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The Role of Domain-Specific Knowledge in the Reading Comprehension of Adult Readers

by
Virginia Nusca

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The Role of Domain-Specific Knowledge in the Reading Comprehension of Adult Readers

ABSTRACT

The role of domain-specific knowledge in reading comprehension performance was explored within the context of three current theories of reading comprehension skill: the simple view of reading, verbal efficiency theory, and the construction-integration model of comprehension. According to these theories, domain-specific knowledge is not implicated in the on-line processing of text, or in comprehension processes associated with basic meaning construction or with the creation of a text-base model. The role of domain-specific knowledge in the on-line processing of text and in reading comprehension was explored in two knowledge domains: astronomy and computers. In a study of fluent adult readers, those with relatively high levels of astronomy knowledge named astronomy words more accurately and more quickly compared to control words of the same length and frequency than fluent adult readers with relatively low levels of astronomy knowledge. Astronomy and computer knowledge were also significant predictors of reading rate: higher levels of domain-specific knowledge were associated with faster reading rates. These data suggest that domain-specific knowledge may affect the speed with which individual domain-specific words are processed as well as the rate at which text is processed. Domain-specific knowledge was a significant predictor of reading comprehension performance in both the astronomy and computer domains after controlling for other variables such as word recognition skill and general language comprehension skill, indicating that domain-specific knowledge has a role to play in reading comprehension performance. While domain-specific knowledge had a consistently facilitative effect on reading comprehension performance for fluent adult readers, it had a facilitative effect for those with a reading disability only in the computer condition. The implications for these results for models of reading comprehension are discussed.

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CHAPTER ONE
Introduction

Readers bring all kinds of knowledge to bear on texts they are trying to comprehend. That they apply knowledge of orthography, phonology, semantics, syntactics, and other types of word and discourse knowledge has long been accepted as fundamental to the reading process. Often, however, knowledge about the content or topic of texts - that is, domain-specific knowledge - has not been considered a factor in reading comprehension skill even though a number of studies have demonstrated that domain-specific knowledge has a robust effect on reading comprehension performance (e.g., Chi, 1978; Haenggi & Perfetti, 1994; Spilich, Vesonder, Chiesi, & Voss, 1979).

Despite the fact that studies consistently report that high knowledge readers comprehend better than low knowledge readers, the question of how domain-specific knowledge might interact with or influence other reading skills has rarely been addressed. Does domain-specific knowledge have a direct effect on reading comprehension skill or is it an extra component, one which is not essential to reading comprehension skill? Does domain-specific knowledge interact with or influence other reading skills such as word recognition, propositional encoding, or inferencing?

The impulse that sparked this thesis was the idea that our understanding of the component processes of reading comprehension skill may be incomplete without the addition of domain-specific knowledge as a variable. In addition to decoding, word recognition, and language processing skills, domain-specific knowledge may play a significant role in the development and exercise of reading comprehension skill. In order to provide a context for an exploration of the role of domain-specific knowledge in reading comprehension skill, the concept, domain-specific knowledge, will be briefly described. Recent models of reading comprehension will be reviewed and the role of domain-specific knowledge in these models will be discussed.

Domain-Specific Knowledge Described

Knowledge about the content or topic of a reading passage has been variously labelled as prior knowledge, background knowledge, or domain-specific knowledge. These terms have been used interchangeably in the literature and refer to knowledge specific to a particular domain or field of study such as knowledge about the Panama Canal (Haenggi & Perfetti, 1994), or knowledge about baseball (Spilich, Vesonder, Chiesi, & Voss, 1979). Domain-specific knowledge can refer not only to the declarative knowledge a reader may have, but also to the procedural and metacognitive knowledge associated with a particular domain (Alexander, 1992).

In general, the concept of domain-specific knowledge has not been clearly articulated (Alexander, 1992) and differences in the way in which domain-specific knowledge is conceptualized and/or operationalized may influence the impact it has on reading performance. While this difficulty is not important for the purpose of the discussion which follows, it is an issue that will be returned to later.

Role of Domain-Specific Knowledge in Models of Reading Comprehension

If the goal of reading is to derive meaning from text, then understanding reading comprehension skill is essential to any understanding of reading ability. Indeed, reading ability is often operationalized as reading comprehension skill, i.e., a person's ability to demonstrate comprehension of what he or she has read, either by answering comprehension questions or by recalling what has been read (e.g., Bell & Perfetti, 1994; Gough, Hoover, & Peterson, 1996; Moravcsik & Kintsch, 1993; Perfetti, 1985).

The vast majority of theories and models of reading and/or reading comprehension ability take a component process approach (Carr & Levy, 1990). According to a component process approach, reading comprehension ability is seen as the result of the operation, integration, and interaction of a number of component processes, processes which are usually organized into two major categories: lexical level processes and discourse level or language comprehension processes (cf. Levy & Carr, 1990). Lexical level processes include decoding or word attack skill and word recognition skill. Discourse level processes include propositional

encoding and integration as well as inferencing, and comprehension monitoring. For most reading theorists reading comprehension occurs when a reader exercises lexical and discourse component processes.

Research into individual differences in reading skill has provided most of the evidential framework for models of reading comprehension skill. Given the fact that domain-specific knowledge has not been included as a variable in most studies of individual differences in reading ability, it is not surprising to find that it has also not been included as a variable in many models of reading comprehension. For most theorists, domain knowledge is thought to have no impact on lexical level processes such as decoding, word recognition or the sense activation component of semantic encoding. Its impact is confined to the discourse level. However, the role domain knowledge takes at the discourse level depends on which model of reading comprehension is being considered. What follows is a brief discussion of the role of domain knowledge in three current models of reading comprehension: the Simple View of reading, verbal efficiency theory, and the construction-integration model.

Simple View of Reading

According to the Simple View of reading, reading comprehension skill is a function of decoding skill and language comprehension skill. More formally, the theory states that

$$r = d \times c$$

where r is reading comprehension skill, d is decoding skill and c is comprehension ability (Gough & Tunmer, 1986; Hoover & Gough, 1990). Decoding skill can be operationalized as accuracy or latency in reading words or nonwords. Comprehension skill is a general language comprehension facility which is thought to underlie both listening or oral language skill and reading comprehension skill. Decoding and language comprehension skill are related in a multiplicative fashion: if either d or c equals 0, there can be no reading comprehension.

The importance of decoding and general language comprehension changes as reading comprehension skill develops (Gough & Tunmer, 1986; Gough, Hoover, & Peterson, 1996; Hoover & Gough, 1990). For normal beginning readers, language comprehension ability is assumed to be relatively well developed, while decoding skills are just developing. Thus,

decoding skill will be a more important variable for beginning readers. Conversely, for fluent adult readers who have mastered the decoding aspects of reading, language comprehension facility will be the more important determinant of reading comprehension skill.

In early validations of the Simple View of reading, domain knowledge was not considered as a variable (Hoover & Gough, 1990). Recently, however, domain knowledge has been included in a study of fluent adult readers (Peterson, 1993). Peterson asked 127 U.S. Naval Reservists to listen to and read passages on the topics of baseball and computers. They were given measures of their baseball and computer knowledge as well as measures of their decoding skills and reading and listening comprehension of the passages. Results indicated that domain knowledge was more highly correlated with listening and reading comprehension than with decoding skill (see Table 1.1) for both baseball and computer passages.

As Table 1.1 illustrates, domain knowledge appeared to have a similar impact on reading and listening comprehension, reflecting the impact domain-specific knowledge has on general language comprehension skill. The correlations between decoding skills across passages were very high, but decoding skill was not correlated with domain-specific knowledge. While decoding skill was highly correlated across passages, the correlations between reading and listening comprehension and knowledge across passages were lower. Thus, the effect of domain-specific knowledge was not generalized across passages, but rather restricted to the passages based on that particular domain or knowledge. Based on this pattern of correlations, Gough et al. (1996) argued that, for fluent readers

> Reading...has two dimensions, decoding and comprehension. Reading...is both general and specific; decoding is general, and comprehension is specific (page 10).

Decoding represents a general skill underlying all reading. Variations in domain-specific knowledge can result in variations in reading comprehension across passages, reflecting a more passage or knowledge specific skill. Thus, for fluent adult decoders, variations in reading comprehension will most likely be the result of variations in language comprehension skill, a skill that is dependent, in part, on domain-specific knowledge.

Intercorrelations among variables from Peterson's study (1993)

	2.	3.	4.	5.	6.	7.	8.
1. Baseball Reading Comprehension	.62	.25	.71	.35	.19	.30	.29
2. Baseball Knowledge		.10	.60	.19	.13	.12	.14
3. Baseball Decoding Skill			.24	.17	.26	.88	.33
4. Baseball Listening Comprehension				.37	.37	.29	.41
5. Computer Reading Comprehension					.44	.29	.54
6. Computer Knowledge						.39	.56
7. Computer Decoding Skill							.43
8. Computer Listening Comprehension							

Table 1.1

Verbal Efficiency Theory

According to Verbal Efficiency Theory (Perfetti, 1985), successful reading comprehension depends on the efficient execution, management and allocation of lexical and discourse level processes. In general, lexical and discourse level processes make ongoing demands of readers; resources always need to be allocated to these processes. However, with practice and increasing skill, lexical level processes such as word recognition can become more efficient and use less resources. As fluent skill in reading processes develop, the processes become modular and impenetrable (Perfetti, 1989). In other words, reading processes execute automatically and quickly, and are unaffected by any other cognitive process. Thus, while the

decoding ability of beginning, less skilled readers might be affected by other factors such as the context of the passage (Perfetti & Roth, 1981), the hallmark of a fluent reading process such as word recognition is its automaticity and impenetrability.

To the extent that there are individual differences in the speed and efficiency with which any of the modules of reading skill operate, there will be individual differences in reading comprehension skill, even for fluent adult readers (Perfetti, 1985). For example, high ability readers are more efficient decoders, leaving more resources available for discourse level processing, and thus, their reading comprehension skills are better (Bell & Perfetti, 1994; Perfetti & Hogaboam, 1975).

According to Verbal Efficiency Theory, domain-specific knowledge is not a component intrinsic to reading ability (Perfetti, 1985; Perfetti, 1989; Perfetti, Marron & Foltz, 1996). Reading is a restricted-general ability which relies on the application of impenetrable, modular reading processes such as lexical access and sentence parsing (Perfetti, 1989). Domain-specific knowledge cannot affect the operation of these modules and thus cannot contribute to a construction of a "basic meaning representation." It is the basic meaning representation constructed from the text which defines basic reading comprehension skill and it involves both lexical and language comprehension - or discourse level - processes. As Perfetti et al. (1996) state:

> ...it has typically been assumed that...knowledge is an extra component, not intrinsically part of comprehension. Indeed, we have made exactly this claim, trying to argue for a concept of general language comprehension that is completely free of knowledge (page 146).

By this formulation, language comprehension processes operate independently and distinctly from domain-specific knowledge. In other words, there is a linguistic ability which is separable from content or domain-specific knowledge (Perfetti, 1989).

However, domain knowledge has an important impact on some discourse level processes. Processes such as inferencing and comprehension monitoring may not be invoked or triggered without relevant content knowledge (Perfetti et al, 1996). For example, it may be

difficult to notice text inconsistencies, a comprehension monitoring skill, without some knowledge of the content of a passage. When domain-specific knowledge is involved, inferentially rich processes occur. These processes are alternatively characterized as text modelling processes (Perfetti, 1985) which involve integrating the basic meaning representation derived from the text with a reader's knowledge base. Readers can add relevant knowledge - their knowledge of discourse structures and content knowledge - to their text representation in order to fill in gaps and to help interpret the text more fully. In this way, discourse processes involved at the inference rich level of comprehension are penetrable by other processes. They can be influenced by both the output of basic meaning construction processes and by a reader's world or domain-specific knowledge.

To summarize, there are two kinds of reading comprehension performance, one which results in a basic meaning construction and another which leads to an inference rich construction. However, reading ability comprises only one of these kinds of constructions: basic meaning construction. Reading ability is the ability to form a basic meaning representation of a text which requires the application of modular, impenetrable lexical and discourse level processes. An inference rich representation can be also constructed but it is not considered essential or necessary to basic reading comprehension skill. Domain-specific knowledge is not involved in the construction of a basic meaning representation, but it may be involved in rich inference processing where it may enhance a reader's comprehension of a passage by integrating it with her knowledge of the topic of the passage. Thus, according to Verbal Efficiency Theory, the application of domain-specific knowledge is an "extra component" of reading comprehension skill rather than an intrinsic one.

Construction-Integration Model of Text Comprehension

Over the last 18 years, Kintsch and his collegues have elaborated a model of text comprehension (Kintsch & van Dijk, 1978; Kintsch, 1988; Kintsch, 1998; van Dijk & Kintsch, 1983) that has focussed on modelling, predicting, and explaining discourse level processes. At the discourse level, Kintsch (1988) has proposed that a reader constructs a mental representation of a text, a text base, in order to comprehend it. The reader uses her knowledge

base - an associative net of knowledge - to construct the text base which is also an associative net. When a reader constructs a representation for a proposition, she applies information from her knowledge net to the text base. Initially, this information consists not only of concepts directly derived from the text, but also associated concepts and information taken from the reader's long term store of knowledge.

Construction processes are closely followed by various levels of integration. A rich and elaborate network of concepts and propositions can be constructed, but only a portion of them will be integrated into the final text base representation of a passage. It is in the integration phase that some concepts and propositions are dropped and where the strength of association between concepts and propositions within a text base are stabilized. The Construction-Integration process occurs in processing cycles with levels of integration occurring within and at the end of each processing cycle.

Knowledge is an important component of text-based comprehension. Kintsch states (1988, page 180):

> Text bases combine two sources of information: the text itself and knowledge - knowledge about language as well as knowledge about the world. To construct even a single proposition, an appropriate frame must be retrieved from one's store of knowledge, and its slots must be filled in the way indicated by the text.

However, according to the Construction-Integration model of comprehension, a text-base level of comprehension is relatively superficial. That is, it utilizes knowledge that is general to the basic linguistic, semantic, and rhetorical features of a text (Kintsch, 1994). Domain-specific knowledge is not one of the kinds of knowledge used to construct a text base. Instead, domain-specific knowledge is used to construct a deeper understanding of a text, or as Kintsch has characterized it, to construct a situation model. When a reader constructs a situation model of a text, he or she is integrating textual information with prior or domain-specific knowledge (Kintsch, 1994). While the construction of a text base may be sufficient for simple recall of a text, the construction of a situation model is a prerequisite for learning from a text. That is, a situation model must be constructed for a reader to draw inferences from a text, to apply

information from the text to a novel situation, or to use information from a text to solve a problem.

It is important to note that the two levels of comprehension - a text base and a deeper situation model - do not correspond to two different mental representations of the information from a text. Only one representation is constructed (Kintsch, 1994). The extent to which a mental representation of a text reflects the construction of a situation model depends on the extent and elaborateness of a reader's domain-specific knowledge. Thus, domain-specific knowledge is important to the quality of a constructed situation model; it has no role to play in the construction of a text base.

Although the focus of much of Kintsch's work has been on discourse level processes involved in text comprehension, the Construction-Integration model has been applied to lexical processing (Kintsch, 1988). According to the Construction-Integration model, lexical access occurs automatically for fluent readers. That is, word recognition processes automatically activate all the semantic senses that a reader has stored for the particular words being recognized (Kintsch & Mross, 1985). Thus, sense activation for words happens in a bottom-up or data driven fashion. Very quickly, however, the appropriate sense(s) of a word is selected from those that are activated based on the thematic context in which the word occurs. For example, if a person recognized the word *bank* in a passage, the senses of river bank and financial institution would both be activated automatically. The thematic context of the passage - whether the passage was about financial institutions or rivers - would determine which sense of the word *bank* was selected. Thus, sense selection is influenced by the context of a text, although it is characterized as a post-lexical effect (Kintsch & Mross, 1985).

These two types of semantic processing, sense activation and sense selection, correspond to construction and integration processes, respectively. In sense activation, all associated senses or meanings of a word are activated, a construction process. In sense selection, irrelevant senses are dropped while relevant, thematically appropriate senses are reinforced and integrated into the mental representation of the text. The cycles of Construction-Integration that occur at the level of semantic processing mirror the more

complex Construction-Integration processes that occur at the discourse level.

Kintsch does not explicitly address the possible role of domain-specific knowledge in word recognition. However, some claims seem to logically follow from his articulation of the Construction-Integration model of comprehension. Domain-specific knowledge, considered as a top down effect, should have no impact on the sense activation phase of semantic encoding since this happens automatically as a result of word recognition (Kintsch & Mross, 1985; Kintsch,1988). In the sense selection phase of semantic processing, the appropriate sense of the word is retained and integrated into the text base and/or situation model. In many respects, sense selection can be considered a discourse level process in that discourse level components provide a context within which word senses are selected. The type of comprehension engaged in - text base vs. situation model - would determine the kind of context available as new words were encountered and integrated into a reader's mental representation of the text. Thus, domain-specific knowledge could have an effect on the sense selection process, but only if the reader was constructing a situation model.

Comparison of the Three Models

Although the preceding provides only a brief overview of three models of reading or text comprehension, some claims about the role of domain knowledge in reading comprehension can be discerned. According to all three models, domain knowledge should have no effect on lower level lexical processes such as decoding and word recognition. In the Simple View of reading, word recognition skills include only the activation of orthographic and phonological representations, i.e., decoding skills. For both Verbal Efficiency Theory and the Construction-Integration model, lexical access processes include both decoding and semantic encoding processes. Both Perfetti (1989) and Kintsch (1988) argue for a modular, automatically executing word recognition process which includes the sense activation phase of semantic encoding.

The three models provide somewhat different accounts of how domain-specific knowledge may affect discourse level or language comprehension processes. In the Simple View of reading, domain-specific knowledge has an effect on language comprehension

processes; it can be considered a component of language comprehension processing. Reading comprehension performance will vary from text to text partly as a function of variation in domain-specific knowledge. However, how domain-specific knowledge may affect language comprehension processes is not clearly specified.

According to Verbal Efficiency Theory, domain-specific knowledge is not an intrinsic component of reading comprehension skill. Perfetti (1989) argues that the basic meaning construction processes which are essential and fundamental to reading ability are modular processes which are not affected by other cognitive processes such as domain-specific knowledge. However, interpretive and inferentially rich comprehension processes may be employed which elaborate on the basic meaning construction. These rich interpretive processes, while not essential to reading ability per se, are affected by domain-specific knowledge.

In many ways, Perfetti's description of language comprehension or discourse level processes parallels the Construction-Integration model. In this model, readers construct a text base consisting of propositions assembled and integrated from the text. They may also create a situation model which integrates information from their knowledge base with text information. The text base is similar to Perfetti's basic meaning construction processes, while the situation model is similar to the interpretively and inferentially rich comprehension processes described by Perfetti. This two tier conception of text comprehension - and consequently of the role domain-specific knowledge in text comprehension - has been influential in reading research. When the Construction-Integration model of reading comprehension is applied to other reading comprehension research, it is generally assumed that domain-specific knowledge is not involved in the construction of a text base, but rather, is involved only in the construction of a situation model (e.g., Royer, Carlo, Dufresne & Mestre, 1996; Voss & Silfies, 1996).

While both Verbal Efficiency Theory and the Construction-Integration model of comprehension describe two levels of reading comprehension skill, the emphasis they give to each level is not the same. For Verbal Efficiency Theory, the study of reading ability involves the study of processes essential to basic meaning construction. In other words, reading ability

is equated with basic meaning construction. Thus, the focus and emphasis of research and debate is on processes associated with basic meaning construction. Inferentially rich constructions are not essential to reading ability. Consequently, domain-specific knowledge, a component that is applied to interpretive and inferential processing, is not emphasized.

For the Construction-Integration model, the two different types of comprehension are seen to serve two different functions. For recall and reiteration purposes, the construction of a text base is sufficient. However, for comprehension that results in learning and the ability to apply textual information to new situations, the construction of a situation model is essential. Because domain-specific knowledge is needed to construct a situation model, it has an important role to play in comprehension for the Construction-Integration model.

Another important difference between Verbal Efficiency and Construction-Integration models has to do with the role of domain-specific knowledge in the on-line processing of text. For Verbal Efficiency Theory, only those components essential to basic meaning construction are involved in the on-line processing of text (Perfetti, 1989). Consequently, domain-specific knowledge cannot be involved in a direct fashion in the on-line processing of text. For the Construction-Integration model, however, both the text-base and the situation model are constructed on-line. No distinction is made between the two in terms of the immediacy with which either kind of comprehension can occur. Thus, domain-specific knowledge may be involved in the on-line processing of text to the extent that the reader is constructing a situation model.

In summary, all the models reviewed suggest that domain-specific knowledge is a component of reading of a higher order than the processes involved in word recognition and language comprehension processing. Domain-specific knowledge is an optional component in that comprehension - at some level at least - can occur successfully without its application.

Description of Present Research

Two central claims regarding the role of domain-specific knowledge emerge from a review of recent theories of reading comprehension. The first claim is that domain-specific

knowledge should have no effect on lower level lexical processing. As readers encounter words in a text, the extent of their knowledge of the topic of the text should not affect the speed or efficiency with which a word is recognized. The second claim is that domain-specific knowledge does not have a direct effect on basic comprehension or text-based comprehension processing. It is an optional component applied when deeper comprehension is desired. The veracity of these two claims will be assessed in the chapters which follow. Chapter Three describes tests of the hypothesis that domain-specific knowledge can influence word recognition skill. Chapter Four examines the role of domain-specific knowledge on the rate at which texts are read. If domain-specific knowledge has an effect on reading rate, this would suggest that domain-specific knowledge is implicated in the on-line processing of text, i.e., in the on-line construction of meaning. This would challenge the viewpoint of Verbal Efficiency Theory where domain-specific knowledge should not be involved in the on-line processing of text, i.e., in the construction of basic meaning (Perfetti, 1989). Chapter Five continues the examination of a direct role for domain-specific knowledge in the construction of basic meaning or a text base by developing and testing a model of reading comprehension which includes domain-specific knowledge as a variable. Chapter Six explores the role of domain-specific knowledge in explaining individual differences in reading comprehension skill. In this chapter comparisons are made between fluent adult readers, and adults with a reading disability.

The investigations to be described explore the role of domain-specific knowledge within the context of the reading comprehension models discussed above. Consequently, measures were constructed which tapped lexical processing and language comprehension skills as well as domain-specific knowledge. Chapter Two provides a rationale for and description of the various measures used.

CHAPTER TWO

General Method, Measures, and Preliminary Analyses

The overall goal of the present research was to explore the role of domain-specific knowledge in various aspects of reading comprehension performance: in word recognition, reading rate or on-line processing of text, and in reading comprehension skill. To this end measures were identified which tapped not only domain-specific knowledge, but also the lexical and language comprehension processes which are fundamental to recent models of reading comprehension skill. Subsumed under this general goal was the objective of extending previous research to include domain-specific knowledge as a variable. Thus, rather than developing new reading comprehension and language comprehension measures, wherever possible materials used were similar to ones used in previous research. Specifically, reading and listening passages from two previous studies - one based on the simple view of reading (Peterson, 1993) and the other based on verbal efficiency theory (Bell & Perfetti, 1994) - were used in order to replicate and extend previous research to include domain-specific knowledge. Two different sets of passages tapping two distinct domains of knowledge were used. In this way, results of each research question could be replicated, providing an opportunity to evaluate the generalizability of results.

While not a major goal of the present research, another objective was to explore a variety of measures of domain-specific knowledge. While multiple choice tests are a common way to measure domain-specific knowledge (e.g., Haenggi & Perfetti, 1994; Peterson, 1993), it is not clear whether other measures might be equally valid. Thus, four different types of measures of domain-specific knowledge were developed.

The measures can be categorized as reflecting either comprehension skill, decoding or word recognition skill, and domain-specific knowledge. Table 2.1 contains a summary of all the measures collected from subjects. In the following sections, the general method used is described. Individual measures are described in detail, and preliminary analyses are reported. Preliminary analyses were conducted to evaluate and compare individual measures, as well as to provide a basis for constructing composite variables where appropriate.

Types of Measures

Reading Comprehension	Language Comprehension Skill	Decoding Skills	Domain-Specific Knowledge
Nelson-Denny Reading Test 1. Raw score 2. Reading rate Reading Comprehension Test from experimental passages on astronomy and computer topics 1. Raw score on multiple choice test 2. Reading rate 3. Difficulty rating 4. Interest rating	WAIS-R Vocabulary Subtest 1. Raw score Listening Comprehension Test from experimental passages on astronomy and comptuer topics 1. Raw score on multiple choice test 2. Reading rate 3. Difficulty rating 4. Interest rating	Domain-specific word naming task 1. Accuracy 2. Response time General word naming task 1. Accuracy 2. Response time Pseudoword naming task 1. Accuracy 2. Response time	Multiple Choice Tests of Knowledge in domains of astronomy and computers Semantic Decision Task 1. Accuracy 2. Response time Number of courses taken in astronomy and computer domains Ratings of knowledge and interest in domains of astronomy and computers

Table 2.1

GENERAL METHOD

Subjects

Two groups of subjects participated: fluent adult readers (NLD) and adults with a specific reading disability (LD). Fluent adult readers consisted of 72 undergraduate students from the University of Waterloo who volunteered to participate. In order to ensure a diverse pool of participants, fluent adult readers were recruited in 3 ways. Some subjects were taking a first year psychology course and received credit for participating. Others were paid for their participation and were either recruited from a pool of students who were interested in volunteering for a variety of psychology experiments or from an undergraduate astronomy course. Due to software failure, 2 participants were unable to complete the semantic decision task. Four participants failed to return for a second session and thus did not complete the prior knowledge and comprehension measures. As a result, the number of fluent adult readers reported for each analysis was 66.

Twenty undergraduate students with reading disability participated. They were attending either the University of Waterloo or Wilfred Laurier University and were recruited through the Services for Persons with Disabilities Offices at these universities. These 20 students were registered with Disability Services because of a specific learning disability in the area of reading. In order to be registered with either Disability Service Office, students provided documentation verifying the existence of a learning disability. Typical documentation consisted of a psychological assessment conducted by or supervised by a registered psychologist. The participants with learning disabilities had no other disability aside from a learning disability.

Tables 2.2, 2.3, and 2.4 contain summaries of the two groups in terms of gender, faculty, and year in program respectively. As can be seen from these tables, the gender distribution of NLD and LD groups was comparable. In addition, LD and NLD subjects were distributed across all faculties and years in program. The mean age of both groups was 21 years old (mean of NLD = 21.52, mean of LD = 21.84).

Number of males and females by group (LD vs NLD)

	Male	Female	Total
NLD	32	34	66
LD	11	9	20

Table 2.2

Distribution of NLD and LD groups by faculty

	Math	Engineering	Science	Arts	Applied Health Studies	Total
NLD	18	11	6	26	5	66
LD	3	1	4	9	3	20

Table 2.3

Distribution of NLD and LD groups by year in program

	Year 1	Year 2	Year 3	Year 4	Total
NLD	30	22	8	5	65*
LD	8	4	6	2	20

*One student did not report year in program

Table 2.4

Table 2.5 provides a comparison of the NLD and LD groups' scores on the reading comprehension measure of the ND and the WAIS-R Vocabulary subtest. The raw scores of the NLD group on the ND reading comprehension measure were significantly higher than those of the LD group ($t(84)=5.74, p < .001$). On the WAIS-R vocabulary subtest, the standard scores of the NLD group were significantly higher than those of the LD group ($t(84)=3.54, p = .001$), although it is important to note that both the NLD and LD groups' mean standard scores fell within the Average range (i.e., within 1 standard deviation or 3 standard score points of the mean = 10) compared to the standardization sample (see Table 2.5 for means and standard deviations).

In addition, raw scores of fluent adult readers on the WAIS-R Vocabulary subtest and the ND were compared as a function of gender, faculty, and year in program. One-way ANOVA's revealed no differences in scores on the ND according to gender ($F(1,64)=.36$, $p=.55$), faculty ($F(4,61)=1.02$, $p=.40$), or year ($F(3,61)=1.53$, $p=.22$). Vocabulary subtest raw scores were not significantly different according to gender ($F(1,64)=1.11$, $p=.30$) or faculty ($F(4,61)=.79$, $p=.54$). However, vocabulary subtest scores did differ significantly according to year of study ($F(3,61)=5.88$, $p=.001$). Using Scheffe's test for a post hoc comparison, year one students scored significantly lower than year two and year four students.

Mean reading comprehension and vocabulary skills of NLD and LD groups

Group	N	Nelson-Denny Reading Test: Raw Scores	WAIS-R Vocabulary Standard Scores
NLD	66	30.29 (5.67)	10.55 (1.82)
LD	20	21.50 (7.02)	8.95 (1.57)

Table 2.5

Measures

Comprehension Measures

Two sets of passages on topics from two distinct knowledge domains provided the basis for many of the comprehension measures. The two sets of passages - two on the topic of astronomy and two on the topic of computers - were used in previous research by Bell and Perfetti (1994) and Peterson (1993). In the previous research one passage from each set was used to measure reading comprehension while the other was used to measure listening comprehension. The listening comprehension measure was used to assess general language comprehension skill, the assumption being that the language comprehension skills underlying reading and listening are essentially the same (Gough & Tunmer, 1986).

The following criteria were used to select the passages. Both sets of passages had been used in previous research and thus results from the present research could be compared to the previous research where these same materials had been used. The passages were drawn from magazines - *Readers Digest* in the case of the astronomy passages, and *Bytes Magazine* in the case of the computer passages - and thus were assumed to reflect ecologically valid samples of adult reading material. All of the passages were relatively lengthy - over 900 words - and thus enabled an assessment of comprehension based on a text in which a topic was developed in some detail.

In addition to measures based on the astronomy and computer passages, two other measures of comprehension were used, the Nelson-Denny Reading Test (1993), and the Vocabulary subtest of the Wechsler Adult Intelligence Scale - Revised (1981). The Nelson-Denny Reading Test has been frequently used as a measure of reading comprehension skill and much research on the component processes important to reading ability is based on its use. It was used in the present research primarily to explore individual differences in reading comprehension skill (Chapter 6). The Vocabulary subtest was used as a measure of general language comprehension skill. It is widely accepted as a reliable measure of general verbal comprehension skill (Kaufman, 1990). Each comprehension measure is described in more detail below.

Reading and Listening Comprehension Tests: Four passages formed the basis for the reading and listening comprehension tasks. Two passages, used by Peterson (1993), were on the topic of computers. Both computer passages were based on articles which had appeared in the commercially available magazine *Bytes*. The two remaining passages, which were on astronomy topics, were adapted from two passages used by Bell and Perfetti (1994). These passages were shortened versions of articles appearing in *Reader's Digest Magazine*. The astronomy passages were shortened to about 1000 words so that they were comparable in length to the computer passages. Table 2.6 provides information on the titles of the passages, number of words, sentences, and paragraphs, and readability ratings. The four passages were comparable in readability, rated at about a Grade 11 to 12 level of difficulty using the Flesch-Kincaid method of calculating readability. See Appendix B for a copy of the four passages. Passages were counterbalanced across subjects such that each subject listened to one astronomy passage and one computer passage and read the other astronomy and computer passages.

Comprehension of the passages was measured using multiple choice tests. A subject's score consisted of the number of multiple choice questions answered correctly. For each passage there was a set of 10 multiple choice comprehension questions. Each question had 4 choices. The items for both computer comprehension measures were taken from those used by Peterson (1993). The items based on the passage, *Light: Messenger of the Universe*, were taken from those used by Bell & Perfetti (1994). Items based on the passage, *Birth of the Sun*, were constructed by the author.

Appendix B contains a copy of multiple choice questions for each passage. The author and her supervisor rated all the questions in terms of whether they could be answered on the basis of information in the text, or whether prior knowledge or domain-specific knowledge was necessary in order to answer the questions. Recalling what was explicitly stated in the text is an example of text-based or basic comprehension (Kintsch, 1994). The majority of the questions tapped information explicitly stated in the text. All of the astronomy questions were rated as tapping explicitly stated information. All but two of the

Analysis of Passages

	A Bus Tour	Object-Oriented Databases	Birth of the Sun	Light: Messenger of the Universe
Number of words	1022	956	1036	1176
Number of paragraphs	21	18	7	10
Number of sentences	58	63	36	47
Number of sentences/ paragraph	3.4	4.5	6	5.2
Number of words/sentence	17.3	15	28.6	24.9
Flesch-Kincaid readability	Grade 11.1	Grade 12.0	Grade 12.0	Grade 12.0

Table 2.6

questions from the set of computer questions could be answered on the basis of information explicitly mentioned in the text, i.e., they did not require the reader to integrate domain-specific knowledge with information from the text. Thus, the comprehension tests can be considered to tap basic comprehension processes, or a reader's text-based model. The two questions which required the reader to consider information not presented in the text were application questions. They required the reader to apply information from the text to a new situation (question 9 from *A Bus Tour*, and question 6 from *Object-oriented Databases*). These latter questions may be considered to reflect what a reader has learned from the text and thus to draw on a reader's situation model (Kintsch, 1994), a process which involves the integration of prior

knowledge and textual information.

