

THE ROLE OF COGNITIVE CAPACITY AND INFORMATION PROCESSING
PREFERENCES IN FORECASTING AND PREDICTION ACCURACY

by

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A Dissertation
Submitted to the
Graduate Faculty
of
George Mason University
in Partial Fulfillment of
The Requirements for the Degree
of
Doctor of Philosophy
Psychology

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Date: _____ Fall Semester 2013
George Mason University
Fairfax, VA

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Fall Semester 2013
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Acknowledgements

I would like to thank many people for the roles they played along the course of my doctoral process. I would like to thank Dr. Steve Zaccaro for the helpful direction and advice throughout the dissertation process. Dr. Eden King – your guidance and support over the years were immensely valuable. Without you as my informal advisor, I can honestly say that I might not have made it through. Dr. Jim Thompson – thanks for helping me go outside the normal bounds of I/O psychology. Working with you has been a highlight of my graduate school career. I hope to find opportunities to collaborate with all of you again in the future.

I would also like to thank my friends and colleagues at both George Mason and PDRI. To work with such high caliber researchers at has been integral to my development. I feel very fortunate to have been surrounded by such talented individuals.

To my family and friends outside of I/O, thank you so much for your tolerance, encouragement, and support. Your love and friendship have given me the strength to persevere. Finally, a special thanks to my parents for encouraging me to never stop learning and believing in me every step of the way.

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Abstract

THE ROLE OF COGNITIVE CAPACITY AND INFORMATION PROCESSING PREFERENCES IN FORECASTING AND PREDICTION ACCURACY

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The cognitive process of forecasting is important for decision making, problem solving, and planning, but has been under researched in psychology. The present research looked at the relationship between the amount and detail of forecasts and the accuracy of predictions in a driving time prediction context. In addition, individual differences in working memory capacity and visual/ spatial information processing were examined for their impact on forecasting activity. The results indicated that forecasting detail, but not forecasting amount, was related to prediction accuracy; however, both were moderated by participants' task experience. Furthermore, working memory capacity interacted with object imagery usage to predict the amount of detail in participants' forecasts; however, the impact of working memory and object imagery was not transmitted to prediction accuracy. Overall, the findings from this study contribute to the literature on forecasting by highlighting important factors in the forecasting process.

Introduction

Future oriented thinking is ubiquitous in everyday life, and one such process in particular – forecasting – is receiving increasing attention from researchers in many areas of psychology. Within industrial/ organizational psychology, forecasting has been cited as a critical variable in areas such as leader vision formation (Shipman et al., 2010), evaluation of ethical considerations (Stenmark, Antes, Thiel, Caughron, Wang, & Mumford, 2011; Stenmark, Antes, Wang, Caughron, Thiel, & Mumford, 2010), creative idea evaluation (Dailey & Mumford, 2006; Mumford, Lonergan, & Scott, 2002), and creative problem-solving (Byrne, Shipman, & Mumford, 2010). Similarly, forecasting plays numerous roles in complex cognitive processes such as planning (Hayes-Roth & Hayes-Roth, 1979; Mumford, Shultz, & Osburn, 2002). For example, forecasting is used to envision future and goal states (Haith, 1997), to predict the affordances that will come into or leave from the environment, and to predict the effectiveness of an initial plan, make modifications as necessary, and test a final plan for validity and feasibility (Mumford et al., 2001; Mumford, Shultz, & Osburn, 2002). In addition, forecasting is used to make estimates of resource requirements, such as the amount of time needed to complete a project or to complete a task (Dailey & Mumford, 2006).

Despite the importance of forecasting, little is known about what leads to successful and decisionally beneficial forecasts, and very little is known about how

forecasts are formed. In order to begin to address these gaps, the present work will examine mental simulation as a contributing mechanism for forecasting. Mental simulation, in a forecasting context, can be seen as the process of manipulating mental representations of current situations, based on one's understanding of causal factors, to extrapolate conditions likely to unfold in future situations. Mental simulation has also played a significant role in many other psychological theories and been identified as a mechanism in many important processes. For instance, Klein and Crandall (1995) proposed that mental simulation is the mechanism by which experts generate, test, and make decisions in the real world (see also, Kahneman & Tversky, 1982). Mental simulations have also been hypothesized as mechanisms for reasoning and problem solving (Einhorn & Hogarth, 1986; Hegarty, 2004; Trickett & Trafton, 2007), and for solution evaluation (Christensen & Schunn, 2009).

Based on forecasting and mental simulation literatures, I will identify potential individual differences that may play a role in the forecasting activities an individual engages in and the functional outcomes of forecasting activities. In particular, I will explore the role of knowledge and experience in making forecasts more accurate, and the role of working memory capacity and visual/ spatial imagery usage in producing more forecasting activity. Determining the relative importance of these factors should contribute to an understanding of how the process of forecasting is conducted and when it is likely to be beneficial.

Forecasting and Mental Simulation

Forecasting

Forecasting is the process of mentally simulating imagined future scenarios or events. It is used by decision makers to anticipate potential obstacles and hindrances, or to play out a course of action and evaluate its potential for success. In Mumford, Lonergan, and Scott's (2002) model, forecasting is used when evaluating creative solutions as a means of examining potential outcomes and necessary resources. These forecasts are then appraised and used to inform subsequent decisions. Similarly, in creative problem solving, forecasting is used as a form of complex prediction and should lead to better evaluations of idea quality, originality, and elegance; and to higher quality, more original, and more elegant plans for idea implementation (Byrne et al., 2010). Byrne and colleagues tested this hypothesis and found that the extensiveness of forecasts was positively related to ratings of solution quality, originality, and elegance; and positively related to ratings of implementation plan quality, originality, and elegance.

In a similar study, Dailey and Mumford (2006) examined factors influencing evaluations of creative ideas and identified forecasting as a critical component in the evaluation process. According to Dailey and Mumford, forecasting allows the creative problem solver to increase the quality of a creative solution by identifying the most viable ideas to spend time and resources pursuing, providing an examination of ideas in the light of the present context, and simulating revisions needed to enhance the impact of solutions. Though these researchers did not measure forecasting activities directly, they asked participants to use their forecasts to make ratings of resource requirements and social outcomes of a solution to a problem. Dailey and Mumford found that people show some accuracy in their predictions of resource requirements and outcomes (in contrast to

previous research; e.g., Dörner & Schaub, 1994; Langholtz, Gettys, & Foote, 1995). One factor contributing to the accuracy of forecasts was the expertise of the forecaster. When participants in Daily and Mumford's study were more familiar with a domain, they tended to be more accurate in their forecasts of the impact of ideas and the difficulties likely to be encountered in implementing ideas. Interestingly, though familiarity was associated with more accuracy, the participants also tended to overestimate the positive outcomes and underestimate the time and money required for the solution.

Shipman, Byrne, and Mumford (2010) examined how forecasting may be involved in the vision setting functions of leaders. In this context, forecasting is used to anticipate an organization's future environment and to generate a general strategy for reaching organizational goals in that environment. Shipman et al. modified a research paradigm used by Mumford and Strange (2005) to incorporate written statements of predictions for the future. This required that participants make their forecasts explicit so they could later be evaluated by raters. The researchers found that extensiveness of forecasts predicted the quality of the vision statements that participants produced. Moreover, vision quality was higher when forecasting activity considered time and resource requirements. As noted by Shipman et al. (2010), given this positive relationship, leader forecasting activity has been under examined by the research community.

Stenmark and colleagues (Stenmark, Antes, Thiel, Caughron, Wang, & Mumford, 2011; Stenmark, Antes, Wang, Caughron, Thiel, & Mumford, 2010) highlighted the importance of forecasting in ethical decision making. These authors point out that ethical

decisions tend to be complex and have significant consequences, and therefore, forecasting activity is critical to the ethical decision making process. Stenmark et al., (2010) collected evidence that suggests that forecasting quality relates to more ethical decisions. They also found that higher quality forecasts were produced when the most critical causes were analyzed, but high quality forecasts did not necessarily result from the number of causes that were analyzed.

As the above literature illustrates, many industrial/ organizational psychologists have studied forecasting for its impact on many different outcomes. One area in particular that should receive more research is the use of forecasting to predict resource requirements. This form of prediction is important because predicting time requirements is necessary scheduling work and coordinating smaller tasks for the successful completion of larger projects (Halkjelsvik & Jorgensen, 2012). Moreover, these predictions are often biased downward, at least within the context of predicting how long it will take to complete a project (for review, see Buehler, Griffin, & Peetz, 2010). As the above research demonstrates, forecasting has an important role in complex cognitions such as problem solving and decision making. To begin to examine what individual differences are most important for forecasting activities, it would be helpful to examine the underlying process of mental simulation in more detail.

Mental Simulation

Mental simulation is a widely used term in psychology, though it is also variably defined. As it will be used here, the cognitive act of mental simulation is the “running” of a mental model (Hegarty, 2004; Trickett, 2004; Trickett & Trafton, 2007). Mental models

are the “knowledge and cognitive processes that allow humans to understand, reason about, and predict the behavior of complex physical systems” (Hegarty, 2004, p 280). In this sense, a mental model is a knowledge structure that can be recalled from memory in order to answer questions one might have. Mental modeling of hypothetical or real phenomena appears to be a fundamental process used in support of human reasoning (Gentner & Stevens; 1983; Johnson-Laird, 1983).

The above definition of mental simulation is similar to the definition offered by Moulton and Kosslyn (2011). They define mental simulation as “an epistemic device that operates by sequential analogy” (Moulton & Kosslyn, 2011, p. 99). As an “epistemic device,” mental simulation is used to access stored knowledge or generate knowledge (see Fisher, 2006). By “sequential analogy” Moulton and Kosslyn mean that a mental simulation has an analogous temporal structure as the event that is simulated. In other words, the steps in a mental simulation correspond to the steps in the actual event, though often steps are omitted in mental simulation and simulations are almost always condensed.

Both of these definitions imply that mental simulation is the dynamic use of mental models. Gilhooly (1987) describes mental modeling as an information processing function designed to represent the external world. Mental modeling and mental simulation are largely analogous. Through information gathering processes, the mind collects perceptual inputs and constructs a general model of how the world works, along with expectancies for how it might work in any given situation. This information allows prediction of future situations through mental simulation of constructed models of the

world. Mentally simulating the model of a system can be used to infer future states of the system, allowing an individual to form a plan of action.

Unfortunately, very little is known about *how* one mentally simulates.

