics

	Interface Type	N	Mean	Std. Deviation	Std. Error Mean
Time to Mid-point	Video - Data	29	3.2759	1.75044	.32505
	Video - Model	29	3.2021	.49124	.09122
Time to End-point	Video - Data	29	4.9310	1.73063	.32137
	Video - Model	29	5.3536	.70333	.13061

Independent Samples Test

			Time to Mid-point		Time to End-point	
			Equal variances assumed	Equal variances not assumed	Equal variances assumed	Equal variances not assumed
Levene's Test for Equality of Variances		F	16.077		8.341	
		Sig.	.000		.006	
t-test for Equality of Means		t	.219	.219	-1.218	-1.218
		df	56	32.383	56	37.004
		Sig. (2-tailed)	.828	.828	.228	.231
		Mean Difference	.07379	.07379	-.42252	-.42252
		Std. Error Difference	.33761	.33761	.34690	.34690
	95% Confidence Interval of the Difference	Lower	-.60251	-.61357	-1.11743	-1.12539
		Upper	.75010	.76116	.27240	.28036

Statistical Modelling Outputs – Experiment 5 (SPSS™ version 17)

```
GET   FILE='E:\PhD Work\Thesis\Appendices\Chap 6\model-data-expt-2.sav'. MEANS TABLES=tcentral tframe tpropeller ttotal errors BY group   /CELLS MEAN COUNT STDDEV.
```

Means

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 6\model-data-expt-2.sav

Case Processing Summary

	Cases					
	Included		Excluded		Total	
	N	Percent	N	Percent	N	Percent
tcentral * group	200	100.0%	0	.0%	200	100.0%
tframe * group	200	100.0%	0	.0%	200	100.0%
tpropeller * group	200	100.0%	0	.0%	200	100.0%
ttotal * group	200	100.0%	0	.0%	200	100.0%
errors * group	200	100.0%	0	.0%	200	100.0%

Report

group		tcentral	tframe	tpropeller	ttotal	errors
Static	Mean	524.52799	619.95513	650.57690	682.83974	84.67
	N	100	100	100	100	100
	Std. Deviation	30.139913	32.296970	32.742832	33.798547	13.352
Dynamic	Mean	388.60266	484.54759	499.56941	515.48241	1.42
	N	100	100	100	100	100
	Std. Deviation	67.777024	73.763069	74.302957	74.904913	1.695
Total	Mean	456.56533	552.25136	575.07315	599.16108	43.04
	N	200	200	200	200	200
	Std. Deviation	85.903316	88.501894	94.917905	101.965101	42.796

MEANS TABLES=t_model e_model BY group /CELLS MEAN COUNT STDDEV.

Means

[DataSet2] E:\PhD Work\Thesis\Appendices\Chap 6\watson-data-sim.sav

Case Processing Summary

	Cases					
	Included		Excluded		Total	
	N	Percent	N	Percent	N	Percent
Model Time * Instruction Type	20	100.0%	0	.0%	20	100.0%
Model Errors * Instruction Type	20	100.0%	0	.0%	20	100.0%

Report

Instruction Type		Model Time	Model Errors
Static	Mean	692.23974	8.6000
	N	10	10
	Std. Deviation	105.859990	.84327
Dynamic	Mean	513.78241	.1000
	N	10	10
	Std. Deviation	71.047988	.31623
Total	Mean	603.01108	4.3500
	N	20	20
	Std. Deviation	126.807454	4.40424

DATASET ACTIVATE DataSet1. T-TEST GROUPS=group(1 2) /MISSING=ANALYSIS /VARIABLES=ttotal /CRITERIA=CI(.95).

T-Test

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 6\model-data-expt-2.sav

Group Statistics

	group	N	Mean	Std. Deviation	Std. Error Mean
ttotal	Static	100	682.83974	33.798547	3.379855
	Dynamic	100	515.48241	74.904913	7.490491

Independent Samples Test

			ttotal	
			Equal variances assumed	Equal variances not assumed
Levene's Test for Equality of Variances		F	35.085	
		Sig.	.000	
t-test for Equality of Means		t	20.365	20.365
		df	198	137.708
		Sig. (2-tailed)	.000	.000
		Mean Difference	167.357330	167.357330
		Std. Error Difference	8.217717	8.217717
	95% Confidence Interval of the Difference	Lower	151.151848	151.108104
		Upper	183.562812	183.606556

T-TEST GROUPS=group(1 2) /MISSING=ANALYSIS
/VARIABLES=errors /CRITERIA=CI(.95).

T-Test

[DataSet1] E:\PhD Work\Thesis\Appendices\Chap 6\model-data-expt-2.sav

Group Statistics

	group	N	Mean	Std. Deviation	Std. Error Mean
errors	Static	100	84.67	13.352	1.335
	Dynamic	100	1.42	1.695	.169

Independent Samples Test

			errors	
			Equal variances assumed	Equal variances not assumed
Levene's Test for Equality of Variances		F	140.363	
		Sig.	.000	
t-test for Equality of Means		t	61.856	61.856
		df	198	102.190
		Sig. (2-tailed)	.000	.000
		Mean Difference	83.250	83.250
		Std. Error Difference	1.346	1.346
	95% Confidence Interval of the Difference	Lower	80.596	80.581
		Upper	85.904	85.919