Reading-rate for Reading Comprehension Measures: Reading time in words per minute was calculated on the astronomy and computer passages that subjects read.

Difficulty and Interest Ratings for Listening and Reading Comprehension Measures: Subjects were asked to rate how well they had understood each passage they read or listened to using a four point scale. Higher difficulty ratings were associated with greater difficulty understanding the passage. Subjects were also asked to rate on a four point scale how interested they were in what they had read or listened to. Higher interest ratings were associated with greater interest in reading or listening to the passage. The difficulty and interest ratings were solicited at the beginning of each listening or reading comprehension test (see copies of comprehension tests in Appendix B).

Vocabulary Test: The Vocabulary subtest of the Wechsler Adult Intelligence Scale - Revised (Wechsler, 1981) was used as a measure of general language comprehension. Subjects were asked to orally define a series of words. This measure was administered as described in the manual which accompanies the Wechsler Adult Intelligence Scale - Revised. In order to retain all the individual difference information on this measure, raw scores rather than standard scores were used. Reliability of the vocabulary subtest is .96 (Wechsler, 1981).

Nelson-Denny Reading Test: The Nelson-Denny Reading Test (Brown, Fishco, & Hanna, 1993) is a commercially available, standardized measure of reading comprehension for adults attending post-secondary institutions. There are two subtests, a reading vocabulary and a reading comprehension measure. Only the reading comprehension measure was used. Participants had 20 minutes to read seven short passages and answer 38 multiple choice questions. Two measures were taken: reading rate and comprehension scores. Participants were timed as they read for the first minute. The reading rate score was the number of words read during the first minute of reading. The reading comprehension score was the number of items answered correctly.

Knowledge Measures

A variety of domain-specific knowledge measures have been used in previous research.

The formats of domain-specific knowledge measures have ranged from multiple choice items to open-ended questions, identifying places on a map, or sorting tasks. Usually, a number of items are constructed to assess knowledge of key concepts which are drawn from the same knowledge domain as the reading passage(s). However, there is no consistency with respect to the relationship between the information covered by the domain-specific or 'prior' knowledge measure and the reading passage. Sometimes, researchers note that the questions asked do not cover information explicitly presented in the reading passage (e.g., McNamara & Kintsch, 1996), whereas in other cases, it is not specified whether or not knowledge assessed in the domain-specific knowledge measure overlapped with information covered in the reading passage (e.g., Adam, Bell, & Perfetti, 1995; Peterson, 1993). In some cases, the knowledge assessed by domain-specific knowledge measures does overlap with information covered in the reading passage. For example, Haenggi and Perfetti (1994) used a reading passage which described U.S. Policy towards the Panama Canal and how the canal was constructed. They note that the open-ended questions they used in their domain-specific knowledge measure "...covered the characteristics of the canal and both earlier and more recent events in the U.S. policy towards Panama" (p. 88), and that the comprehension questions covered the "...main events, states, and actions that led to the construction of the canal..." (p. 88). Similarily, McNamara & Kintsch (1996) used a sorting task which involved grouping related concepts together. The words used in the sorting task were taken from the reading passages.

For the present research, four domain-specific knowledge measures were constructed to assess knowledge in a wide variety of ways: 1) prior knowledge multiple choice test, 2) semantic decision task, 3) number of domain-specific courses taken, and 4) self-report ratings of interest and knowledge in the domains. The measures can be characterized as assessing both general levels of expertise in a particular domain (e.g., the number of courses taken can be viewed as a general measure of domain-specific expertise) and more specifically, the concepts covered by the reading and listening passages (e.g., the semantic decision task uses concepts drawn from the passages). The prior knowledge multiple choice measure assessed both knowledge from the same general domain as the reading and listening passages, as well as

concepts and information covered in the reading and listening passages. The prior knowledge multiple choice measure was adapted from previous research (Peterson, 1993) and the self report measure and number of courses taken in a particular knowledge domain are similar to those used by Voss and Silfies (1996). All four measures are described in detail below.

Prior Knowledge Multiple Choice Test: Two 30 item multiple choice tests were constructed, one which measured astronomy knowledge and the other which measured computer knowledge. The items for the astronomy knowledge test were constructed by the author. Twenty of the questions (items 1 to 20) were designed to tap general background knowledge of astronomy. Ten of the questions (items 21 to 30) related to information covered in the two astronomy passages, e.g., the concept of parallax in the *Light* passage. The 5 questions related to the *Light* passage (items 26 to 30) were taken from the set of multiple choice comprehension questions created by Bell & Perfetti (1994). An astronomy professor at the University of Waterloo reviewed the multiple choice questions on the astronomy prior knowledge test to ensure their accuracy and validity as background knowledge questions.

Twenty-five of the 30 items for the computer knowledge test were drawn from those used by Peterson (1993) to assess computer knowledge. Four additional items were taken from Peterson's tests of reading and listening comprehension: 2 from the reading comprehension passage and 2 from the listening comprehension passage. The final item was composed by the author. Of the 30 items on the computer knowledge test, 20 (items 1 to 20) were judged to assess general background computer knowledge, 5 (items 21 to 25) were related to information covered in the *Bus* passage, and 5 (items 26 to 30) were related to information covered in the *Database* passage.

Each multiple choice item contained 4 choices. Participants read the questions and circled the correct answer. See Appendix C for a copy of the astronomy and computer knowledge tests.

Semantic Decision Task: In this task subjects were asked to decide as quickly as possible if words presented one at a time on a computer screen belonged to the category of astronomy or computers. The semantic decision task constructed here is similar to semantic

decision tasks used in recent studies where activation of word meanings is desired (e.g., Jared & Seidenberg, 1991). The astronomy and computer words were selected from the passages on astronomy and computers described above. In this way, accuracy and latency measures could tap knowledge of important concepts covered in the texts. The semantic decision measure tapped knowledge of material in the text without giving the reader any additional information and using a method quite unlike the method used to measure listening and reading comprehension.

Fourteen astronomy words and 14 computer words were drawn from the reading and listening passages. An additional 28 words served as foils. See Appendix D for a list of astronomy and computer words and their foils.

There were 3 blocks of trials presented: a practice block of words, a block of astronomy words and their foils, and a block of computer words and their foils. The order of block presentation remained constant over subjects: 1) the practice block, 2) the astronomy block, and 3) the computer block. Words within each block were presented in random order. The astronomy and computer blocks consisted of 28 decisions each, 14 true responses and 14 false responses. The practice trial, where participants were asked to decide if a word belonged to the category of living things, consisted of 8 decisions, 4 true and 4 false responses.

The semantic decision task was programmed by the author using MEL2 Professional (Schneider, Rodgers, Maciejczyk, Zuccolotto, & St. James, 1995) and presented on an IBM compatible computer with a 16" monitor. At the beginning of each trial, the category name for each block appeared in the center of the screen for 2 seconds, e.g., the word astronomy for the astronomy trial. Immediately afterwards, a fixation point - an x - appeared in the middle of the screen for 500 milliseconds. Immediately afterward, a word appeared and participants pushed one key if the word belonged to the category and another key if the word did not belong to the category. A font size of 12 was used for category names, fixation point, and target words. Latency and accuracy measures were recorded automatically by computer.

Immediately after making a response, the word disappeared from the screen and subjects received feedback about the accuracy of their response. If their response was

incorrect, the computer 'beeped' and the word wrong appeared on the screen for 500 milliseconds. If their response was correct, the word correct appeared on the screen. On correct responses, subjects also received information about their overall accuracy rate (expressed as a percentage correct) and the time (expressed as seconds) it took them to make the correct response. Feedback for correct responses remained on the screen for 1500 milliseconds. This feedback was included to encourage quick and accurate responding. The next trial began immediately after the feedback disappeared from the screen.

Astronomy and computer courses taken: Subjects were asked to list all astronomy and computer courses taken at university or high school (See Appendix A for a copy of the student information questionnaire asking for this information). Only university level courses taken were counted. Subjects received two points for every astronomy or astrophysics course taken, two points for every 'math-based' computer course taken, and 1 point for every 'arts-based' computer course taken. Astronomy and computer course scores reflected total number of points.

Ratings of interest and knowledge of astronomy and computer topics: Students completed a series of ratings (see Appendix A) regarding their interest and knowledge of astronomy and computer topics. Five items tapped interest and knowledge in each domain. For each item there were four ratings. A number from 1 to 4 was assigned to each rating, and the five ratings were added together to form a total score for each domain.

Decoding Measures

Subjects completed two decoding tasks: a word naming task and a pseudoword naming task. These two tasks are commonly used to assess decoding or word recognition skill (e.g., Chen & Vellutino, 1997; Cunningham, Stanovich & Wilson, 1990). Unlike previous research (but see Peterson, 1993), some of the words subjects were asked to read were domain-specific, i.e., they were astronomy or computer words drawn from the 4 reading and listening passages described above. In this way both general decoding or word recognition skill and domain-specific word recognition skill could be assessed. A total of three measures were constructed: domain-specific word naming, general word naming, and pseudoword naming.

Domain-specific word naming measure: A total of 56 words were selected for participants to read as quickly and accurately as they could. These 56 words were the same words used in the semantic decision task described above. Half the words were selected from the 4 listening and reading passages described above. These 28 words not only reflected the content of the passages but were also representative of the domains of astronomy and computers, e.g., words such as gravitation and gas from the astronomy domain, and words such as desktop and software from the computer domain. Twenty-eight additional control words were selected to match the domain words in terms of number of letters, number of syllables and word frequency. Thus, there were 4 groups of words: 14 astronomy words, 14 astronomy control words, 14 computer words, and 14 computer control words.

Words ranged from 5 to 12 letters in length, and from 1 to 4 syllables in length. Word frequency was calculated using The Educator's Word Frequency Guide (Zeno, Ivens, Millard, & Duvvuri, 1995). The word frequency of words ranged from 32.9 SFI[1] to 66.7 SFI. The average frequency of astronomy words and matched controls was 52.08 SFI. The average frequency of computer words and their matched controls was somewhat lower, at 44.78 SFI. Considered as a group, the words selected were comparable in frequency to low frequency words used in other studies (e.g., Haenggi & Perfetti, 1994; Bell & Perfetti, 1994). See Appendix D for a list of all words and their frequencies.

Words were presented on an IBM compatible computer with a 16" monitor. The computer program used to present the words was adapted from one used by Kennedy (1995) in her study of adult word recognition skill. A practice trial of 5 words was presented first. After the practice trial, the 56 words were presented one at a time in random order on a computer monitor. Words were presented in the middle of the screen. At the beginning of each trial, an X appeared on the monitor for 1 second to serve as a fixation point and get ready signal. Immediately after the X disappeared, a word appeared in the middle of the monitor. A

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[1]Standard Frequency Index (SFI) is a logarithmic transformation of a word's frequency per million words. A word with SFI 40.0 has a frequency per million 10 times higher than the frequency per million of a word with SFI 30. Words with SFI 30 have an approximate frequency of 1 per million.

font size of 18 was used for words.

Participants were told simply to read the words out loud as quickly and accurately as they could. They were not told that some of the words were from the domains of astronomy or computers. A voice key measured latency to begin naming the word after it appeared on the screen, and the examiner recorded the accuracy of the response. After recording the accuracy of the response, the examiner pushed the return key to begin the next trial.

General word naming measure: In addition to a domain-specific word naming measure, a measure of general word recognition skill was desired. A general word naming measure was constructed using data from the domain-specific word naming measure. Accuracy and latency data from the 14 astronomy and 14 computer control words were used as a measure of general word naming skill. Thus, the general word naming measure consisted of a total of 28 words. These 28 words were administered as part of the domain-specific word naming measure described above.

Pseudoword naming measure: Twenty pronounceable pseudowords from the list of pseudowords used by Bell & Perfetti (1994) were selected. Pseudowords ranged from 5 to 8 letters in length and from 1 to 3 syllables in length. Pseudowords were selected such that there were 5 one syllable 5 letter strings, 5 two syllable 5 letter strings, 5 two syllable 8 letter strings, and 5 three syllable 8 letter strings. Appendix E contains a list of the pseudowords used.

Pseudowords were presented on an IBM compatible computer, one at a time. A practice trial of 5 pseudowords was presented first. Then the 20 pseudowords were presented one at a time in random order on a 16" computer monitor. The computer program used to present the words was adapted from one used by Kennedy (1995) in her study of adult word recognition skill. Pseudowords were presented in the middle of the screen. At the beginning of each trial, an X appeared on the monitor for 1 second to serve as a fixation point and get ready signal. Immediately after the X disappeared, a pseudoword appeared in the middle of the monitor. A font size of 18 was used to present words.

Participants were told simply to read the pseudowords outloud as quickly and

accurately as they could. A voice key measured latency to begin naming the pseudoword after it appeared on the screen, and the examiner recorded the accuracy of the response. After recording the accuracy of the response, the examiner pushed the return key to begin the next trial.

General Design and Procedure

Participants completed the measures in two sessions. Time elapsing between sessions one and two ranged from 1 to 7 days. In the first session, subjects completed the student information questionnaire[2], the word naming, pseudoword naming, semantic decision task, Vocabulary subtest, and Nelson-Denny Reading test individually. The word naming, pseudoword naming, and semantic decision tasks were completed using a computer. All subjects completed these measures in the same order: student information questionnaire, word naming task, pseudoword naming task, semantic decision task, Vocabulary subtest, and Nelson-Denny Reading Test.

In the second session, subjects completed the measures either individually or in small groups ranging from 2 to 6 people in size. They completed the following measures in the following order: prior knowledge multiple choice tests, listening comprehension tasks, and reading comprehension tasks. The listening passages were read aloud by the author. The order of administration of astronomy and computer knowledge, listening and reading tasks was counterbalanced across subjects such that half completed the astronomy condition of each task first, i.e., astronomy prior knowledge test followed by computer prior knowledge test, and half completed the computer condition of each task first.

PRELIMINARY ANALYSES

Preliminary analyses were conducted using data from the subjects described in the General Method section. Analyses conducted include calculation of reliabilities of measures, comparison of measures, rationales for either including or deleting measures from subsequent

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[2]Fourteen subjects recruited from an undergraduate astronomy course completed the student information questionnaire as a way of indicating interest in participating in the study. Thus, they completed this form prior to the first session.

Chronbach's Alpha of Reading and Listening Comprehension Tests (10 items/test)

	Reading Test	Listening Test
A Bus Tour[a]	.69	.41
Object-Oriented Databases[a]	.60	.35
Birth of the Sun[b]	.57	.41
Light: Messenger of the Universe[c]	.69	.51

[a]N=36; [b]N=35; [c]N=37.

Table 2.7

analyses, and a description of the method used to construct composite measures where appropriate.

Comprehension Measures

Reliabilities of the Listening and Reading Comprehension Measures: Two reliabilities were calculated for each comprehension test: one for its use as a listening comprehension test, and one for its use as a reading comprehension test. Table 2.7 contains Chronbach's alpha's for each comprehension test when used as either a listening or reading comprehension test.

Mean Comprehension as a Function of Counterbalancing of Passages: Passages were counterbalanced across subjects such that each subject listened to one astronomy passage and one computer passage and read the other astronomy and computer passages. Table 2.8 contains the mean comprehension scores for subjects as a function of whether they listened to or read each passage. While listening comprehension was comparable across passages in the astronomy condition ($t(64)=-1.23, p = .22$), subjects' reading comprehension was significantly better for the *Light* passage than the *Sun* passage ($t(64) = -3.16, p = .002$). Comprehension was significantly better on the *Database* passage than on the *Bus* passage in both the listening ($t(64) = -3.45, p = .001$) and reading ($t(64) = -2.11, p = .04$) conditions.

Mean comprehension scores (s.d.) by passage and condition (listening vs reading)

	Reading	Listening
Astronomy Passages		
Sun[a]	5.00 (2.12)	5.73 (1.88)
Light[a]	6.58 (1.92)	6.36 (2.30)
Computer Passages		
Bus[b]	5.21 (2.46)	5.09 (2.12)
Databases[c]	6.34 (1.86)	6.71 (1.66)

[A] N=33; [b] N=32; [c] N=34

Table 2.8

Mean Difficulty and Interest Ratings as a Function of Counterbalancing of Passages: Several t-tests were conducted to determine whether the ratings assigned to a particular comprehension condition, i.e., listening or reading, varied as a function of which passage was used. Mean difficulty and interest ratings are summarized in Tables 2.9 and 2.10, respectively. The *Light* and *Sun* passages were rated as equally difficult in both the listening ($t(64) = -1.86, p = .07$) and reading comprehension conditions ($t(64)=1.01, p =.32$) as were the *Database* and *Bus* passages [listening comprehension ($t(64)=.75, p =.45$), reading comprehension ($t(64)=-.23, p =.82$)]. Moreover, *Light* and *Sun* passages were rated as equally interesting in both the listening comprehension ($t(64) = .62, p = .54$) and reading comprehension conditions ($t(64) = .88, p =.38$) as were *Database* and *Bus* passages [listening comprehension ($t(64) = .09, p = .93$), reading comprehension conditions ($t(64) = -.08, p = .94$)].

Comparison of Astronomy and Computer Conditions: A 2x2 repeated measures design was used to compare the comprehension measures across the domains of astronomy and

Mean difficulty ratings (s.d.) by passage and condition (listening vs reading)

	Reading	Listening
Astronomy Passages		
Sun[a]	2.27 (.84)	2.15 (.76)
Light[a]	2.06 (.86)	2.52 (.83)
Computer Passages		
Bus[b]	3.15 (.78)	3.19 (.74)
Databases[c]	3.19 (.64)	3.06 (.65)

A N=33; [b] N=32; [c] N=34

Table 2.9

Mean interest rating(s.d.) by passage and condition (listening vs reading)

	Reading	Listening
Astronomy Passages		
Sun[a]	2.91 (.88)	2.85 (.80)
Light[a]	2.73 (.80)	2.52 (.83)
Computer Passages		
Bus[b]	1.76 (.92)	1.78 (.83)
Databases[c]	1.78 (.83)	1.76 (.70)

[a] N=33; [b] N=32; [c] N=34

Table 2.10

computer (topic) and between the listening and reading versions of each comprehension task (modality). Comprehension of the passages as measured using the 10 item comprehension tests was equivalent across topic ($F(1,65) = .17, p = .68$) and modality ($F(1,65) = 1.46, p = .23$), and there was no interaction of topic x modality ($F(1,65) = .13, p = .72$). Table 2.11 contains a summary of comprehension scores.

Table 2.12 contains a summary of difficulty ratings of astronomy and computer passages in both listening and reading conditions. A 2x2 repeated measures ANOVA was conducted with topic (astronomy vs computer) and modality (reading vs listening) as within-subjects measures. The main effect of topic was significant ($F(1,65) = 105.70, p < .001$). As Table 2.12 illustrates, subjects rated the computer passages as more difficult than the astronomy passages. The effect of modality was insignificant ($F(1,65) = .91, p = .34$). The interaction of topic and modality was significant ($F(1,65) = 4.33, p = .04$). As Table 2.12 illustrates, while subjects rated the computer passages as equally difficult, they rated the astronomy listening more difficult than the reading.

A 2x2 repeated measures ANOVA was conducted on the interest ratings of passages with topic (astronomy vs computer) and modality (reading vs listening) as within-subjects measures. The main effect of topic was significant ($F(1,65) = 97.85, p < .001$). As Table 2.13

Mean comprehension scores (s.d.) by knowledge domain and modality (N=66)

	Reading	Listening
Astronomy	5.79 (2.16)	6.05 (2.11)
Computer	5.76 (2.25)	5.92 (2.05)

Table 2.11

Mean difficulty ratings (s.d.) by knowledge domain and modality (N=66)

	Reading	Listening
Astronomy	2.17 (.85)	2.33 (.81)
Computer *	3.17 (.71)	3.12 (.69)

*Computer passages rated significantly more difficult than astronomy passages.

Table 2.12

illustrates subjects found the astronomy passages to be more interesting than the computer passages. The remaining effects of modality ($F(1,65) = .01, p = .92$) and the interaction of topic x modality were not significant ($F(1,65) = .12, p = .74$).

A t-test comparison of reading rate, as measured in words read per minute, revealed that subjects read the astronomy passages ($x = 223.12$, s.d. = 53.15) significantly faster than the computer passages ($x = 193$, s.d. = 40.75; $t(65) = 6.32, p < .001$).

Summary: Comprehension of the astronomy and computer passages was equivalent. On all but one measure, subjects rated listening and reading passages as equally difficult and interesting. In other words, differences in the way passages were experienced (i.e., listened to or read) appeared to have little effect on how difficult or interesting they were perceived to be. However, subjects found the computer passages more difficult and less interesting than the astronomy passages. In the reading condition, subjects read the astronomy passages significantly more quickly than the computer passages. The difficulty and reading rate results suggest that subjects found the astronomy passages easier to comprehend than the computer passages.

The difference in perception of difficulty is interesting in light of the analysis of the four passages summarized in Table 2.6. As Table 2.6 illustrates, the four passages were of comparable readability. If anything, the analysis of passages suggests that the astronomy

Mean interest ratings (s.d.) by knowledge domain and modality (N=66)

	Reading	Listening
Astronomy	2.82 (.84)	2.79 (.79)
Computer*	1.77 (.87)	1.77 (.76)

*Computer passages rated significantly less interesting than astronomy passages.

Table 2.13

passages might have been more difficult because they contained much longer sentences than the computer passages (an average of 24.9-28.6 words per sentence in the astronomy passages compared to an average of 15-17.3 words per sentence in the computer passages). However, the astronomy passages were perceived to be less difficult and more interesting. Since the astronomy and computer passages were not equivalent in perceived difficulty and interest, nor in the rate at which they were read, interpretations of subsequent analyses may need to take these differences into account.

General Language Comprehension Measures

Two measures of general language comprehension were taken: a listening comprehension measure and a vocabulary measure. Means and Pearson Product Moment correlation coefficients of the listening comprehension and vocabulary measures are summarized in Table 2.14. In many studies (e.g., Bell & Perfetti, 1993; Cunningham, Stanovich, &, 1990; Gough & Tunmer, 1990; Peterson, 1993) listening comprehension measures similar to those used here have been employed to reflect general language comprehension. However, as Table 2.7 illustrates, the reliabilities of the listening comprehension measures used for this research were quite low.[3] Many subsequent analyses

[3]Peterson (1994) used a 12 item comprehension test to measure listening comprehension. Ten of those items were identical to the *Bus* listening comprehension condition used in the present research. Peterson reported a Chronbach alpha of .53 for her measure based on 127 subjects.

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was not used in any subsequent analyses. Data from 68 of the 72 subjects described in the General Method section were available. Three items from the astronomy condition (light, galaxy, and light-years) and three items from the computer condition (circuit, programming, software) had 0 variance because everyone responded to them correctly. As a result only 11 items were used to calculate the reliabilities of the astronomy and computer conditions. Reliabilities were .33 for the astronomy condition and .37 for the computer condition. It is likely that the small number of items used, i.e., 11 words from each condition, were factors in the relatively low reliabilities obtained.

Reliabilities (Chronbach's alpha) were .86 for ratings of astronomy interest and knowledge and .85 for ratings of computer interest and knowledge. Seventy-one subjects contributed data for the calculation of reliabilities of this self-report measure.

Comparison of Domain-specific Knowledge Measures: Tables 2.15 and 2.16 contain summaries of the means and intercorrelations among these measures in the astronomy and computer knowledge domains, respectively. Three of the domain-specific measures had consistently moderate correlations with one another across both knowledge domains: prior knowledge multiple choice test, number of courses taken in the domain, and self-report ratings of interest and knowledge in the domain.

The two measures from the semantic decision task did not have consistent correlations with the other domain-specific knowledge measures. The latency measure from the semantic decision task did not correlate significantly with four of the five astronomy domain-specific knowledge measures (see Table 2.15), and was significantly correlated with only two of the four measures in the computer domain (see Table 2.16). Semantic decision accuracy was significantly correlated with all but the semantic decision latency measure in the computer domain, but was significantly correlated with only the prior knowledge multiple choice test, and number of courses taken in the astronomy domain.

It was expected that each measure would tap a different aspect of domain-specific knowledge, and thus moderate as opposed to high correlations between the different measures were expected. The three variables of prior knowledge multiple choice test, number of

Intercorrelations, means and standard deviations of domain-specific knowledge measures in the Astronomy condition

	Prior Knowledge Test	Semantic Decision Accuracy	Semantic Decision Latency	Courses Taken	Ratings of knowledge and interest
Prior Knowledge Test		.37*	-.30*	.67*	.56*
Semantic Decision Accuracy			.00	.40*	.16
Semantic Decision Latency				-.11	-.13
Courses Taken					.49*
Means (s.d.)	14.61 (5.66)	12.76 (1.22)	614 (98)	.62 (1.02)	8.79 (3.04)

*$p < .05$

Table 2.15

university courses taken, and self-ratings of interest and knowledge met this expectation. In addition, adequate reliability was an important factor since it would affect the power and reliability of analyses involving these measures. As outlined above, the prior knowledge measures and self-rating measure had reliabilities over .80 in both the astronomy and computer conditions. Reliability could not be calculated for the number of courses taken since it was a 1 item measure.

The semantic decision task was a new experimental measure developed for this study to assess the domain-specific knowledge covered by the astronomy and computer passages. Unfortunately, semantic decision latency was poorly correlated with other domain-specific measures, suggesting that domain-specific knowledge was not an important factor in performance on this measure. As a result, semantic decision latency was not used in subsequent analyses. The semantic decision accuracy measure had poor reliability (.33 in the astronomy condition and .37 in the computer condition). Some of the items were too easy, and

reliability would probably have improved with the use of more than 14 items per condition. However, it was felt that the measure assessed important aspects of domain-specific knowledge, and, for the most part, the semantic decision accuracy measure had moderate correlations with other domain-specific measures. As a result, it was retained as a measure of domain-specific knowledge.

Construction of a Composite Measure of Domain-specific Knowledge: When a domain-specific knowledge variable was used in subsequent analyses, a composite score was constructed using the prior knowledge multiple choice test, number of courses taken, self-report ratings of interest and knowledge in the domain, and accuracy on the semantic decision task. These four measures were used to construct separate composite scores in both domains. Raw scores for each of the four measures were standardized and the standardized scores were added together to form a composite score. The reliabilities of the 4 measure composites were .88 in the astronomy domain and .89 in the computer domain.

Intercorrelations, means and standard deviations of domain-specific knowledge measures in the Computer condition

	Prior Knowledge Test	Semantic Decision Accuracy	Semantic Decision Latency	Courses Taken	Ratings of knowledge and interest
Prior Knowledge Test		.50*	-.40*	.47*	.66*
Semantic Decision Accuracy			-.01	.44*	.39*
Semantic Decision Latency				-.18	-.38*
Courses Taken					.45*
Means (s.d.)	17.89 (4.85)	10.85 (1.46)	610 (97)	2.48 (3.46)	9.08 (3.05)

* $p < .05$

Table 2.16

Decoding Measures

Subjects were asked to name 28 words (general word naming task) and 20 pseudowords (pseudoword naming task) quickly and accurately. A trimming procedure was applied to response times on the general word naming and pseudoword naming tasks. Correct responses for each participant were screened for outliers, and extreme outliers were trimmed, i.e., eliminated, using a trimming procedure described by Van Selst and Jolicoeur (1994). A computer program, developed by P. Jolicoeur and M. Ingleton, was used to perform the trimming procedure. For each subject's set of response times, a recursive trimming procedure was applied. First, the most extreme observation of the subject was temporarily excluded, and a mean and standard deviation were calculated based on the remaining response times. An algorithm was then applied to establish cutoff values. The algorithm used to determine high and low cutoff values was:

$$V_{low} = X - C * s.d. \qquad V_{high} = X - C * s.d.$$

where V_{low} and V_{high} are the high and low cutoff values, X is the mean response time for a given subject, C is the criterion value, and $s.d.$ the standard deviation. Following Van Selst and Jolicoeur (1994), the value of C, the criterion value, varied as a function of the number of correct responses obtained by a given subject, such that the obtained cutoff scores were not biased because of differences in the number of correct responses obtained across subjects. The smallest and largest observations for a given subject were compared against the cutoff values, V_{low} and V_{high}. If one or both were outside the bounds, then they were defined as outliers and excluded from further consideration. If an outlier was found, then the algorithm was applied anew to the remaining data set for a given participant. [See Van Selst & Jolicoeur (1994) for further details regarding the use of a trimming procedure to eliminate bias introduced when small numbers of response times are used, and when the number of obtained response times varies from subject to subject.] Using this trimming procedure, 2.11% of the general word naming response times were eliminated, and 1.83% of the pseudoword response times were

eliminated.

Measures of accuracy and response times for correctly pronounced words or psuedowords were taken. Means and Pearson Product Moment correlation coefficients among these decoding measures are summarized in Table 2.17. The highest correlation (r=.69) was between word and pseudoword response times. Word and pseudoword naming errors were not significantly correlated with each other. In addition, word and pseudoword naming errors were not consistently correlated with response time (see Table 2.17).

Construction of a Composite Measure of Decoding Skill: When a measure of decoding skill was required in subsequent analyses, a composite score was constructed in which the general word and pseudoword response times were combined. General word response times were standardized and added to standardized pseudoword response times to form a composite score. Given the lower correlations between the accuracy and latency measures, it was felt that the accuracy measures would add little to a composite score.

Intercorrelations, means and standard deviations of decoding measures

	Word Response Times	Pseudoword Response Times	Word Naming Errors	Pseudoword Naming Errors
Word Response Times		.69*	.24	.27*
Pseudoword Response Times			.25*	.18
Word Naming Errors				.08
Means (standard deviations)	561 (86)	708 (156)	1.50 (1.19)	3.68 (2.25)

*P < .05

Table 2.17

CHAPTER THREE

Effect of Domain-Specific Knowledge on Lexical-Level Processing

According to recent models of reading comprehension, particularly the ones reviewed in the introductory chapter, word recognition is a modular, impenetrable, and automatic process for fluent readers (Kintsch, 1988; Mross & Kintsch, 1985; Perfetti, 1989). It involves the application of data-driven orthographic and/or phonological processes. Other levels and types of processing - including semantic processes - have no impact on lexical processing (Gough, Hoover, & Peterson, 1996; Kintsch, 1988; Mross & Kintsch, 1986; Perfetti, 1989). As such, orthographic and phonological processes are the important factors in efficient word recognition. For the Simple View of reading and Verbal Efficiency Theory, decoding and/or lexical access, i.e., the orthographic and phonological processing involved in word recognition, comprise a fundamental component of general reading ability. Faster, more efficient decoding leads to better comprehension. The efficiency of on-line textual processing is a function of the basic verbal processes involved in word recognition.

The independence of decoding or word recognition skill from higher-level conceptual processing is an important feature of all the models reviewed in the introductory chapter (e.g., Mross & Kintsch, 1986; Perfetti, 1989). Higher-level conceptual processes such as semantic processing and domain-specific knowledge affect discourse-level processing, not lexical-level processing. For instance, retrieval of semantic information is argued to occur automatically as a result of orthographic and/or phonological processing (Mross & Kintsch, 1986). Semantic processing is initiated by lexical access; as such it is a post-lexical process.

Kintsch (Kintsch, 1988; Mross & Kintsch, 1985) has described two types of semantic processing, both of which occur post-lexically. The first type, sense activation, occurs automatically as the output of lexical access, i.e., the results of orthographic and phonological processing. Here, all the senses of a word are activated when the word has been identified. Thus, for the word *bug*, both the sense of *bug* as an insect and the sense of *bug* as a secret listening device would be activated. The second type of semantic processing, sense selection,

involves selecting the sense of the word that is appropriate to the context. Thus, in a sentence or passage on insects, while both the senses of *bug* would be initially activated, the sense of *bug* as an insect would continue to be activated because it is reinforced by the context, while the sense of *bug* as a listening device would become inhibited or deactivated.

Given Kintsch's account of semantic processing, there is no role for semantic processing in such word recognition tasks as reading aloud a list of individually presented words. Indeed, in some lexical decision and word naming tasks, responses may be made with very little to no semantic processing occurring (Jared & Seidenberg, 1991; Joordens & Becker, 1997). By extension, domain-specific knowledge should have no effect on similar word recognition tasks. Consequently, word naming accuracy and speed should measure only decoding skills, i.e., orthographic and phonological processing.

