MODELING, ESTIMATION, AND OPERATIONAL POLICIES FOR HUMAN PERFORMANCE WITH TEMPORAL MOTIVATION

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ABSTRACT

In the contemporary workplace, companies, trainees, and workers are under increasing time pressure as organizations respond to broader competition, shorter staffing, and greater customer expectations. One observable time management device found in practice is the ubiquitous use of deadlines for both cognitive and manual work. Deadlines are known to increase productivity by helping companies and workers manage time efficiently, although many unaddressed questions remain regarding individual differences in performance, measurement, and appropriate deadline settings.

For example, compared to individuals with longer deadlines, those who work with frequent and shorter deadlines exhibit longer work times and more completed tasks, while very short deadlines are known to reduce work performance and quality. Few studies have quantitatively modeled individualized pacing behavior and applied it to the workplace with a focus on conceptualization.

The purpose of this dissertation is to model and estimate individual behavior related to deadlines, then to propose an improved design for time management policies. To do so, several experimental (an air-traffic control setting and online learning settings with eye-tracking measurements), field (Bayesian estimations to the course website data), and simulation (queueing simulations) investigations were conducted. The dissertation concludes with four major findings. First, the dissertation examines effective factors in generating models for aligning time pacing in the presence of deadlines, finding that task complexity and group size affect individual performance with
temporal motivation in an air-traffic control setting. Second, the dissertation improves
the quality of estimation for individual time-pressure reactivity by using a parametric
Bayesian estimation approach. Third, it models the relationships between individual
pacing with work productivity. Both the quality (e.g., GPA and class scores) and
quantity (e.g., task completion time) of performance are found to be related to
individual time pacing based on course website and eye-movement data that was
analyzed using a structural equation model. Fourth and lastly, the dissertation proposes
designs and policies for time management that improve productivity; prioritizing tasks
via early due dates is recommended to increase individual productivity, based on the
results from a queueing simulation. The result of this research contributes to generating
policies or designing personalized learning by considering individual differences in
time-pressure reactivity that had been previously ignored or oversimplified in their
practical application.
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Glossary of Terms and Acronyms

A  Undiscounted Work Rate - A represents the fastest speed at which the worker can perform the task and that the participants were likely to approach the fastest rate at some point, especially for very close deadlines. A can be calculated from the exponential and the hyperbolic function for the explanation of deadline rush (König & Kleinmann, 2005).

AAWC  Anti-Air Warfare Coordinator - A decision-making task based on an air-traffic coordinator simulation to train and measure participants’ performance (Thiruvengada et al., 2004; Macht et al., 2014).

ANOVA  Analysis of Variance – Statistical models to identify significant differences between two or more means

D  The Time of the Deadline - D is indicated in the exponential and the hyperbolic function for the explanation of deadline rush.

DCA  Defense Counter Aircraft – In an AAWC simulation, DCA identified unknown aircraft and sent updated information back to the rules of engagement (ROE) in a timely manner.

EDD  Earliest-Due-Date First - In a queueing system, EDD first policy processed first entities with earliest deadlines.

FIFO  First-In-First-Out – In a queueing system, FIFO policy processed first the first entity.

HCPP  High-Complexity-Preempt-Priority – In a queueing system, the HCPP policy prioritized the high-complexity task. As soon as the high-complexity assignment arrived, the server switched to the high-complexity job.

k  Time-Pressure Reactivity – An index of the extent to which individuals discount the value of future outcomes, an individual difference variable. k denotes the slope of the exponential and the hyperbolic function for the explanation of deadline rush (König & Kleinmann, 2005).

kData Only  Time-Pressure Reactivity Fitted from Data Only – Using point estimates, time-pressure reactivity fitted from individual data into exponential
model of deadline rush. I called \( k^\text{Data Only} \) in order to distinguish it from \( k \) parameters used in likelihood or posterior distributions.

\( k^\text{Posterior} \)  
**MLEs of Posterior Distributions of Time-Pressure Reactivity** – Time-pressure reactivity obtained from MLE of posterior distribution using parametric empirical Bayesian estimation.

\( L \)  
**Task Proportion Late** - A late response was indicated when participants could not identify an aircraft during the time available for the given track (within the deadline), whereas the response was on-time when the deadline was met in an AAWC simulation. \( L \) was calculated from the ratio of the number of late responses to the total number of responses.

\( \text{LCPP} \)  
**Low-Complexity-Preempt-Priority** – In a queueing system, the LCPP policy prioritized the low-complexity task. When the low-complexity and the high-complexity tasks were given at the same time, servers switched to the low-complexity tasks to perform the high-priority job.

\( \text{LIFO} \)  
**Last-In-First-Out** – In a queueing system, the LIFO policy processed the last entity first.

\( \text{M/G/1 queue} \)  
**Markovian/General/1 server** – Poisson process (Markovian) showed interarrival rates, service rates followed general distribution, and one server was in the system.

\( \text{MLE} \)  
**Maximum-Likelihood Estimate** – In Bayesian estimation, the mode of posterior distribution is calculated as MLE (e.g., Gelman et al., 2014).

\( \text{MSE} \)  
**Mean Squared Error** – A statistical measure of accuracy predicting models. In MSE, the error term represents the difference between the estimated and the original data.