Researchers often invoke the term “mental simulation” to explain cognitive processes, though they rarely describe the explanatory mechanisms behind mental simulation. To say that planning, forecasting, reasoning, problem solving, and naturalistic decision-making all require mental simulation, and in some cases, *are* mental simulation, is not a meaningful way to describe these cognitive functions. Without a deeper understanding of what mental simulation entails, it is impossible to determine whether the mental simulation explanation is feasible or whether mental simulation performance can be predicted by situational or individual factors. The next section provides a theoretical framework underlying the proposed model for a cognitive process of mental simulation. This framework will provide support for the individual differences that are hypothesized to contribute to forecasting and prediction accuracy.

If forecasting is done through the cognitive process of mental simulation, one question then becomes, what leads an individual to make accurate and useful simulated forecasts? It is assumed that everyone engages in forecasting, however, some individuals should be expected to forecast better than others. There has been little research that connects mental simulation abilities and predictions mechanisms with individual differences. When used in planning, mental simulations of forecasted futures must be commanded and controlled in order to produce integrated simulations necessary for creating viable plans (cf Klein & Crandall, 1995). The present work examines three

classes of individual differences that may play a role in the forecasting process: knowledge, information processing preferences (i.e., visual/spatial/verbal preferences), and information processing capacities (i.e., working memory capacity).

Present Research

The underlying conceptual model of the present research is this: during mental simulation, association networks of long-term memory are continuously activated and used as a resource to frame mental imagery. Subjectively, this produces a stream of imagery and internal representations which allow an individual to project him or herself mentally into another place, time, or person (see Buckner & Carroll, 2007). During planning, the simulation of imagery allows an individual to construct internal representations of a predicted (though hypothetical) future. This enables the individual to evaluate and select options for navigating toward the most optimal future. The success of activities such as strategizing or planning depends heavily on the accuracy of these simulated representations.

Forecasting allows decision makers to manipulate mental models of the present situations and extrapolate about the future. Forecasting plays an important role in planning by allowing one to anticipate future situations and the outcomes of proposed actions. Decisions are made based on the anticipation of outcomes. Therefore, the extent, quality, and character of forecasting activities should be an important antecedent to the quality of decisions. In planning, these decisions pertain to the feasibility, required resources, or outcomes of a course of action. The present research will explore the role of forecasting in predicting required resources, namely, time requirements. Beginning with

the right combination of knowledge and individual differences, forecasting activities can yield accurate predictions. Therefore, a key relationship to be tested is that forecasting activities are positively related to prediction accuracy.

More specifically, this research will examine forecasting amount and detailedness because these basic facets of forecasting have been linked to decision quality in previous research (e.g., Byrne et al., 2010; Stenmark et al., 2010, 2011). While related, these two forecasting activity variables are expected to be distinct and to capture unique variance in prediction accuracy. Forecasting amount is simply the amount of time that an individual spends during forecasting. Forecasting detail is the thoroughness of the forecasting activities, or the extent to which a forecaster considers a range of possibilities in causes and outcomes. These two forecasting activity variables are both expected to relate to prediction accuracy in a positive manner.

H1a: Forecasting amount predicts accuracy of predictions.

H1b: Forecasting detail predicts accuracy of predictions.

The human tendency to forecast and make predictions is strong despite the fact that many complex systems can be extremely difficult to predict. There are a number of computational factors that impact prediction success, such as how strongly events are related or how frequently they occur. One of the prerequisites for successful forecasting is that events must be nonrandom. If there are no causal relationships between cues in the present environment and occasions in the future environment, then there is no way, outside of luck, to predict what will transpire. The brain, however, will still attempt to generate a probabilistic expectation from this random input (Schubotz & von Cramon,

2002). That is, even random input can sometimes generate an illusion of a pattern (Chapman, 1967; Kahneman & Tversky, 1971) and lead to false confidence in predictions.

Given these difficulties, it is unsurprising that the predictions that people make are often inaccurate (Dörner & Schaub, 1994, Pant & Starbuck, 1990). However, perhaps with the right model, we may identify individual characteristics that facilitate prediction accuracy. In the next section, I outline a model that suggests moderators of the relationship between forecasting activities and prediction accuracy. In addition, I examine antecedent variables that encourage individuals to engage in forecasting.

Knowledge, Forecasting, and Prediction Accuracy

The role of knowledge in forecasting is critically important. Those with the more accurate knowledge structures should be better at making predictions than those with less accurate knowledge structures, at least in noncomplex domains. Gilhooly (1987) claimed that mental simulation is primarily driven by memory resources: both long-term memory and working memory. Long-term memory holds general schemas and domain specific knowledge, and working memory operates on that information to use it in situ. The focus of this section is long-term memory – knowledge in perceptual and abstract forms. Working memory will be addressed in the next section.

The present research assumes a baseline level of domain familiarity. Using this knowledge, participants are expected to actively generate forecasts; however, the utility of those forecasts in producing accurate predictions will depend on a specific set of knowledge. In other words, while knowledge itself is an antecedent of forecasting, large

amounts of accurate, domain specific knowledge is what converts forecasting activity into accurate predictions.

The imagery that results from mental simulations is used to examine stored knowledge and make it accessible for reasoning and prediction (Fisher, 2006; Moulton & Kosslyn, 2011; Trickett & Trafton, 2007). Domain specific knowledge of the most important causal variables is essential to ensuring that forecasts are appropriately targeted (Dailey & Mumford, 2006; O'Connor, 1998). Since so much reasoning and prediction depend on the knowledge made accessible through mental simulation, an expectation for the current research is that:

H2a: Domain specific knowledge moderates the relationship between forecasting amount and prediction accuracy, such that more knowledge and more forecasting lead to more accurate predictions.

H2b: Domain specific knowledge moderates the relationship between forecasting detail and prediction accuracy, such that more knowledge and more detailed forecasting lead to more accurate predictions.

As Glass and Holyoak (1986) have pointed out, knowledge has aspects pertaining to what is represented and how it is processed. In their words, “knowledge must be stored, or represented, in memory, and it must be used, or processed, to perform cognitive tasks” (Glass & Holyoak, 1986, p. 5). To Glass and Holyoak, representation and processing are related in such a way that how information is represented determines how it can be used. This account of knowledge mirrors findings in the planning literature that demonstrate that much of the knowledge that is used in the early planning phases comes

from past experience (Berger & Jordan, 1992; Hershey, Walsh, Read, & Chulef, 1990; Mumford et al., 2001; Mumford, Shultz, & Osburn, 2002). The role of past experience in contributing key knowledge cannot be overlooked. Using past experience to generate future plans is a process of manipulating schemata “to construct them afresh” (Bartlett, 1932, p. 206). Past experience is a critical factor for forecasting, as shown in research into episodic future thought (Szpunar, 2010; Szpunar, Chan, & McDermott, 2009) and the constructive episodic simulation hypothesis (Schacter & Addis, 2007a, 2007b). Past experience is important because of the type of knowledge it provides and its application to future situations.

Berger and Carol (1992) compared different sources of knowledge that were used in plans by having participants think aloud as they generated action plans for social interactions and hypothetical goals (e.g., becoming a millionaire, requesting a date, ingratiating oneself with a roommate, and persuading another person). The sources of knowledge Berger and Carol identified included individual past episodes, sets of past episodes, or hypothetical episodes. They found that each of these sources were used to form action plans for various hypothetical goals, though for each goal, specific past episodes and sets of past episodes were used more often than hypothetical episodes. The only exception was that when planning to request a date, past episodes and hypothetical episodes were equally frequent. When participants formed plans for becoming a millionaire, they used episodes (both past memories and hypothetical episodes) relatively infrequently. Instead, participant used exemplar role models as the basis of their plans, since they had little of their own experience in such situations. Based on this research, it

is expected that experience strengthens the relationship between forecasting activities and prediction accuracy.

H3a: Task experience moderates the relationship between forecasting amount and prediction accuracy, such that task experience strengthens the relationship between forecasting and prediction accuracy.

H3b: Task experience moderates the relationship between forecasting activities and prediction accuracy, such that task experience strengthens the relationship between forecasting and prediction accuracy.

Working Memory Capacity and Forecasting

Working memory is not often studied in conjunction with forecasting, but it is examined in connection with planning. Planning is inherently an error prone process since it relies on human information processing (Dörner & Schaub, 1994). Even experts are often inaccurate in their forecasts (Pant & Starbuck, 1990) and predictions (Tetlock, 2005). The implication is that knowledge may be necessary, but not sufficient for producing accurate forecasts and predictions. Knowledge forms the schemas from which plans are constructed or interpreted and provides the parameters for the interacting components within a forecast. However, constructing and activating these knowledge structures through mental simulation takes effort and sustained attention. This capacity comes through working memory- the component of memory that holds currently important information active for manipulation and calculations.

The use of imagination to represent future worlds or mental simulation to test actions in a problem space requires cognitive resources (Mumford et al., 2001; Reuland,

2010). Moreover, when there is a large distance between a current state and a desired future state, or when the path between the two is dynamic and complex, cognitive resource demands are greatly increased (Dörner, 1996; Dörner & Schaub, 1994; Mumford et al., 2001). The cognitive resources required for successful planning come from the ability to focus attention on the problem, the ability to hold the required information in mind, and the ability to transform that information through mental simulation. These abilities are derived from working memory capacity.

Working memory is important because it grants the planner more resources for mental simulation and more flexibility and freedom in the mental simulations he or she creates. For example, greater working memory capacity would help the planner to more fully mentally manipulate the component stages of a plan. Pulos and Denzine (2005) argued that planning ahead requires working memory because action steps must be sequenced into a course of action. Pulos and Denzine predicted that online planning – planning that is updated as actions are taken – would require fewer cognitive resources because information is apparent in the situations and does not need to be stored in memory. These authors found that working memory was related to solution time. They reasoned that this result was due to the length of action sequences, or partial plans, that were formed. Individuals with larger working memory capacities formed longer partial plans before executing those plans. Individuals with shorter working memory capacities formed relatively short partial plans.

There have been a few investigations of the relationship between working memory and planning through tasks such as the Tower of Hanoi (Emick & Welsh, 2005),

the Tower of London (Gilhooly, Wynn, Logie, & Della Sala, 2002; Newman, Carpenter, Varma, & Just, 2003; Phillips, Gilhooly, Logie, Della Sala, & Wynn, 2003; Pulos & Denzine, 2005; Unterrainer & Owen, 2004), or Luchin's (1942) water jug problem (Delaney, 2001). This research generally shows a strong relationship between planning and working memory capacity. However, these studies operationalized planning as short-range solutions to immediate problems. These tasks require visualizing how physical objects might be manipulated to reach solutions. Therefore, the working memory needed for performance on these planning tasks is mainly visual or spatial. For example, Gilhooly et al. (2002) examined performance on 20 Tower of London tasks of varying difficulty and found that performance on these tasks loaded on visio-spatial working memory, rather than processing speed or verbal working memory.