However, there is some debate as to whether semantic level processing occurs only post-lexically. While some theorists maintain that semantic effects on word recognition are strictly post-lexical (e.g., Forster, 1979; Norris, 1986), others have argued that semantic processing can affect lexical access, i.e., have a pre-lexical effect (e.g., C. Becker, 1985; Neely, 1991). Many studies have demonstrated semantic priming effects in lexical decision and word naming tasks (see Neely, 1991, for a review) as well as within sentence contexts (e.g., Stanovich & West, 1983).

In a typical single-word semantic priming experiment (Neely, 1991), a semantic context is provided by presenting a single word which serves as a prime. The prime is followed by a target word to which subjects respond. Subject responses typically consist of either naming the target word or making a lexical decision about the target word. Target words are either related or unrelated to the prime word. Semantic priming is determined by comparing the amount of time it takes a subject to name (or make a lexical decision to) a target word that is related to the prime versus a target word that is unrelated to the prime. Although beyond the scope of this paper to discuss in detail, a complex pattern of facilitation and inhibition has been obtained in semantic priming studies, a pattern which depends on a variety of factors including word frequency, stimulus quality, and the proportion of nonwords used. In general, faster

response times have been found for target words when the preceeding word is associatively related to it (e.g., *bread* and *butter*) compared to situations where the two words are unrelated or where the target word is preceeded by a neutral prime, e.g., XXX. Thus, the context provided by the priming word has been shown to facilitate recognition of an associatively related word.

No one mechanism has been advanced which can account for the variety of data generated by semantic priming studies (Neely, 1991). However, for pronunciation or word naming tasks, spreading activation can account for many of the findings reported (Neely, 1991).[1] The spreading activation account incorporates a model of knowledge representation in which conceptual knowledge, i.e., the knowledge of word meanings, is represented as a semantic network (Collins and Loftus, 1975). Each concept or word is represented by a node in the network, and conceptual nodes are connected to each other into a network of interrelated or associated concepts.[2] In spreading activation, a word or lexical node which is recognized becomes activated. Activation spreads from this word to close associates in the semantic network, thus lowering the threshold of activation for those associates. If the next word presented is one of those associates, it will be recognized more quickly than usual because its threshold of activation will have been lowered.

However, any facilitation effect has been found to be short-lived and restricted in scope. If one or more items separate the prime from its target, the facilitation effect disappears (but see Joordens & Becker, 1997). Some types of semantic associates, e.g., category name as

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1Although Neely (1991) and Norris (1986) review a number of mechanisms which might account for semantic priming effects, many of them are proposed to handle complicated findings arising from a lexical decision paradigm. Since the focus of this paper is on the use of word naming as a measure of word recognition skill, spreading activation seems sufficient as an explanatory starting point. However, this is not meant to rule out the possibility that other mechanisms may also provide credible accounts of semantic priming in word recognition.

2This discussion is neutral with respect to whether a distributed or unitary representation of concepts or word meanings is appropriate. Either type of semantic representation could be incorporated into this discussion. For simplicity only, it is assumed that each node is associated with one concept or word meaning.

prime and low-dominance exemplar as target - *bird* - *goose* - do not exihibit facilitation in word naming studies, and word-pairs need to be very close associates in order for priming effects to be reliably found. Thus, even when semantic processes affect word recognition, the degree to which they do so may be limited.

Although limited in scope, then, semantic level information can influence word recognition via spreading activation. Domain-specific knowledge may influence word recognition in much the same way. Differences in domain-specific knowledge may be reflected in individual differences in the breadth and arrangement of semantic networks as well as in variations in the strength of associations between semantic nodes in the networks. Through the process of spreading activation over a more extensive domain-specific network, high knowledge people could have an advantage over low knowledge people when it comes to recognizing and naming domain-specific words.

If domain-specific knowledge were shown to have an effect on word recognition performance, it would have two implications for current theories of reading and/or text comprehension. Firstly, it would demonstrate that the effects of domain-specific knowledge extend down to the lexical level of processing, i.e., that domain-specific knowledge effects are not restricted to discourse-level processes. Secondly, it would suggest that domain-specific knowledge has an effect on the on-line processing of text.

The following study was conducted to explore whether or not domain-specific knowledge could affect word recognition. Subjects were asked to read aloud a list of words, some of which were drawn from the knowledge domains of astronomy and computers. Accuracy and word naming times for domain-specific words were compared to accuracy and word naming times on control words that were matched to the domain-specific words in terms of letter length, syllable length and word frequency. Thus, the control words - words that were not semantically related to each other or to the domain-specific words - served as a measure of general decoding or word recognition skill. If domain-specific knowledge has an influence on the accuracy and word naming times of domain-specific words, then the accuracy and word naming times of domain-specific words should be faster for high knowledge subjects vs.

low knowledge subjects after the effects of decoding or word recognition skill have been partialled out.

METHOD

Subjects

Data from the 66 undergraduate students described in the General Method section were used.

Measures and Procedure

Two measures were used: 1) the domain-specific word naming task, and 2) a composite measure of domain-specific knowledge (see page 55 for a description of the construction of this composite measure.) Descriptions of these measures and the procedures used to administer these measures are described in detail in the General Method section of Chapter Two.

RESULTS

For the domain-specific word naming measure, each subject read aloud a total of 56 words presented in random order: 14 astronomy words, 14 astronomy control words, 14 computer words, and 14 computer control words. The same 56 words appeared in the semantic decision task where subjects had to decide whether a word belonged to the semantic category of astronomy in the astronomy condition or computers in the computer condition. Thus, the semantic decision task provided information about which words subjects knew belonged to either astronomy or computer domains. Only the words that subjects correctly identified as belonging to the astronomy or computer domains in the semantic decision task were used as data in the word naming analyses. Correspondingly, only the control words that matched each subject's correctly identified domain-specific words were used as data in the word naming analyses. In other words, the word naming data included only *known* domain-specific words and their matched controls.

Preliminary Analyses

Preliminary analyses were conducted to provide descriptive information regarding the word types used. Descriptive analyses provided information regarding the domain-specific and control words along dimensions of word frequency, letter length, and syllable length.

Mean error rates and response times were calculated for each of the word types and comparisons between domain-specific and control words were made.

Analysis of Factors Affecting Response Times: Effects of word frequency, word length, and number of syllables have been demonstrated for word naming times. Higher word frequency is associated with faster word naming times (Seidenberg, 1985), while longer word length and numbers of syllables are associated with slower word naming times (Bell & Perfetti, 1994). However, these factors were not used as the basis for selecting domain-specific words. Domain-specific words were allowed to vary unsystematically with respect to word

Intercorrelations of word types with word frequency, word length, and syllable length.

	1.	2.	3.	4.	5.	6.	7.	8.	9.
1. Astronomy word naming times									
2. Astronomy control word naming times	.62								
3. Frequency of astronomy words	-.71	-.79							
4. Word length of astronomy words	.62	.64	.02						
5. Syllable length of astronomy words	.54	.65	-.48	.23					
6. Computer word naming times	.08	.34	-.33	.49	.37				
7. Computer control word naming times	.29	.32	-.57	.02	.24	.36			
8. Frequency of computer words	-.69	-.79	.98	-.60	-.48	-.27	-.58		
9. Word length of computer words	.06	-.17	-.10	-.22	-.68	.23	.43	-.01	
10. Syllable length of computer words	-.17	-.46	.16	-.43	-.12	.25	.30	.23	.86

Note: $r > .53$ are significant at $p < .05$

Table 3.1

frequency, word length and number of syllables. Nevertheless, because domain-specific words and their controls were matched in terms of word frequency, word length, and syllable length, it was expected that word naming times would be associated with these variables.

Table 3.1 summarizes the intercorrelations between word naming response times, word frequency, word length, and syllable length for all four types of words. Astronomy word naming times were significantly correlated with astronomy control word naming times, word frequency, word length, and syllable length. A similar pattern was obtained for the astronomy control word naming times. In both cases, higher word frequency was associated with faster word naming times, while longer word and syllable lengths were associated with slower word naming times. Thus, the expected relationships between word naming times and word variables was obtained for astronomy words and their matched controls.

Table 3.1 also contains the intercorrelations for computer words and their matched controls. Word naming times between computer words and their matched controls were not significantly correlated. Computer word naming times were not significantly correlated with any of word frequency, word length or syllable length. Computer control words were only significantly correlated with word frequency. As word frequency increased, word naming times became faster. Thus, the expected relationships between word naming times and word variables such as word frequency, word length, and number of syllables was not obtained for computer words and their matched controls.

Word Naming Accuracy: Error rates for each of the four conditions were analyzed by subject. Only error rates for known domain-specific words (see page 43) and their controls were analyzed. Table 3.2 contains the mean number of errors for each word type. In general, error rates were very low, ranging from 0 to 1 errors per subject for astronomy words and from 0 to 3 errors for computer control words. However, error rates for astronomy words were significantly lower than for astronomy control words ($t(65)=-4.80, p<.001$). Likewise, error rates for computer words were significantly lower than for computer control words ($t(65)=-3.99, p<.001$).

Mean error rates, standard deviations and ranges by word type

Word type	Mean	Stan. Dev.	Range	
			Min.	Max.
Astronomy words	.09	.29	0	1
Astronomy control words	.62	.82	0	3
Computer words	.30	.53	0	2
Computer control words	.70	.72	0	3

Table 3.2

Word Naming Response Times: Only word naming times for correctly named words were analyzed. Word naming times for known domain-specific words and their matched controls were analyzed by subject and by item. In analyses by item, there were no significant differences in the mean word naming times of known astronomy and astronomy control words ($t(13) = -1.20, p = .25$) or known computer and computer control words ($t(13) = -1.88, p = .08$). However, when analyzed by subject, known astronomy words were named significantly more quickly than astronomy control words ($t(65)=-4.09, p <.001$). Known computer words were named significantly more quickly than computer control words ($t(65)=-6.10, p <.001$). Table 3.3 contains a summary of mean word naming times for each of the astronomy, astronomy control, computer, and computer control words analyzed by subject.

Summary of Preliminary Analyses: Analyses of response times revealed that they were related to word frequency for astronomy words, astronomy control words, and computer control words. Faster response times were associated with higher frequency words. As letter length and number of syllables increased, response times for astronomy words and their controls became longer. There was no significant correlation between increases in letter length or number of syllables for computer words or their controls.

In both the astronomy and computer conditions, error rates were significantly lower for domain-specific words than control words. Similarily, response times were significantly faster

Mean word naming times for known words with standard deviations analyzed by subject

Word type	Mean	Stan. Dev.
Astronomy words	529	79
Astronomy control words	550	89
Computer words	539	82
Computer control words	580	104

Table3.3

for domain-specific words than control words. While these results suggest a general priming effect for domain-specific words, they do not address the issue of whether or not differences in domain-specific knowledge may affect error rates or response times. Regression analyses, using the model testing procedure described below, were conducted to examine the role of domain-specific knowledge in the lexical processing of astronomy and computer words.

Model Testing Procedure

Regression analyses were conducted because all the variables used were continuous. Separate analyses were conducted for accuracy and response time data. The same regression model was used as a test for both accuracy and response times. The regression model to be tested was

$$dw = cw + dk + (cw \times dk)^3$$

where *dw* represents the accuracy or word naming times for known domain-specific words, *cw* represents the accuracy or word naming times for matched control words, and *dk* is domain knowledge. In this model, control words and domain knowledge were used as predictors of known domain-specific word accuracy or response times. Since domain-specific words and

[3]For the sake of simplicity, coefficients of each independent variable as well as the constant have been omitted from this equation and all subsequent equations. When reading these equations, please assume the inclusion of the constant and coefficients, i.e., $dw = b_1cw + b_2dk + b_3(cw \times dk) + c$, where b_x represents the coefficient terms, and c represents the constant.

control words were matched for letter and syllable length and word frequency, the control word variable represents general decoding (or word recognition) accuracy and response times. Domain-specific knowledge was entered after the control word variable in order to partial out variance associated with word recognition skill. The linear equation above can be interpreted in the same way as an ANOVA model: *cw* and *dk* represent the 'main effects' of word recognition and domain-specific knowledge respectively, and *(cw x dk)* represents the interaction of word recognition skill and domain-specific knowledge (Aiken & West, 1991). Following Aiken and West (1991), word naming times and error rates for the control words were standardized. The composite measure for domain-specific knowledge was expressed as a standard score. Separate regression analyses were conducted for the astronomy and computer conditions.

Regression Analyses for Word Naming Accuracy

Table 3.4 summarizes results of regression analyses in the astronomy condition. Error rates for astronomy control words were entered first and accounted for a very small, insignificant proportion of variance. Astronomy knowledge, entered next, was a significant predictor of astronomy word error rates. Higher domain-specific knowledge was associated with lower error rates. The interaction of control word error rates and astronomy knowledge was insignificant, indicating that the effect of astronomy knowledge on error rates was constant across levels of word recognition skill, i.e., at any given level of word recognition skill, increases in astronomy knowledge were associated with lower error rates of the same magnitude.

Table 3.4 also summarizes the results of regression analyses in the computer condition. As documented in Table 3.4, no effects were significant.

Regression Analyses for Word Naming Response Times

Table 3.5 summarizes results of regression analyses in the astronomy condition. Astronomy control words accounted for 79% of the variance in astronomy word naming times ($F(1,64) = 238.15$, $p < .0001$), reflecting the fact that general word recognition skill was a significant contributor to astronomy word naming times. Astronomy knowledge, when added

Regression analyses: Predicting word naming errors

	R^2	R^2 Change	F	Significance of F
Astronomy Condition				
1. Control word naming errors	.01		.81	.37
2. Astronomy knowledge	.08	.07	4.28	.04
3. Control word errors x astronomy knowledge	.09	.01	1.70	.18
Computer Condition				
1. Control word naming errors	.04		2.81	.10
2. Computer knowledge	.04	.00	.06	.81
3. Control word errors x computer knowledge	.06	.02	.89	.38

Table 3.4

after the control words, was also a significant predictor of astronomy word naming times ($F(2,63) = 12.62, p = .0007$). Increases in domain-specific knowledge were associated with faster word naming times. The interaction of word recognition skill and astronomy knowledge was not significant, indicating that the effect of astronomy knowledge on astronomy word naming times was constant across levels of word recognition skill, i.e., at any given level of word recognition skill, increases in astronomy knowledge were associated with faster word naming times.

Table 3.5 also summarizes results of regression analyses in the computer condition. Computer control words accounted for 73% of the variance in computer word naming times ($F(1,64) = 176.90, p < .0001$). Neither computer knowledge nor the interaction term added

Regression analyses: Predicting word naming times

	R^2	R^2 Change	F	Significance of F
Astronomy Condition				
1. Control word naming times	.79		238.15	<.01
2. Astronomy knowledge	.82	.03	12.60	<.01
3. Control word errors x astronomy knowledge	.82	.00	.11	.91
Computer Condition				
1. Control word naming errors	.73		176.90	<.01
2. Computer knowledge	.74	.01	1.93	.17
3. Control word errors x computer knowledge	.74	.00	.19	.85

Table 3.5

significant unique variance to computer word naming. Thus, in the computer condition, only word recognition skill was significantly associated with computer word naming times.

DISCUSSION

Domain-specific knowledge affected both the error rates and word naming times in the astronomy condition. High knowledge subjects made fewer word recognition errors on astronomy words than low knowledge subjects after the effect of general word naming accuracy was controlled. Similarily, high knowledge subjects named astronomy words faster than low knowledge subjects after the effect of general word naming speed was controlled. The effect in both cases was facilitative: increases in domain-specific knowledge were associated with lower error rates and faster word naming times. This facilitative effect is compatible with

a spreading activation account of the way in which knowledge is represented in memory, i.e., as a semantic network with some associations more strongly associated than others. When subjects encountered the astronomy words, activation may have spread through their 'astronomy domain network.' Subjects with high astronomy knowledge may have a more elaborate and strongly interrelated semantic network of astronomy concepts, and thus associated words would have been recognized accurately and more quickly. Alternatively, subjects may have established an expectancy for astronomy words and thus preferentially activated their 'astronomy domain network.' Again, subjects with high astronomy knowledge may have a more strongly interrelated semantic network of astronomy concepts, and thus recognized domain-specific words more accurately and quickly.

The facilitative effect of domain-specific knowledge that was demonstrated in the astronomy condition should not be confused with a semantic priming effect. In order to demonstrate a priming effect, domain-specific words would have to be named faster or more accurately when preceeded by a semantic prime, i.e., another domain-specific word, than when preceeded by a non-associative or neutral prime. The fact that the mean error rates were lower for astronomy words compared to their controls, and that naming times were significantly lower for astronomy words than their controls, suggests a semantic priming effect. However, such a semantic priming effect applies to all readers and does not differentiate high from low knowledge readers. Although the semantic knowledge networks of all readers may contain a network of astronomy associations, the associative networks of high knowledge readers may be quantitatively and/or qualitatively different from the networks of low knowledge readers. A difference in the strength and/or pattern of connections among astronomy words may help to explain why domain-specific knowledge was a significant predictor of word naming accuracy and naming times.

In contrast to the astronomy condition, domain-specific knowledge had no effect on the accuracy or word naming times of computer words. However, many computer words are borrowed from other domains and it may be that the ones used for this study, e.g., *bus, architecture, hardware, etc.*, did not clearly differentiate the computer domain from other

knowledge domains. Unlike the astronomy condition, where many of the words were clearly and historically associated with astronomy, e.g., *solar, light-years, parallax, etc.*, the computer words may not have been associated with the 'computer domain network' to the same extent because other non-computer related meanings could have been more strongly associated with those words even among high knowledge subjects.

While an effect of domain-specific knowledge did not extend across both domains, the results suggest that, under some conditions at least, domain-specific knowledge can have an impact on the speed and efficiency with which domain-specific words are recognized. Thus, domain-specific knowledge can have an effect on lexical processing. Domain-specific knowledge may have a facilitative effect on word recognition in situations where a domain of knowledge is repetitively and consistently activated in semantic memory. Such a situation would not be expected to occur when a reader reads aloud a list of semantically unrelated words, but rather to occur when a reader is reading a passage on a particular topic. In the latter case, words associated with the knowledge domain would be repetitively activated, and in the process, activation could spread to other words associated with that domain of knowledge, lowering their threshold for activation.

Thus, these results suggest that domain-specific knowledge may have a facilitative effect on the on-line processing of text, i.e., by affecting the word recognition of domain-specific words. Although the facilitative effect of domain-specific knowledge on word recognition occurred within the context of reading aloud a list of words, and not within the context of reading a passage on a given topic, all the domain-specific words were taken from passages on the topics of astronomy or computers. Consequently, the co-occurance of domain-specific words was the same in the word naming task as it was in the reading and listening passages.

Although a facilitative effect of domain-specific knowledge on word recognition is not explicitly predicted by proponents of the Construction-Integration model of reading comprehension, it can be seen to be consistent with that model. Recall that according to the construction-integration model of reading comprehension a reader constructs a mental

representation of a text, a text base, in order to comprehend it (Kintsch, 1988). The reader uses her knowledge base - an associative network of knowledge - to construct the text base which is also an associative net. When a reader constructs a representation for a proposition, she applies information from her knowledge network to the text base. Initially, this information consists not only of concepts directly derived from the text, but also associated concepts and information taken from the reader's long term store of knowledge. Construction processes are closely followed by various levels of integration. In the integration phase, information that is irrelevant is dropped and relevant associations are strengthened and stablized. The construction-integration process occurs in processing cycles which occur very quickly, within milliseconds. In other words, the construction-integration process occurs on-line, with levels of integration occuring within and at the end of each processing cycle.

This conceptual framework can be applied to the process of word recognition or lexical access. Within a given processing cycle, a word is identified and a number of word senses are activated. A rich network of concepts and propositions is constructed. However, only those senses which are consistent with the context or topic of the passages will be retained, strengthened, and elaborated on. The process of sense selection represents the integration phase of semantic encoding, where appropriate senses are retained and strengthened and thematically inappropriate senses are dropped. Readers with high levels of domain-specific knowledge can draw on a richly elaborated and interrelated store of domain knowledge from their long term memory in order to form a text base. For instance, they may retrieve more information which is redundant with the text than readers with less domain-specific knowledge. Thus, their superior knowledge may enable them to construct and integrate information from the text more quickly and efficiently than readers with low levels of relevant domain-specific knowledge. This effect may be seen not only in their comprehension of a passage, but also in their on-line processing of individual words, phrases and sentences. The present results from the astronomy domain suggest that this is indeed a possibility.

Verbal Efficiency and the Construction-Integration models of reading comprehension explicitly state that word retrieval or lexical access occurs in an automatic 'bottom-up' way,

and that semantic access in particular is post-lexical in that it occurs *as a result* of the orthographic and phonological processes involved in word recognition. While there may be instances when semantic processing is not involved in word recognition (e.g., in some lexical decision tasks), there may be instances where semantic encoding is included in word recognition. For example, it is very likely that readers reading a text are processing words for meaning, and in these instances, just as in the case of the astronomy condition reported here, semantic access is an integral feature of word recognition, particularly for fluent adult readers. Thus, it may be artificial to separate orthographic and phonological aspects of lexical processing from semantic aspects of lexical processing in most ecologically valid instances of lexical processing. Results from the astronomy condition of the present study are consistent with a cascaded model of word recognition, one in which information from higher level processors can interact with information from lower level orthographic or phonological processors (Coltheart, Curtis, Atkins, & Haller, 1993). When semantic access is an integral feature of lexical access, domain-specific knowledge may play a facilitative role. Such a facilitative effect may influence the speed and efficiency with which text is processed, and thus, have an effect on the on-line processing of text.

CHAPTER FOUR

Role of Domain-Specific Knowledge in Reading Rate

PART ONE

Does domain-specific knowledge predict reading rate?

Although there has been ample demonstration of the role of domain-specific knowledge in reading comprehension performance, little research has explored the role it might play in reading rate. Does domain-specific knowledge affect reading rate to the same degree as it affects reading comprehension performance? If domain-specific knowledge is a factor in reading rate, then domain-specific knowledge would be implicated in the on-line processing of text. In this way, domain-specific knowledge could be considered an integral component of the reading process for fluent adult readers.

Although very few studies have explored the relationship of domain-specific knowledge to reading rate, studies have examined the contribution of a variety of other component processes or factors: text-based factors, lower-order or elementary verbal processes, and higher-order or discourse-level processes. Research evidence regarding the role each of these three factors may play in reading rate will be reviewed. Research related to a possible role for domain-specific knowledge will also be reviewed. Based on this review, a model of the component processes thought to be involved in reading rate will be constructed. This model, which will include domain-specific knowledge as a component, will be used to examine the role of domain-specific knowledge in predicting reading rate.

Role of text-based factors in reading rate

Text coherency and genre, i.e., narrative vs expository, are the types of text-based factors which have been empirically related to reading rate. McNamara and Kintsch (1996) found that readers read less coherent text, i.e., text in which all the information was not explicitly stated or related, significantly more slowly than more coherent text. Graesser, Hoffman, and Clark (1980) and Petros, Bentz, Hammes, and Zehr (1995) found that the genre, i.e., narrative vs expository, was a significant predictor of reading rate. Indeed, in Graesser et al.'s study, genre accounted for 70% of the predicted variance in reading rate. In both studies,

readers read expository text more slowly than narrative text, suggesting that they found the former more difficult than the latter. In general, text-based factors can be considered to be measures of the difficulty of a passage. More difficult passages, i.e., expository or less coherent texts, are read more slowly than easier passages.

Role of lower-order processes in reading rate

For many researchers, reading rate is thought to reflect the operation of lower-order, elementary verbal processes (e.g., Carver, 1990; Graesser, Hoffman & Clark, 1980; Jackson & McLelland, 1979; Perfetti, 1985; Petros, Bentz, Hammes, and Zehr, 1990). An important lower-order process implicated in reading rate has been general symbol activation and retrieval (e.g., Jackson & McLelland, 1979). The speed with which a reader can access a name, symbol or lexical code is reflected in her reading rate as well as in the speed with which she can name letters, pictures or words. Quick and efficient symbol activation and retrieval is a concept fundamental to Verbal Efficiency Theory (Perfetti, 1985, 1989). The more efficient symbol activation and retrieval is, the more resources there are available for higher-order conceptual and comprehension processes. Better comprehenders are able to activate and retrieve elementary symbolic information more quickly than poor comprehenders. Consequently, speed of lexical access or speed of symbol activation and retrieval is an important rate-limiting factor in reading ability (Perfetti, 1985). For Verbal Efficiency Theory, individual differences in symbol activation and retrieval persist into adulthood and - under certain circumstances - can account for differences in the reading comprehension performance of fluent adult readers (Perfetti, 1985; Bell & Perfetti, 1994).

Verbal Efficiency Theory is reductionist in the sense that symbol or name activation and retrieval processes are presumed to underlie word recognition skill, reading rate and reading comprehension skill. Symbol activation and retrieval affects the speed of lexical access which in turn affects reading rate which in turn affects reading comprehension skill. Thus, measures of symbol activation and retrieval processes should be related to measures of word recognition, reading rate and reading comprehension. Although the degree of correlation may be modest in fluent adult readers because of their generally high level of verbal efficiency, relationships

should still be discernable (Perfetti, 1985). In addition, because symbol activation and retrieval processes are thought to underlie all three reading measures, reading rate should be correlated with both word recognition and reading comprehension.

What evidence is there for the role of symbol activation and retrieval in reading skill in general and reading rate in particular? In a very influential study on the processing determinants of reading speed, Jackson and McClelland (1979) identified the ability to quickly match letters on a name match basis, e.g., *Aa*, as a significant predictor of reading ability. This finding was interpreted as reflecting the importance of lower-order, basic verbal processes to reading comprehension and speed, particularly the importance of a general name activation and retrieval processes. However, subsequent studies of fluent adult readers have failed to demonstrate a consistent relationship between lower-order processing skills and reading comprehension, reading speed or word recognition skill (Baddeley, Logie, Nimmo-Smith, & Brereton, 1985; Cunningham et al., 1990; Palmer, McLeod, Hunt, & Davidson, 1985). For example, Palmer et al. (1985) found that letter name matching skill, a measure of symbol activation and retrieval processes, was not significantly related to either reading speed or reading comprehension performance.

Although letter matching in particular has not always been found to be related to reading rate, other lower-level processes have been associated with reading rate. For example, the number of words and content words per proposition has been found to be related to reading rate (Graesser et al., 1980; Petros et al., 1990). Elementary word processing such as the processing involved in simple word searches or matching tasks has also been found to be related to reading rate (Palmer et al., 1985). Thus, lower-order processes, particularly those involved with quick and efficient lexical access, have been implicated in reading rate.

Role of higher-order processes in reading rate

A small number of studies have examined the relationship between higher-order processes and reading rate. In the studies reviewed, higher-order processing was represented by a variety of tasks. For example, semantic decision, or lexical decision tasks were used (Baddeley et al., 1985; Palmer et al., 1985). In the semantic decision task, subjects had to

decide whether a sentence was true or false, e.g., *A copperhead is a snake, A python is a reptile,* items which tapped their semantic knowledge. More complex tasks included multiple choice vocabulary tasks (Baddeley et al., 1985), or picture-sentence verification tasks, where subjects had to decide if a sentence accurately described a picture (Palmer et al., 1985).

Baddeley et al. (1985) found a moderate correlation between lexical decision performance and reading rate ($r = .30$), as well as between vocabulary knowledge and reading rate ($r = .30$). Palmer et al. (1985), using higher-order tasks such as lexical and semantic decision, found significant correlations between these types of tasks and reading speed. In addition, higher-order tasks were found to be equally related to reading speed and reading comprehension, suggesting that higher-order processes are important components of both types of measures. Thus, higher-order semantic and vocabulary processing skills have been shown to be related to reading rate.

Role of domain-specific knowledge in reading rate

For Verbal Efficiency Theory, elementary verbal processes (e.g., lexical access, propositional encoding) may affect reading rate, but domain-specific knowledge should not. As discussed earlier, domain-specific knowledge is not a component of reading ability according to Verbal Efficiency Theory, and as such, should have no effect on the on-line processing of text. Since reading rate is a measure of on-line processing (Graesser et al., 1980), domain-specific knowledge should not be related to reading rate. Basic reading comprehension does not rely on the on-line application of domain-specific knowledge, but rather on the operation of elementary verbal processes involved in decoding and general language comprehension (Perfetti, 1989).

However, a recent study has provided evidence that domain-specific knowlege may affect reading speed under certain circumstances. McNamara and Kintsch (1996) demonstrated that readers with high domain-specific knowledge read less coherent text more slowly than those with low domain-specific knowledge. They argued that high knowledge readers spent the extra time constructing the inferences necessary to fully understand the less coherent text. Low knowledge readers, who did not have the knowledge to make the necessary inferences, did

not spend as long reading the less coherent text.

McNamara and Kintsch interpreted their findings within the context of the Construction-Integration model of text comprehension. In their study, they were interested in the conditions under which readers would form a situation model, i.e., a mental representation which integrates text information with prior knowledge. They argued that the less coherent text encouraged high knowledge readers to form a situation model, and thus learn from the text rather than just remember the text. In other words, when encouraged to construct a situation model, readers were successful in applying text information to relatively complex questions requiring inferences. Thus, high knowledge readers took longer to read the less coherent text because they were constructing a situation model.

It is important to note the specific circumstances under which domain-specific knowledge affects on-line processing according to the Construction-Integration model. Domain-specific knowledge consists of knowledge which a reader uses to construct a situation model. Domain-specific knowledge is not involved in the construction of a text base model, i.e., a mental representation of the propositions of a text which is often reflected in verbatim recall of a passage (Kintsch, 1994). Thus, domain-specific knowledge may not be expected to affect on-line processing of text unless readers are encouraged to form a situation model.

However, Kintsch has argued elsewhere that knowledge of all sorts is necessary to construct either a text base or situation model (Kintsch, 1988). From their long term knowledge store, readers access a wide variety of knowledge as they read text. Although they may generate a large amount of relevant and irrelevant knowledge, very quickly information is selected which is consistent with the theme or content of the passage (Mross & Kintsch, 1986; Kintsch, 1988). In this way irrelevant knowledge is dropped from the mental representation, and knowledge which is relevant is integrated into the reader's mental representation. But, if knowledge in general is needed to construct both a text base and a situation model, it seems plausible to imagine that domain-specific knowledge could be accessed along with general semantic knowledge. Why would readers selectively exclude one kind of knowledge, namely domain-specific knowledge, when constructing a text base? While readers may not always

retrieve sufficient domain-specific knowledge to draw inferences which would reflect the construction of a situation model, it is possible that they may draw on some aspects of their domain-specific knowledge in order to construct a text base. Thus, domain-specific knowledge may affect reading rate under a wider variety of situations than those outlined by McNamara and Kintsch (1996).

More specifically, domain-specific knowledge may serve to make the selection and integration of relevant information more efficient for high knowledge readers relative to low knowledge readers. Evidence from the previous chapter on word naming offers some, albeit limited support for this suggestion. Recall that high knowledge subjects named astronomy words more quickly than low knowledge subjects. Domain-specific knowledge, when instantiated, may lead to faster lexical access as well as to faster integration of relevant knowledge. Comprehension may be facilitated because domain-specific knowledge can be used to quickly integrate relevant knowledge. In this way, domain-specific knowledge could make an important contribution to the rate of on-line text processing.

Model of reading rate

As reviewed in the previous sections, four kinds of variables have been related to reading rate: text difficulty, lower-order lexical processes, higher-order semantic processes, and domain-specific knowledge. Many of the results reported above treat these variables as independent contributors to reading rate, i.e., as main effects. For example, speed of lexical access is thought to be a major independent predictor of reading rate. Very few studies have explored interactions among variables. The one example from this review is the finding that domain-specific knowledge interacts with text coherence, i.e., less coherent text takes longer to read for those with a high level of domain-specific knowledge. Thus, the question remains as to whether each of these four types of variables predict reading rate when they are considered together in one model of reading rate. Are each of these variables significant predictors of reading rate for fluent adult readers? Are these variables additive and/or interactive in predicting reading rate? Most importantly for this discussion, does domain-specific knowledge predict reading rate when considered within the context of other variables thought to affect

reading rate? A linear model which captures the additive and interactive possibilities of three of the four types[1] of variables is

$$Rr = lp + sp + dk + (lp \times sp) + (lp \times dk) + (sp \times dk) + (lp \times sp \times dk)$$

where *Rr* is reading rate, *lp* is lexical processes, *sp* is semantic processes, and *dk* represents domain-specific knowledge. The *lp*, *sp*, and *dk* terms reflect the main effects of these variables on reading rate, whereas the remaining terms represent all possible interactions among terms. All the possible additive and interactive components are included since this is an exploratory model which attempts to determine which variables may contribute to reading rate.

In the study described below, this full model is tested against reduced models to determine which combination of factors best explains reading rate. A measure of decoding skill was used to represent lexical processes. Since lexical processes have been shown to underlie both word recognition and reading rate, these two variables should be correlated, with their shared variance reflecting the role that lexical processing plays in both abilities. Scores from the Vocabulary subtest of the Wechsler Adult Intelligence Scale - Revised were used as a measure of higher-order semantic processing. Compared to other measures of semantic processing used, it can be seen as reflecting complex, higher-order processing skills. Four measures of domain-specific knowledge were added together to form a composite measure of domain-specific knowledge. Based on the review of research described above, it is expected that lexical and semantic processes will significantly predict reading rate either as main effects or as components of interaction terms. If domain-specific knowledge has a more generalized role in reading rate than suggested by McNamara and Kintsch (1996), then it too should significantly predict reading rate.

METHOD

Subjects

Data from the sixty-six undergraduate students described in the General Method section were used.

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[1] Text difficulty was not manipulated in the study to be described and thus is not considered.

Measures and Procedure

Four measures, which are described in detail in the General Method section, were used: 1) reading rate, 2) domain-specific knowledge, 3) decoding skill, and 4) vocabulary skill. Reading rate was measured as the average number of words read per minute for one astronomy and one computer passage. A composite measure of domain-specific knowledge, described in detail on page 55, was used to represent domain-specific knowledge in the domains of astronomy and computers, respectively. Procedures for administering these measures are outlined in the General Method section.

RESULTS

Preliminary Analyses

Table 4.1 presents the intercorrelations among variables in the astronomy and computer conditions. In general, reading rate had negligible to moderate correlations with other variables. This pattern of low correlations is not an uncommon finding in studies examining individual difference variables related to reading rate (e.g., Baddeley et al., 1985). Readers read the astronomy passages at a significantly faster rate than they read the computer passages ($t(65)=6.32, p < .001$). The mean reading rate for the astronomy passage was 223.14 words per minute compared to 193.00 words per minute for the computer passages.

Model Testing Procedure

A model testing procedure was used to determine which combination of variables best predicted reading rate. The full model is

$$Rr = lp + sp + dk + (lp \times sp) + (lp \times dk) + (sp \times dk) + (lp \times sp \times dk)$$

where *rr* is reading rate, *lp* is lexical processes, *sp* is semantic processes, and *dk* represents domain-specific knowledge. Two tests of the model were made. In the first test, the full model was compared to a reduced model which did not contain the 3 way interaction term, *lp x sp x dk*, to determine whether the 3 way interaction term added significant variance and thus should be retained in the equation. If the 3 way interaction did not add significant variance, then the reduced model

$$Rr = lp + sp + dk + (lp \times sp) + (lp \times dk) + (sp \times dk)$$

was retained. In the second test, the reduced model was compared to a main effects model

$$Rr = lp + sp + dk$$

to determine whether the 2 way interaction terms added significant variance. If the 2 way interaction terms did not add significant variance then the main effects model was retained.

Intercorrelations among variables

	1.	2.	3.	4.	5.	6.	7.
1. Astronomy reading rate							
2. Computer reading rate	.69						
3. Astronomy knowledge	.38	.11					
4. Computer knowledge	.34	.21	.47				
5. Astronomy reading comprehension	-.01	-.10	.44	.34			
6. Computer reading comprehension	.07	-.01	.08	.49	.24		
7. Decoding skill	-.18	-.23	-.25	-.24	-.20	-.28	
8. WAIS-R Vocabulary	.38	.44	.30	.29	.34	.30	-.31

Note: $r > .24$ are significant at the $p < .05$.

Table 4.1

Regression Analyses

Regression analyses using the model testing procedure outlined above were conducted to determine which combination of variables significantly predicted reading rate. Separate regression analyses were conducted for the astronomy and computer conditions. Reading rate in words per minute was used as the dependent variable in each of the astronomy and computer conditions. Lexical processing skill was represented by the composite measure of decoding skill described on page 41. Semantic processing was represented by the WAIS-R Vocabulary subtest. Domain-specific knowledge was represented by a composite measure described on page 39. All predictor variables were standardized.

Predicting reading rate in the astronomy condition: Hierarchical regression analyses

Step	R^2	R^2 Change	F	Significance of F
1. Decoding skill (*lp*)	.03		2.22	.14
2. WAIS-R Vocabulary (*sp*)	.15	.12	8.31	<.01
3. Astronomy knowledge (*dk*)	.22	.07	5.76	.02
4. 2-Way interactions	.29	.07	1.96	n.s.
5. 3-Way interaction	.30	.01	1.25	.27
	$Rr = -.01lp + .28sp^* + .09dk^*$			

$^*p = .02$

Table 4.2

Table 4.2 summarizes the results of hierarchical regression analyses for the astronomy domain. Neither the 3-way or 2-way interactions added significant variance to reading rate, and thus a main effects model was retained. As the regression equation for the main effects model illustrates (see Table 4.2), vocabulary skill and domain-specific knowledge were significant predictors of reading rate (for vocabulary skill, $t(62)= 2.34, p=.02$; for domain-specific knowledge $t(62)=2.40, p=.02$). Increases in vocabulary skill and domain-specific knowledge were associated with faster reading rates. Decoding skill was not a significant predictor of reading rate either when entered alone or in combination with vocabulary skill and domain-specific knowledge.

Table 4.3 summarizes the results of hierarchical regression analyses for the computer domain. The 3-way interaction term did not add significant variance, and thus the full model was rejected. The 2-way interaction terms added a significant 15% of variance to reading rate, and thus, a reduced model comprised of 1st and 2nd order terms i.e.,

$$Rr = lp + sp + dk + (lp \times sp) + (lp \times dk) + (sp \times dk)$$

was retained. The regression equation for the reduced model of main effects and 2nd order interaction terms is contained in Table 4.3. No terms involving decoding skill were significant

Predicting reading rate in the computer condition: Hierarchical regression analyses

Step	R^2	R^2 Change	F	Significance of F
1. Decoding skill (*lp*)	.05		3.64	.06
2. WAIS-R Vocabulary (*sp*)	.20	.15	11.92	<.01
3. Computer knowledge (*dk*)	.21	.01	.35	.56
4. 2-Way interactions	.36	.15	4.61	<.05
5. 3-Way interaction	.37	.01	.91	.34

$$Rr = -.04lp + .44sp^{*} - .04dk - .06(lpxsp) + .11(spxdk)^{*} + .02(lpxdk) - .10$$

*P < .01

Table 4.3

predictors of reading rate. Vocabulary skill was a significant predictor of reading rate ($t(59)=3.66$, $p=.0005$) as was the interaction of vocabulary skill and domain-specific knowledge ($t(59)=2.78$, $p=.007$). The interaction of vocabulary skill and domain-specific knowledge is illustrated in Figure 4.1. For those with high vocabulary skill (i.e., one standard deviation above the mean vocabulary score), higher domain-specific knowledge was associated with faster reading rates, which corresponds to the results in the astronomy domain. For those with low vocabulary skill (one standard deviation below the mean vocabulary score), however, higher domain-specific knowledge was associated with slower reading rates.

DISCUSSION

The purpose of this set of analyses was to determine which combination of variables best predict reading rate, and whether domain-specific knowledge played a role in predicting reading rate. As passages were drawn from two different content domains, astronomy and computers, an assessment could be made as to whether patterns among variables generalized beyond one particular text. It was hypothesized that variables which had been found to be significantly related to reading rate in previous studies, i.e., lexical processes, semantic processes, and domain-specific knowledge, would all play a role in predicting reading rates. In

Interaction of Vocabulary Skill and Domain-specific Knowledge in the Computer Condition

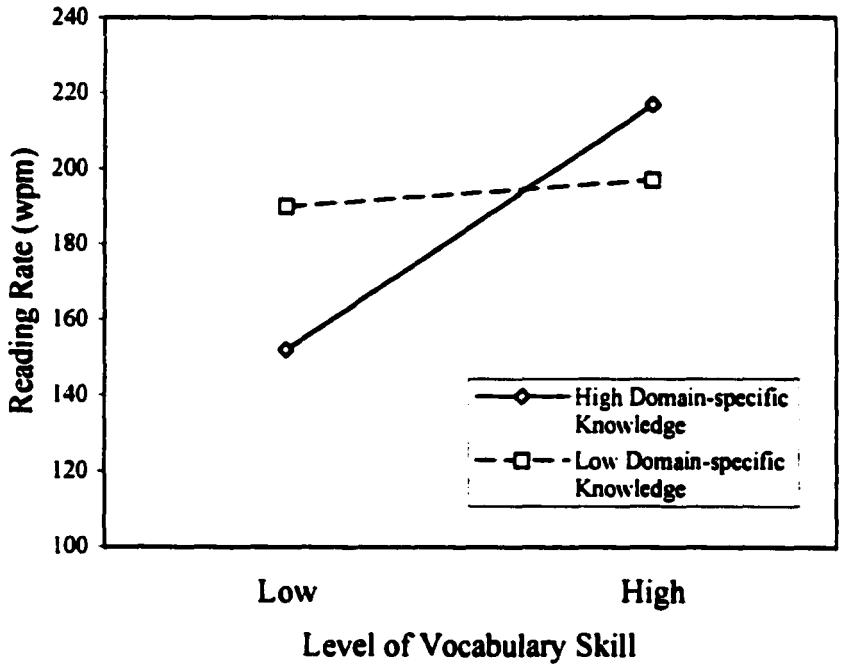

Figure 4.1

addition, previous studies had not explicitly examined the way in which these variables may interact or combine to predict reading rate. A linear model was proposed which included both additive and interactive terms so that each variable could be considered within the context of the remaining variables.

Many of the findings generalized across both knowledge domains. In both domains, lexical processing was not a significant predictor of the reading rates of fluent adult readers. Given that some of the same elementary verbal processes should be involved in both decoding skill and reading rate, this finding suggests that lower-level processes may not be that important a determinant of reading rate for fluent adult readers. Contrary to the claim of Verbal Efficiency Theory that individual differences in lexical access continue to exist for fluent adult readers, there may be little variation in lexical access efficiency for fluent adult readers (for a similar argument see Petros et al., 1990). Alternatively, it is possible that a word naming task such as the one used here may be only a crude indicator of lower-level processes, and that a task such as word matching might have tapped these processes more effectively.

In contrast to the lack of a role for lexical processing, vocabulary skill, a measure of higher-order semantic processing, was a significant predictor of reading rate in both domains. Increases in vocabulary skill were associated with faster reading rates. Domain-specific knowledge was also a significant predictor of reading rate. Increases in domain-specific knowledge were associated with faster reading rates for readers in the astronomy condition. In the computer condition, the effect of domain-specific knowledge was moderated by vocabulary skill. This pattern of results suggests that higher-order variables such as vocabulary and domain-specific knowledge are important contributers to reading rate, whereas lower-order variables such as word naming skill do not contribute to the reading rate of fluent adult readers. In other words, general and specific knowledge may have a greater role to play in reading rate than fast and efficient lexical access.

The role of domain-specific knowledge in reading rate was somewhat inconsistent across domains. In the astronomy condition, increases in domain-specific knowledge were associated with faster reading rates. In the computer condition, while increases in domain-

specific knowledge were associated with faster reading rates for readers with high vocabulary skill, for readers with low vocabulary skill, increases in domain-specific knowledge were associated with slower reading rates. However, it is difficult to interpret the interaction of vocabulary and domain-specific knowledge in predicting reading rate without considering the effect that different combinations of knowledge and reading rate might have on reading comprehension. For example, although the faster reading rates in the astronomy condition were associated with both higher vocabulary and higher domain-specific knowledge, it is not clear whether this led to better or worse comprehension. Similarily, in the computer condition, readers with high domain-specific knowledge but low vocabulary skill read at a slower rate than other readers in that condition (Figure 4.1). Did the slower reading times result in better comprehension? The role that reading rate might play in conjunction with higher-order processes to produce comprehension is examined next.

PART TWO

The relationship between reading rate, vocabulary skill, and domain-specific knowledge in predicting reading comprehension

A recurring view in reading research over the last 20 years is that the same factors or component processes underlie both reading rate and reading comprehension. Consistent with this view has been the use of measures of *reading efficiency*, where reading ability is expressed as a function of both comprehension accuracy and reading rate (e.g., Bell & Perfetti, 1994; Carr, Brown, Vavrus, & Evans, 1990; Jackson & McLelland, 1979). Indeed, Perfetti equated reading rate and reading comprehension skill in his definition of reading ability (Perfetti, 1985, page 10):

> ...it is quite sensible to define reading skill as including either high comprehension *or* high rate, with either of these components above some minimum.

However, this view has been challenged by research that suggests that component processes may contribute differently to reading rate and reading comprehension skill. For example, Palmer, McLeod, Hunt and Davidson (1985) demonstrated that while higher-order semantic processing tasks were equally related to reading speed and reading comprehension,

elementary word search and matching tasks were more related to reading speed than reading comprehension. Factors or components that affect reading comprehension may or may not affect reading rate. On the basis of these findings, Palmer et al. concluded that reading rate and reading comprehension skill comprised two distinct abilities. Because their findings also included a moderate correlation between reading rate and comprehension, they also concluded that, though distinct, these two abilities were related.

Whether reading rate and reading comprehension are seen as two sides of the same coin, or whether they are seen as distinct but related abilities, both viewpoints predict a correlation between reading rate and reading comprehension skill. However, the nature of the correlation, i.e., whether it is positive or negative, differs from model to model. Verbal Efficiency Theory predicts that faster reading rates are associated with higher levels of reading comprehension (Perfetti, 1985). In contrast, the Construction-Integration model predicts that for difficult, less coherent texts, readers with high domain-specific knowledge take longer to read a passage than readers with low domain-specific knowledge (McNamara & Kintsch, 1996).

While the results reported here do not directly address the relationship between reading rate and reading comprehension, they suggest that the nature of the relationship may be a complex one which depends, in part, on the roles vocabulary skill and domain-specific knowledge play in both reading rate and reading comprehension. Although increases in vocabulary skill and domain-specific knowledge were associated with faster reading times, it was not clear whether these faster times were in turn associated with better comprehension. In contrast, in the computer condition, the slowest readers had high levels of domain-specific knowledge but low vocabulary skill. In this latter case, slower reading may have led to better comprehension. That is, readers with high domain-specific knowledge but lower vocabulary skill may have slowed their reading rate in order to ensure better comprehension.

In summary, the results of the first reading rate study left two issues unresolved. Firstly, the role of reading rate in reading comprehension skill needed to be addressed within the context of other component processes of reading, particularly in relation to domain-specific knowledge. Secondly, the question of whether faster or slower reading times were associated

with better reading comprehension was not addressed by the first study. In order to address these issues, a second set of analyses was conducted to explore the way in which reading rate, vocabulary knowledge and domain-specific knowledge combine to predict reading comprehension performance. No measure of lexical level processing was included in these analyses because lexical level processing had failed to be a significant predictor of reading rate.

For this set of analyses, the full linear model was

$$Rc = sp + dk + rr + (sp \times dk) + (sp \times rr) + (dk \times rr) + (sp \times dk \times rr)$$

where *Rc* is reading comprehension performance, *sp* is semantic processing, *dk* is domain-specific knowledge, and *rr* is reading rate. The full model considers all additive and interactive possibilities among variables. A model testing procedure was used to test the full model against reduced models to determine which set of terms best predicted reading comprehension.

METHOD

Subjects

Data from the sixty-six undergraduate students described in the General Method section were used.

Measures and Procedure

In addition to the reading rate, domain-specific knowledge, decoding skill, and vocabulary skill measures employed in the study described in Part One of this chapter, a reading comprehension measure was used. As described in the General Method section, subjects answered two sets of multiple choice questions to test their comprehension of two reading passages: one on a topic from the astronomy domain and one on a topic from the computer domain.

RESULTS

Preliminary Analyses

Table 4.1 contains the intercorrelations among variables. Of note is the negligible zero-order relationship between reading rate and reading comprehension in both domains ($r = -.01$ for both astronomy and computer conditions).

Model Testing Procedure

A model testing procedure was used to determine which combination of variables best predicted reading comprehension. The full model is

$$Rc = rr + sp + dk + (rr \times sp) + (rr \times dk) + (sp \times dk) + (rr \times sp \times dk)$$

where *rc* is reading comprehension, *rr* is reading rate, *sp* is semantic processes, and *dk* represents domain-specific knowledge. Two tests of the model were made. In the first test, the full model was compared to a reduced model which did not contain the 3 way interaction term, *rr x sp x dk*, to determine whether the 3 way interaction term added significant variance and thus should be retained in the equation. If the 3 way interaction did not add significant variance, then the reduced model

$$Rc = rr + sp + dk + (rr \times sp) + (rr \times dk) + (sp \times dk)$$

was retained. In the second test, the reduced model was compared to a main effects model

$$Rc = rr + sp + dk$$

to determine whether the 2 way interaction terms added significant variance. If the 2 way interaction terms did not add significant variance then the main effects model was retained.

Regression Analyses

Regression analyses using the model testing procedure outlined above were conducted to determine which combination of variables significantly predicted reading comprehension. Separate regression analyses were conducted for the astronomy and computer conditions. Reading comprehension was the dependent variable and raw scores, i.e., number of items correctly answered, for each of the astronomy and computer comprehension tests was used. Reading rate for each of the astronomy and computer conditions was calculated in words per minute. Semantic processing was represented by the WAIS-R Vocabulary subtest. Domain-specific knowledge was represented by a composite measure. All predictor variables were standardized.

Table 4.4 summarizes the results of hierarchical regression analyses in the astronomy condition. Neither the 3-way or 2-way interactions added significant variance to reading comprehension, and thus, a main effects model was retained. The main effects model accounted for 31% of the variance in reading comprehension. In the main effects model (Table

Role of reading rate in reading comprehension in the astronomy condition: Hierarchical regression analyses

Step	R^2	R^2 Change	F	Significance of F
1. Main effects (*rr* + *sp* + *dk*)	.31		9.24	<.01
2. 2-Way interactions	.33	.02	.59	n.s.
3. 3-Way interactions	.36	.03	2.64	.11
	$Rc = -.30rr^* + .31sp^* + .15dk^*$			

$^*p < .03$

Table 4.4

4.4), reading rate (t(62)=-2.47, p = .02), vocabulary skill (t(62) = 2.70, p = .009), and domain-specific knowledge (t(62) = 3.96, p = .0002) were significant predictors of reading comprehension. As the regression equation for the main effects model illustrates (Table 4.4), increases in vocabulary skill and domain-specific knowledge were associated with increases in reading comprehension performance. Slower reading rates were associated with better reading comprehension performance.

Although the zero-order correlation between reading rate and reading comprehension in the astronomy condition was negligible, Figure 4.2 illustrates the way in which reading rate influenced reading comprehension when considered within the context of vocabulary skill and domain-specific knowledge. Slower readers (i.e., one standard deviation below the mean reading rate) consistently outperformed faster readers (i.e., one standard deviation above the mean reading rate). Within slow and fast reading groups, those with higher vocabulary skill and domain-specific knowledge outperformed those with less vocabulary skill and domain-specific knowledge.

The results of hierarchical regression analyses for the computer condition are contained in Table 4.5. Neither the 3-way or 2-way interactions added significant variance in predicting reading comprehension, and thus, a main effects model was retained. The main effects model accounted for 27% of the variance in reading comprehension performance. Within the main

Effect of Reading Rate on Astronomy Comprehension

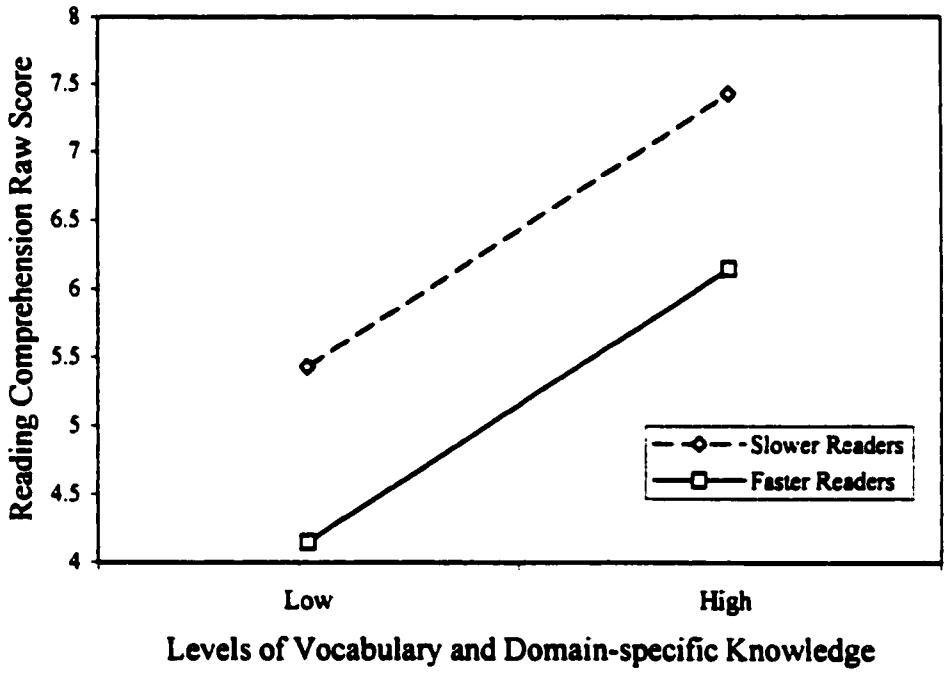

Figure 4.2

Role of reading rate in reading comprehension in the computer condition: Hierarchical regression analyses

Step	R^2	R^2 Change	F	Significance of F
1. Main effects (*rr* + *sp* + *dk*)	.27		7.46	<.01
2. 2-Way interactions	.28	.01	.27	n.s.
3. 3-Way interactions	.30	.02	1.23	.27
	$Rc = -.17rr + .14sp + .15dk^*$			

$^*p < .01$

Table 4.5

effects model, reading rate (t(62)=-1.38, p = .17), and vocabulary skill (t(62)= 1.16, p =.25) were not significant predictors of reading comprehension. Only domain-specific knowledge significantly predicted reading comprehension performance (t(62) = 4.21, p = .0001). However, as the regression equation for the main effects model illustrates (Table 4.5), the pattern of relationships among variables was the same in the computer condition as it was in the astronomy condition. This pattern is depicted in Figure 4.3. Slower readers (i.e., one standard deviation below the mean reading rate) comprehended better than faster readers (i.e., one standard deviation above the mean reading rate). Within slow and fast reading groups, those with higher vocabulary skill and domain-specific knowledge outperformed those with less vocabulary skill and domain-specific knowledge.

DISCUSSION

When reading rate was considered in relation to other component processes with which it was significantly correlated, i.e., vocabulary skill and domain-specific knowledge, results indicated that slower rather than faster reading rates were associated with better comprehension. A negative relationship between reading rate and reading comprehension was obtained in both the astronomy and computer conditions, lending it some degree of generalizability. This finding is contrary to that predicted by Verbal Efficiency Theory, which would have expected faster reading rates to reflect higher verbal efficiency and thus better

Effect of Reading Rate on Computer Comprehension

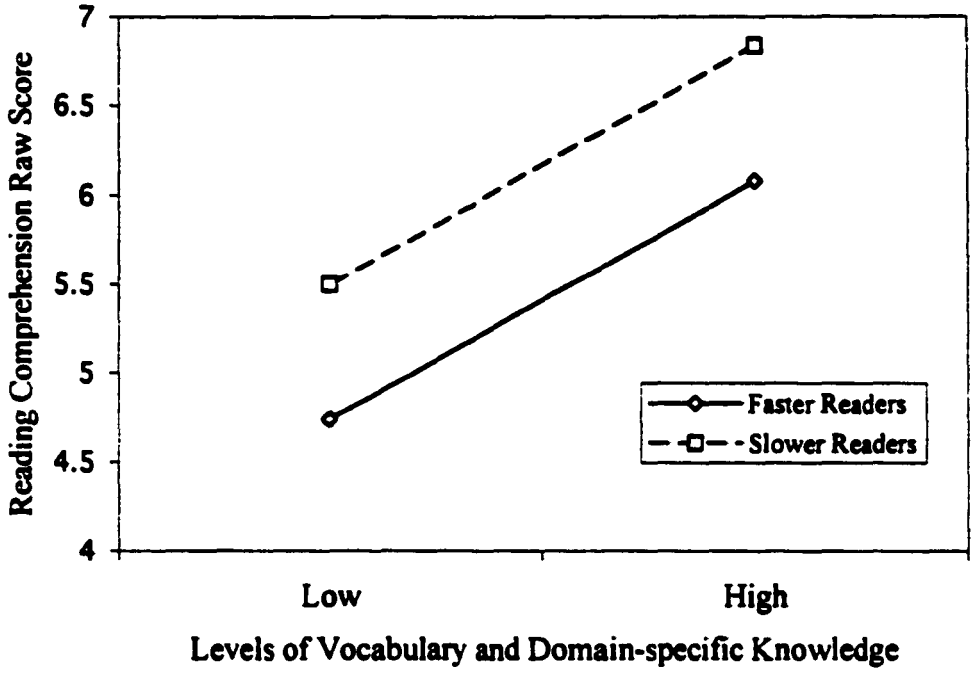

Figure 4.3

comprehension. In addition, Verbal Efficiency would not have predicted that higher-level components such as vocabulary skill and domain-specific knowledge would need to be incorporated into a model of the relationship between reading rate and reading comprehension.

Indeed, the present results reflect a case of classical suppression (Cohen & Cohen, 1975). In classical suppression, one independent variable is uncorrelated with the dependent variable but is correlated with other independent variables which are also correlated with the dependent variable. In both the astronomy and computer conditions, the unpartialled or zero-order correlation between reading rate and reading comprehension is negligible, but reading rate is positively correlated with general language comprehension and domain-specific knowledge, variables which are, in turn, positively correlated with reading comprehension performance. The path diagram of Figure 4.4 provides one plausible interpretation of this suppression effect, an interpretation which integrates the results of Part One, i.e., the regression of general language comprehension and domain-specific knowledge on reading rate, with the results of Part Two, i.e., the regression of general language comprehension, domain-specific knowledge, and reading rate on reading comprehension performance. As the path diagram in Figure 4.4 depicts, reading rate has a direct effect on reading comprehension (path *a*) as well as spurious effects via general language comprehension and domain-specific knowledge (paths *eb, fc, edc, fdb*). As a further illustration, Figure 4.5 provides the path coefficients for the astronomy condition. The sum of the direct and spurious effects equals the zero-order correlation between reading rate and reading comprehension. For the astronomy condition, the correlation of reading rate with reading comprehension may be decomposed as follows:

$$r_{rr,rc} = -.30 + (.28)(.31) + (.28)(.46) + (.28)(.30)(.46) + (.28)(.30)(.31) = -.01$$

The direct and spurious effects are of approximately equal value but of opposite sign, and thus cancel each other out, resulting in a negligible zero-order correlation. As a result, the zero-order correlation of reading rate and reading comprehension can be considered uninformative because the underlying negative relationship between the two variables is obscured by spurious effects. In other words, the effects of general language comprehension and domain-specific knowledge need to be controlled in order to observe the negative relationship between reading rate and

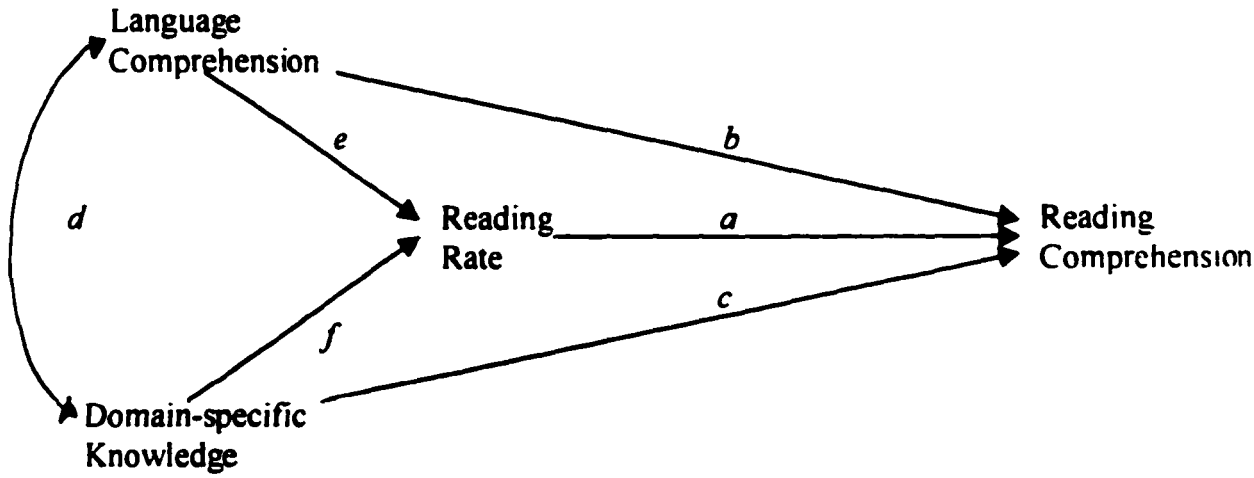

Figure 4.4

Path Diagram of the Relationship between
Reading Rate and Reading Comprehension

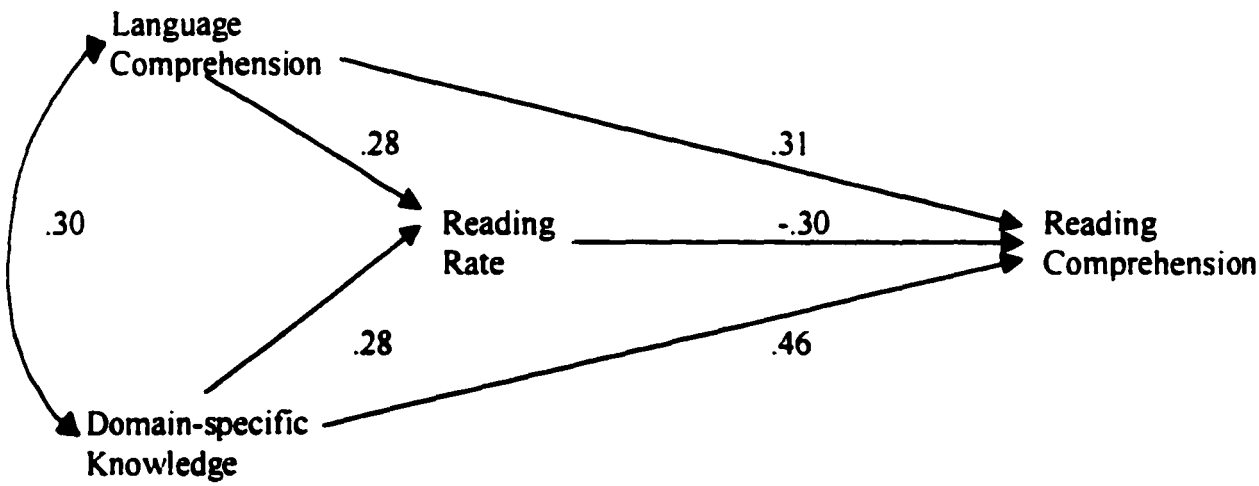

Figure 4.5

**Path Diagram of the Relationship between
Reading Rate and Reading Comprehension
In the Astronomy Condition**

reading comprehension.

As the path diagram illustrates, the relationship between reading rate and reading comprehension is not a simple, straightforward one, but may be complicated by other factors. Failing to control for these factors may help to explain why there are such inconsistent correlations obtained for reading rate and reading comprehension in the literature.[2] For instance, Palmer et al. (1985) have suggested that whether or not a reading comprehension test is completed within time limits affects the relationship between reading rate and reading comprehension. A significant relationship may be obtained using a timed comprehension measure because the two variables, rate and comprehension, are confounded. Those who read more slowly get less done and thus have lower comprehension scores. Thus, task demands may interact with component skills in the determination of reading rate.

The results of this study, in which there was no time limit on either passage reading or question answering, suggest that other variables, such as the goals of the reader, may influence reading rate. As Figures 4.2 and 4.3 illustrate, higher levels of vocabulary skill and domain-specific knowledge on their own did not result in the best comprehension. Only when these skills and knowledge were combined with a relatively slower reading rate did the best reading comprehension occur. It may be that the goal of comprehension is more important for slower readers than faster readers.

The possible influence of the reader's goals can also be seen when one considers the results reported in Part One. Although faster reading rates were associated with higher levels of vocabulary skill and domain-specific knowledge, this may not automatically translate into better reading comprehension. Indeed, in the computer condition, the slowest readers were also those with high domain-specific knowledge. A slower reading speed for those readers may have resulted in better reading comprehension. This interpretation is consistent with that given

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[2] Small to negligible relationships, such as those obtained here, have been reported elsewhere (e.g., Petros et al., 1990). While some studies (e.g., Baddeley et al., 1985) have found a significantly positive relationship, others have found a significant negative relationship (e.g., Graesser et al., 1980).

by McNamara and Kintsch (1996) to explain the slower reading speed of high domain-specific knowledge readers reading low-coherence text. McNamara and Kintsch (1996) suggested that readers with high-domain-specific knowledge slowed down in order to make the inferences necessary to learn from the text. That is, the goal to learn from the text interacted with the type of text to influence reading speed.