Few researchers have empirically investigated the relationship between working memory and mental simulation. In one case, researchers examined the effort required to form mental models of complex equations (i.e., those produced by Einstein's (1905) theory of special relativity; Qin & Simon, 1992). In this study, Qin and Simon had participants read sections from the 1905 paper, and create mental images to represent the equations presented. The authors reported that participants could create images and simulate those images mentally in order to watch the evolution of processes and draw conclusions. However, Qin and Simon also reported that when the mental image was used to problem solve (i.e., to derive Einstein's equations) the participants exerted great short-term memory load. Individuals with greater working memory capacity may be more inclined or more able to forecast more fully. Therefore,

H4a: Working memory capacity predicts forecasting activity, such that greater working memory capacity leads to more forecasting.

H4b: Working memory capacity predicts prediction accuracy, such that greater working memory leads to more accurate predictions.

Since Hypotheses H1a and H1b predicted a positive relationship between forecasting activities and prediction accuracy, it is likely that some of the effect of working memory on prediction accuracy is transmitted through forecasting activities. Therefore,

H4c: Forecasting activity partially mediates the relationship between working memory capacity and prediction accuracy.

Information code use

In order for information to be stored, it must be coded into some representation – an internal depiction for external content. As discussed above, representations can be analog or symbolic, and the way information is stored determines how it can be used (Glass & Holyoak, 1986). Code usage is a term used to describe the information processing preferences and abilities of individuals along the dimensions of visual and verbal/symbolic orientations.

According to Mayer and Massa (2003), there are stable individual differences in both the form of representation used in thinking and the form of representation preferred in learning. Based on these individual differences, researchers in educational psychology have been classifying people as visualizers or verbalizers depending on which representation they tend to use more in learning and problem solving. However,

researchers have also treated these dimensions as independent of one another such that individuals possess the capacity to process information in both forms. For example, Blazhevskova and Kozhevnikov (2009; see also Clark & Paivio, 1991; Paivio, 1986) argue that imagery is a unitary construct. People are high or low in imagery use, and they have different modalities for using imagery (visual, verbal, as well as others). This means that someone can be high in the use of visual imagery as well as high in verbal imagery, or low in both, or any other combination.

Visual information procession. As a species, we are heavily dependent on vision in daily life and over half of the human brain is devoted to processing visual information (Anderson, 2010). As such, memories of past episodes tend to be highly visual. Since individuals store past experiences in visual code, and use past experiences to predict future experiences, a preference and facility for visual code should provide clear and convincing simulation of the future.

Visual abilities are often examined in conjunction with spatial abilities and the two are often grouped together in research as visuo-spatial abilities. Carroll (1993) proposed that visual ability is a subfactor of spatial intelligence. He called visual ability the “ability in forming internal mental representations of visual patterns and in using such representations in solving spatial problems” (Carroll, 1993, p. 363). However, the tendency to group visual and spatial abilities together may obscure important differences between two codes and there is some evidence that they should be treated separately to more effectively predict the uses of these codes (Blazhenkova & Kozhevnikov, 2009).

Visual information is processed in two ways in the brain. There is a pathway that processes *what* the object of vision is, and there is a pathway that processes *where* the object of vision is. Based on this understanding of the cognitive neuroscience of vision, Kozhevnikov and colleagues (Kozhevnikov, Kosslyn, & Shephard, 2005; Blazhenkova & Kozhevnikov, 2009) argued for the inclusion of an object subscale (for processing *what*) and a spatial subscale (for processing *where*) in measurement approaches to visual imagery preferences and abilities. Blazhenkova and Kozhevnikov (2009) created a measure of imagery usage that demonstrated better fit to a three factor structure (object, spatial, and verbal) than a two factor structure (visual and verbal). On the criterion side, they also found that scores on the object subscale correlated with performance in visual art classes. Scores on the spatial subscale correlated with performance in physics classes. Finally, scores on the verbal subscale correlated with performance in writing classes. This suggests that a tendency to use a specific type of information conveys a benefit for tasks that are heavily reliant on that information type.

Individual differences in object imagery use. Object imagery – pertaining to the appearance, shape, color, or texture of visual imagery – may be marginally related to forecasting activities, though it is not expected to be related to prediction accuracy. Much of the experimental evidence for the functionality of visual imagery that exists has been generated in domains of simple, short-term, or concrete problems. There is less evidence that visual imagery is used in complex problem solving such as that required for long-range planning. D'Argembeau and Van der Linden (2006) examined the role of object imagery in participants' forecasts of their future. They found that individuals that

use highly vivid visual imagery tend to simulate more details in their forecasts, and they forecast more important and emotionally-laden events. D'Argembeau and Van der Linden suggested that the same characteristics that enable highly visual people to remember information from the past enable them to create predictions of the future. This argument parallels the connection between remembering the past and predicting the future that has been suggested by many other researchers (e.g., Atance & O'Neill, 2001; Schacter & Addis, 2007, 2008; Suddendorf & Corballis, 1997; Tulving, 1985).

Based on theory grounded in information processing, Kosslyn (1980) proposed that visual imagery is made up of components such as image generation, image maintenance, and image transformation. Poltrock and Brown (1984) measured performance on visual imagery and spatial ability tasks that correspond to the cognitive components outlined by Kosslyn's (1980) mental imagery model. They found that these cognitive components were unrelated to one another, suggesting separate stages in cognition that contribute to performance on visual/ spatial tasks. Having separate stages for generating, maintaining, and transforming imagery implies that imagery creates numerous demands on cognitive resources. Therefore, the benefits of visual information processing are likely to be enhanced in the presence of sufficient working memory.

Just as working memory may facilitate visualization processes, working memory capacity limitations may be partially remediated by visualization. Since a picture is sometimes worth ten thousand words in problem solving (Larkin & Simon, 1987), visualization may produce a reduction in cognitive load by chunking multiple items into one coherent picture. The ability of visual information processing to compensate for low

working memory capacity is suggestive of an interaction between visual information use and working memory capacity. The ability to maintain and manipulate clear visual images in working memory may contribute to the extent of forecasting activities.

Therefore,

H5a: Object imagery use and working memory capacity have an interactive effect on forecasting amount such that the relationship between working memory and forecasting amount becomes more positive as object imagery use increases.

H5b: Object imagery use and working memory capacity have an interactive effect on forecasting detail such that the relationship between working memory and forecasting detail becomes more positive as object imagery use increases.

Individual differences in spatial imagery use. If an individual is using mental simulation to mentally travel through time and think out a plan, then there will be a time component of the imagery that is used for the simulation. Forecasting future events through mental simulation is a means of mentally moving through time and playing out a temporal unfolding of events. Planning requires ordering actions in time. We use a spatial metaphor for describing time, possibly because we use a spatial metaphor to think about time. For example, we think of moving through time in a similar way as we think of moving through space (e.g., as moving “forward” or “back”). Individuals that construct an accurate mental model, and are able to simulate the model’s dynamics through time, may be better at forecasting future outcomes based on that model.

Moreover, there is some evidence that spatial ability is related to the ability to estimate quantities and approximate accurately (Dehaene, 1997; Hogan & Brezinski, 2003). Some of the greatest challenges in planning is the estimation of how long things will take (Buehler & Griffin, 1994; Buehler & Griffin, 2003; Buehler, Griffin, & Peetz, 2010) or how many resources will be necessary. For example, estimating how long a process will take is so often inaccurate, that the consistent underestimation in this regard is known as the planning fallacy (Kahneman & Tversky, 1979). If spatial abilities translate into temporal abilities as has been suggested, then we would expect spatial abilities to contribute to the temporal structure of forecasting abilities.

H6a: Spatial imagery use predicts forecasting activities.

H6b: Spatial imagery use predicts the accuracy of predictions.

H6c: Spatial imagery use and working memory capacity interact such that the relationship between working memory capacity and forecasting activities becomes more positive as spatial imagery use increases.

Individual differences in verbal code use. Walsh (2003) proposed that doing exact calculations requires access to language. He suggested that a system for determining the magnitude of something (e.g., its quantity, size, or timespan) is localized in a region of the brain implicated in word associations – the left inferior prefrontal lobe. Dehaene, Spelke, Pinel, Stanescu, and Tsivkin (1999) demonstrated that language is necessary for exact calculations, but people can approximate without language. Exact calculations are probably not made during mental simulations, but rather are made outside and imported in. Therefore, verbal code use may have an impact on predictions,

though this expectation is weaker. In fact, there is little theory or evidence describing the role of verbal code in forecasting and prediction. Since the present research will measure forecasting with a verbal protocol, it is likely that verbal code use will be related to forecasting activities. However, this relationship is driven by methodological factors and not theoretical factors. Because of these factors, no hypotheses will be formed around the role of verbal code use.

Method

Study Overview

The present research investigates individual differences that contribute to forecasting activities and prediction accuracy in estimating time requirements. A laboratory setting was used to test the above hypotheses. Participants were presented with three driving scenarios and for each, asked to imagine making a trip by car from one location (between 17 and 28 miles away) to the parking lot of their university campus. A driving scenario was chosen because it was believed that there would be adequate variation in required knowledge in a college student population. In addition, a driving scenario affords the opportunity to create a time requirement estimation task that can be objectively verified with web-based estimates of travel times factoring in traffic delays.

Participants

This study included 103 undergraduate students from the psychology subject pool who had enrolled in research to partially fulfill course requirements. Due to a lost audio recording, one person was dropped from the dataset, for a final sample of 102. The average age of participants was 20.7, with a standard deviation of 4.42 years. Ages ranged from 18 to 47. Most participants were female (68.9%) reflecting the broader subject pool. The ethnicity of the sample was 13.6 percent African American, 10.7 percent Asian, 50.5 percent Caucasian, 5.8 percent Hispanic, 1.0 percent Native

American, 4.9 percent Middle Eastern, and 13.6 percent reported mixed parentage. Many participants were in their freshman year at the University (41.7%), while sophomores made up 14.6 percent, juniors made up 23.3 percent, seniors made up 18.4 percent. Two participants were completing post-graduate course work (about 2%). More than half of the participants were working at least part-time (41.7 % reported working part-time, 11.7% reported working full time). The other 46.6 percent reported not currently working. Fifty-four participants (52.4%) said they grew up in the local area. Sixty-nine (67%) reported having a car in the area.