The results reported in this chapter reinforce the importance of higher-level components such as vocabulary skill and domain-specific knowledge in the determination of reading rate. In the study reported in Part One, it was demonstrated that domain-specific knowledge was a significant predictor of reading rate. In the study reported in Part Two, both general language comprehension and domain-specific knowledge needed to be controlled or accounted for in order to understand the relationship between reading rate and reading comprehension. Thus, domain-specific knowledge is implicated in the on-line processing of text. If domain-specific knowledge is implicated in the on-line processing of text, then it would appear to constitute an important and essential component of the reading comprehension skill of fluent adult readers.

CHAPTER FIVE

Modelling Reading Comprehension: Including Domain-specific Knowledge as a Component

Of the three models of reading comprehension discussed in the introductory chapter, only the Simple View of reading attempts to mathematically model reading comprehension skill. Recall that for the Simple View, reading ability can be expressed as

$$Rc = d \times c$$

where Rc is reading comprehension skill, d is decoding skill, and c is language comprehension skill (Gough & Tunmer, 1986). This model identifies the two major components of reading - decoding and comprehension processes - which have been shown to make separate contributions to reading skill (Cunningham, Stanovich, & Wilson, 1990). According to the Simple View of reading, reading comprehension skill is a function of the product of decoding and language comprehension skill. In other words, if either decoding skill or language comprehension skill are zero, then there is no reading comprehension. Each of decoding and language comprehension are necessary for reading to occur but neither alone is sufficient.

The mathematical expression, $rc = d \times c$, is intended to capture the major theoretical claims of the architects of the Simple View of reading. The first claim is that reading comprehension is a function of only two major components: decoding skill and comprehension skill. All component processes involved in reading comprehension can be seen as derivatives of one of these two components. The second claim is that a multiplicative function is necessary in order to reflect the claim that neither decoding nor comprehension alone is sufficient for reading comprehension to occur.

Most often, the multiplicative model is contrasted with an additive model. In an additive model, e.g., $rc = d+c$, it is possible for reading comprehension to occur if only one component were functional. For example, if one had no decoding skill but some language comprehension skill, reading comprehension could occur. This possibility is rejected by the Simple View of reading.

Hoover and Gough (1990) tested the multiplicative model by assessing the reading comprehension skills of English-Spanish bilingual students ranging from Grades 1 to 4. The model was tested at each grade level separately. The model Hoover and Gough tested was

$$Rc = d + c + (dxc)$$

Although the equation, $rc = d + c + (dxc)$ contains both additive and product terms, it is equivalent to a test of the multiplicative model, $rc = dxc$ (see Arnold & Evans, 1979, for further discussion). A significant interaction effect indicates that the two component terms, decoding skill and language comprehension, are contingent on one another (Aikin & West, 1991). If the interaction term is significant, a simple additive model can be rejected.

Hoover and Gough (1990) predicted that if the multiplicative model, i.e., $rc = dxc$, was correct, the product or interaction term, dxc, should contribute significant variance over and above the variance contributed by the additive components, $d + c$. At each grade level, the additive components of the model, i.e., $d + c$, accounted for 72% to 85% of the variance in reading comprehension. In addition, the product term, (dxc), contributed a significant amount of additional variance, ranging from 1% to 7%. They concluded that a simple additive model could be rejected and that a multiplicative model captured the contingent nature of the relationship between decoding and language comprehension.

In a study of fluent adult readers, Peterson (1993) tested an additive model against a multiplicative model. In her study, Peterson compared the variance accounted for by a simple additive model, $rc = d+c$, to a multiplicative model which contained <u>only</u> the product term, $rc = dxc$. While the equation she used for the additive model provided an appropriate test of the additive model, the equation she used to represent the multiplicative model is questionable. An appropriate test of the multiplicative model needs to include the additive terms (Arnold & Evans, 1979). In other words, the equation needed to test the multiplicative model is $rc = d + c + (dxc)$. Consequently, only the results she reported with respect to the additive model are interpretable. The additive model, $rc = d+c$, applied to two different passages, accounted for 29% to 50% of the variance in reading comprehension.

In an attempt to replicate the multiplicative model with children, Chen & Vellutino

(1997) assessed the reading comprehension skills of English speaking children in Grades 2 through 7. The model

$$Rc = d + c + (dxc)$$

was used to determine whether the product term, *dxc*, added significant variance to the regression equation.[1] At each grade level, none of the interaction terms was significant after the additive components had been entered. The amount of variance accounted for by the interaction term ranged from 0% to 3%. The additive components, $d + c$, accounted for 55% to 80% of the variance in reading comprehension.

Although the findings of Chen & Vellutino (1997) failed to support a multiplicative model, they argued that detecting interaction effects is difficult because the power of an interaction effect is dependent on the reliabilities of the terms making up the interaction. Thus their failure to find a significant interaction effect could have been the result of insufficient power. Consequently, Chen and Vellutino (1997) argued that a weaker version of the Simple View of reading, a model which contained both additive and multiplicative features, should be retained, i.e., a combined additive/multiplicative model, $rc = d + c + (dxc)$. However, this conclusion does little to resolve matters. Unfortunately, it is not possible to demonstrate empirically whether a multiplicative or combined additive/multiplicative model provides the best explanation of reading comprehension skill, since the same results with the same equation are required to demonstrate either model (Arnold & Evans, 1979). The test of either the pure multiplicative or combined additive/multiplicative model involves testing whether the interaction term, (dxc), adds significant variance to reading comprehension. Since both the equation used and the test conducted are the same for either model, a distinction cannot be made between the two models.

Both models use the same equation, $rc = d + c + (dxc)$, because the 'pure'

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[1]Both Chen & Vellutino (1997) and Hoover & Gough (1990) compared a model in which the product term was entered before the additive terms, $rc = (dxc) + (d+c)$, to a model in which the additive terms were entered before the product term, $rc = (d+c) + (dxc)$. Only results from the model, $rc = (d+c) + (dxc)$, are reviewed here since the model, $rc = (dxc)$, cannot be interpreted as a test of the multiplicative model.

multiplicative model, $rc = dxc$, cannot be tested using hierarchical regression without the inclusion of the additive components. Without the addition of the additive terms, the product term, entered on its own, reflects the simple correlation between the product term and the dependent variable. As Cohen (1978) points out, the simple correlation between the product term and the dependent variable (and the independent variables on which the product term is based) varies as a function of the scaling properties or linear transformations of the dependent and independent variables. Thus, the relationship obtained in an equation involving only the product term is more a reflection of the scaling properties of the independent variables comprising the product term than of any meaningful relationship between the product term and dependent variable. In contrast, when the additive terms are added to the equation before the product term, the contribution of the product term reflects the semipartial correlation between the product term and the dependent variable, i.e., a relationship from which the variance attributable to the independent variables comprising the product has been partialled. It is this semipartial correlation which represents the interaction of the independent variables, and tests of significance involving this semipartial correlation do not vary as a function of the scaling properties or linear transformations of their constituent variables (Cohen, 1978).

Table 5.1 contains a summary of the amount of variance accounted for by the additive and multiplicative models in the three studies reviewed. As illustrated in Table 5.1, the additive model accounts for a significant amount of variance in reading comprehension. Not only does the additive model account for a significant amount of variance, but also, in two of the three studies, the additive rather than multiplicative model was supported. Taken altogether, these results offer only meagre support for a purely multiplicative model. Indeed, the results suggest that an additive model is sufficient to explain the way in which decoding and language comprehension skill predict reading comprehension. However, this model does not make explicit the role of domain-specific knowledge in reading comprehension skill, an issue which is explored next.

Proportion of variance accounted for by additive vs multiplicative models of reading

Study	N	Proportion of variance: *(d+c)*	Proportion of variance: *(dxc)*	Effect size *(dxc)*
Peterson (1993)				
1. Adults-baseball reading passage	127	.71		
2. Adults - computer reading passage	127	.54		
Hoover & Gough (1990)				
1. Grade 1 students	210	.72	.01*	.04
2. Grade 2 students	206	.73	.02*	.08
3. Grade 3 students	86	.78	.07*	.47
4. Grade 4 students	55	.85	.05*	.50
Chen & Vellutino (1996)				
1. Grade 2 students	163	.80	.00	.00
2. Grade 3 students	131	.68	.00	.00
3. Grade 6 students	129	.66	.00	.01
4. Grade 7 students	37	.56	.03	.07

*$p<.05$.

Table 5.1

Including Domain-Specific Knowledge in a Model of Reading Comprehension

Figures 5.1, 5.2, and 5.3 provide graphical summaries of the role of domain-specific knowledge according to the Simple View of reading, Verbal Efficiency Theory, and the Construction-Integration model. There are two important points to highlight when comparing these three models. Firstly, the Simple View (Figure 5.1) postulates a one-tier conception of

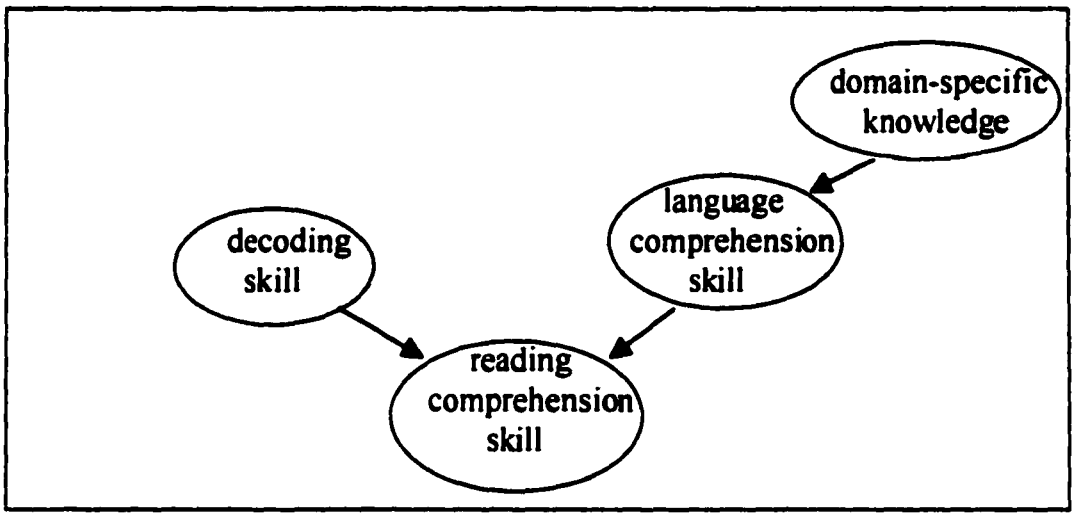

Figure 5.1
Diagram of the Simple View of Reading

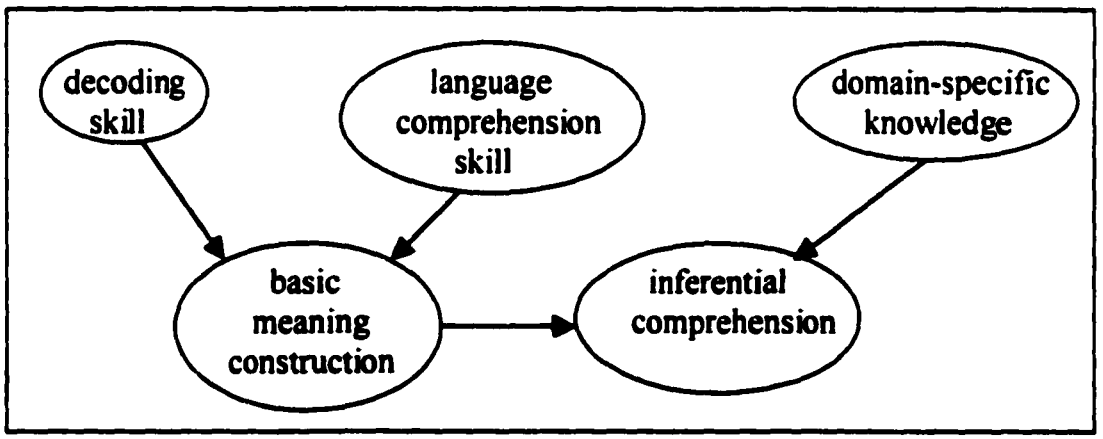

Figure 5.2
Diagram of Verbal Efficiency Model

reading comprehension, in contrast to the verbal efficiency (Figure 5.2) and Construction-Integration models (Figure 5.3) which argue for a two-tier conception of reading comprehension performance. Secondly, the effect of domain-specific knowledge on reading comprehension is either indirect or conditional on the type of comprehension which occurs. For the Simple View (Figure 5.1), domain-specific knowledge does not make an independent contribution to reading comprehension performance, but rather is a derivative of language comprehension skill (Peterson, 1993). For Verbal Efficiency Theory and the Construction-Integration model (Figures 5.2 and 5.3, respectively), domain-specific knowledge only has an effect when a more sophisticated form of reading comprehension, i.e., situation modelling or inferentially-rich processing, occurs.

An alternative hypothesis is depicted in Figure 5.4. This model is identical to the Simple View except for the hypothesized relationship between domain-specific knowledge and reading comprehension skill. In contrast to the Simple View, this model indicates that domain-specific knowledge makes an independent, direct contribution to reading comprehension skill. Domain-specific knowledge can contribute to the on-line processing of text, as demonstrated in Chapters 2 and 3. As such, it is implicated in the immediate processing underlying basic reading comprehension skill. Thus, a model which includes a direct path from domain-specific knowledge to reading comprehension skill seems warranted.

In the following study, the model implied by the Simple View of reading (Figure 5.1) is compared to the model depicted by Figure 5.4. In other words, the model,

$$Rc = d + c$$

is compared to the model

$$Rc = d + c + k$$

where *rc* is reading comprehension skill, *d* is decoding skill, *c* is language comprehension skill, and *k* is domain-specific knowledge. If the Simple View (Figure 5.1) is correct, then domain-specific knowledge, *k*, should not add significant variance after the variance attributable to language comprehension, *c*, has been accounted for. In other words, if domain-specific knowledge contributes only indirectly to reading comprehension via language comprehension

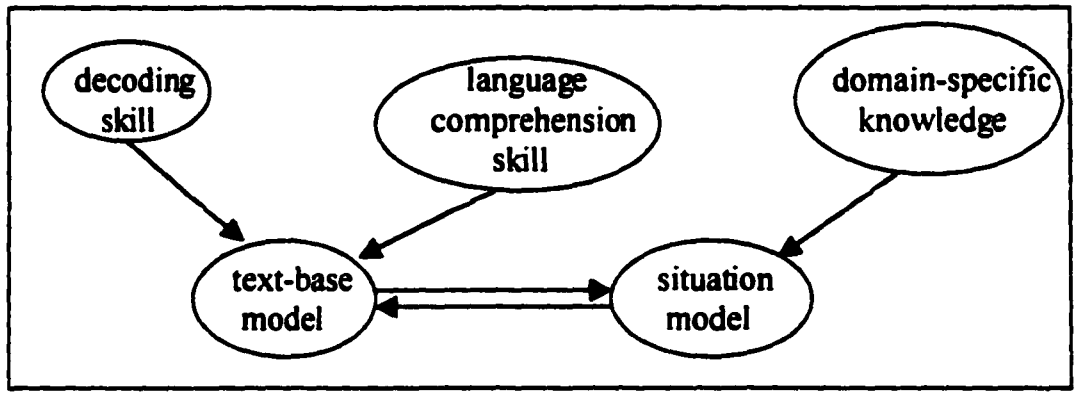

Figure 5.3
Diagram of the Construction-Integration Model

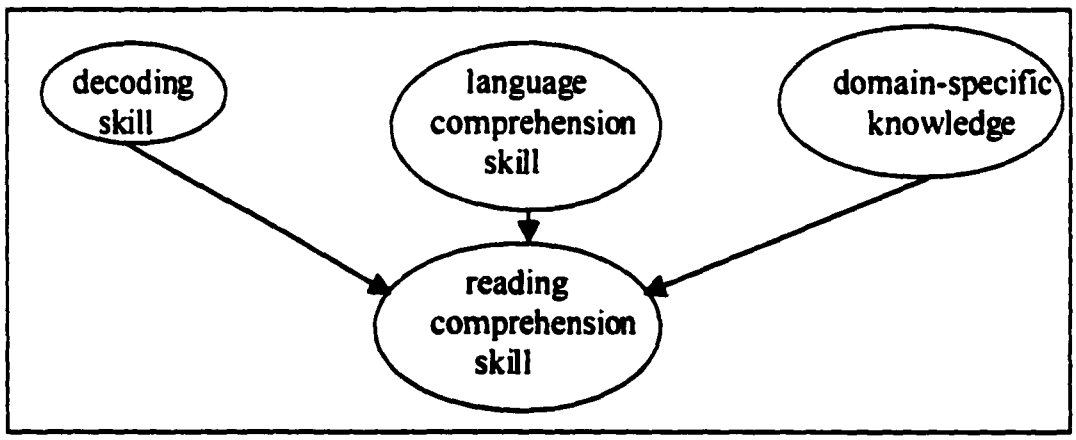

Figure 5.4
Diagram of a Direct Relationship
Between Domain-Specific Knowledge
And Reading Comprehension Skill

skill, all the variance attributable to domain-specific knowledge should be accounted for by language comprehension skill. Alternatively, if the model depicted in Figure 5.4 is correct, then domain-specific knowledge, *k*, should contribute significant unique variance to reading comprehension skill, i.e., when considered as the last variable entered into the regression equation.

While the model testing procedure outlined in the previous paragraph provides a test between a model based on the Simple View of reading (Figure 5.1) and the model depicted in Figure 5.4, it does not provide a means to test the role of domain-specific knowledge in the verbal efficiency and Construction-Integration models (Figures 5.2 and 5.3 respectively) because two reading comprehension outcomes are hypothesized by the two latter models. The reading comprehension measures used in this study did not make a distinction between text-based versus situation modelling levels of comprehension. Thus, the results reported below are limited to a test of the role of domain-specific knowledge in a one-tier conception of reading comprehension performance.

In addition to providing a test of the role of domain-specific knowledge in reading comprehension performance, there were two supplementary objectives of this study, both of which pertain to the way in which reading comprehension has been modelled according to the Simple View of reading. Firstly, an analysis including a listening comprehension measure, the measure most often used to represent general language comprehension (e.g., Hoover & Gough, 1990; Peterson, 1993), was used even though the reliability of these measures was poor. (See Chapter Two for a discussion of the reliability of listening comprehension measures.) However, it was felt important to provide an analysis which exactly replicated the one used by Peterson (1993) to test the Simple View of reading. Secondly, a simple additive model, e.g., $Rc = d + c + k$, was compared to a combined additive/multiplicative model, e.g., $Rc = d + c + k + (dxc) + (dxk) + (cxk) + (dxcxk)$, in order to test the claim of the Simple View of reading that a multiplicative or interactive component to reading comprehension performance is required. All possible interaction terms were included, since there was no previous research to indicate whether or not domain-specific knowledge would have a moderating effect on decoding or

general language skill. However, it was expected, given the findings of the previous research described above, that a simple additive model would be sufficient to explain reading comprehension performance.

METHOD

Subjects

Data from the 66 undergraduate students described in the General Method section were used.

Measures and Procedure

Five measures, which are described in detail in the General Method section, were used: 1) reading comprehension, 2) listening comprehension, 3) domain-specific knowledge, 4) decoding skill, and 5) vocabulary skill. Separate reading comprehension, listening comprehension, and domain-specific knowledge measures were constructed for the two knowledge domains of astronomy and computers. Procedures for administering these measures are outlined in the General Method section.

Composite scores were used to represent decoding skill and domain-specific knowledge. The construction of those composite scores is described in Chapter Two. Two measures were used to represent the language comprehension variable: listening comprehension scores from astronomy or computer conditions, and the vocabulary subtest of the Wechsler Adult Intelligence Scale - Revised. Each of these measures has been used in the past to represent language comprehension skill (see Gough & Tunmer, 1986, or Hoover & Gough, 1990, for a discussion of the use of both listening comprehension and vocabulary knowledge as a measure of language comprehension skill). The listening comprehension measure is often preferred, the argument being that the language comprehension skills required for listening and reading comprehension are identical (Gough & Tunmer, 1986; Kintsch & van Dijk, 1978). However, in this case, the listening comprehension measure may not be the best measure to use to represent language comprehension skill. The listening comprehension measures used in this study were confounded with domain-specific knowledge since the passages used to evaluate

listening comprehension were on specific topics, i.e., astronomy or computers.[2] In addition, the reliability of the listening comprehension measures was quite poor (for astronomy listening comprehension, Chronbach's Alpha = .55; for computer listening comprehension, Chronbach's Alpha = .38). Poor reliability in a predictor increases chances of either a false negative or false positive result, i.e., of finding a significant effect of listening comprehension where there is none, or of finding an insignificant effect of listening comprehension where there is one. In contrast, the vocabulary measure has very high reliability (Chronbach's Alpha = .96) and is not confounded with knowledge of astronomy or computer domains.

RESULTS

A model testing procedure was used to contrast a model without domain-specific knowledge to one in which domain-specific knowledge had a direct effect on reading comprehension skill (Aiken & West, 1991). In the first test, the model

$$Rc = d + c$$

was compared to a model

$$Rc = d + c + k$$

which included domain-specific knowledge. In these models *rc* represents reading comprehension skill, *d* decoding skill, *c* language comprehension skill, and *k* domain-specific knowledge. In the second test, the additive model,

$$Rc = d + c + k$$

was compared to a full model

$$Rc = d + c + k + (dxc) + (dxk) + (cxk) + (dxcxk)$$

in order to determine whether an additve model or a combined additive/multiplicative model best described the relationship among decoding skill, language comprehension and domain-specific knowledge. In order to examine possible multiplicative relationships, interactions were

[2]Recall that the reading and listening passages used in this study are the same as those used by Bell and Perfetti (1994) and Peterson (1993). Thus, for those studies as well, domain-specific knowledge was confounded with listening comprehension skill.

Intercorrelations among variables

	1.	2.	3.	4.	5.	6.	7.
1. Astronomy reading comprehension							
2. Astronomy listening comprehension	.43						
3. Astronomy knowledge	.44	.43					
4. Computer reading comprehension	.24	.45	.08				
5. Computer listening comprehension	.47	.39	.35	.32			
6. Computer knowledge	.34	.44	.47	.49	.42		
7. WAIS-R Vocabulary	.34	.31	.30	.21	.32	.29	
8. Decoding skill	-.20	-.21	-.25	-.28	-.32	-.24	-.31

Note: $r > .24$ are significant at $p < .05$.

Table 5.2

tested in an hierarchical way, i.e., a test of the significance of the 3-way interaction, followed by a test of the significance of the 2-way interactions (Aiken & West, 1991).

Two analyses were conducted for each of the astronomy and computer conditions: one in which the WAIS-R vocabulary measure was used to represent language comprehension skill, and one in which the listening comprehension measure was used to represent language comprehension skill. In both cases, all variables were standardized. Table 5.2 provides the correlations among the variables.

Table 5.3 summarizes the results of hierarchical regression analyses conducted in the astronomy and computer conditions using the vocabulary measure as a measure of language comprehension skill. In both conditions, the additive combination of decoding skill and language comprehension skill significantly predicted reading comprehension. In both domains, domain-specific knowledge was a significant predictor of reading comprehension after decoding and language comprehension skill had been entered (for astronomy condition: $F(2,63)=9.53$, $p=.003$; computer condition: $F(2,63)=14.43$, $p=.0003$). Interaction terms did not add

Including Domain-specific Knowledge as a component of reading comprehension skill: Hierarchical regression analyses using the WAIS-R Vocabulary subtest as a measure of general language comprehension skill

Step	R^2	R^2 Change	F	Significance of F
Astronomy Condition				
1. Decoding + language comprehension ($d + c$)	.12		4.50	.01
2. Domain-specific knowledge (k)	.24	.12	9.64	<.01
3. All 2-way interactions	.28	.04	1.09	n.s.
4. 3-Way interaction	.29	.01	.78	.38
$Rc = -.05d + .22c + .12k^*$				
Computer Condition				
1. Decoding + language comprehension ($d + c$)	.10		3.36	.04
2. Domain-specific knowledge (k)	.27	.17	14.43	<.01
3. All 2-way interactions	.27	.00	.16	n.s.
4. 3-Way interaction	.27	.00	.00	.99
$Rc = -.09d + .03c + .14k^*$				

$^*p < .01$

Table 5.3

significant variance to the equations in either the astronomy or computer conditions, suggesting that the relationship among variables is additive rather than multiplicative.

Table 5.4 summarizes the results of hierarchical regression analyses conducted in the astronomy and computer conditions using the listening comprehension measures as a measure of language comprehension skill. In both conditions, the additive combination of decoding skill

and language comprehension skill significantly predicted reading comprehension. In both domains, domain-specific knowledge was a significant predictor of reading comprehension after decoding and language comprehension skill had been entered (for astronomy condition: $F(2,63)=5.99$, $p=.02$; computer condition: $F(2,63)=11.63$, $p=.001$). Interaction terms did not add significant variance to the equations in either the astronomy or computer conditions, again suggesting that the relationship among variables is additive rather than multiplicative.

Including Domain-specific Knowledge as a component of reading comprehension skill: Hierarchical regression analyses using listening comprehension as a measure of general language comprehension skill

Step	R^2	R^2 Change	F	Significance of F
Astronomy Condition				
1. Decoding + language comprehension ($d + c$)	.20		7.95	<.01
2. Domain-specific knowledge (k)	.27	.07	5.99	.02
3. All 2-way interactions	.28	.01	.11	n.s.
4. 3-Way interaction	.28	.00	.21	.65
$Rc = -.04d + .29c^* + .10k^*$				
Computer Condition				
1. Decoding + language comprehension ($d + c$)	.14		5.02	.01
2. Domain-specific knowledge (k)	.27	.13	11.63	<.01
3. All 2-way interactions	.32	.05	1.24	n.s.
4. 3-Way interaction	.32	.00	.07	.79
$Rc = -.08d + .10c + .13k^*$				

* $p < .03$

Table 5.4

An examination of the regression equations reflecting the additive model, i.e., $c = d + c + k$, displayed in Tables 5.3 and 5.4 provides additional information about the relationship of the components to reading comprehension. The pattern of relationships is the same across both the astronomy and computer conditions. Although the effect did not reach significance, the negative coefficient for decoding indicates that faster decoding times were associated with better reading comprehension. Higher language comprehension skills and domain-specific knowledge were also associated with better reading comprehension skill. It is noteworthy that, when all three components are considered together in predicting reading comprehension for fluent adult readers, only domain-specific knowledge adds significant unique variance in all conditions and using both measures of language comprehension skill.[3] Taken together, these results support an additive model which includes decoding skill, language comprehension skill, and domain-specific knowledge as components of reading comprehension skill.

DISCUSSION

The results of this study demonstrate the importance of domain-specific knowledge to the reading comprehension performance of fluent adult readers. As Tables 5.3 and 5.4 summarize, decoding skill and language comprehension make significant contributions to reading comprehension, but so too does domain-specific knowledge. Indeed, as the regression equations in Tables 5.3 and 5.4 depict, domain-specific knowledge is the only variable to consistently contribute unique significant variance across both knowledge domains and using both vocabulary skill and listening comprehension as language comprehension measures. This is a finding which is quite consistent with the results of other research which have also found that domain-specific knowledge predicts the reading comprehension performance of fluent adult readers better than other component processes (Haenggi & Perfetti, 1996; Peterson, 1993).

The model implied by the Simple View of reading (Figure 5.1) was disconfirmed. The

[3]The only other significant predictor of reading comprehension was the astronomy listening comprehension measure in the astronomy condition (Table 5.4).

fact that domain-specific knowledge added significant variance to reading comprehension skill after the addition of a language comprehension variable demonstrates that domain-specific knowledge is not an effect mediated by language comprehension skill, the prediction made by the Simple View of reading (Figure 5.1). In addition to finding that domain-specific knowledge is a significant predictor of reading comprehension skill for fluent adult readers, the results supported an additive as opposed to a multiplicative or combined additive/multiplicative model of reading comprehension skill. The addition of 2 and 3 way interaction terms did not add significant variance in any conditions or analyses.

The results also suggest that domain-specific knowledge had a direct unique contribution to make to a reading comprehension measure that tapped primarily text-based or basic comprehension processes, a finding which is inconsistent with the Verbal Efficiency/Construction-Integration models of reading comprehension (Figures 5.2 and 5.3). As outlined in the General Method section, the listening and reading comprehension measures were comprised of questions which tapped information explicitly stated in the text, and thus encouraged the use of text-based or basic reading comprehension processes.[4] However, neither the Verbal Efficiency or Construction-Integration models were directly assessed. A test of the role of domain-specific knowledge according to Verbal Efficiency and Construction-Integration models would require a study which includes two comprehension measures, one which assesses basic meaning construction and another which assesses inferential processes or situation modelling. In addition, a more sophisticated statistical method than heirarchical regression may be needed, e.g., LISREL or Amos, one which could accommodate two criterion variables and a variety of relationships among predictor variables. However, as will be discussed in the last chapter, a two-tier conception of reading comprehension may not be

[4]Recall that while all the astronomy comprehension questions covered information explicitly stated in the text, 1 question from the *Database* passage and 1 question from the *Bus* passage may have required the reader to integrate prior knowledge with information covered in the passage, i.e., relied on the construction of a situation model rather than simply a text-based model. Data from the computer condition were reanalyzed using only those questions based on information explicitly covered in the text. Results obtained replicated the results reported in Tables 5.3 and 5.4.

required to explain reading comprehension performance. If instead of a two-tier conception of reading comprehension, a one-tier conception is assumed, the present results are straightforward: domain-specific knowledge has a direct, independent contribution to make to the reading comprehension of fluent adult readers.

CHAPTER SIX

The Role of Domain-specific Knowledge in the Reading Comprehension Skill of Adults with Reading Disability

Reading disability is a subtype of learning disability that is characterized by specific deficits in the processing of written text. More specifically, phonological processing deficits (Siegel, 1994; Stanovich, 1988; Wagner & Torgesen, 1987) have been identified as the core difficulty of reading disability. Phonological processing deficits, namely weakly developed phonemic awareness skills, hamper the development of decoding skills, i.e., the ability to associate letters and spelling patterns with their respective sounds, which in turn inhibits the development of fluent, efficient word recognition skills. Studies of adults with reading disabilities reveal that relative weaknesses in phonological processing, decoding and word recognition skills persist into adulthood (Bruck, 1990) and are evident in those who attend post-secondary institutions (Shafrir & Siegel, 1994).

Interpreted within the framework of the models of reading comprehension outlined in previous chapters, reading disability involves difficulties with decoding skills. For example, according to the Simple View of reading, dyslexia represents a deficit in the *d* or decoding variable of the equation, $rc = d \times c$ (Gough & Tunmer, 1986). According to Verbal Efficiency Theory, a failure to acquire fluent, automatic processing of words means that resources that could be devoted to comprehension processes are involved in lexical access. The lexical access processes of reading disabled children and adults are less efficient than their non-disabled counterparts and thus their comprehension suffers (Perfetti, 1985).

Although difficulties in language comprehension processing skills can accompany a reading disability, it is felt by a number of researchers that these difficulties are not core deficits in reading disability, but rather are secondary to the phonological processing difficulties required to develop decoding and word recognition skills. For example, Perfetti (1985) argues that while the syntactic processing skills of many reading disabled children are immaturely developed compared to their peers, the development of syntactic processing abilities may be

"...considerably modified by reading and academic learning"(p. 195). In other words, difficulty in the development of word recognition skills can result in less access to written materials, and thus to less opportunity to develop language comprehension skills. Stanovich (1986; Stanovich & West, 1989) has described this phenomenon as a Matthew Effect where those with good decoding skills develop better language comprehension skills while those with less well developed decoding skills also have less exposure to printed materials and thus acquire less language comprehension skills. In one study of adult readers, print exposure - measured as the number of authors recognized by subjects - was positively correlated with phonological processing abilities: those with better phonological processing skills had more print exposure (Stanovich & West, 1989). Thus, for adults with reading disability, who may have had less exposure to written text, language comprehension skills as well as decoding skills may be less well developed than their non-disabled peers.