Experimental tasks

The experimental task consisted of three forecasting opportunities where participants are presented with a driving situation and asked to describe the route they would take. Participants were asked to imagine they were at a location (between 17 and 28 miles away) and they had to drive to campus on a Friday at 4:00PM. They were then asked to respond verbally (i.e., “think aloud”) to three prompts. First, they were asked to describe the way they would go in order to get to campus. Then, they were asked to think about the factors that would impact their ability to get to campus as quickly as possible. Finally, participants were asked to think about how their travel time from one location to campus would be affected if the situation was not Friday at 4:00PM. After each response from the participant, a follow up question was asked (i.e., “are there any other details to include?”, “are there any other factors or obstacles?”, or “are there any other differences based on day of the week or time of day?” for the three questions, respectively). These were the only questions asked during the exercise to standardize the amount of prompting

participants received. Verbal responses to these prompts were audio recorded, transcribed, and subsequently coded. The “think aloud” protocol script is presented in Appendix B.

After participants completed the “think aloud” portion of the scenario, they were asked to make estimates of time requirements for the travel required of the situation. They were asked to predict how long it would take to reach a well-known meeting spot on campus and to provide their degree of confidence in their prediction, from 0 percent to 100 percent. They were also asked to give a range of how long it might take, and to estimate how long the drive would take in the rain.

Measures

Demographics. All demographic information was self-reported. The demographic questions that were asked can be found in Appendix A: Measures. Information collected included age, sex, year in school, college major, overall GPA, native language, English proficiency, and work experience.

Information code use. Individuals’ usage of different information modalities will be measured using the Object-Spatial Imagery and Verbal Questionnaire (OSIVQ; Blazhenkova & Kozhevnikov, 2009). This 45 item scale has object, spatial, and verbal subscales, each with 15 items. The OSIVQ is a self-report measure in which participants rate the extent to which the items describe their preferences. Blazhenkova and Kozhevnikov (2009) found an internal consistency of (object $\alpha = .85$, spatial $\alpha = .79$, and verbal $\alpha = .74$) and test-retest reliability (object $r = .75$, spatial $r = .84$, and verbal $r = .73$) of these subscales. They also provided evidence for the predictive and discriminant

validity through confirmatory factor analysis (study 2) and the ecological validity by relating OSIVQ scores to performance in different academic classes such as physics, visual arts, and writing (study 3). The present study used only spatial and object visual subscales, which had 14 and 15 items, respectively. The spatial subscale only had 14 items due to an error in the survey administered to participants. The coefficient alpha for the object imagery subscale was .85; coefficient alpha for the spatial imagery subscale was .81.

Working memory capacity. Working memory capacity was measured using two computer-based complex span tasks; the automated operational span and the automated reading span tasks (Unsworth, Heitz, Schrock, & Engle, 2005); available from Engle and colleagues' *Attention and Working Memory Lab* at Georgia Institute of Technology). In these tasks, participants are required to store strings of letters in short term memory while engaging in some other task, such as reading or doing math. In the operational span task, participants must solve an addition or subtraction problem, and remember a letter that follows the problem. They follow this with another addition or subtraction problem and another letter. This is repeated a number of times and at the end of the trial, participants must recall the string of letters they were presented with. Similarly, in the reading span task, participants must read a sentence and remember a letter presented at the end. Internal consistency evidenced in Kane et al. (2004; see also Conway et al., 2005) and test-retest reliability is evidenced in Conway et al. (2005). More detailed information about these measures is available from Unsworth, Heitz, Schrock, and Engle (2005).

What Unsworth and colleagues (2005) describes as the absolute score was used for this variable. The absolute score is the total number of letters correctly recalled within completely recalled sets of letters. For example, if the participant recalled four out of four (4/4), four out of five (4/5), three out of four (3/4), and three out of three (3/3), their score would be seven: $(4 + 0 + 0 + 3 = 7)$.

Knowledge. Knowledge was measured with a single self-report item that asked participants to rate his or her confidence in his/her ability to locate [start location] on a map in under 20 seconds (0% confident, 25% confident, 50% confident, 75% confident, or 100% confident). Participants answered other knowledge items, however, these were not easily combined into a composite score due to scale differences and the formative nature of the items. For example another question asked participants to list as many driving instructions as they could for the scenario and they were given a score based on how many steps in the route they were able to recall. This item yielded a count variable, which cannot be averaged with the Likert scale above. However, there were strong correlations among these knowledge items indicating that these items were measuring different components of participants' knowledge. The knowledge questions were administered after the forecasting session to avoid cueing the participant into what to think about during forecasting.

Experience. Experience was examined with a unique set of self-report questions. These questions pertained to specific experiences with the problems at hand. For each scenario, participants responded to four questions about their past experiences on a 4-point Likert scale. The items include: How many times have you been to the [start

location] area? (0=never, 1=only a few times, 2=often, 3=very often); How often have you driven yourself between the [start location] area and Fairfax campus? (0=never, 1=only a few times, 2=often, 3=very often); How often have you been driven by someone else between the [start location] area and Fairfax campus? (0=never, 1=only a few times, 2=often, 3=very often); In addition, the item, “how familiar are you with the roads between [start location] and here?” was rated on a 4-point Likert scale (0=not at all familiar, 1=a little familiar, 2=familiar, 3=very familiar). Experience items were given after the forecasting session to avoid cueing the participants. For the first scenario, internal consistency reliability was $\alpha = .78$. For Scenarios 2 and 3, internal consistency reliability coefficients were both $\alpha = .87$.

Dependent variables

Forecasting amount. A “think aloud” protocol was used in the present research to elicit forecasts so that their extent and quality could be examined. The forecasting portion of the study was audio recorded with time-stamps at the beginning and end of each prompt question. For each prompt in the think aloud, the amount of forecasting activities was measured by the amount that the participant said in response to the prompts (in terms of the number of words) and the amount of time the participant spent responding to the scenario. The standardized values were computed for amount of time and amount of words forecasted, before these two values were averaged to create the “forecasting amount” variable.

Forecasting detail. In addition, transcripts of the first and second prompts were coded for the amount of detail in forecasting activity by two coders very familiar with the

roads used in the scenarios. Amount of detail was evaluated in the beginning and end of the forecasted route because it is common for forecasters to quit forecasting prematurely (Dörner & Schaub, 1994). A two way, mixed effects model was used to compute interrater reliability for each scenario. In the first scenario, the intraclass correlation (ICC) across ratings from the first and second halves of the forecasts was .933. In the second scenario, the average ICC was .954. For the third scenario, the average ICC was .907. Overall, these ICCs indicate high internal consistency between raters.

Prediction accuracy. After forecasting, participants were asked to make final estimates about the time they would need for each trip. Prediction accuracy was measured through a comparison of these estimates and the estimates provided by Google Maps™. Each prediction opportunity asked about travel times on a Friday afternoon at 4:00pm. Prior to the initiation of this study, the travel times, including traffic delays, were recorded every Friday at 4:00PM for 43 weeks. It was raining on five of these 43 Fridays. Incidentally, it did not snow on any of these days. The average travel times, including and excluding rain, respectively, were: Scenario 1, 59 and 73 minutes; Scenario 2, 51 and 53 minutes; and Scenario 3, 61 and 66 minutes. Prediction accuracy was determined by taking the absolute value of the difference between these actual travel times and the participants' predicted travel times. Prediction accuracy scores were multiplied by negative one (-1) so that larger scores reflected more accurate predictions.

Then, prediction scores were weighted by confidence, which participants rated after each prediction on a scale from 0 to 100 percent. Calculating a *confidence weighted prediction accuracy*² score helps control for guessing. Since the participants in this study

were verbally asked to make estimates of the travel time required for each scenario, they may have felt compelled to provide an answer, even when they were unsure of their response.¹

Confidence weighted prediction accuracy was calculated by subtracting 100 plus confidence scores to prediction accuracy difference scores. As an example, consider two participants whose estimates deviated from the true travel time by 5 minutes. The first was 100 percent confident and therefore received a weighted prediction accuracy score of -5 (5 minute difference - 100 + 100% confident). The second participant was 75 percent confident and therefore received a weighted prediction accuracy score of -30 (5 minute difference - 100 + 75% confident).

¹ The only difference in the results between weighted and unweighted accuracy emerged in H3b. The moderating effect of task experience on the forecasting detail – unweighted prediction accuracy relationship was not significant.

Results

Means, standard deviations, and zero order correlations are presented in Table 1. Hypotheses were evaluated using hierarchical linear modeling with HLM 7 software, available from Scientific Software International, Inc. (Raudenbush, Bryk, Cheong, Congdon, & de Toit, 2011). Accuracy, knowledge, experience, forecasting detail, and forecasting amount were level 1 (within person) variables, working memory capacity, object imagery usage, and spatial imagery usage were level 2 (between persons) variables. Full maximum likelihood estimation was used, and all variables were group mean centered when entered in the regression, except where specified.

Hypothesis 1

Hypothesis 1 pertained to the relationship between forecasting activities and prediction accuracy. Specifically, *H1a* said that *forecasting amount* is positively related to prediction accuracy; *H1b* said that *forecasting detail* is positively related to prediction accuracy. Just under thirty-six percent (35.6%) of the total variance in accuracy was between persons. Therefore, 64.4 percent of the variance in accuracy was within persons. Hypothesis 1 (like Hypotheses 2 and 3 below) examines within person variance in accuracy with level 1 variables. To test *H1a*, prediction accuracy was regressed on forecasting amount with no level 2 variables specified. Using this model, forecasting amount was not a significant predictor of accuracy ($B = 2.85$, $t(203) = 1.37$, $p > .05$).

Therefore, H1a was not supported. However, when prediction accuracy was regressed on forecasting detail, forecasting detail was a significant predictor ($B = 9.38$, $t(203) = 3.90$, $p < .05$). Forecasting detail was significantly positively related to prediction accuracy.

Therefore, H1b was supported.

Hypothesis 2

Hypothesis 2 stated that domain specific knowledge moderates the relationship between forecasting activities and prediction accuracy, such that prediction accuracy is increased with more knowledge and more forecasting. This hypothesis was tested separately for forecasting amount (H2a) and forecasting detail (H2b). For both hypotheses, prediction accuracy was regressed on knowledge and forecasting in one model, and the improvement in the model when the product of knowledge and forecasting activity was entered was evaluated using a chi square difference test. When comparing nested models, this test provides information on whether the more complex model shows improved fit to the data above the simpler model.

The chi square difference test for the models that included knowledge and forecasting amount on the one hand, and knowledge, forecasting amount, and the interaction term on the other, resulted in a chi square of 2.81, which was not significant on one degree of freedom. Therefore, the inclusion of the interaction term did not aid in prediction – knowledge does not moderate the relationship between forecasting amount and prediction accuracy. H2a was not supported. As would be expected, knowledge was a significant predictor of accuracy ($B = 9.56$, $t(201) = 4.17$, $p < .05$).