Like language comprehension skill, a lack of domain-specific knowledge relative to age peers may be a secondary result of reading disability (Snider & Tarver, 1987). A recurrent finding is that while less-skilled readers answer textually explicit comprehension questions as well as skilled readers, less-skilled readers demonstrate less ability to answer textually implicit or inferential comprehension questions than skilled readers (Holmes, 1983; Taft & Leslie, 1985). Since textually implicit questions require readers to use prior knowledge to help them draw inferences about information not explicitly stated in the text, one interpretation of this difference in ability to answer inferential questions is that some poor readers may lack the necessary prior knowledge to draw the correct inferences (Snider, 1989). Indeed, Snider (1989) demonstrated that when adolescents with reading disability were given direct instruction in the topic knowledge covered in a set of passages, their ability to answer textually explicit as well as textually implicit comprehension questions was significantly better than a control group of non-disabled age peers who had not received knowledge instruction. In another study, topic familiarity - knowledge of the topic of the text - had a facilitative effect on the comprehension performance of children with and without reading disability (Carr & Thompson, 1996). The results of these studies indicate that domain-specific knowledge may be as important a factor

in the reading comprehension of children and adolescents with reading disability as it is in the reading comprehension of non-disabled children and adults.

A number of studies have demonstrated that domain-specific knowledge may vary greatly in skilled and less-skilled readers, and that high levels of domain-specific knowledge can be used to compensate for less well developed reading or general language comprehension skills. For example, Adams, Bell and Perfetti (1995) found that the text comprehension of children in Grades 4, 5, 6, and 7 was affected by both reading skill and domain-specific knowledge (in this case, knowledge of football). Skilled readers answered more comprehension questions correctly than less-skilled readers and high knowledge readers performed better than low knowledge readers. In other words, less-skilled/high knowledge readers used their higher football knowledge to compensate for less-skilled reading ability and skilled/low knowledge readers used their skilled reading ability to compensate for low football knowledge. In another study, differences in general language comprehension ability did not affect the text comprehension or recall of children in Grades 3, 5, and 7 (Schneider, Korkel, & Weinert, 1989) when differences in domain-specific knowledge were included in the analysis.[1] Soccer experts outperformed soccer novices at every grade level. However, the comprehension performance of high aptitude readers was similar to that of low aptitude readers. Domain-specific knowledge and not general language comprehension ability accounted for reading comprehension performance differences.

These two studies demonstrate that domain-specific knowledge may enable less-skilled readers to perform better than expected in domains with which they are familiar. In the Schneider, Korkel and Weinert (1989) study, soccer experts had comparable levels of soccer knowledge regardless of ability level and age suggesting that levels of domain-specific

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[1]Schneider, Korkel, and Weinert (1989) used the term general aptitude and not general language comprehension ability. However, the measure they used to determine aptitude was the verbal aptitude component of a German cognitive ability test, i.e., one involving the assessment of "...verbal comprehension as well as verbal reasoning skills." (pg. 307). Thus, their aptitude test is, in fact, a measure of general language comprehension, a term which is more consistent with the context of this discussion.

knowledge may vary independently of aptitude or reading ability. This kind of reasoning may apply not only to less-skilled readers in general, but also to those with reading disability. While the decoding, general language comprehension skills, and general reading comprehension skills of those with a reading disability may be less well developed than their non-disabled peers, they may develop expertise in a number of domain-specific areas. When the content of a text falls within their areas of expertise, high levels of knowledge may enable persons with reading disability to compensate for weaker reading skills.

For many theorists, including those who support a Simple View of reading or Verbal Efficiency Theory, the differences between reading disabled readers and their non-disabled peers are quantitative in nature. That is, reading disabled readers have less decoding skill and may have less language comprehension skill than non-disabled readers, resulting in poorer comprehension performance (e.g., Perfetti, 1985; Siegel, 1989; Stanovich, 1988).

A recent study of adult readers supports this view. Bell and Perfetti (1994) selected participants so that they reflected the characteristics of either fluent adult readers, dyslexic adult readers, or 'garden variety' poor readers. The 'dyslexic' readers were ones who scored lower than fluent adult readers on the Nelson Denny Reading Test (ND) and on the verbal portion of the Scholastic Aptitude Test (SAT) but relatively well on the quantitative portion of the SAT. 'Garden variety' poor readers scored lower than fluent adult readers on the ND and both the verbal and quantitative portions of the SAT. Both the 'dyslexic' and 'garden variety' readers had slower word and pseudoword naming times than fluent adult readers. On listening comprehension and vocabulary measures, the fluent adult readers obtained higher scores than one or both of the reading delayed groups. In addition, the reading comprehension performance of the fluent adult readers was better than one or both of the reading delayed groups on a number of reading comprehension passages. In general, there was little difference in the performance of 'dyslexic' and 'garden variety' poor readers, supporting the view that both reading disability and poor reading ability fall at the lower end of a continuum of reading ability.

Differences in domain-specific knowledge between reading disabled and non-disabled

readers are also characterized as quantitative in nature. As the discussion above suggests, some theorists suggest that those with a reading disability may have acquired less knowledge than their non-disabled peers because of their reading disability. In contrast, other research suggests that domain-specific knowledge may vary independently of the more general skills related to reading comprehension performance, e.g., decoding and general language comprehension skills. Thus, within their areas of expertise, those with a reading disability may be able to use their domain-specific knowledge to compensate for less well developed decoding and general language comprehension skills.

Few studies have explored the contribution domain-specific knowledge may make to the reading comprehension performance of adults with a reading disability. In this study, the reading comprehension performance of fluent adult readers (NLD) was compared to that of adults with a reading disability (LD). Three questions were addressed:

1. Do LD university students perform less well than NLD students on the decoding, language comprehension, and reading comprehension measures reported in Chapter 2?

2. Is there a difference between the levels of astronomy and computer knowledge of LD versus NLD university students, i.e., do they have comparable levels of domain-specific knowledge in the areas of astronomy and computers?

3. Do decoding skill, language comprehension skill, reading rate and domain-specific knowledge play the same roles in predicting the reading comprehension performance of LD university students as they do with NLD students?

The first question addresses the common finding that LD children and adults perform less well than NLD children and adults on a variety of reading and reading related measures. It was expected that LD's would demonstrate slower decoding and reading times, less language comprehension skill, and less reading comprehension skill than their NLD counterparts. In addition, it was expected that they would perceive the reading passages to be more difficult than NLD readers.

With respect to the second question, two hypotheses can be generated from the

research reviewed above: 1) LD adults will demonstrate less domain-specific knowledge because of their history of reading difficulty, or 2) the range and variability of domain-specific knowledge will be comparable in the two groups. Since both the LD and NLD readers were students of the same post-secondary institution and were enrolled in similar programs, the second hypothesis seemed more likely, i.e., that LD and NLD university students would have developed comparable levels of expertise in both astronomy and computer domains. In other words, it was expected that the range and variability of astronomy and computer knowledge of LD and NLD students would be comparable.

The third question extends the results of research reported in Chapters 4 and 5 to include LD readers. In Chapter 5, it was demonstrated that only domain-specific knowledge was a significant predictor of reading comprehension performance in both the astronomy and computer conditions. Decoding skill and general language comprehension did not add significant variance after the effects of domain-specific knowledge were partialled out. In Chapter 4, reading rate was found to be a significant predictor of reading comprehension performance in the astronomy condition when included in a regression equation involving general language comprehension and domain-specific knowledge. In both the astronomy and computer conditions, slower reading rates were associated with better reading comprehension after the effects of general language comprehension and domain-specific knowledge were controlled. However, these results were based on a sample of fluent adult readers attending university who may be expected to demonstrate high levels of decoding and general language comprehension skill. In contrast, a sample of LD university students would have less skill in the decoding and language comprehension areas. Consequently, the variables of decoding skill, language comprehension skill, reading rate, and domain-specific knowledge may play different roles for a group of LD readers compared to NLD readers.

It was expected that while decoding skill was not a significant predictor of reading comprehension for NLD readers, it may be significant for LD readers. For example, according to Verbal Efficiency Theory, LD readers may need to devote more cognitive resources to decoding and lexical access processes and thus have less resources available for higher order

comprehension processes. Thus, it was expected that decoding efficiency would be a greater factor in the reading comprehension performance of LD readers compared to NLD readers. It was expected that the role of the remaining variables would be the same for LD and NLD readers. More specifically, it was expected that domain-specific knowledge would be a significant predictor of reading comprehension for both LD and NLD readers. Slower reading rates would be associated with higher reading comprehension performance for both LD and NLD readers. Higher levels of language comprehension skill would be associated with better reading comprehension for both NLD and LD readers.

METHOD

Subjects

Data from 66 fluent adult readers and 20 adult readers with reading disability were used. See the General Method section for more information on the characteristics of these subjects.

Measures and Procedure

Six measures, which are described in detail in the General Method section, were used: 1) reading comprehension, 2) domain-specific knowledge, 3) decoding skill, 4) vocabulary skill, 5) reading rate, and 6) difficulty ratings of reading passages. Separate reading comprehension, reading rate, difficulty ratings, and domain-specific knowledge measures were obtained for the two knowledge domains of astronomy and computers. Procedures for administering these measures are outlined in the General Method section.

RESULTS

Comparison of LD and NLD readers on reading and reading-related measures

Several t-tests were conducted to compare the learning disabled (LD) group with the non-learning disabled group (NLD) on the decoding, vocabulary, reading comprehension, and reading rate measures. Effect sizes as well as statistical measures of significant differences are reported for the vocabulary and reading comprehension measures in order to provide a

qualitative assessment of the significance or 'meaningfulness' of obtained differences. Effect sizes were also used to estimate the power of obtaining a difference so that the reliability of statistical results could be evaluated. For each t-test, Levene's test for equality of variances between the two groups was conducted. Results from Levene's test will not be reported unless variances of the two groups on a particular measure were not equal. For the difficulty ratings, a repeated measures design was used to compare possible differences between passage type (astronomy vs computer) as well as between groups.

Decoding Measures: Table 6.1 contains a summary of the means and standard deviations of decoding measures by group. Variability in accuracy and response times on both the word naming and pseudoword naming tasks was much greater for the LD group than the NLD group. As a result, Levene's test for equality of variances among the two groups was significant for all decoding measures (for word naming accuracy: $F(1, 84) = 22.07, p < .001$; for word naming response times: $F(1,84) = 23.04, p < .001$; for pseudoword naming accuracy: $F(1,84) = 6.45, p < .02$; for pseudoword naming response times: $F(1,84) = 19.39, p < .001$).

Mean decoding skills of NLD and LD groups

	NLD	LD
Word naming errors	1.50 (1.19)	3.30 (2.27)
Pseudoword naming errors	3.68 (2.25)	8.55 (4.11)
Word naming response time (ms)	560 (87)	725 (181)
Pseudoword naming response time (ms)	708 (156)	1104 (497)

Table 6.1

LD subjects were significantly less accurate than NLD subjects on both the word naming ($t(22.26) = -3.4, p = .003$) and pseudoword naming tasks ($t(22.57) = -5.07, p < .001$). Similarily, the response times of LD subjects were significantly slower on both the word naming ($t(21.64) = -3.95, p = .001$) and pseudoword naming tasks ($t(20.15) = -3.50, p = .002$).

General Language Comprehension Measure: Table 6.2 contains a summary of the means, standard deviations, and effect size of the NLD and LD groups on the vocabulary measure. On the WAIS-R Vocabulary subtest the raw scores of the LD group were significantly lower than those of the NLD group ($t(84) = 3.86, p < .001$).

Reading Comprehension Measures: Table 6.3 contains a summary of means, standard deviations, and effect sizes for the astronomy and computer reading comprehension measures. On both of the reading comprehension measures, the LD group demonstrated less comprehension than the NLD group. However, the difference between LD and NLD groups in the astronomy condition was not significant ($t(84)=1.32, p = .19$) while the difference between the LD and NLD groups in the computer condition was significant at the .05 level of significance ($t(84) = 2.00, p = .049$). The effect sizes for the difference in astronomy (effect size = .35) and computer (effect size = .50) reading comprehension performance could be considered moderate in size (Cohen, 1988), and thus to reflect a meaningful difference in comprehension performance. However, there was insufficient power to detect a significant difference in the astronomy condition (power = .27).

Mean vocabulary skills of NLD and LD groups

	NLD	LD	Effect Size
WAIS-R Vocabulary raw score	50.55 (6.91)	43.70 (7.09)	.93

Table 6.2

Mean reading comprehension scores (s.d.) for NLD and LD groups

	NLD	LD	Effect Size
Astronomy condition	5.79 (2.16)	5.05 (2.26)	.35
Computer condition	5.79 (2.25)	4.65 (2.16)	.50

Table 6.3

Reading Rate: The rate at which LD and NLD groups read the reading passages was compared. The LD group read the astronomy and computer passages significantly more slowly than the NLD group (for astronomy passages: $t(84)=4.41, p < .001$; for computer passages: $t(84)=4.47, p < .001$). See Table 6.4 for a summary of mean reading rate in words per minute and standard deviations.

Ratings of Difficulty: The NLD and LD groups rated how difficult to understand they found the astronomy and computer reading passages. A MANOVA was conducted with group (NLD versus LD) as a between subjects factor and knowledge domain (astronomy versus computer) as a within subjects factor. There was a main effect of group

Mean reading rates in words per minute (s.d.) for NLD and LD groups

	NLD	LD
Astronomy condition	223 (53)	166 (42)
Computer condition	193 (41)	148 (34)

Table 6.4

Mean difficulty ratings (s.d.) for NLD and LD groups

	NLD	LD
Astronomy condition	2.17 (.85)	2.60 (.82)
Computer condition	3.17 (.71)	3.55 (.60)

Table 6.5

($F(1,84)=77.88, p < .001$) and of domain ($F(1,84)=6.27, p < .01$). The interaction of group x domain was not significant ($F(1,84)=.05, p=.82$). Both groups rated the computer passages as more difficult to understand than the astronomy passages. The LD group rated both the astronomy ($t(84)=-2.17, p=.03$) and computer passages ($t(84)=-2.01, p<.05$) as significantly more difficult to understand than the NLD group (see Table 6.5).

Comparing the domain-specific knowledge of LD and NLD readers

Tables 6.6 and 6.7 contain summaries of means, standard deviations, and effect sizes for the LD and NLD groups on domain-specific knowledge measures in the astronomy and computer conditions, respectively. Levene's test of equality of variances was applied to all t-test comparisons. Scores for the NLD group were significantly more variable than the LD group ($F(84)=5.89, p = .02$) on the astronomy prior knowledge multiple choice test. Variances on all other domain-specific measures were comparable across the two groups.

Within the astronomy condition, the LD group's scores were significantly lower than the NLD group's scores on the prior knowledge multiple choice test ($t(38.78)= 2.98, p = .005$). There were no significant differences between the LD and NLD groups on any other astronomy knowledge measure (for semantic decision accuracy: $t(84)=1.12, p = .27$; for astronomy courses taken: $t(84) = .48, p = .62$; for self-ratings of knowledge and interest in astronomy: $t(84) = 1.57, p = .12$).

Effect sizes for the prior knowledge multiple choice test and semantic decision accuracy

measure were large (Cohen, 1982), and power in both cases was .80 or greater, suggesting adequate power to detect a significant difference. Thus, the results for these two measures can be considered reliable. The effect size for the self-ratings of knowledge and interest in astronomy was moderate in size, although power (.34) was insufficient to detect a significant difference. In other words, given sufficient power, a significant difference between groups on the self-rating measure may have been obtained. The very small effect size for the number of courses in astronomy (.12) suggests that there was no meaningful difference between groups on this measure.

Within the computer condition, the LD group's scores were significantly lower than the NLD group's scores on the prior knowledge multiple choice test ($t(84) = 2.30, p = .02$). The LD group's accuracy on the semantic decision task was also significantly lower than the NLD group's accuracy ($t(84) = 2.12, p = .04$). There were no significant differences between the LD and NLD groups on either the number of computer courses taken ($t(84) = .54, p = .59$) or self-ratings of knowledge and interest in computers ($t(84) = .48, p = .63$). The very small effect

Mean scores (s.d.) on domain-specific knowledge measures in the astronomy condition for the NLD and LD groups

	NLD	LD	Effect Size
Prior knowledge multiple choice test	14.61 (5.67)	10.95 (4.52)	.71
Semantic decision accuracy	12.76 (1.22)	12.40 (1.35)	.36
Number of astronomy courses taken	.62 (1.02)	.50 (.89)	.12
Self-ratings of knowledge and interest in astronomy	8.79 (3.04)	7.60 (2.70)	.40

Table 6.6

Mean scores (s.d.) on domain-specific knowledge measures in the computer condition for the NLD and LD groups

	NLD	LD	Effect Size
Prior knowledge multiple choice test	17.89 (4.85)	15.05 (4.80)	.60
Semantic decision accuracy	10.85 (1.46)	10.05 (1.54)	.52
Number of computer courses taken	2.48 (3.46)	2.00 (3.83)	.14
Self-ratings of knowledge and interest in computers	9.08 (3.05)	8.70 (3.05)	.13

Table 6.7

sizes for the number of computer courses taken (.14) and self-ratings of knowledge and interest in computers (.13) suggests that there was no meaningful difference between groups on this measure.

Although the LD group obtained significantly lower scores than the NLD group on the astronomy multiple choice test, the computer multiple choice test, and the computer semantic decision accuracy measure, all three of the measures required the use of word recognition and language comprehension skills and it is possible that proficiency in decoding and language comprehension skills was confounded with knowledge. As reported above, the LD group was significantly poorer on all decoding tasks and the vocabulary measure, and thus, their poorer performance on these three domain-specific knowledge measures may have been a consequence of weaker decoding and/or language comprehension skills rather than the result of a difference in domain-specific knowledge.

In order to test the hypothesis that group differences on the two prior knowledge multiple choice tests and the computer semantic accuracy decision accuracy measure could be attributed to decoding and/or language comprehension skill rather than domain-specific knowledge, the following regression equations were used:

$$Dk = d + g$$

$$Dk = c + g$$

In these two equations, *dk* represents a domain-specific knowledge measure, i.e., either astronomy multiple choice test, computer multiple choice test, or computer semantic decision accuracy measure, *g* represents the group variable (i.e., LD versus NLD), *d* represents decoding skill, and *c* represents language comprehension skill. Decoding skill consisted of a composite of word naming and pseudoword naming times. Word naming and pseudoword naming times were standardized and the standardized scores for each subject were added together to form a composite decoding skill measure. Standardized raw scores on the WAIS-R Vocabulary subtest were used to reflect language comprehension skill. Separate regression analyses were conducted for each domain-specific knowledge measure.

The two equations, $dk=d+g$ and $dk=c+g$, can be considered analogous to using decoding skill or language comprehension skill as covariates. Results of t-tests reported above indicate that the group variable will be significant when entered on its own into a regression equation predicting domain-specific knowledge, i.e., $dk=g$. If the group variable remains significant after the effects of decoding skill or language comprehension skill have been partialled out, then group differences on the domain-specific knowledge measures could not be entirely attributable to decoding or language comprehension skill differences. If, however, the group variable was no longer a significant predictor, then differences on the domain-specific knowledge measures could be attributable to decoding or language comprehension skill differences as well as differences in domain-specific knowledge.

Using raw scores on the astronomy prior knowledge multiple choice measure as the criterion variable, the group variable was a significant predictor when entered on its own, reflecting the fact that the LD group obtained significantly lower scores than the NLD group

on the astronomy multiple choice test (see Table 6.8). However, with the addition of decoding to the equation, the group variable was no longer significant ($t(84)=-1.58$, $p=.12$). Similarily, when vocabulary was added to the regression equation, i.e., $dk=c+g$, group differences were no longer significant ($t(84)=-1.24$, $p=.22$). Either decoding skill or vocabulary knowledge could account for the differences between the LD and NLD groups in their performance on the astronomy multiple choice test. In other words, differences in either decoding skill or vocabulary skill, as well as differences in domain-specific knowledge, could account for group differences on the astronomy multiple choice test. Table 6.8 provides a summary of these regression analyses.

When raw scores on the computer prior knowledge multiple choice test were used as the criterion variable, the group variable was a significant predictor when added on its own to the equation, i.e., $dk=g$, reflecting the finding that the LD group obtained significantly lower scores than the NLD group on this measure (see Table 6.8). However, with the addition of either decoding skill or vocabulary skill, the LD and NLD groups were no longer significantly different. See table 6.8 for a summary of F values and corresponding p values for group differences in both cases. Thus, for this measure, as well as for the corresponding measure in the astronomy domain, differences in either decoding skill or vocabulary skill, as well as differences in domain-specific knowledge, could account for group differences in performance on the computer multiple choice test.

When number of errors on the computer semantic decision accuracy measure were used as the criterion variable, the group variable was a significant predictor when added on its own to the equation, i.e., $dk=g$, repeating the finding that the LD group obtained significantly lower scores than the NLD group on this measure (see Table 6.8). However, with the addition of either decoding skill or vocabulary skill, the LD and NLD groups were no longer significantly different. See table 6.8 for a summary of F values and corresponding p values for group differences in both cases. Thus, differences in either decoding skill or vocabulary skill, as well as differences in domain-specific knowledge, could account for group differences in performance on the computer semantic decision accuracy measure.

Regression analyses comparing NLD and LD differences on selected domain-specific knowledge measures controlling for the effects of decoding and language comprehension skill

	F	Significance of F
Astronomy prior knowledge multiple choice test		
1. Group	6.96	.01
2. Group controlling for decoding skill	2.50	.12
3. Group controlling for vocabulary skill	1.54	.22
Computer prior knowledge multiple choice test		
1. Group	5.31	.02
2. Group controlling for decoding skill	1.74	.19
3. Group controlling for vocabulary skill	2.04	.16
Computer semantic decision accuracy measure		
1. Group	4.48	.04
2. Group controlling for decoding skill	1.51	.22
3. Group controlling for vocabulary skill	.88	.35

Table 6.8

Role of Domain-Specific Knowledge in the Reading Comprehension of LD versus NLD readers

In Chapter 5, the relationship among decoding skill (d), language comprehension skill (c), and domain-specific knowledge (k) in predicting reading comprehension performance was explored. It was found that a simple additive model

$$Rc = d + c + k$$

provided the best explanation of the way in which these three variables combined to predict reading comprehension in both the astronomy and computer domains. In both the astronomy and computer domains, domain-specific knowledge was the only variable to significantly predict reading comprehension skill, highlighting the importance of domain-specific knowledge to the reading comprehension performance of fluent adult readers. In addition, in Chapter 4, it was found that when reading rate (rr) was added to the equation, i.e.,

$$Rc = d + c + rr + k$$

better comprehension was associated with slower reading rates in both the astronomy and computer conditions.

In this set of analyses, the simple additive model, $Rc = d + c + rr + k$, was applied to LD readers as well as NLD readers. The question of interest is whether there are qualitative differences in the way in which decoding skill, language comprehension skill, reading rate, and domain-specific knowledge account for the reading comprehension performance of LD versus NLD readers. For instance, while decoding skill was not a significant factor in the reading comprehension performance of NLD or fluent adult readers (Chapter 5), it may be a significant factor for LD readers who demonstrated significantly slower word and pseudoword naming times. In order to test this hypothesis, interactions involving the group variable (g), i.e., dxg, cxg, $rrxg$, kxg, were added, one at a time, to the simple additive model, $Rc = d + c + rr + k$, to test whether there were qualitative differences in the way in which variables affected the reading comprehension performance of LD versus NLD readers. For example, to examine whether decoding skill differentially affected the reading comprehension of LD versus NLD readers the interaction term, dxg, was added to the equation

$$Rc = d + c + rr + k + g$$

to determine if it added significant variance. If the interaction term, *dxg*, added significant variance, then decoding skill had different effects on the reading comprehension performance of LD and NLD readers. Each of the interaction terms involving the group variable was tested in the same way, i.e., by adding each interaction term to the simple additive model to determine whether it added significant variance.

In these analyses, all predictor variables for the 66 NLD and 20 LD subjects were standardized. Standardized scores from the Vocabulary subtest of the WAIS-R were used as a measure of language comprehension and standardized scores of reading rates in words per minute were used as a measure of reading rate. The decoding and domain-specific knowledge measures were composite measures. To construct the composite decoding skill measure, the mean word and pseudoword naming time scores (from trimmed data) for each participant were converted to z-scores and the resulting z-scores were added together. For the composite measure of domain-specific knowledge, raw scores for each of the 4 individual measures - multiple choice test, semantic decision accuracy, number of domain-specific courses taken, and self-ratings of interest in and knowledge of domain - were converted to z-scores for each participant. The resulting z-scores were added together to comprise the composite measure of domain-specific knowledge. Separate analyses were conducted for the astronomy and computer conditions.

Table 6.9 contains a summary of regression analyses for the astronomy condition. The simple additive model accounted for 30% of the variance in reading comprehension performance. Decoding skill, vocabulary skill, domain-specific knowledge, and reading rate were all significant predictors of reading comprehension. Higher levels of vocabulary skill and domain-specific knowledge were associated with higher reading comprehension. Slower reading rates were also associated with higher reading comprehension.

Two interaction terms involving the group variable were significant when added to the simple additive model. The group x decoding and group x domain-specific knowledge interactions were significant, indicating significant differences in the way in which decoding and

Group differences in predicting reading comprehension performance in the astronomy condition: Regression analyses

	F	Sig of F
Main effects model:	6.91	< .001
$Rc = .11d^{a} + .39c^{*} + .12k^{*} - .24rr^{*} - .34g + .08$		
Group effects:		
1. Decoding skill *(dxg)*	3.81	.05
2. Language comprehension skill *(cxg)*	.06	.80
3. Reading rate *(rrxg)*	.47	.50
4. Domain-specific knowledge *(kxg)*	4.03	.05

$^{*}p < .05$; $^{**}p < .01$; $^{a}p < .06$

Table 6.9

domain-specific knowledge affected the reading comprehension of LD and NLD readers. In order to explore group differences, post-hoc tests were conducted in which regression equations were calculated for each group separately. Using this procedure, decoding skill had little effect on the reading comprehension performance of NLD readers ($t(65)=-.49, p=.63$) but was a significant predictor of reading comprehension for LD readers ($t(19)=2.42, p=.03$). In contrast, domain-specific knowledge was a significant predictor of reading comprehension for NLD readers ($t(65)=3.85, p<.01$) but not for LD readers ($t(19)=.10, p=.92$).

The effect of decoding skill on reading comprehension performance for LD readers is illustrated in Figure 6.1. Slower LD decoders (i.e., one standard deviation above the decoding mean) comprehended much less than faster LD decoders (i.e., one standard deviation below the decoding mean), and than their fast and slow NLD counterparts. Thus, slow inefficient decoding skill had a negative impact on the reading comprehension performance of LD readers.

Interaction of Decoding with Group (NLD vs LD)

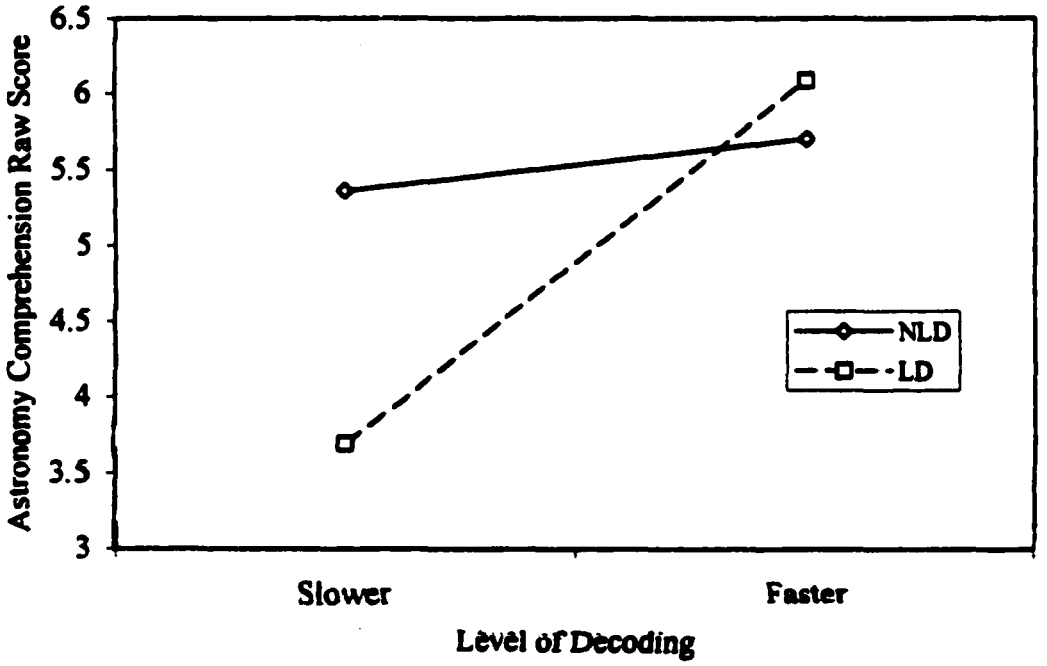

Figure 6.1

Figure 6.2 illustrates the interaction of group and domain-specific knowledge on reading comprehension performance in the astronomy condition. While higher astronomy knowledge (i.e., one standard deviation above the mean astronomy knowledge) was associated with better reading comprehension for the NLD group, astronomy knowledge had little effect on the reading comprehension performance of the LD group.

Table 6.10 provides a summary of regression analyses in the computer condition. The simple additive model accounted for 30% of the variance in reading comprehension performance. Only computer knowledge was a significant predictor of reading comprehension in the simple additive model ($t(84) = 4.61, p < .001$). None of the interaction terms added significant variance to the equation, indicating that there were no differences between the LD and NLD groups in terms of the way in which variables predicted reading comprehension in the computer condition.

Group differences in predicting reading comprehension performance in the computer condition: Regression analyses

	F	Sig of F
Main effects model:	6.92	< .001
$Rc = -.06d + .14c + .15k^{*} - .18rr - .21g + .05$		
Group effects:		
1. Decoding skill *(dxg)*	2.98	.09
2. Language comprehension skill *(cxg)*	.00	.96
3. Reading rate *(rrxg)*	.01	.93
4. Domain-specific knowledge *(kxg)*	.01	.92

$^{*}p < .01$

Table 6.10

Interaction of Astronomy Knowledge with Group (NLD vs LD)

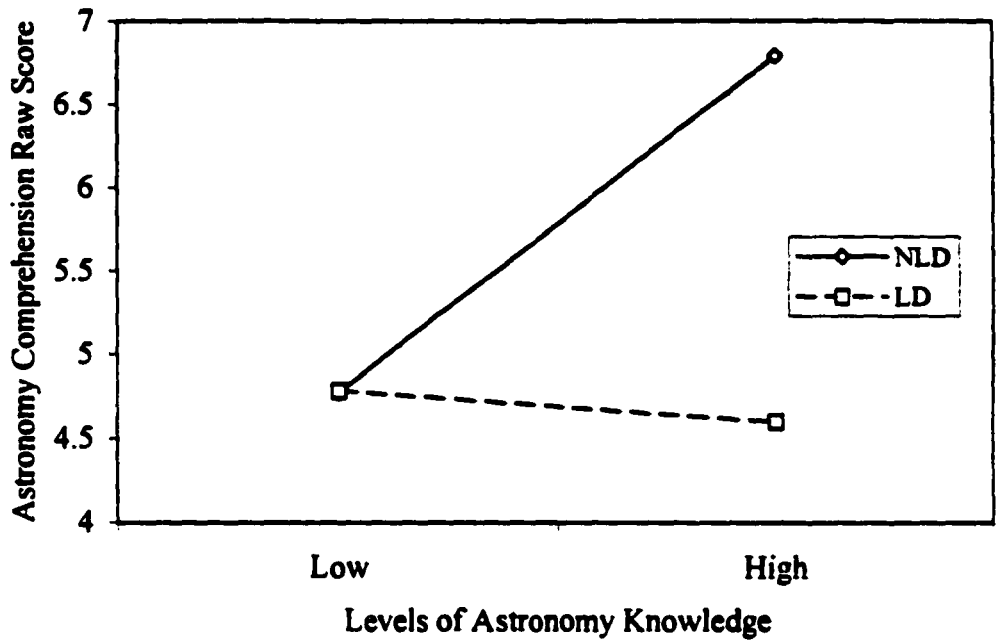

Figure 6.2

DISCUSSION

Three issues were addressed: 1) differences between LD and NLD groups on reading and reading related measures, 2) differences between LD and NLD groups on measures of domain-specific knowledge; and 3) differences between LD and NLD groups in the way in which decoding skill, language comprehension, reading rate, and domain-specific knowledge predicted reading comprehension performance. Expected differences between LD and NLD groups on the decoding, vocabulary, reading rate, and difficulty ratings were found. The LD group's word recognition and decoding skills were less accurate and they named words and pseudowords more slowly than the NLD group. The vocabulary skills of the LD group were significantly lower than those of the NLD group, although the means for both groups fell within average limits. The LD group read both the astronomy and computer passages more slowly than the NLD group. The LD group rated the astronomy and computer passages as more difficult to understand than the NLD group, although both groups rated the computer passages as more difficult than the astronomy passages.

There were significant differences in the reading comprehension performance of LD and NLD groups on the Nelson-Denny Reading Test measure of reading comprehension. While the LD group's reading comprehension accuracy was lower than the NLD group's on both the astronomy and computer reading comprehension measures, this difference was significant only in the computer condition. The failure to find a significant difference in the astronomy condition can be attributable to insufficient power. Bell and Perfetti (1994), using a longer version of the astronomy passages used in this study, found large significant differences between good and poor readers. However, in the Bell and Perfetti study, they used a 27 item comprehension measure as compared to the 10 item measure used here. Thus, their comprehension measure allowed for more variability in performance and thus for greater differences between groups.

Within the astronomy domain, the NLD and LD group were comparable on all domain-specific measures except the prior knowledge multiple choice test, where the NLD obtained significantly higher scores than the LD group. Within the computer domain, the NLD and LD

groups had similar exposure to computer science courses, and gave comparable ratings of interest and knowledge of computers. However, on measures tapping knowledge of computer science vocabulary (i.e., the semantic decision task), and computer concepts (i.e., the prior knowledge multiple choice test), the NLD group demonstrated significantly more knowledge than the LD group. However, the multiple choice test and semantic decision measures confounded reading skill with domain-specific knowledge, since the LD group, which has demonstrably weaker decoding and vocabulary skills, were required to demonstrate their knowledge via a reading measure. When the effects of decoding and/or language comprehension skill were controlled, differences between the LD and NLD groups on the prior knowledge multiple choice tests and the computer semantic decision task disappeared, suggesting that differences on these tasks were a function of differences in decoding and/or language comprehension skill may overlap with differences in domain-specific knowledge.

Importantly, on the two measures in which decoding skill and language comprehension skill were not confounded with domain-specific knowledge, the LD and NLD groups were comparable. Both groups had comparable exposure to astronomy and computer knowledge in terms of number of courses taken. In addition, there were no differences in the way in which LD and NLD readers perceived their knowledge of and interest in astronomy and computer domains.

The role of domain-specific knowledge in predicting reading comprehension performance was different for LD and NLD readers in the astronomy condition. For NLD readers, high levels of astronomy knowledge had a facilitative effect on reading comprehension. However, astronomy knowledge did not affect reading comprehension performance for LD readers: their comprehension scores were similar regardless of level of astronomy knowledge. While decoding skill had little effect on the reading comprehension of NLD readers, slower decoding times were associated with lower reading comprehension scores for LD readers. Thus, in the astronomy condition, decoding skill appeared to play a significant role in the reading comprehension of LD readers whereas domain-specific knowledge was a significant factor in the reading comprehension of NLD readers.

The pattern of results for LD readers in the astronomy condition is consistent with Verbal Efficiency Theory. For LD readers with slower decoding times, reading comprehension suffered, suggesting that the cognitive resources they devoted to lexical access detracted from their ability to conduct higher order processing. Indeed, the fact that domain-specific knowledge had no effect on the reading comprehension performance of LD readers provides further support for the Verbal Efficiency model. Even though LD and NLD readers had comparable levels of astronomy knowledge, LD readers could not take advantage of that knowledge because of the resources they were devoting to lexical access. However, Verbal Efficiency Theory does not explain the pattern of results for NLD readers. According to the theory, inefficient lexical access should be a factor in the reading comprehension performance of both LD and NLD readers: increases in decoding skill should be associated with increases in reading comprehension performance. Instead, the results from the astronomy condition for NLD readers suggest that once decoding skills have reached fluency, decoding skill ceases to be a factor in reading comprehension performance. Indeed, the effect size for the difference between the naming times of LD and NLD readers exceeded 1 standard deviation indicating that, for the most part, the decoding skill of LD readers fell below the range of scores for NLD readers. In other words, the LD sample was qualitatively different from the NLD sample in terms of decoding skill. Consequently, Verbal Efficiency Theory may apply to LD adult readers but not to NLD or fluent adult readers. For fluent adult readers, domain-specific knowledge may be the only significant determinant of reading comprehension performance.

In the computer condition, higher levels of computer knowledge were associated with better reading comprehension for both LD and NLD readers. Indeed, only domain-specific knowledge was a significant predictor of reading comprehension performance, a finding which replicates the results reported in Chapter 5. In other words, the addition of 20 LD subjects had no impact on the overall pattern of results in the computer condition.

It is not immediately evident why there were differences in the pattern of results in the astronomy and computer conditions. One possibility is related to the perceived difficulty of the astronomy versus computer reading passages. Both LD and NLD readers rated the

computer passages as significantly more difficult to understand than the astronomy passages even though both passages had the same level of readability using readability measures. It may be that the most difficult texts are difficult to understand precisely because of the level of domain-specific knowledge required to comprehend them, and under these circumstances variations in decoding skill or general language comprehension are irrelevent.

CHAPTER SEVEN
General Discussion

In the introduction, three models of reading comprehension, the Simple View of reading, Verbal Efficiency Theory, and the Construction-Integration model, were described. These three models make certain claims about the role of domain-specific knowledge in reading comprehension performance. With respect to the role of domain-specific knowledge in lower order processing such as lexical access, they all agree that domain-specific knowledge should have no role. Verbal Efficiency Theory argues that lower order or basic processes are implicated in on-line processing, and thus, domain-specific knowledge should have no impact on the on-line processing of text either. For all three models, the role of domain-specific knowledge is restricted to higher order processing demands, such as the demands of drawing inferences or constructing a situation model. For the Simple View of reading, domain-specific knowledge could have an indirect effect on reading comprehension via general language comprehension skills. Thus, domain-specific knowledge is not an important factor in basic comprehension or meaning construction, but rather applied indirectly, or to suit a particular reading purpose.

The results presented in previous Chapters challenge these claims. In the model of reading comprehension tested in Chapter 5, it was demonstrated that domain-specific knowledge had a direct effect on reading comprehension performance, and this effect was replicated across two different knowledge domains. Domain-specific knowledge played a role in basic meaning construction and its effect was not mediated by general language comprehension skills. Indeed, domain-specific knowledge was the only variable to consistently predict reading comprehension performance in the two knowledge domains used. Thus, for fluent adult readers, domain-specific knowledge has a direct and independent role to play in reading comprehension performance.

Results from Chapters 3 and 4 demonstrate that domain-specific knowledge may be implicated at all levels of the reading process from lexical access through to reading rate and

reading comprehension performance. In Chapter 3, domain-specific knowledge affected the accuracy and speed with which fluent adult readers named astronomy words. In Chapter 4, domain-specific knowledge and general language comprehension skill were predictors of reading rate, a measure of on-line text processing. In contrast, decoding skill was not a predictor of reading rate, suggesting that higher-order and not lower-order skills are implicated in the reading rate of fluent adult readers. Thus, the claim that domain-specific knowledge is not a factor in either lexical access or the on-line processing of text was disconfirmed.

The findings reported in the previous Chapters have implications for models of reading comprehension. In the remainder of this Chapter some of these implications will be explored further. In addition, a number of other issues arising from these studies will be discussed. They include issues related to research design, factors affecting the replication of results across knowledge domains, and the ways in which domain-specific knowledge is operationalized both in these studies and in other research.

Implications for Models of Reading Comprehension

The fact that domain-specific knowledge had a direct and significant role in the reading comprehension performance of fluent adult readers has implications for models of reading comprehension. Models of reading comprehension, in order to be comprehensive, need to include domain-specific knowledge as a variable, especially when attempting to explain the reading comprehension skills of fluent adult readers.

There are two implications for the Simple View of reading. Firstly, reading comprehension skill is more complex than suggested by the expression, $Rc = d \times c$. It is likely that not only domain-specific knowledge, but other variables such as text difficulty (e.g., Petros et al., 1990), text coherence (e.g., McNamara et al., 1996), and the goals of readers (e.g., Haas & Flower, 1992) make contributions to reading comprehension performance. Secondly, an additive model is sufficient to explain the relationship among variables predicting reading comprehension performance.

For Verbal Efficiency Theory, the results implicate domain-specific knowledge in both lexical access and the on-line processing of text, and thus, domain-specific knowledge needs to

be considered an essential component of reading ability for fluent adult readers. The results also demonstrate that verbal efficiency, i.e., efficient operation of lower level processes such as lexical access, is not a significant factor in the reading comprehension performance of fluent adult readers, although it does affect the reading comprehension of adults with a reading disability. This pattern of results suggests that verbal efficiency is not monotonically related to reading comprehension performance for all readers, but rather may reach an asymptotic level for fluent adult readers. Beyond a certain level of decoding fluency - a level achieved by the fluent adult readers but not the LD readers in this study - individual differences in higher-order variables such as domain-specific knowledge may be sufficient to account for differences in reading comprehension performance.

The Verbal Efficiency and Construction-Integration models of reading comprehension consist of a two-tier conception of reading comprehension. At one level, basic meaning construction occurs or a text-based model of comprehension is constructed. At another level, more complex comprehension processes are active, such as inferential processing or the reading to learn processing involved in the construction of a situation model. According to both models, domain-specific knowledge has a role to play only at the more complex inferential level. As discussed in Chapter 5, this hypothesis could not be directly tested using the measures and model testing procedures outlined in that Chapter. However, the fact that a reading comprehension measure was used which was comprised of questions assessing information explicitly stated in the text, i.e., a comprehension measure that 'pulls' for a text-base model or basic meaning construction, suggests that domain-specific knowledge may have a direct role to play in the construction of a text-base model.

Indeed, what differentiates text-base modelling from situation modelling may not be the exclusive use of domain-specific knowledge in the latter, but rather, the way in which domain-specific knowledge is used. It may be that readers who construct a situation model are engaging domain-specific knowledge in a strategic way which enables them to integrate new, textual information with old information so that it can be applied at a later date to new situations. In other words, the difference between a reader who constructs a text-base model

and one who constructs a situation model may be due to differences in the way in which metacognitive knowledge and procedures are applied to the reading process. Important components of a reader's metacognitive knowledge may be domain-specific (e.g., Chi, 1978) and the breadth and depth of an individual's domain-specific knowledge may interact with the quality of metacognitive knowledge available for use. However, it may not be domain-specific knowledge *per se* that leads to different reading comprehension outcomes, i.e., whether a text-base or situation model are constructed, but rather the way in which domain-specific knowledge interacts with metacognitive factors.

An analogous finding has been reported in studies exploring the writing process. Bereiter and Scardamalia (1987) have used the writing process as a springboard to explore knowledge building in general. A recurrent finding is that there appears to be two general types of writing produced by writers. The first type is characterized as knowledge telling, where the writer provides a simple recounting of what he or she has read. Often the writing product of knowledge tellers follows the same organization as the reading source. The second type of written product is characterized as knowledge transforming, where the writer transforms source information to suit his or her own purpose, a purpose that is distinct from the purpose of the source material.

A major difference between knowledge tellers and transformers appears to be in their application of metacognitive knowledge. In studies of adult writers, Flower and her colleagues (Flower, Stein, Ackerman, Kantz, McCormick, & Peck, 1990) have found that even when writers have access to exactly the same information, some writers set a goal of simple recounting whereas others set more complex transforming goals. Thus, goal-setting, a metacognitive skill, seems to play an important role in the type of writing that is produced. Similarily, differences in the reading comprehension performance of fluent adult readers may be due to differences in the goals they set for reading (e.g., van Dijk, 1999) as well as in the way they use metacognitive knowledge and skills to organize and integrate textual information.

Studies conducted by Bereiter and Scardamalia (1987) reveal that knowledge telling is the only strategy employed by young children, and that for some adolescents and adults it

continues to be the dominant mode. Knowledge transforming is a later developing ability, which is consistent with developmental notions about the acquisition and application of metacognitive knowledge and skills (Flavell, 1987). Thus, a distinction between either knowledge telling and transforming or text-based modelling and situation modelling may be an issue for more mature writers and readers and may not apply to children.

Some types of reading comprehension tests or measures may also lend themselves more easily to a knowledge telling versus a knowledge transforming mode. For instance, simple recall of a passage may encourage a knowledge telling set of executive processes. Reading comprehension measures which require solving a new problem, however, are more reliant on a reader's ability to transform textual information, integrate it with prior knowledge, and apply it successfully to a new situation. In other words, some of the differences in reading comprehension performance may be due to the task demands of the comprehension test, to what the reader does with his or her mental representation of the text *after* reading.

Two hypotheses emerge from this discussion. One is that differences in metacognitive knowledge and not domain-specific knowledge may explain differences in the construction of a text-based model as opposed to a situation model. Another is that domain-specific knowledge may interact with metacognitive knowledge and skill to produce qualitatively different types of comprehension, and that this may occur in response to task demands after reading rather than as an automatic consequence of reading a passage.

Issues Related to Research Design

Both regression and analysis of variance designs have been used in reading comprehension research exploring the role of domain-specific knowledge. Each method has its limitations. In many ANOVA or t-test analyses, reading ability and/or domain-specific knowledge are treated as categorical between-subjects variables (e.g., Haenggi & Perfetti, 1994; McNamara & Kintsch, 1996). In other words, a continuous measure of reading ability and/or domain-specific knowledge is dichotomized into high and low categories resulting in a loss of variability and power to detect differences.

In addition, in a number of these studies, many individual comparisons are made

between high and low ability subjects, a method that ignores the intercorrelations among variables, i.e., the effect a particular variable may have or not have when considered together with another variable. For example, in a study by Haenggi and Perfetti (1993), fluent adult readers were divided into high and low reading ability groups based on their performance on the Nelson-Denny Reading Test. The two groups were then compared on a variety of measures of word recognition, decoding skill, and working memory measures. Unfortunately, a comparison of the domain-specific knowledge of the two groups was not reported. The low ability group invariably performed significantly less well than the high ability group on all of the measures, a finding that suggests that the high reading ability group demonstrates higher reading comprehension skill *because of* better developed word recognition, decoding, and working memory skills. However, when Haenggi and Perfetti entered these same measures into a regression analysis, domain-specific knowledge was the only consistently significant predictor of reading comprehension. Thus, although the two groups differed on a number of reading related skills, these skills were not significantly related to reading comprehension performance when considered together with domain-specific knowledge.

The regression method employed in the studies reported here provided an opportunity to utilize continuous variables and to explore a number of variables simultaneously, and thus to examine if a single variable makes a significant contribution after all other variables in the equation have been considered. Using this method it was possible to discern that decoding skill may be a more important factor in the reading comprehension performance of LD than NLD readers, while domain-specific knowledge appears to be consistently related to better reading comprehension of NLD or fluent adult readers, but not always to the reading comprehension performance of LD readers.

However, regression methods have their limitations as well. The results of regression models are dependent on the types of variables entered both as criterion and as predictors. In some studies, the predictor variables may be significantly related to the criterion because they share a similar measurement method. For example, in a study by Cunningham et al. (1990), they used a timed comprehension test, the Nelson-Denny Reading Test, as their criterion

variable, and they also used naming times to words and pseudowords as predictor variables representing decoding or word recognition skill. Results of regression analyses indicated that decoding skill was a significant predictor of reading comprehension performance, but there was no acknowledgement that this result may be restricted to cases in which a limited time is available to complete the reading comprehension measure. In other studies (e.g., Peterson, 1993; Bell & Perfetti, 1994), a listening comprehension measure was used as a measure of general language comprehension skill that has exactly the same format as the criterion reading comprehension measure, i.e., multiple choice test. In these cases, common method variance may serve to inflate the degree of relationship between decoding skill and general language comprehension skill on the one hand, and reading comprehension skill on the other hand.

Regression analyses are also limited in terms of the kinds of relationships that can be discerned among predictor and criterion variables. Regression analyses can be used to determine whether a particular predictor variable adds unique variance when considered together with other predictor variables. In other words, regression analysis lends itself to a description of additive models. Although interactions can be examined, the power of finding a significant interaction can be compromised by the reliability of the predictors involved in the interaction. As discussed in Chapter 5, a number of researchers have pointed out the difficulties involved both in obtaining a significant interaction (e.g., Gough & Tunmer, 1986) and in interpreting a significant interaction (e.g., Arnold, 1982). More important, however, is the possibility that reading comprehension skill cannot be adequately explained using either an additive or a combined additive/multiplicative model. If nothing else, the studies reported here demonstrate that a model of reading comprehension skill needs to include at least three variables, i.e., decoding skill, language comprehension skill, and domain-specific knowledge. It is likely that other variables such as metacognitive skill and text difficulty need to be included as well. Thus, more complex theoretical and statistical models may need to be developed in order to better understand the relationships among reading variables for fluent adult readers.

Factors Affecting the Replication of Results

Reading passages from two knowledge domains, astronomy and computers, were used in order to examine the generalizability of results across domains. In terms of modelling reading comprehension skill, the results were consistent across knowledge conditions: domain-specific knowledge is a significant predictor of reading comprehension performance. When only data from fluent adult readers were involved in the analyses, domain-specific knowledge was the only variable to consistently predict reading comprehension performance in both domains. Decoding skill was never a significant predictor and general language comprehension was a significant predictor only in the astronomy condition. These results are consistent with results from previous research (e.g., Peterson, 1993; Haenggi & Perfetti, 1994) and demonstrate that domain-specific knowledge has a stable, robust role to play in explaining the reading comprehension performance of fluent adult readers.

The role of domain-specific knowledge in reading rate and word recognition skill was not consistent across knowledge conditions. In the astronomy condition, astronomy knowledge was associated with faster reading rates and faster and more accurate word naming times for all subjects. In the computer condition, domain-specific knowledge had a facilitative effect for readers with high vocabulary skill, but, for readers with low vocabulary skill, high levels of computer knowledge were associated with slower reading rates. For readers with relatively low vocabulary skill, domain-specific knowledge did not affect reading rate. In word recognition, computer knowledge had no effect on word naming times or accuracy. However, domain-specific knowledge was the only significant predictor of reading comprehension performance in the computer condition. Indeed, domain-specific knowledge continued to be the only significant predictor of reading comprehension performance even after the variability of decoding and general language comprehension measures was increased by adding a group of subjects with learning disabilities. Why would domain-specific knowledge have a consistent facilitative effect in one domain but not in another?

In many respects the computer condition was a more difficult condition than the astronomy condition. Subjects rated the computer passages as significantly more difficult to

understand than the astronomy passages. Their perception of difficulty was supported by reading rate and word naming data. Subjects read the computer passages significantly more slowly than the astronomy passages, and made more word naming errors on the computer words than astronomy words.

But what makes one text more difficult than another? Results from the astronomy condition suggest that when domain-specific knowledge can have a facilitative effect at the lexical and on-line text processing levels, domain-specific knowledge can be applied to the process of reading comprehension in a fairly efficient and relatively effortless way. In contrast, results from the computer condition suggest that the advantage high computer knowledge readers had in reading comprehension performance may have been due to a more effortful and strategic use of domain-specific knowledge. In turn, the differences between relatively effortless and effortful uses of domain-specific knowledge may have to do with how much redundancy there is between the prior knowledge of readers and the concepts discussed in a passage. The almost perfect accuracy for astronomy words on the semantic decision tasks suggests that subjects were more familiar with the astronomy concepts covered in the astronomy passages than they were with the computer concepts covered in the computer passages.

The possibility of a relatively easy application of astronomy knowledge, on the one hand, and a more effortful, strategic application of computer knowledge, on the other, is supported by results from the study of reading rate. In the computer condition, one subgroup of readers, those with low vocabulary knowledge but high computer knowledge, read the computer passages much more slowly than all other readers. This suggests a conscious effort on the part of low vocabulary/high computer knowledge subjects to take the time to understand a text that was more difficult for them because of their relatively weaker general language skills. Indeed, slower reading rates were associated with better reading comprehension in general, again suggesting that the goals of the reader may play a role in the on-line processing of text. Thus, in the computer condition, a lack of consistent effects of domain-specific knowledge at lower levels of the reading process may indicate that, in general, the concepts

covered were less familiar. However, readers with higher levels of computer knowledge could more successfully use their knowledge to understand the text, resulting in better reading comprehension performance than readers with low levels of computer knowledge.

What seems clear from this discussion is that much more needs to be done to understand the way in which domain-specific knowledge affects reading comprehension performance. Although domain-specific knowledge was a significant predictor of reading comprehension performance in both the astronomy and computer conditions, a finding that has been replicated in other studies as well, it may have been used in different ways in the two conditions. Thus, to say that domain-specific knowledge has a direct effect on the reading comprehension performance of fluent adult readers is just the first step. In order to understand the role of domain-specific knowledge in reading comprehension performance, its role in a variety of levels of the reading process will need to be explored further.

In addition, the results of this study may capture some aspects of the role domain-specific knowledge plays in the reading comprehension of fluent adult readers and adult readers with a reading disability, but they do not speak to the possible role domain-specific knowledge may play in the development of reading comprehension skills. It may be that for younger, less experienced readers, domain-specific knowledge may play a less important role, particularly as lexical and language comprehension skills are being developed and consolidated. Further studies are needed to explore developmental trends in the role of domain-specific knowledge in reading comprehension skill.

Operationalizing Domain-specific Knowledge

The domain-specific knowledge measures used cast a wide net over the types of prior knowledge a reader might have about astronomy or computers. However, although a relationship between the knowledge assessed by these measures and reading rate and reading comprehension performance was established, it is not clear what aspects of domain-specific knowledge were useful to comprehension. For example, is it simply a given quantity of background knowledge which is useful or does the organization, structure, or coherence of a reader's knowledge have a role to play?

While the extent or quantity of information in a particular domain was assessed by the domain-specific knowledge measures used, the depth or organization of subjects' knowledge was not considered. In addition, domain knowledge can be considered to consist of declarative knowledge, procedural knowledge, and images. Only declarative knowledge was assessed by the prior knowledge multiple choice test and the semantic decision task. The measures dealing with number of courses taken and self-report of knowledge and interest in the domains could reflect all three kinds of knowledge, although no attempt was made to distinguish various kinds of domain knowledge.

It may be that the extent of a reader's knowledge is sufficient to account for the effect of domain-specific knowledge on reading comprehension performance, and results from these studies suggest that this may be so. In other words, the fact that domain-specific knowledge is a significant predictor of reading comprehension performance may reflect the fact that the quantity or extent of either or both topic or domain knowledge is positively associated with reading comprehension performance. However, it is tempting to speculate that differences in the depth and structure or organization of domain knowledge may affect the kind of comprehension that occurs. It may be that in order to learn from text, as opposed to just recount what is contained in a text, a certain quality of knowledge organization is required. In other words, the degree to which knowledge is elaborated or organized may influence the degree to which it can be applied to new situations. Thus, one of the differences between the construction of a text-base and a situation model may lie in way in which knowledge is organized. Knowing 'stuff' or declarative knowledge may lead to a better text-base model of the text. Rich elaboration and organization of prior knowledge, and an attempt to integrate textual information with that richly elaborated knowledge base, may lead to the construction of an effective situation model. Thus, domain-specific knowledge may be helpful at both levels of comprehension but in different ways at each level.

Implicit in Kintsch's (1994, 1998) discussion of domain-specific knowledge is the notion that domain-specific knowledge consists of a well-organized, coherent structure of knowledge in a particular domain. He and others (e.g., Alexander, 1992) may argue that topic

knowledge, i.e., knowledge of the information to be covered in a given text, or a simple collection of declarative knowledge in a particular domain may not qualify as domain-specific knowledge. However, if what we are interested in explaining is the role that domain-specific knowledge may play in reading comprehension performance, then it seems reasonable to accept that readers will vary in terms of both the quantity and quality of the domain-specific knowledge they have. It may be more useful to determine what quantity and quality of domain-specific knowledge is necessary to facilitate understanding of particular texts or to achieve a particular kind of comprehension of text than to argue about whether the kind of knowledge a reader has qualifies as domain-specific knowledge. In order to achieve this goal, however, different measures of domain-specific knowledge will have to be developed which attempt to discriminate and specify the extent and organization of the domain they are assessing.

The semantic decision task used in this set of studies could be adapted to explore in more depth not just the quantity but also the structure of knowledge of a given knowledge domain. For example, pilot testing of domain-specific words could determine which words were central to a given domain and which were more peripheral. Differences in the centrality of concepts could be used to discriminate expert and less expert responders. On the basis of this information, hypotheses could be generated in terms of the number and type of concepts which would be correctly responded to on a semantic decision task. A response time measure could be developed to estimate the centrality of the concept to a person's internal domain-specific knowledge network.

The ease with which the semantic decision task can be administered addresses one of the difficulties encountered by researchers attempting to tap the structure of domain-specific knowledge, i.e., to develop a task which is not too onerous for subjects to complete and which also allows one to discriminate different dimensions and/or sources of knowledge. For example, Ferstl and Kintsch (1999) reported that the use of multi-dimensional scaling, a procedure commonly used to assess structure of knowledge, would have to involve many pairs of concepts in order to do justice to the interconnections of any knowledge domain, and that

under those conditions, would take too long for subjects to complete. As an alternative, Ferstl & Kintsch (1999) used a cued association task in which subjects were presented a list of words associated with a give domain and asked to generate up to three associations in response to each word. This procedure could be completed by subjects in about 10 minutes, and enabled them to explore the kinds of connections or associations subjects had between concepts in their knowledge networks as well as to compare the associative networks of readers with the associations implied by the the structure of a reading passage. In this way, the relative contributions of domain-specific knowledge and textual information could be assessed. More research of this type, which attempts to specify the structure of knowledge of readers, is needed if we are to understand the contribution domain-specific knowledge makes to reading comprehension.

Concluding Remarks

Taken together, the results presented in this series of investigations suggest that the role of domain-specific knowledge in reading comprehension is not restricted to a particular type of comprehension process, e.g., learning from text, or inferential processing, but may pervade all aspects of the reading process. Through experience and learning, a domain of knowledge may be constructed which then serves as a filter through which a text from that domain is processed. This filter may be construed as a predisposition to interpret incoming information in a particular way, and thus to affect the way in which a text-base is constructed by the reader. In other words, domain-specific knowledge may provide a mental set, a set of expectations, or a context within which a text may be understood. As is the case in basic visual and auditory perceptual processing, the context within which a given stimulus - in this case a text - is perceived may be crucial to the way in which it is perceived or understood. Just as the expertise of the art critic influences the way in which she visually processes a piece of art, i.e., the visual features she chooses to attend to, the amount of time she devotes to particular features, the way in which she understands a particular feature, domain-specific knowledge may influence the salience with which particular words and phrases are processed, as well as the way in which those words and phrases are elaborated. While the conscious and strategic

use of domain-specific knowledge in the reading process has been explored in previous studies, e.g., in the construction of inferences (Perfetti, 1989), the results reported here suggest that the influence of domain-specific knowledge may also operate automatically, and without conscious application.

APPENDIX A

Student Information Form

Student Information and Questionnaire

Name:_____Student ID#:_____

Age:___First Language:_____Second Languages:_____

Faculty:_____Major:_____Year:_____

Phone Number:_____Best times to call: morning __
afternoon __
evening __

Part A: Background Knowledge and Interests

I. List computer courses taken at secondary school, college, or university:

II. List astronomy or astrophysics courses taken at secondary school, college, or university:

III. Please indicate how interested and knowledgeable you feel you are in the areas of computers and astronomy. Read each of the following sentences carefully. For each sentence circle the **one bolded word** that best describes you. Circle only <u>one</u> word for each sentence.

1. I am **very** **moderately** **somewhat** **not** interested in astronomy.
2. I am **very** **moderately** **somewhat** **not** interested in computers.
3. I am **very** **moderately** **somewhat** **not** knowledgeable about astronomy.
4. I am **very** **moderately** **somewhat** **not** knowledgeable about computers.

(continued on back.....)

Student Information and Questionnaire Continued

Part B: Reading Background

Read each statement carefully and decide how frequently you think the activities in each statement describe you.

	Often	Sometimes	Seldom	Almost Never
I read novels	4	3	2	1
I read the newspaper	4	3	2	1
I read journal or magazine articles	4	3	2	1
I read textbooks	4	3	2	1
When I get the chance, I read books or magazine articles on astronomy	4	3	2	1
When I get the chance, I watch TV programs on astronomy	4	3	2	1
When I get the chance, I read books or magazine articles on computer technology	4	3	2	1
When I get the chance, I watch TV programs on computer technology	4	3	2	1

Thank you for completing this information sheet and questionnaire. Please put this form into the envelope. You can return the envelope to me by bringing it to your next class or by dropping it in on-campus mail.

APPENDIX B

Reading and Listening Passages
and
Comprehension Questions

Light: Messenger of the Universe

Every piece of astronomical evidence is like one of the bricks in a delicate, openwork wall: each brick is supported by hundreds of others and helps to support as many more. The whole structure of interlocked, intellectual interpretation rests on strict and subtle logic. The logic, in its turn, is supported by facts and figures that have been determined with refined precision. At the foundation of the structure, supporting everything else, is the same universal phenomenon of nature: light -- the many-eyed messenger of the universe.

Some of the uses of light are comparatively simple and straightforward. For example, the only direct way to measure how far away the lights of the stars are in the sky is by a trick of geometry known as parallax. Parallax is a measure of the amount by which an object seems to move, in relation to its background when an observer looks at it from two different places. Anyone can judge the parallax of something very near to him, for example a candle on a table in relation to a wall. As one looks first with one eye, and then with the other, the candle will appear to move. In the same way, two astronomers positioned in their observatories several thousand miles apart can determine the parallax of a planet by sighting it against the backdrop of stars at the same moment on the same night. By this means also, astronomers have learned to measure the parallax of some 6,000 of the nearest stars. They observe them during opposite seasons of the year when the complete revolution of the earth around the sun has provided them with a base 186 million miles long.

The nearest stars are so far away that even a base line of 186 million miles is still quite short. After centuries of attempts by other astronomers, Bessel in 1838 finally measured the parallax of 61 Cygni, one of the nearest stars. The parallactic displacement he saw, back and forth over the sky every six months, was an angle of only .3 second -- three tenths of a 60th of a 360th of a full circle. Yet this minute measurement means that 61 Cygni is 65 trillion miles away from the earth. Astronomers call this distance 11 light-years -- a light-year being the distance light travels in a year, or six trillion miles.

Within months of Bessel's great measurement, Thomas Henderson in South Africa had found that Alpha Centauri was only 4.3 light-years away. It is now known to be the sun's nearest bright neighbour. Soon after in Russia, Friedrich Wilhelm Struve, the great-grandfather of the late Otto Struve who was

director of the National Radio Astronomy Observatory in West Virginia, had calculated the distance to Vega as 27 light-years. Beyond a distance of some 400 light-years -- where the angle of parallax falls below 0.008 second -- these geometric means of measurement are essentially useless.

Eventually astronomers may be able to measure parallaxes of more distant stars, or even of remote galaxies, by taking advantage of the sun's own revolution around the hub of the Milky Way. But since it takes 110 million years for the sun to go halfway around the hub, the results will not be in for some time. In the meanwhile, astronomers have learned to measure distances beyond the range of parallax by other methods, which depend, in their turn, on other oddities of the stars' light. The light from stars within parallactic range has revealed that some stars belong to certain clearly defined and easily recognisable classes which always have the same real brightness. When other stars of the same sort are found beyond the range of parallax, astronomers can estimate their distance by the decrease in their brightness. In conjunction with theoretical calculations about how stars burn and what makes them bright, this method has served to measure cosmic distances of millions of light-years -- millions of millions of years.

Classifying the stars so as to judge their distances -- and their motions and masses -- involved new understandings of light's properties: qualities of seeming unruliness but actual consistency that Newton had never suspected. One such unruliness was discovered in 1802 by William Wollaston, an English chemist. Newton had shown that white sunlight, bent apart by a prism, becomes a rainbow of all the colors. But Wollaston found that the sun's spectrum was not a perfect rainbow but instead was slashed by dark lines. Pursuing this discovery, a German optician named Joseph von Fraunhofer carefully plotted the locations of as many of these lines as he could see, although he did not understand their significance. Today scientists know there are thousands of these lines, and they are fully understood. In the 19th century, however, it took more than 40 years of research to discover that the light emitted by the common elements, when heated until gaseous in the laboratory, showed bright slashes in their spectra and that these slashes perfectly coincided with

the lines of darkness that are now named after von Fraunhofer.

Today, all this is understood in terms of atomic theory. Each element -- or kind of atom -- can emit and absorb energy only at the specific wave lengths dictated by its atomic structure. In the spectrum of an incandescent gas, the bright lines are produced by atoms emitting energy at their prescribed wave lengths. In the spectrum of the sun, the dark lines are produced by the action of elements in the solar atmosphere that absorb radiation at their prescribed wave lengths. In the mid-19th Century, when this explanation was unknown, absorption and emission lines in the spectrum brought about an intensive investigation that was finally crowned by the discovery of light's true nature and its place among other forms of energy.