The chi square difference test for the models that included knowledge and forecasting detail on the one hand, and knowledge, forecasting detail, and the interaction term on the other, resulted in a chi square of 0.38, which was not significant on one degree of freedom. Again, the inclusion of the interaction term did not improve prediction and knowledge does not moderate the relationship between forecasting detail and prediction accuracy. Therefore, H2b was not supported.

Hypothesis 3

Hypothesis 3 stated that task experience moderates the relationship between forecasting activities and prediction accuracy, such that task experience strengthens the relationship between forecasting and prediction accuracy. H3a looks at the moderating effect of experience on the relationship between forecasting amount and prediction accuracy. H3b looks at the moderating effect of experience on the relationship between forecasting detail and prediction accuracy. The same approach that was used to analyze the proposed interaction effect in Hypothesis 2 will be used for Hypothesis 3.

When examining the moderating effect of experience on the relationship between forecasting amount and prediction accuracy (H3a), the chi square difference test was significant ($\chi^2(1) = 4.24, p < .05$). Adding the interaction term improved the fit between the model and the data and the interaction term was a significant predictor of prediction accuracy ($B(201) = -4.24, p < .05$). This two-way interaction was examined more closely using a simple slopes analysis (Cohen, Cohen, Aiken & West, 2003). Slopes were computed for the relationship between forecasting amount and prediction accuracy at one

standard deviation above the mean on task experience and one standard deviation below the mean on task experience.

At one standard deviation above the mean on experience, the relationship between forecasting amount and prediction accuracy was not significant ($B = .45$, $t(302) = .151$, $p > .05$). At one standard deviation below the mean on experience, the relationship between forecasting amount and prediction accuracy was significant ($B = 7.61$, $t(302) = 4.23$, $p < .05$). A graph of this interaction is depicted in Figure 1. This pattern does not support H3a.

The chi square difference test comparing the models examining experience and forecasting detail versus the model examining experience, forecasting detail, and the interaction term was also significant ($\chi^2(1) = 21.794$, $p < .05$), indicating that including the interaction term improves model fit. The interaction term was a significant predictor of accuracy ($B = -4.56$, $t(201) = -2.263$, $p < .05$). A simple slopes analysis showed that the relationship between forecasting detail and prediction accuracy was significant for individuals with low task experience ($B = 12.22$, $t(302) = 4.02$, $p < .05$). For those with high task experience, the relationship between forecasting detail and prediction accuracy was not significant ($B = 3.92$, $t(302) = 1.86$, $p > .05$; see Figure 2). This pattern does not support H3b.

Hypothesis 4

Hypothesis 4 pertained to the effects of working memory capacity. Specifically, H4a stated that working memory capacity predicts forecasting activity; H4b stated that working memory capacity predicts prediction accuracy; and H4c stated that forecasting

activity partially mediates the relationship between working memory capacity and prediction accuracy. For H4a, forecasting amount and forecasting detail were each regressed onto working memory capacity in two HLM analyses.

In the intercept only model, about 60.7 percent of the variance in forecasting amount is between persons. About 49.1 percent of the variance in forecasting detail is between persons. In both cases, there is sufficient between persons variance to be predicted by level 2 predictors. Despite the presence of adequate between person variance, working memory capacity was not a significant predictor of forecasting amount ($B = .000$, $t(100) = 0.03$, $p > .05$) or forecasting detail ($B = .003$, $t(100) = 0.44$, $p > .05$). Therefore, H4a was not supported.

For H4b, prediction accuracy was regressed onto working memory. Working memory was not a significant predictor of prediction accuracy ($B = -.04$, $t(100) = -0.24$, $p > .05$). Therefore, H4b was not supported. Since these two direct paths were not significant in H4a and H4b, the indirect path from working memory capacity to prediction accuracy, as mediated through forecasting activity cannot be significant. Therefore, H4c was not supported.

Hypothesis 5

Hypothesis 5 stated that object imagery and working memory capacity have an interactive effect on forecasting activities such that the relationship between working memory and forecasting becomes more positive as object imagery use increases. H5a examines the interaction between working memory and object imagery on forecasting amount, while H5b examines the interaction between working memory and object

imagery on forecasting detail. These hypotheses were tested in the same manner as Hypotheses 2 and 3, namely, by conducting two HLM analyses and then comparing improvement in model fit (using the chi square difference test) resulting from adding the interaction term.

When object imagery and working memory capacity are used as predictors of forecasting amount, neither is a significant predictor (for object imagery, $B = 0.19$, $t(99) = 1.05$, $p > .05$; for working memory capacity, $B = -0.002$, $t(99) = -.26$, $p > .05$). The interaction terms was not significant either, but it was approaching significance ($B = 0.02$, $t(98) = 1.72$, $p = .089$). The chi square difference test was not significant ($\chi^2(1) = 2.91$, $p > .05$), but the observed probability of the obtained chi square was below $p = .10$.

With forecasting detail as the dependent variable, working memory ($B = 0.000$, $t(99) = 0.057$, $p > .05$) and object imagery ($B = 0.275$, $t(99) = 1.73$, $p > .05$) were not significant predictors (though object imagery had a regression coefficient that was approaching significance, $p = .087$). The interaction term was a significant predictor of forecasting detail ($B = 0.03$, $t(98) = 2.70$, $p < .05$), and the chi square difference test was significant as well ($\chi^2(1) = 7.06$, $p < .05$).

A simple slope analysis was conducted at one standard deviation above and one standard deviation below the mean of object imagery. The slopes of both lines showed a significant relationship between working memory capacity and forecasting detail. At one standard deviation above the mean in object imagery, working memory had a positive relationship with forecasting detail ($B = .099$, $t(98) = 8.60$, $p < .05$). At one standard deviation below the mean on object imagery, working memory had a negative

relationship with forecasting detail ($B = -.015$, $t(98) = -2.34$, $p < .05$). Therefore, H5b was supported. This interaction is depicted in Figure 3.

Hypothesis 6

Hypothesis 6 dealt with the use of spatial imagery. H6a stated that spatial imagery use predicts forecasting activities. This was tested with two HLM analyses. With forecasting amount as the dependent variable, spatial imagery was not a significant predictor ($B = -0.03$, $t(100) = -0.21$, $p > .05$). With forecasting detail as the dependent variable, again, spatial imagery use was not a significant predictor ($B = .14$, $t(100) = 0.92$, $p > .05$). Therefore, H6a was not supported.

H6b stated that spatial imagery use predicts prediction accuracy. Like forecasting activities, this was tested an HLM analysis with prediction accuracy regressed on spatial imagery use. Spatial imagery did not account for prediction accuracy ($B = 6.91$, $t(100) = 1.40$, $p > .05$). Therefore, H6b was not supported.

H6c stated that spatial imagery use and working memory capacity interact such that the relationship between working memory capacity and forecasting activities becomes stronger as spatial imagery use increases. This was tested by comparing two HLM analyses, with and without the inclusion of the product term like the other hypotheses that predicted interactions (H2, H3, and H5). With forecasting amount as the dependent variable, neither working memory capacity nor spatial imagery use were significant predictors ($B = 0.000$, $t(99) = 0.040$, $p > .05$ and $B = -0.028$, $t(99) = -0.202$, $p > .05$, respectively). The interaction term was not a significant predictor ($B = -0.009$, $t(98) = -1.12$, $p > .05$) and the chi square difference test was not significant ($\chi^2(1) = .989$,

$p > .05$). With forecasting detail as the dependent variable, working memory and spatial imagery were again, not significant predictors ($B = 0.003$, $t(99) = 0.410$, $p > .05$ and $B = 0.135$, $t(99) = 0.910$, $p > .05$, respectively). The interaction term was not a significant predictor ($B = 0.009$, $t(98) = 0.975$, $p > .05$), and the chi square difference test was not significant ($\chi^2(1) = .745$, $p > .05$). Therefore, H6c was not supported.

Discussion

Forecasting – the mental simulation of potential future consequences or events – has been identified as an important cognitive process by previous research domains such as problem solving (Byrne et al., 2010; Einhorn & Hogarth, 1986; Hegarty, 2004; Trickett & Trafton, 2007), vision formation (Shipman et al., 2010), ethical decision making (Stenmark et al., 2010; 2011), and planning (Hayes-Roth & Hayes-Roth, 1979; Mumford et al., 2001). In these domains (and in many others) the forecasting process is used as an explanatory mechanism underlying how people reason and make decisions about the future. The present study sought to contribute to these literatures in two ways: by establishing a connection between forecasting and an objective criterion (i.e., accuracy in predicting amount of time required), and by examining individual differences that may contribute to forecasting. The results of this study provide insights into the process of forecasting, which in turn informs the growing literature that cites forecasting as a mechanism for prediction, planning, and other forms of problems solving. The results also suggest theoretical and methodological lessons for future research in this domain.

Unlike previous research which obtained ratings from subject matter experts (e.g., Byrne et al., 2010; Dailey & Mumford, 2006), the present study linked forecasting to an index of prediction accuracy that was based on deviations of predictions from an objective estimate. This approach enabled this study to test the link between one's

forecasting activities and his or her accuracy in predicting the amount of time required to meet an objective. This is important because it allows the researcher to establish the correctness of predictions as opposed to more subjective metrics such as the quality or elegance of predictions.

The present research showed that forecasting detail was related to accuracy; however, forecasting amount was not related to accuracy. These results suggest that the conceptual distinction between the forecasting amount and forecasting detail is important to consider when designing research. Whereas previous studies have shown the forecasting amount can have a positive impact on outcomes, the present research suggests that more forecasting is not always better. For example, in the ethical decision making context (Stenmark et al., 2010), it may be beneficial to forecast a variety of factors and numerous perspectives, however, in the present context where the outcomes was evaluated in terms of accuracy, the amount of factors forecasted was less important in predicting estimates.

Task knowledge did not moderate the forecasting-prediction accuracy relationship, though it was by itself related to prediction accuracy. When task knowledge was evaluated alongside of forecasting detail, both predictors were related to the accuracy of predictions. The fact that task knowledge was not a moderator suggests that knowledge was important for planning and making accurate predictions, but the forecasting component was important as well. Perhaps the participants forecasted more general traffic considerations and obstacles to adjust their estimates. For example, they may have used what they knew about the scenario (time of day, day of week) to adjust their

predictions. The lack of a relationship could also have been a methodological factor caused but the collinearity between forecasting and task knowledge. The process of forecasting uses knowledge in the form of mental models, so it is difficult to extricate the two variables. Therefore, it is not surprising that a strong correlation between the two was found.

Unlike task knowledge, task experience did moderate the relationship between forecasting and prediction accuracy, but not in the hypothesized direction. For both forecasting amount and forecasting detail, the pattern of interaction showed a stronger effect for low experience individuals than high experience individuals. Though high experience individuals were more accurate on average, low experience individuals boosted their performance through more forecasting. For high experience individuals, there was no relationship between forecasting amount and prediction accuracy. Similarly, even though high experience individuals were more accurate overall, low experience individuals became much more accurate through forecasting in rich detail versus high experience individual who forecasted in rich detail. One interpretation of this is that, in the context of the present research, not all forecasting is equal – some forecasting activity may be wasted effort or even negatively biasing, while other forecasting activity is beneficial for planning and decision making. The high experience individuals may have seen more obstacles in the past, and may have thought of those obstacles during forecasting. These high experience individuals may have been overly inclusive of obstacles in their thinking, or overly focused on the most memorable obstacles, which led them to provide overly pessimistic predictions.

The major finding of this research was that forecasting detail was predicted by the combination of working memory and object imagery. Individuals high in both object imagery usage and working memory capacity provided the most detailed forecasts. Individuals low in object imagery produced less richly detailed forecasts, even when they also had the information processing requirements to handle complex and elaborate forecasts. This supports the assertion that forecasting is a resource intensive, visual thinking process. It requires both the information processing resources and the visual information processing resources to be effective.

This interaction has implications for research on the impact of visual skills. Some past studies have failed to demonstrate an effect of object imagery (or visual/spatial skills more broadly) on decision making or problem solving outcomes. This may be the result of omitting working memory from the model. The same would apply for working memory research. In many contexts, visual imagery is a necessary ingredient in assessing the impact of working memory on performance. However, there are probably domains are not aided by visualization, and in such contexts, working memory may work alone or with unidentified constructs. Future research will need to address the boundary conditions that make visual skills important or not.

Of ultimate interest is the mediated effect of object imagery by working memory on prediction accuracy through forecasting. Such a relationship would indicate that individuals who are high in working memory capacity and object imagery usage are also more accurate in their predictions. This pattern would have far reaching implications for

the functional value of visual imagery; however, subsequent analyses did not find a relationship between the interaction of object imagery use and working memory on the one hand and prediction accuracy on the other. In other words, the predictor is related to the proposed mediator, but not to the ultimate criterion, despite the relationship between the mediator and that criterion. We cannot definitively conclude that the component of forecasting detail that contributes to prediction accuracy originated from the interactive effects of object imagery and working memory capacity.

While a mediated relationship would be interesting, it is not surprising that one did not emerge. In fact, this mediation was not predicted because object imagery was hypothesized to enhance any forecast, not just accurate forecasts. However, spatial imagery was hypothesized to predict accuracy, so it was surprising that this relationship was not significant. Spatial imagery usage did have a significant zero-order correlation with prediction accuracy, but it was a small effect (i.e., $r = .113$). There were no significant relationships between spatial imagery and forecasting amount or forecasting detail, and there was no moderation effect when working memory capacity was introduced. There are likely other important factors that were not included in the model, and this may be to blame for the lack of a relationship. These factors are either unidentified or the result of interactions between factors already in the model. Some possible unidentified factors are described in the next section.

The present research began to identify predictors and moderators of forecasting, however, the results indicate that the model is far from complete. For example, motivation is a key part of the model that was not examined in the present study.

Motivation is important because forecasting requires mental effort. To be thorough, the forecaster must put effort into a complete mentally simulation. The assumption was that participants would be motivated to perform the task and would put effort into their performance. This assumption is not always upheld in practice. In addition, numerous other individual differences would have been interesting to examine, but were beyond the scope of the present research. For example, personality may be interesting to measure in future research in order to examine the effects of personality on characteristics of forecasts.

The present study also reveals many areas for development for future research in terms of measurement of constructs. In particular, knowledge could be measured in a number of different ways to facilitate the exploration of different aspects of forecasting. In the present study, knowledge was conceptualized as the degree of task specific knowledge completeness. However, knowledge could also be measured through more open-ended mental model elicitation techniques and connected to forecasting in other ways. In addition, studies conducted in other contexts might treat knowledge differently, such as examining the effects of knowledge from multiple domains.

Finally, this approach to studying forecasting may be greatly augmented by incorporating more direct (physiological, neurological) measurement approaches. As discussed above, many researchers have described the brain as a prediction-oriented machine (e.g., Bar, 2007; Buckner, 2010; Schacter, Addis, & Buckner, 2007; Szpunar 2010; Szpunar, Chan, & McDermott, 2009). Some researchers have even connected specific brain networks to this type of cognitive functioning (e.g., Buckner, 2010;

Buckner et al., 2008; Schacter et al., 2007, 2008). Through the use of fMRI and insights from the present research, brain regions of interest can be examined for their role in forecasting and prediction accuracy. The results of this study would suggest rich and detailed forecasts are produced through an interaction of dorsolateral prefrontal cortex mediating working memory capacity (e.g., Owen, 1997) and fusiform gyrus (Kraemer, Rosenberg, Thompson-Schill, 2009) or ventral visual stream through the occipital and inferior temporal lobes (Cabeza & Nyberg, 2000) for mediating object imagery use. In practice, the brain areas involved in this type of processing are likely to be dispersed and many (Smith & Jonides, 1999), but an fMRI approach may lead to additional insights into the differentiation of functional and dysfunctional forecasting. Similarly, EEG researchers are discovering and classifying the cortical dynamics of episodic memory formation (e.g., Hanslmayr, Spitzer, & Bäuml, 2009; Zion-Golombic, Kutas, & Bentin, 2010) which may open the door to future investigations of episodic memory retrieval. Such research, though still in the early phases, may have implications for measuring forecasting activity using EEG.

In summary, forecasting is increasingly recognized as an important process in I/O psychology. As a form of mental simulation, forecasting is invoked in many diverse domains such as planning, reasoning, problem solving, and naturalistic decision-making contexts. This study was a first attempt at forming a deeper understanding of what forecasting entails, whether it can be predicted by individual factors, and whether it is related to real functional outcomes. Forecasting activity was related to prediction accuracy, but the detail in forecasts was more important than the sheer amount of

forecasting that occurred. In addition, the results were consistent with the hypothesis that, in forecasting, working memory capacity supplies the information processing resources to coordinate visual imagery in mental simulations. It was discussed how subsequent research can probe deeper into forecasting and further our understanding of this potentially valuable process.

Table 1. Means, standard deviations, and zero-order correlations

	M	SD	Task Knowledge	Task Experience	Forecasting Detail	Forecasting Amount	Working Memory	Object Use	Spatial Use
Prediction Accuracy	57.62	33.73	.41**	.40**	.39**	.12	.00	.05	.11
Task Knowledge	.31	.41		.62**	.51**	.19 ⁺	.03	.07	.29*
Task Experience	1.67	.69			.54**	.12	.19 ⁺	.11	.14
Forecasting Detail	.96	1.12				.25*	.04	.14	.07
Forecasting Amount	0.00	.98					.00	.11	-.02
Working Memory	44.16	13.77						.23*	.07
Object Use	3.55	.57							.00
Spatial Use	2.72	.55							

n=102. With two tailed probabilities: ⁺ = p < 0.10; * = p < 0.05; ** = p < 0.01

Table 2. The effects of forecasting on prediction accuracy

H1a	Coefficient	SE	t-ratio	df	p-value
Intercept, β_{00}	-57.62	2.48	-23.25	101	<0.01
Forecast Amount, β_{10}	2.85	2.14	1.33	203	0.18
H1b					
Intercept, β_{00}	-57.62	2.52	-22.91	101	<0.01
Forecast Detail, β_{10}	9.38	2.30	4.08	203	<0.01

Table 3. Interaction between forecasting amount and knowledge on prediction accuracy

H2a	Coefficient	SE	t-ratio	df	p-value
Intercept, β_{00}	-57.62	2.52	-22.91	101	<0.01
Forecast Amount, β_{10}	-0.61	2.97	-0.20	202	0.84
Knowledge, β_{20}	9.78	2.35	4.16	202	<0.01
Intercept, β_{00}	-57.20	2.55	-22.43	101	<0.01
Forecast Amount, β_{10}	-0.66	2.96	-0.22	201	0.82
Knowledge, β_{20}	9.56	2.35	4.07	201	<0.01
Interaction, β_{30}	-1.67	1.50	-1.11	201	0.27

Table 4. Interaction between forecasting detail and knowledge on prediction accuracy

H2b	Coefficient	SE	t-ratio	df	p-value
Intercept, β_{00}	-57.62	2.52	-22.91	101	<0.01
Forecast Detail, β_{10}	7.47	2.43	3.07	202	<0.01
Knowledge, β_{20}	7.03	2.37	2.96	202	<0.01
Intercept, β_{00}	-58.05	2.68	-21.68	101	<0.01
Forecast Detail, β_{10}	6.77	2.44	2.77	201	0.01
Knowledge, β_{20}	7.45	2.44	3.06	201	<0.01
Interaction, β_{30}	0.57	1.25	0.46	201	0.65

Table 5. Interaction between forecasting amount and experience on prediction accuracy

H3a	Coefficient	SE	t-ratio	df	p-value
Intercept, β_{00}	-57.62	2.48	-23.26	101	<0.001
Forecast					
Amount, β_{10}	3.03	2.10	1.45	202	0.15
Experience, β_{20}	14.39	3.19	4.51	202	<0.001
Intercept, β_{00}	-57.25	2.44	-23.50	101	<0.001
Forecast					
Amount, β_{10}	3.39	2.16	1.57	201	0.12
Experience, β_{20}	14.47	3.17	4.56	201	<0.001
Interaction, β_{30}	-4.25	1.97	-2.15	201	0.03

Table 6. Interaction between forecasting detail and experience on prediction accuracy

H3b	Coefficient	SE	t-ratio	df	p-value
Intercept, β_{00}	-57.62	2.52	-22.91	101	<0.001
Forecast Detail,					
β_{10}	6.40	2.44	2.62	202	0.01
Experience, β_{20}	10.70	3.44	3.11	202	0.01
Intercept, β_{00}	-57.62	2.10	-27.39	101	<0.001
Forecast Detail,					
β_{10}	8.07	1.90	4.24	201	<0.001
Experience, β_{20}	14.72	3.10	4.75	201	<0.001
Interaction, β_{30}	-4.56	2.12	-2.15	201	0.03

Table 7. The effects of working memory capacity on forecasting activities and prediction accuracy