The realization which led to a clearer concept of light, and to much of modern physics, was that visible light makes up only a tiny fraction of the whole spectrum. Above the brightest visible blues in the spectrum are shorter, invisible ultraviolet waves, X rays, gamma rays of trillionth-of-an-inch wave length and even rays of shorter wave lengths yet unknown to man. Below the darkest visible reds are the longer, invisible infrareds, microwaves and radio waves that reach wave lengths of thousands of miles.

Spectroscopes that fanned out the peacock tails of starlight were soon being used in every major observatory on earth. In early models, the fanning was done by prisms, in later models by diffraction gratings of lines closely ruled on glass. Either way, the white radiance of the cosmos could be shattered into rainbows, revealing by their spectral lines the identity of atoms pulsating billions of miles away. Over the years, the spectral lines proved to hold amazing quantities of other information, too. An analysis of spectral lines reveals the speed of a star moving toward or away from the solar system, the rapidity of a star's rotation, the temperature of its surface, the strength of its magnetic field, and even the amount of gas that is drifting in space between it and the earth.

Light: Messenger of the Universe
Comprehension Questions

Name:_____

Ratings

1. How difficult did you find the passage, Light: Messenger of the Universe, to understand? (Circle only one rating)

   very easy somewhat easy somewhat difficult very difficult

2. How interesting did you find the passage, Light: Messenger of the Universe? (Circle only one rating)

   not interesting a little interesting somewhat interesting very interesting

Multiple Choice Questions

There are 10 multiple choice questions. Read each question carefully and circle the one best answer.

1. Parallactic measurement of the stars requires

a one observation point at the same interval of time
b two observation points at the same interval of time
c one observation point at two different time intervals
d two observation points and two different time intervals

2. The baseline for measuring a star's distance by parallax can be established by

a the earth's movement from winter to summer
b the increase in the star's brightness
c the decrease in the star's brightness
d the distance between the observer's eyes

3. Calculating a star's distance by parallax is difficult because

a telescopes distort the effects
b scientists disagree on how to measure parallax
c stars are very far away compared with the baseline
d stars are too close compared with the baseline

4. The parallax method can be used

a even for the most distant stars
b only for stars within a certain distance from the sun
c more effectively for near stars than distant stars
d more effectively for distant stars than near stars

5. The distance from the earth of the most remote stars can be measured

a by their brightness
b by either parallax or brightness
c can only be estimated
d can be calculated exactly

6. Fraunhofer plotted the dark lines of the sun

a with a spectroscope
b in terms of their wavelengths
c to prove his theory that there was a single electromagnetic spectrum
d without understanding what they meant

7. The first theory of light included the fact(s) that

a white light consisted of all the visible colours
b white light consists of short wave lengths
c only part of the spectrum is visible
d both a and c

8. In the mid 19th century, astronomers were pushed into intensive research on light

a to verify Newton's theory of light
b to figure out the dark lines in the spectrum
c to understand parallax
d to measure the effects of electromagnetic fields

9. Scientists have come to realize that the invisible portion of the light spectrum contains

a microwaves
b radio waves
c only waves of very short length
d waves of short and long length

10. The earliest spectroscopes analyzed light with

a microwaves
b refraction lines
c prisms
d photographic plates

Birth of the Sun

Astronomers today have a remarkably consistent idea of how the sun was born and of how it will ultimately die. The early stages have been worked out by the astronomer Gerard P. Kuiper, of the University of Arizona. According to Kuiper and other astronomical detectives who helped supply clues for his theory, the sun came into being about five billion years ago, or at least five billion years after the formation of the Milky Way Galaxy itself. The gas -- a dark substance full of swirls and eddies -- out of which the sun condensed was much like the gas which wanders in clouds between the stars of the Milky Way today. Its substance was almost all hydrogen -- but not quite all, because the pure, primordial hydrogen from which the cosmos is thought to have originated had already been contaminated by other elements created and thrown off by nuclear transformations in the earliest stars.

What made the gas of the future sun begin to condense was presumably a chance eddy that brought together enough atoms in one region so that their total gravity overcame the momentum of their individual movements and held them together in a single, collapsing cloud. Very slowly the matter of the cloud began to fall inward on eddies where the gas was densest; and by far the largest of the eddies was the protosun. Its overwhelming gravitational influence shaped the rest of the cloud into a huge, rotating disk. Every additional bit of gravitational contraction worked to speed up the disk's rotation -- just as a whirling ice skater quickens his spin by bringing his outstretched arms in closer to his body. Every increase in rotation speed proceeded to flatten the disk further. Within the disk the helter-skelter movements of atoms and molecules were slowly evened out by collisions, and the heat of the collisions was radiated off into space. In this way, the energy of the cloud's many internal motions was reduced and the primordial particles were reined in until they mostly whirled in orderly fashion around the protosun or around the lesser eddies in the cloud. These lesser eddies, rolling lazily around on one another like ball bearings, were the

protoplanets. As the protoplanets sorted out their internal motions and began to contract, the heavy substances in them tended to condense first and to congregate toward their centres.

In the meanwhile, the jostling crush of atoms falling into the protosun was creating heat inside it -- heat that accumulated more quickly than it could be shed. The temperature in the protosun's core rose steadily. As the core's temperature passed the million-degree mark, thermonuclear reactions between heavy and light hydrogen atoms began adding appreciable amounts of energy to the heat already being released by contraction. The surface of the sun turned slowly red and hot, orange and hotter, then yellow and glowing. Its first red rays, falling on the half-begotten protoplanets, began to rise away the smoke of matter in which they had been born and on which they were still feeding and growing. Soon the protoplanets were no longer tumbling around like ball bearings but flying as separately as bees around a flower.

As the mists of creation were dissipated and the scene gradually brightened, the innermost planets lost most of the light chemical elements from their outer gassy regions and retained mainly the heavy irons and rocks -- and the liquids and gases trapped inside them -- which had already formed into solid masses. Mercury and Mars, which had been condensing rather slowly out of somewhat rarefied regions in the primordial cloud, had little in the way of solid cores to hold on to, so they became small planets. The Earth and Venus had done better and remained larger. In the asteroid belt the solid condensates had never had time to pull together at all and were destined to be separate lumps for all eternity. Beyond the asteroid belt where the young sun's radiation was weakened by distance, several huge accretions existed which could hold on to most of their light elements. They became Jupiter, Saturn, Uranus and Neptune, and they retained almost as large a percentage of light substances -- like hydrogen and helium -- as there must have been in the primordial

cloud itself.

Beyond Neptune, where the gravitational influence of the protosun had been weak, the primordial cloud had been less flattened into a disk and its motions had been less regularised. As the outflowing light of the sun drove off the gassy remnants of the cloud from these outer regions, millions of small bodies were left behind, too weak gravitationally to condense into solid spheres, but strong enough to resist being driven out of the system altogether by the push of the faint sunlight that reached them. There they remain to this day -- celestial fossils pursuing their primeval orbits and revealing in their loose, snow-filled structure what the earliest condensations of the solar system must have been like. They are, of course, the comets. As one of them approaches the sun today and grows a tail of evaporating gas pointing out to space, it gives a picture in miniature of what the protoplanets must have looked like when the young sun drove away their gassy outer envelopes.

The first light of the sun was very dim because the sun was still contracting and the thermonuclear fuel in the sun's core was cooler and less tightly packed than it is now. Once the sun stopped contracting -- a culmination that took approximately one million years -- the solar energy rose to within 20 percent of its present value, driving off the last of the primordial cloud and leaving the planets to work out their further evolution alone. In the first 100 million years, six lost satellites like Neptune's Triton were recaptured by their parent planets into retrograde orbits. Since then, some asteroids have been swallowed by collisions with Jupiter, the earth, the moon and the other planets and satellites; some gobs of iron and rock have resettled themselves in the interiors of planets; and some trapped gases and liquids have escaped to augment the atmospheres which the planets managed to retain during the evaporation period. By and large the solar system has probably remained much the way it was created.

Birth of Sun
Questions

Name:_____

Ratings

1. How difficult did you find the passage, Birth of the Sun, to understand? (Circle only one rating)

   very easy somewhat easy somewhat difficult very difficult

2. How interesting did you find the passage, Birth of the Sun? (Circle only one rating)

   not interesting a little interesting somewhat interesting very interesting

Multiple Choice Questions

There are 10 multiple choice questions. Read each question carefully and circle the one best answer.

1. The sun was formed

a 5 billion years after the Milky Way galaxy was formed
b 5 billion years after the universe was formed
c 5 billion years before the Milky Way galaxy was formed
d 5 billion years before the universe was formed

2. The sun and planets of our solar system were formed from

a one large eddy of swirling gas
b a large explosion
c one large cloud of gas
d several swirling eddies, each formed from its own cloud of gas

3. When the atoms and molecules of the condensing protosun collided

a they glowed red and hot
b they glowed yellow and hot
c they caused heat which was radiated off into space
d the heavier substances were radiated off into space

Birth of Sun: Questions

Name:_____

2

4. The temperature of the protosun's core increased because

a it was radiating a bright red light
b it was accumulating heat faster that it can be radiated off into space
c it was accumulating new particles and substances at a very fast rate
d it was radiating heat faster than it can accumulate heat

5. The first light of the sun was

a dim and yellow
b bright and orange
c bright and white
d dim and red

6. The Earth and Venus are larger than Mercury and Mars because

a they had larger solid cores
b they were farther away from the sun
c did not lose most of the light chemicals from their outer regions
d they had larger liquid cores

7. The farther a planet is from the sun

a the more light substances it will contain
b the less light substances it will contain
c the less radiation it will generate
d the more radiation it will generate

8. Beyond Neptune

a is the asteroid belt
b is a large eddy of gas and matter, condensing to form comets
c are small lumps of rock which are continuing to condense to form new planets
d are millions of small bodies which were left behind when the solar system was formed

Birth of Sun: Questions

Name:_____

3

9. While the sun was forming, its core matter

a contained lighter substances which condensed first
b contained thermonuclear fuel
c contained trapped liquids and solids
d contained the remnants of a previous star

10. Today's sun

a will continue to get hotter as the core continues to contract
b has stopped contracting
c will stop contracting in the near future and begin to get cooler
d will continue to get hotter as the core stops contracting

A Bus Tour

If you own a personal computer, you are more or less familiar with the computer's bus. These days debates rage over the relative merits and weaknesses of the IBM PC AT bus versus IBM's new Micro Channel architecture (MCA) or the yet to be released Extended Industry Standard Architecture (EISA). New 32 bit buses, like the Mac II's NuBus, are touted as surpassing older, 8-bit buses in speed and memory capacity.

However, if you crack open your computer, you may be hard-pressed to locate the bus, since it is simply a collection of signals and their protocols, which are used to communicate between boards. A bus is physically embodied in (1) the connectors that carry its signals and (2) the logic on each board that implements the bus protocol and connection.

Industrial Strength Buses

Although it's getting harder to draw a line between personal computer buses and more "industrial" buses like Multibus or VMEbus, there are important distinctions. While multimaster capability is a novelty in personal computer buses, it's a necessity for industrial buses.

In any bus transaction, there is a master and a slave. The master initiates the transaction, and the slave responds. All industrial buses provide general mechanisms to arbitrate the bus and turn mastership over to one of the boards in an add-in slot. The basic hardware is fairly simple; how the feature is used can vary widely. The basic use of a multimaster capability is to allow I/O cards to perform true direct memory access (DMA) and to access data from main memory independently of the central processor. In the XT and AT buses, there is generally only one master, the motherboard.

Outside the personal computer world, a bus without multimaster capability would not even be called a bus. On the other hand, the built-in DMA channels in personal computer buses are unheard of in industrial buses.

In general, a key distinction between an industrial or minicomputer system and a desktop system is the motherboard. Desktop systems have one - industrial systems do not. An industrial bus-based system starts out as an empty card cage. There is no presumption about what type of CPU the designers will use or whether they will

construct a multiuser computer, RISC workstation, process-control system or flight simulator controller.

In the design of a personal computer, it makes sense to put as many functions as possible on the motherboard. Conversely, designers of industrial buses strive to minimize the centralized logic. Most industrial buses require only clock generation logic. Futurebus manages to dispense with even this clock generation and requires no centralized logic at all.

Cost has been another issue separating these bus categories. Personal computer users are cost-sensitive, while industrial system users are more concerned about performance and reliability. As personal computers become more powerful and are increasingly used as servers and multiuser systems, designers and users find the issues of industrial buses becoming more important.

Standard Features and Optional Packages

The basic purpose of a bus is to get bytes moved from one board to another in an efficient and standard way. Many features can be wrapped around this basic "truth." Some features are key to creating reliable, fully functioning systems, while others are bells and whistles.

Data width is a fairly basic feature; essentially, it tells you how many wires the bus has, each one leading to a bit in an address. A bus is generally 8, 16, or 32 bits wide. While the MCA is billed as a 32-bit bus, most MCA slots are 16-bit only.

Direct memory access is a feature of both personal computers and larger machines. However, the name does not mean the same thing in both realms. On the industrial VMEbus, a controller board that is said to do DMA could arbitrate for the bus and act as bus master in transferring data from itself to memory, with no intervention by the main processor board. This simple feat would be hailed as a breakthrough example of multimastering in the world of personal computers.

Although not a technical property, the degree of a bus's openness is one critical feature. The original "closed" Macintoshes (the 128K, 512K, and MacPlus), which have no bus, demonstrated the desperate need for buses. Third parties developed a wide variety of add-in products, including memory expansion, coprocessors, and internal disks. These were installed in machines against Apple's wishes and in

violation of factory warranties. The ingenuity and fearlessness displayed in providing Macs with these and other capabilities illustrate the importance of open buses.

The Magic of Multiprocessing

The most sophisticated systems made possible by multimaster buses are those with true multiprocessor capabilities. Some people confuse multimaster with multiprocessor. A true multiprocessor bus should also have an interrupt scheme that lets any board interrupt any other board; a particularly efficient arbitration method; and provisions for supporting multiple boards with caches.

Arbitration is an operation that keeps all the masters from trying to use the bus at once. The schemes for accomplishing this differ from bus to bus. Multibus I and VME bus use arbitration schemes that involve daisy-chain signals. This is somewhat awkward in that any unused slots must have special jumpers inserted to continue the daisy chain.

In most modern buses, the arbitration for a subsequent data transfer is carried out on a set of lines separate from those used for data transfer. This allows the overlapping of arbitration operations with data transfer. As a result, the arbitration phase adds no time to the resulting operation. When one data transfer is completed, the next one can start immediately.

Caches are becoming more important in both the personal computer and supermicrocomputer markets. Processors are so fast that DRAM cannot keep up. A cache of static RAM is the only way to keep the CPU fed with data. Caches can be complicated, and in a multiprocessor system, they may be especially complicated.

These are the features most often contrasted on current buses. If industrial buses and personal computer buses continue to converge be prepared for the marketing of bus enhancements such as geographical addressing, broadcall transactions, and cache coherency.

A Bus Tour
Comprehension Questions

Name:_____

Ratings

1. How difficult did you find the passage, A Bus Tour, to understand? (Circle only one rating)

   very easy somewhat easy somewhat difficult very difficult

2. How interesting did you find the passage, A Bus Tour? (Circle only one rating)

   not interesting a little interesting somewhat interesting very interesting

Multiple Choice Questions

There are 10 multiple choice questions. Read each question carefully and circle the one best answer.

1. An example of a data width feature is

a a protocol
b 32 bits
c direct memory access
d the interrupt scheme

2. The basic purpose of a bus is to move

a memory
b commands
c bytes
d RAM

3. In the personal computer world there are how many masters?

a None
b one
c two
d several

4. A distinctive feature of the personal computer bus is the

a I/O cards
b minimal central logic
c transactions by a master
d motherboard

5. A controller board working independently of the main processor board would be hailed as a breakthrough in multimastering for

a industrial computers
b multiuser computers
c personal computers
d industrial motherboards

6. Unlike personal computer buses, industrial buses don't have

a multimaster capability
b built-in DMA channels
c a motherboard (bad distractor?)
d arbitration

7. A true multiprocessor bus should have

a an efficient arbitration method
b a continuation scheme
c broadcall transactions
d centralized logic

8. An increasingly critical feature is a bus's

a daisy chain
b interrupt scheme
c direct memory access
d openness

9. In order to photograph a computer bus you would need to focus the camera on the

a RAM cache
b internal disk drive
c CPU
d add-in boards

10. It's essential for industrial buses to have

a built-in DMA channels
b multimaster capability
c an interrupt scheme
d multiprocessing

Object-Oriented Databases

When the dust from the great database debate settled in the early 1980's, the relational data model emerged as the essential database design technology. However, people found that the relational model is weak in handling certain types of applications: specifically, complex design applications, such as CAD and computer-aided software engineering.

For instance, an electrical engineer's CAD software typically includes schema-capturing editors, design-rule checkers, and circuit layout programs: all subsystems that require massive amounts of persistent data. Such complex applications put too many demands on conventional databases. These demands include the ability to model very complex data and evolve the database without affecting the current application. In order to better meet the needs of complex operations, researchers have developed object-oriented database management systems.

Object Orientation

In an object-oriented programming environment, an object is an entity with a private memory and a public interface. You can instruct an object to report on or alter its private memory by using messages. Messages are carried out by procedures (or methods) that have special privileges in accessing the object's private memory. All objects belong to a class (or type) that defines the messages that the object can understand and respond to. In simple terms, an object consists of both private data and the methods that can act on that data.

Object-oriented databases are rooted in the same concepts as object-oriented languages. They add database features such as persistence, concurrency control, resiliency, consistency, and the ability to query the database. You can program an object-oriented database with a computationally complete programming language and include more of the application execution in the database itself. By including more of the application code in the database (which is the locus of sharing), it becomes possible to share the application semantics embedded in the code. The database system can use additional knowledge about these programs to optimize query processing and to control the concurrent execution of transactions.

In the commercial database field, the relational model is still the state of the art. Unlike the relational model, a single object-oriented data model has yet to emerge.

Instead, research continues on a number of models that share several high-level features.

Despite this lack of a single data model, research into designing object-oriented databases has many common goals. One goal is to provide a system with tools for building extensions. You need extensibility because new applications often involve unpredictably complex forms of data that evolve over time. A fixed set of data-structuring primitives won't adequately support arbitrary new design data. By adding extensions, the data model becomes as functional as the built-in primitives.

Database Considerations

Object-oriented databases are first and foremost databases. As such, they must provide the features and functions you'd expect from modern database systems. Among these features are persistence, concurrency control, resiliency, consistency, and associative access (or queries).

1. Persistence. Persistence is an object's ability to outlive the process that created it. A persistent object exists in a memory space that is independent of any single computational entity. The database itself consists of persistent memory space. The database can store a large number of objects, more than will fit into the virtual memory of a process. The database typically provides some special storage structures (e.g., B-trees) that allow you to search and access this collection of objects efficiently.

2. Concurreny Control. Many concurrent processes (or transactions) can share the persistent memory space. The medium of sharing is usually the object. Concurrent access to the shared objects requires that operations from these transactions be synchronized so you don't obtain unexpected results.

3. Resiliency. A database must also be resilient or fault tolerant in the sense that if a system failure occurs (whether hardware or software), inconsistences are prevented. Most database systems approach resiliency by requiring that applications divide their work into transactions. The system will guarantee that a transaction either completes successfully or has no effect on the database at all. This guarantees that transactions behave as units of work that are atomic.

4. Consistency. Each program accessing a database is a potential source of inconsistency. Database systems guard against these errors by describing a set of

constraints that must be maintained by all program updates. A sample constraint might be "Employees cannot make more money than their managers." The system will block any program that attempts to violate a constraint. There is great interest in enriching the type of systems of object-oriented databases in order to incorporate this kind of constraint knowledge.

5. Queries. The final characteristic that an object-oriented database must address is query ability, or associative access. A query is constructed from a set of operations that are defined on *collection types* (e.g., *sets*). These operations return new structures based on the original database. Relational databases have been very successful at achieving these capabilities. Much current research focuses on whether this success can be found with the databases that are object-oriented.

The question is whether object-oriented databases can handle query optimization extensibly and in such a way that storage details are encapsulated or hidden from the interface. Since queries can contain arbitrary combinations of user-defined operations, it's difficult for an optimizer to discover equivalence-preserving transformations.

Relating to the Relational

How do object-oriented databases differ from their relational counterparts? Relational databases present you with a high level view of the persistent data space. This is very convenient for applications that primarily produce reports. It is a hindrance, though, for programs that are at the same level of complexity as a CAD system or program development environment. These programs require tight control over how storage is used. They often need to use data structures like stacks, queues, or streams of bytes. An object-oriented database lets you match the data structures that are needed for intricate tasks by creating abstractions.

Object-Oriented Databases
Comprehension Questions

Name:_____

Ratings

1. How difficult did you find the passage, Object-Oriented Databases, to understand? (Circle only one rating)

   very easy somewhat easy somewhat difficult very difficult

2. How interesting did you find the passage, Object-Oriented Databases? (Circle only one rating)

   not interesting a little interesting somewhat interesting very interesting

Multiple Choice Questions

There are 10 multiple choice questions. Read each question carefully and circle the one best answer.

1. The object-oriented database model is based on

a rules
b abstractions
c transactions
d constraints

2. The key problem for electrical engineers in modeling complex data has been

a graphics resolution
b program expense
c stability of the application
d efficiency of operations

3. You need extensibility because over time new applications evolve forms of data that are unpredicatably

a complex
b massive
c volatile
d persistent

4. Resiliency means that if a transaction isn't completed successfully, it won't have any effect on the

a message
b optimizer
c query
d database

5. By describing a set of constraints for program updates to obey, the database is protected from inputs that

a can't be stored
b cause errors
c crash the system
d deplete memory

6. "Give me the names of all managers sorted by region" is an example of a

a protocol
b query
c message
d command

7. Persistence, concurrency control, resiliency, consistency, and queries are features you'd expect from

a modern database systems
b object-oriented languages
c complex design applications
d identity-based systems

8. It's important that operations from concurrent processes be

a atomic
b synchronized
c clustered
d persistent

9. "Employees cannot make more money than their managers" was an example of a

a program update
b transaction
c data evolution
d constraint

10. Object-oriented database management systems were developed to better meet the needs of

a report production
b complex operations
c data storage
d database indexing

APPENDIX C

Prior Knowledge Multiple Choice Tests

Astronomy Pretest

Name:_____

There are 30 questions. Each question has one best answer. If you can eliminate one or more choices, go ahead and guess. If you don't know the answer at all skip it and go on to the next question.

1. The largest planet in our solar system is

a the Earth
b Mars
c Jupiter
d Saturn

2. If a spacecraft flew at 1 million kilometers per hour the trip from the Earth to the nearest star (other than the sun) would take approximately

a one year
b one decade
c one century
d one millenium (thousand years)

3. The solar system is located

a near the centre of the galaxy
b near the centre of the universe
c at the edge of the galaxy
d half-way between the edge and the centre of the galaxy

4. The most common element in the universe is

a hydrogen
b helium
c carbon
d oxygen

5. The universe first came into being

a 4000 years ago
b 100 million years ago
c 5 billion years ago
d 15 billion years ago

6. Solar systems are

a rare
b formed normally and frequently as stars form
c do not exist aside from our own
d none of the above

7. A person who stayed up all night watching the night sky would notice that

a none of the stars can be seen for the whole night
b the stars appear to move in a north-south direction across the night sky
c the stars appear to move in a west-east direction across the night sky
d the stars appear to rotate clockwise around Polaris

8. A constellation refers to

a a series of nebula named after ancient Greek gods
b a pattern of stars partitioned and named by our ancesters
c stars which can be seen with the naked eye
d the elliptical pattern made by the rotation of the stars around the Milky Way

9. During the winter season the stars which can be seen from the northern hemisphere

a are different than those that can be seen during the summer
b are the same as the ones which can be seen from the southern hemisphere
c are the same as those that can be seen during the summer
d change each night

10. The Big Dipper is

a also known as the Little Dipper
b is an example of a very large star
c is an example of a constellation
d also known as Orion

11. Vast clouds of dust and gas are called

a nebulas
b novas
c black holes
d super novas

12. The solar system contains

a 6 planets
b 9 planets
c 10 planets
d 12 planets

13. A mare is

a a plain on the moon's surface
b a plain on the surface of any moon or planet
c a crater on the surface of Mars
d a crater on the surface of any moon or planet

14. The rings of Saturn are made up of

a elliptical clouds of hydrogen gas
b alternating rings of nitrogen and hydrogen
c millions of tiny moonlets orbitting about the planet
d trillions of tiny moonlets orbitting about the planet

15. The far side of the moon

a is the side we can never see from Earth
b is the side hidden from view as the moon rotates on its axis
c is also known as the dark side of the moon
d is the side we can only see for a short period of time each year

16. A lunar eclipse happens when

a the earth passes between the moon and the sun
b the moon passes between the earth and the sun
c the earth passes between a full moon and the sun
d the full moon passes between the earth and the sun

17. Polaris is the name of a

a constellation
b star
c distant solar system
d galaxy

18. The sun is

a one of the smaller and brighter stars in the Milky Way galaxy
b one of the smaller and dimmer stars in the Milky Way Galaxy
c one of the larger and brighter stars in the Milky Way Galaxy
d one of the larger and dimmer stars in the Milky Way Galaxy

19. Most of the stars which can be seen with the naked eye are

a dimmer but larger than the sun
b brighter and larger than the sun
c brighter than the sun
d larger than the sun

20. The brightest object in the night sky is

a Sirius
b Jupiter
c Venus
d Polaris

21. The space which lies between the stars of the universe

a is a vacuum, devoid of any substances
b is empty everywhere except at the edges of the galaxies which contain clusters of gas clouds
c is filled with a variety of gases including hydrogen
d contains clouds of gas

22. In the earliest stage of the sun's formation

a pure hydrogen became contaminated by elements thrown off by other stars
b clouds of gas condensed into chance eddies
c a large eddy of gas condensed into a flattened disk
d a thermonuclear reaction occurred

23. In order for a star to begin to form, the following ingredients are essential

a gravitational forces and chance eddies of gas
b chance eddies of gas and heat energy
c gravitational forces and heat energy
d gravitational forces, heat energy, and chance eddies of gas

24. The closer a planet is to the sun

a the more gas is contained in their outer regions
b the less gas is contained in their outer regions
c the more gas is contained in their inner regions
d the less atmosphere is contained in their inner regions

25. In the sun's core are

a heavier substances which condensed first when the sun was forming
b thermonuclear reactions
c sun spots
d trapped gases and liquids

26. Parallax is a measure of

a a star's movement
b shifts in the orbits of the stars
c star position at different seasons of the year
d illusory movement

27. Parallactic distance measures depend on

a knowledge of geometry
b knowledge of the principles of light
c knowledge of the speed of light
d knowledge of the star's orbit in the Milky Way

28. A light-year measures

a star brightness
b size of the universe
c cosmic time
d cosmic distance

29. The dark lines in the sun's spectrum are produced by

a elements that absorb and emit radiation of specific wavelengths
b ultraviolet and infrared waves
c distortions in the corona
d heat radiation from the sun

30. One of the shortest measureable wave lengths known is

a a microwave
b a gamma ray
c a radio wave
d an ultraviolet ray

Computer Pretest

Name:_____

Below are 30 questions. Each question has one best answer. If you can eliminate one or more choices, go ahead and guess. If you don't know the answer at all skip it and go on to the next question.

1. To prepare a new disk to receive information it must first be

a standardized
b debugged
c programmed
d formatted

2. Its movement on the desk surface corresponds to pointer movements on the screen:

a light pen
b scanner
c joy stick
d mouse

3. Refers to the number of on/off switches a computer is processing per second:

a kilobyte
b megahertz
c ROM
d CPM

4. Pascal, Basic, and C are all examples of high level _____

a file
b programming
c word processing
d database

5. The smallest unit of information that a computer can process:

a byte
b bit
c chip
d K

6. OOP refers to a type of

a processing unit
b computer virus
c programming
d monitor

7. A group of computers which are connected in order to share resources, typically located in a building or work area:

a LAN (Local Area Network)
b COMCOM (Computer Community)
c WIN (Workstation Information Network)
d MIS (Management Information System)

8. A circuit board you can install that will implement some specialized function your computer otherwise does not support:

a expansion board
b daughter board
c memory board
d caching board

9. Allows you to preview non-commercial software. If you decide to keep the program, you pay the author a registration fee:

a Comdex
b Shareware
c Kermit
d CDRom

10. The disk operating system that governs the IBM PC and compatible computers:

a MS-DOS
b PC-DOS
c IBM-DOS
d XT-DOS

11. In order to connect a peripheral device, go to the back of the computer and plug a cable into a

a gate
b socket
c port
d terminal

12. Means that the material on the screen looks just as it will when it is printed:

a WYSIWYG
b DPI
c NLQ
d Videotex

13. Speeds up work by designating a portion of RAM to store certain information that a program uses repeatedly:

a Turbo Ram
b DOS Extender
c Relay card
d Ram Cache

14. Unless instructed otherwise, the computer will execute the

a backup setting
b filter setting
c standby setting
d default setting

15. One of the most popular online computer bulletin boards:

a CompuServe
b NetWeb
c Smalltalk
d Ethernet

16. If a software package needs 512K to run, this means the PC must have

a at least 512K of RAM installed
b at least 512K installed on a diskette
c at least 512K installed on a hard disk
d any of the above

17. "B-tree" refers to

a indexing
b synthesizing
c multitasking
d spooling

18. Two similar operating systems are:

a UNIX and CP/M
b CP/M and OS/2
c OS/2 and UNIX
d EISA and MCA

19. Lotus 1-2-3 and Excel are two popular _____ programs.

a wordprocessing
b accounting
c spreadsheet
d database

20. To lose data means that

a data was erased from a disk
b the computer crashed
c the amount of data entered exceeded disk capacity
d the data was converted to Assembly

21. A program that performs a specific task, such as word processing, database management, or graphics:

a a start-up
b an accessory
c an application
d an installer

22. One advantage of the object-oriented database is that it

a can be programmed with a computationally complete programming language
b handles associative access
c handles query optimization extensibly
d is available commercially

23. Query optimization hasn't been demonstrated with databases that are

a conventional
b identity-based
c object-oriented
d relational

24. Programming routines or functions which can be reused and put together with other routines or functions in many different applications:

a microcode
b object-oriented code
c machine code
d binary code

25. Used in engineering workstations to design microprocessor models directly on the computer screen:

a common architecture
b CRUSH
c CISC
d CAD

26. Customizing your computer (adding video, co-processing, networking, etc.) would be easier if your system had

a multitasking
b open architecture
c a modem
d in-circuit emulators

27. Which two words best describe a computer bus?

a stacks and queues
b DRAM and RAM
c queries and messages
d connectors and logic

28. Multimaster operation is

a necessary to create a multiprocessor
b the same as multiprocessing
c dependent on caches
d dependent upon multiuser systems

29. Who addressed the problem of "closed" Macintoshes?

a Apple Computer
b IBM competition
c third parties
d end users

30. A unit that uses memory sources and peripherals to manage the flow of information into and out of the microprocessor:

a bus unit
b memory management unit
c control unit
d decode unit

APPENDIX D

Words Used in the Semantic Decision Task

and the

Word Naming Tasks

Semantic Decision and Word Naming Words

Condition	Word	Control	SFI	Letters	Syllable
Astronomy	light	hands	66.7	5	1
	gas	eye	60.8	3	1
	revolution	impossible	58.0	10	4
	cloud	shell	55.7	5	1
	solar	motor	55.7	5	2
	atom	lion	55.0	4	2
	spectrum	downtown	50.7	8	2
	galaxy	studio	49.7	6	3
	comet	armor	48.8	5	2
	brightness	households	47.1	10	2
	gravitation	tributaries	42.5	11	4
	light-years	playwright	41.9	10	2
	asteroid	crevices	41.4	8	3
	parallax	pastoral	40.4	8	3

Condition	Word	Control	SFI	Letters	Syllable
Computer	bus	die	59.1	3	1
	data	fifty	57.4	4(5)	2
	circuit	beating	52.9	7	2
	logic	jelly	49.8	5	2
	extension	guarantee	49.7	9	3
	architecture	expenditures	48.8	12	4
	hardware	mushroom	47.4	8	2
	programming	cleanliness	45.1	11	3
	software	pheasant	40.9	8	2
	query	icing	37.8	5	2
	cache	spars	36.1	5	1
	schema	atolls	32.9	6	2
	bytes	smuts	29.9	5	1
	desktop	globule	27.7	7	2

APPENDIX E

Pseudowords

Pseudowords

blate
kench
murst
touse
wursk

barip
belaf
podin
rebin
tarlo

dackfone
dermidge
hockrase
prestorn
zenkwile

blavigon
keterage
kovether
rifitent
tersomal

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