Forecasting Amount (H4a i)	Coefficient	SE	t-ratio	df	p-value
Intercept, β_{00}	0.00	0.08	0.00	100	0.99
Working Memory, β_{01}	0.00	0.01	0.03	100	0.97
Forecasting Detail (H4a ii)	Coefficient	SE	t-ratio	df	p-value
Intercept, β_{00}	0.00	0.09	0.00	100	0.99
Working Memory, β_{01}	0.00	0.01	0.45	100	0.65
Prediction Accuracy (H4b)	Coefficient	SE	t-ratio	df	p-value
Intercept, β_{00}	-57.62	2.51	-22.91	100	<0.001
Working Memory, β_{01}	-0.04	0.18	-0.20	100	0.84

Table 8. Interaction between object imagery and working memory capacity on forecasting amount

H5a	Coefficient	SE	t-ratio	df	p-value
Intercept, β_{00}	0.00	0.08	0.00	99	0.99
Working Memory, β_{01}	0.00	0.01	-0.25	99	0.80
Object Imagery, β_{02}	0.19	0.15	1.27	99	0.21
Intercept, β_{00}	0.00	0.08	0.00	98	0.99
Working Memory, β_{01}	0.00	0.01	-0.55	98	0.58
Object Imagery, β_{02}	0.20	0.15	1.38	98	0.17
Interaction, β_{03}	0.02	0.01	1.72	98	0.09

Table 9. Interaction between object imagery and working memory capacity on forecasting detail

H5b	Coefficient	SE	t-ratio	df	p-value
Intercept, β_{00}	0.00	0.09	0.00	99	0.99
Working Memory, β_{01}	0.00	0.01	0.06	99	0.96
Object Imagery, β_{02}	0.27	0.16	1.73	99	0.09
Intercept, β_{00}	0.00	0.09	0.00	98	0.99
Working Memory, β_{01}	0.00	0.01	-0.42	98	0.68
Object Imagery, β_{02}	0.30	0.15	1.93	98	0.06
Interaction, β_{03}	0.03	0.01	2.70	98	0.01

Table 10. The effects of spatial imagery on forecasting activities and prediction accuracy

Forecasting						
Amount (H6a i)	Coefficient	SE	t-ratio	df	p-value	
Intercept, β_{00}	0.00	0.08	0.00	100	0.99	
Spatial Imagery, β_{01}	-0.03	0.15	-0.19	100	0.85	
Forecasting Detail (H6a ii)						
	Coefficient	SE	t-ratio	df	p-value	
Intercept, β_{00}	0.00	0.09	0.00	100	0.99	
Spatial Imagery, β_{01}	0.14	0.16	0.85	100	0.40	
Prediction						
Accuracy (H6b)	Coefficient	SE	t-ratio	df	p-value	
Intercept, β_{00}	-57.62	2.49	-23.17	100	<0.001	
Spatial Imagery, β_{01}	6.91	4.53	1.53	100	0.13	

Table 11. Interaction between spatial imagery and working memory capacity on forecasting amount

H6c i	Coefficient	SE	t-ratio	df	p-value
Intercept, β_{00}	0.00	0.08	0.00	99	0.99
Working Memory, β_{01}	0.00	0.01	0.04	99	0.97
Spatial Imagery, β_{02}	-0.03	0.15	-0.19	99	0.85
Intercept, β_{00}	0.00	0.08	0.00	98	0.99
Working Memory, β_{01}	0.00	0.01	0.09	98	0.93
Spatial Imagery, β_{02}	-0.05	0.15	-0.30	98	0.76
Interaction, β_{03}	-0.01	0.01	-1.00	98	0.32

Table 12. Interaction between spatial imagery and working memory capacity on forecasting detail

H6c ii	Coefficient	SE	t-ratio	df	p-value
Intercept, β_{00}	0.00	0.09	0.00	99	0.99
Working Memory, β_{01}	0.00	0.01	0.41	99	0.68
Spatial Imagery, β_{02}	0.13	0.16	0.83	99	0.41
Intercept, β_{00}	0.00	0.09	0.00	98	0.99
Working Memory, β_{01}	0.00	0.01	0.37	98	0.71
Spatial Imagery, β_{02}	0.15	0.16	0.93	98	0.36
Interaction, β_{03}	0.01	0.01	0.87	98	0.39

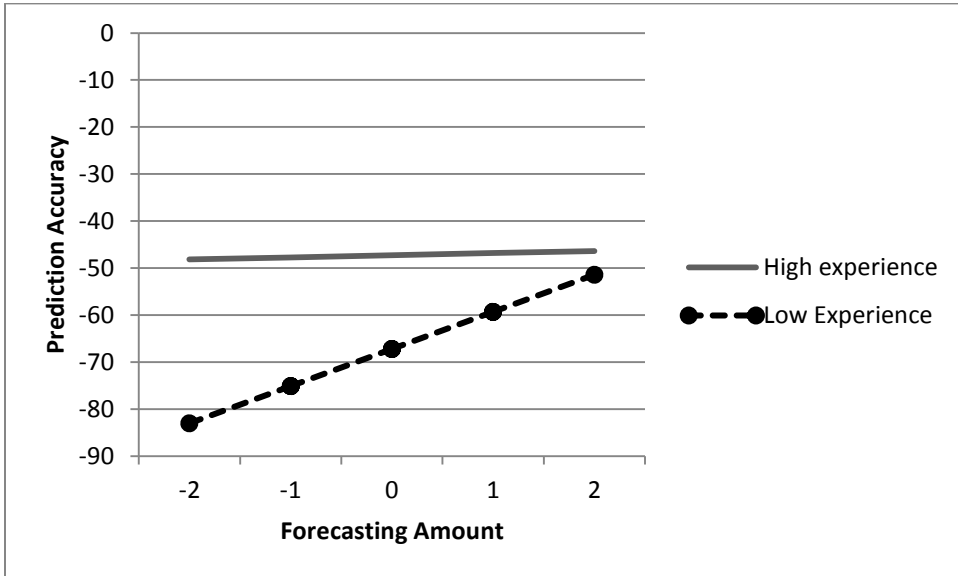


Figure 1. The interaction effect of forecasting amount and experience on prediction accuracy

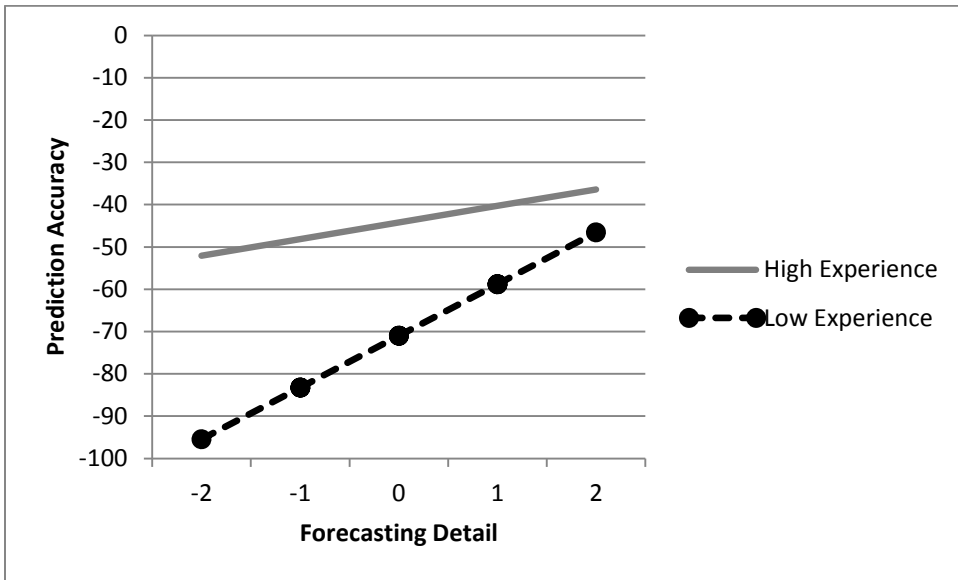


Figure 2. The interaction effect of forecasting detail and experience on prediction accuracy

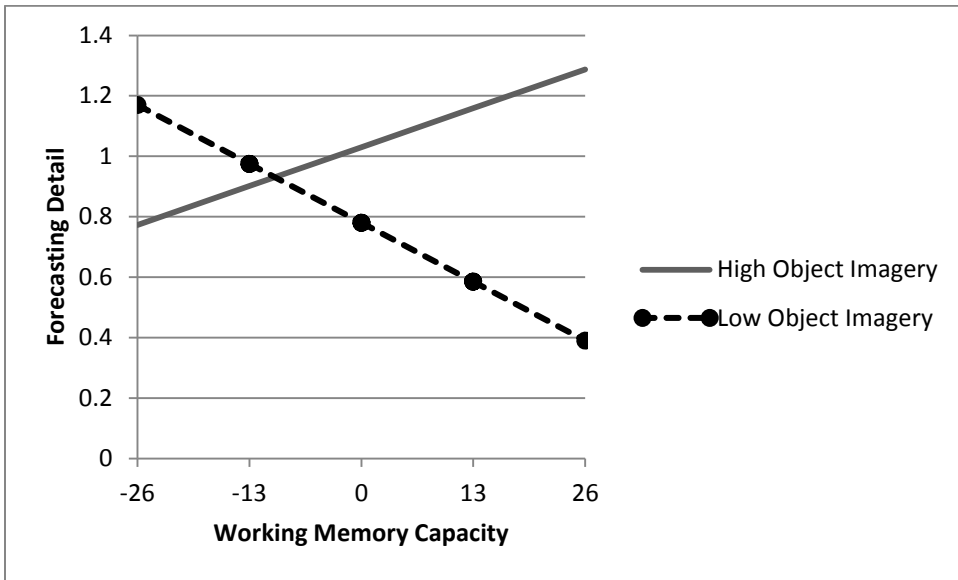


Figure 3. The interaction effect of object imagery use and working memory capacity on forecasting detail

Appendix A: Measures

Demographics:

What is your age? _____

What is your gender? M____ F____

What is your current year in school? _____

What is your major (e.g., psychology, nursing, undecided, etc.)? _____

What is your current overall GPA? _____

What was your overall SAT score? _____

Please indicate your ethnicity.

African-American/Black

Asian, Asian American/Pacific Islander

Caucasian/ White American, European, not Hispanic

Chicano(a)/ Mexican American

Latino(a)/ Hispanic American

Native American/American Indian

Mixed; parents are from two different groups

Other (please specify): _____

What language do you primarily speak at home? _____

How proficient are you in English?

Poor _____ Fair _____ Average _____ Excellent _____ Native/Fluent _____

Please indicate your work status:

_____ not currently working

_____ work part-time

_____ work full-time

Knowledge:

1. How confident are you that you could find Georgetown on a map in less than 20 seconds?
0% _____ 25% _____ 50% _____ 75% _____ 100% _____
2. How confident are you that you could find the Alexandria Waterfront on a map in less than 20 seconds?
0% _____ 25% _____ 50% _____ 75% _____ 100% _____
3. How confident are you that you could find Leesburg on a map in less than 20 seconds?
0% _____ 25% _____ 50% _____ 75% _____ 100% _____

Experience Questionnaire:

4. How many times have you been to the Georgetown area?
Never___; Only a few times___; Often___; Very often___
5. How often have you driven yourself between the Georgetown area and Fairfax campus?
Never___; Only a few times___; Often___; Very often___
6. How often have you been driven by someone else between the Georgetown area and Fairfax campus?
Never___; Only a few times___; Often___; Very often___
7. How familiar are you with the roads between Georgetown and here?
Not at all familiar___; Somewhat familiar___; Familiar___; Very familiar___
8. How many times have you been to the Alexandria Waterfront area?
Never___; Only a few times___; Often___; Very often___
9. How often have you driven yourself between the Alexandria Waterfront area and Fairfax campus?
Never___; Only a few times___; Often___; Very often___
10. How often have you been driven by someone else between the Alexandria Waterfront area and Fairfax campus?
Never___; Only a few times___; Often___; Very often___
11. How familiar are you with the roads between the Alexandria Waterfront and here?
Not at all familiar___; Somewhat familiar___; Familiar___; Very familiar___
12. How many times have you been to the Leesburg area?
Never___; Only a few times___; Often___; Very often___
13. How often have you driven yourself between the Leesburg area and Fairfax campus?
Never___; Only a few times___; Often___; Very often___

14. How often have you been driven by someone else between the Leesburg area and Fairfax campus?
Never___; Only a few times___; Often___; Very often___
15. How familiar are you with the roads between Leesburg and here?
Not at all familiar___; Somewhat familiar___; Familiar___; Very familiar___
16. Did you grow up in Northern Virginia? Y___ N___
17. Do you keep a car in the area? Y___ N___

Object-Spatial Imagery and Verbal Questionnaire (OSIVQ; Blazhenkova & Kozhevnikov, 2009).

Instructions: “This is a questionnaire about the way you think. Please read the following statements and rate each of them on a 5-point scale. Circle 5 to indicate that you absolutely agree that the statement describes you, and circle 1 to indicate that you totally disagree with the statement. Circle 3 if you are not sure, but try to make a choice. It is very important that you answer all the items in the questionnaire.”

- 1 I was very good in 3D geometry as a student
- 2 I have difficulty expressing myself in writing
- 3 If I were asked to choose between engineering professions and visual arts, I would prefer engineering
- 4 My verbal abilities would make a career in language arts relatively easy for me
- 5 Architecture interests me more than painting
- 6 My images are very colorful and bright
- 7 I prefer schematic diagrams and sketches when reading a textbook instead of colorful and pictorial illustrations
- 8 I tell jokes and stories better than most people
- 9 Essay writing is difficult for me and I do not enjoy doing it at all
- 10 My images are more like schematic representations of things and events rather than like detailed pictures
- 11 When reading fiction, I usually form a clear and detailed mental picture of a scene or room that has been described
- 12 If I were asked to choose among engineering professions, or visual arts, I would choose visual arts
- 13 I have a photographic memory
- 14 I can easily imagine and mentally rotate three-dimensional geometric figures
- 15 I enjoy pictures with bright colors and unusual shapes like the ones in modern art
- 16 My verbal skills are excellent
- 17 When thinking about an abstract concept (or building), I imagine an abstract schematic building in my mind or its blueprint rather than a specific concrete building
- 18 When entering a familiar store to get a specific item, I can easily picture the exact location of the target item, the shelf it stands on, how it is arranged and the surrounding articles
- 19 Putting together furniture kits (e.g. a TV stand or a chair) is much easier for me when I have detailed verbal instructions than when I only have a diagram or picture
- 20 My images are very vivid and photographic
- 21 When explaining something, I would rather give verbal explanations than make drawings or sketches
- 22 If someone were to give me two-digit numbers to add (e.g. 43 and 32) I would simply do the adding without visualizing the numbers

- 23 My mental images of different objects very much resemble the size, shape and color of actual objects that I have seen
- 24 I usually do not try to visualize or sketch diagrams when reading a textbook
- 25 I normally do not experience many spontaneous vivid images; I use my mental imagery mostly when attempting to solve some problems like the ones in mathematics
- 26 When I imagine the face of a friend, I have a perfectly clear and bright image
- 27 I have excellent abilities in technical graphics
- 28 When remembering a scene, I use verbal descriptions rather than mental pictures
- 29 I can easily remember a great deal of visual details that someone else might never notice. For example, I would just automatically take some things in, like what color is a shirt someone wears or what color are his/her shoes
- 30 I can easily sketch a blueprint for a building I am familiar with
- 31 In school, I had no problems with geometry
- 32 I am good in playing spatial games involving constructing from blocks and paper (e.g. Lego, Tetris, Origami)
- 33 Sometimes my images are so vivid and persistent that it is difficult to ignore them
- 34 I can close my eyes and easily picture a scene that I have experienced
- 35 I have better than average fluency in using words
- 36 I would rather have a verbal description of an object or person than a picture
- 37 I am always aware of sentence structure
- 38 My images are more schematic than colorful and pictorial
- 39 I enjoy being able to rephrase my thoughts in many ways for variety's sake in both writing and speaking
- 40 I remember everything visually. I can recount what people wore to a dinner and I can talk about the way they sat and the way they looked probably in more detail than I could discuss what they said
- 41 I sometimes have a problem expressing exactly what I want to say
- 42 I find it difficult to imagine how a three-dimensional geometric figure would exactly look like when rotated
- 43 My visual images are in my head all the time. They are just right there
- 44 My graphic abilities would make a career in architecture relatively easy for me
- 45 When I hear a radio announcer or a DJ I've never actually seen, I usually find myself picturing what he or she might look like

Forecasting Activity Coding Criteria (partially adapted from Stenmark, Antes, Wang, Caughron, Thiel, & Mumford, 2010). *Example think aloud statements are in italics.*

Participant ID: _____

Scenario: _____

Forecast word count: _____

Number of obstacles considered: _____

Which obstacles were considered? _____

Detail of Route descriptions:

Is the response very detailed?

Is the response focused on specific issues?

1- Low rating

I would take 66 all the way.

2 – Medium /Low rating

Take 66 westbound until the GMU exit. They take the road off the exit through Fairfax until you reach campus on your left.

3 – Medium Rating

Key Bridge into Virginia, right onto route 50/Lee highway. Take the ramp for 66 west and 66 to the exit at route 123. Then 123 until you reach University boulevard and campus on the left.

4 – Medium/High rating

I would take the Key Bridge into Virginia and after a few lights, turn right onto route 50/Lee highway. Take that until you reach the ramp for 66 west. Take 66 west to the exit at route 123. Then go south on 123 through Fairfax until you reach University boulevard and campus on the left.

5 – High rating

I would take the Key Bridge into Virginia and after two lights – maybe 50 feet – turn right onto route 50/Lee highway. Take that uphill a mile or so until you reach the ramp for 66 west. Take 66 west for about 10 miles to the exit at route 123. Then go south on 123 through Fairfax – probably four or so lights – until you reach University boulevard and campus on the left.

Detail of forecast (beginning): _____

Detail of forecast (end): _____

Appendix B. Think Aloud Protocol

Instructions: You are going to be presented with a series of scenarios that involve you traveling from one location in the area to here: campus. The purpose of this exercise is for you to explain your thought process as you think about the scenario. You will be asked a series of questions (such as which route would you take? How long will it take? Et cetera) You will be given ample time to work out your solution, however, we want you to come up with your answers without looking them up on the computer or your phone.

We are interested in your thinking as you come up with answers, so we would like you to think out loud – to describe whatever comes to mind as you come up with your solution. Please be as descriptive as possible. **Let’s practice the think aloud procedure:**

Imagine you are planning a camping trip and you need to pack a car full of equipment/supplies. Think about the activities that will occur during the trip as you make a list of things to bring. Please describe your thought process as you think ahead to what you will need. Be as detailed as possible.
[provide two minutes for participant to think aloud]

Now that you have had an opportunity to practice verbalizing your thought process, we will begin with the scenarios. Please read Scenario __ while I read it out loud... [read scenario]...Now think through your answer to Scenario __ and describe verbally what you are thinking about. Describe whatever is in your head as you come up with the answer. Be as detailed as possible-- even when you think you are giving too much detail, give more. Try to keep talking for as long as you can about each question I ask you.

Scenario 1	Scenario 2	Scenario 3
Imagine you are in Georgetown and want to get to Fairfax campus to meet with a professor at the Johnson Center. It is 4:00 on a Friday afternoon. You are traveling by car and your goal is to get to campus as quickly as you	Imagine you are in Old Town Alexandria, at the Waterfront, and want to get to Fairfax campus to meet with a professor at the Johnson Center. It is 4:00pm on a Friday afternoon and you are traveling by car. Your goal	Imagine you are at the Outlet Stores in Leesburg, VA and you want to get to Fairfax campus to meet with a professor at the Johnson Center. It is 4:00pm on a Friday afternoon and you are traveling by car. Your goal

<p>can to meet this professor as soon as possible. Assume that it takes you practically no time to find a parking space, and that it takes about ten minutes to get from your car to the Johnson Center. Take a few minutes to map out the way you would go in your head.</p>	<p>is to get to campus as quickly as you can to meet this professor as soon as possible. Assume that it takes you practically no time to find a parking space, and that it takes about ten minutes to get from your car to the Johnson Center. Take a few minutes to map out the way you would go in your head.</p>	<p>is to get to campus as quickly as you can to meet this professor as soon as possible. Assume that it takes you practically no time to find a parking space, and that it takes about ten minutes to get from your car to the Johnson Center. Take a few minutes to map out the way you would go in your head.</p>
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Think aloud protocol questions and prompts

What is the preferred way of going from [Georgetown] to Fairfax campus in order to get there as quickly as possible? Please describe the route with a lot of detail.

Are there any other details to include?

What factors or obstacles are the most important to consider, given that you want to get to campus as quickly as possible?

Are there any other factors or obstacles?

Imagine you were making the trip to campus on a different day or a different time of day. How might your travel time change at a different point in time?

Is there any other differences you might expect based on day of the week or time of day?

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Biography

Cory Scott Adis graduated from Mary Washington College in 2003 with a Bachelor of Sciences degree in psychology. In 2008, he received a Master of Arts degree in psychology with a concentration in industrial / organizational psychology from George Mason University. He finished his Doctor of Philosophy degree in psychology at George Mason University in 2013.