\( n \)  
Notation for individual data sample size.

\( \text{PEB} \)  
**Parametric Empirical Bayesian Estimation** – A statistical method of estimation generating posterior probabilities from prior probabilities and the available data. PEB is helpful when there are relatively small sample sizes for some individuals.

\( R^2 \)  
**R-squared** – goodness-of-fit measure for coefficient of determination (Cameron & Windmeijer, 1997).
ROE  **Rules of Engagement** – Tasks for individual participants corresponding to 1) identifying unknown aircraft tracks and 2) defending the ship against those aircraft by issuing warnings in an AAWC simulation.

SD  **Standard Deviation** – In Bayesian estimation, the spread in the posterior distributions is calculated as SD, indicating the amount of uncertainty.

SE  **Standard Error** – SE represents “how much sample means vary from the standard deviation of the sampling distribution” (Altman & Bland, 2005, p.903)

TCP  **Targeted-Complexity-Prioritization** – In a queueing system, TCP policy was generated by focusing on a single stage where a new job came to the server. TCP policy suggests that when a current job is high in complexity with a long deadline and the new job is low in complexity, stopping the current job and switching to the new job resulted in a greater percentage of deadlines met with more work accomplished.

T-t  Notation for delay for the reward by subtracting the current time $t$ from the rewarding time $T$ (Steel & König, 2006).

V  **Instantaneous Work Rate** - V is indicated in the exponential and the hyperbolic function for the explanation of deadline rush (König & Kleinmann, 2005).

x  Notation for the parameter representing the available data in a Bayesian equation.

Z  Notation for the constant of instant reward to prevent the equation from having an infinite value in the utility function (Steel & König, 2006).

$\alpha$  Notation for the shape parameter of the gamma prior distribution.

$\alpha'$  Notation for the shape hyperparameter of the gamma posterior distribution.

$\beta$  Notation for the scale parameter of the gamma prior distribution.

$\beta'$  Notation for the scale hyperparameter of the gamma posterior distribution.
$\Gamma$ Notation for individual differences in sensitivity for delay in the utility function (Steel & König, 2006).

$\theta$ Notation for the parameter representing the unknown state of nature in a Bayesian equation.

$\mu$ Notation for the summed time to the deadline (in days).

$\mu/n$ Notation for measurement of early activity meaning the time designated to studying prior to a deadline.
Chapter 1

Introduction

In the contemporary workplace, companies, trainees, and workers are under increasing time pressures, as organizations respond to broader competition, shorter staffing, and greater customer expectations. In this context, time can be viewed as a resource to be managed toward the pursuit of improving productivity. Thus, time is one of several potentially scarce resources that might be better managed or operationalized in the interest of organizational efficiency and effectiveness (Bluedorn & Denhardt, 1988). One of the more observable time management devices found in practice is the ubiquitous use of deadlines for both cognitive and manual work. Deadlines are known to increase productivity by enabling companies and their employees to manage time efficiently, though many unaddressed questions exist regarding performance, measurement and appropriate setting of operational policies (e.g., Höffler & Schwartz, 2011; Maule & Svenson, 1993).

Previous studies over the past fifty years have shown that deadlines increase productivity and save time. For example, Latham and Locke’s field study (1975) found that wood-harvesting workers given short deadlines (one or two days to finish work) showed a higher rate of performance than workers given no restriction. More recently,
Fulton et al. (2013) studied the influence of deadlines on online training for health administrators. The results showed that weekly deadlines produced the greatest time spent studying, followed by monthly deadlines, and the end-of-course deadline.

To understand how deadlines increase productivity, researchers investigated how work rate of individuals have changed over time toward deadline. Quantitatively, it is known that longer deadlines cause work pace to slow and that work pace increases as deadlines approach. For example, Bryan and Locke’s (1967) laboratorial research found that when the same number of problems was given to all test participants, individuals who were given longer deadlines took a significantly longer time to complete the problems than individuals who were given shorter deadlines. Waller et al. (2002) conducted an experiment with 38 groups that had either static or dynamic deadlines. They concluded that for all groups, an approaching deadline motivated them to increase their pace. They also concluded that the groups with dynamic deadlines paid more attention to time. Others have found similar behaviors, wherein people pay more attention to time under deadline constraints, motivating them to pace themselves appropriately (Kelly & McGrath, 1985; Lim & Murnighan, 1994; Waller et al., 2001).
1.1. Literature Review

1.1.1. Concept of Time-Pressure Reactivity

Human behavioral patterns in the presence of deadlines have been studied quantitatively, to show that relatively little time is devoted to tasks early on and that most work is performed in close time proximity to the deadline (Mackenzie, 1997). We can find this phenomenon in our everyday lives. Researchers often submit conference papers just a few days before the deadline, and students commonly study in the few days before their exams (König & Kleinmann, 2005). This phenomenon, called deadline rush, may be represented by specific models that predict little early activity followed by a sharp increase in activity immediately prior to the deadline (König & Kleinmann, 2005). Such a theoretical approach to deadline rush can be a useful tool to predict individualized time management.

The phenomenon of increased work pace toward a deadline can be explained as an effective manifestation of Parkinson’s Law. Parkinson’s Law (1957, p.2) famously states that ”work expands so as to fill the time available for its completion.” This statement can also be transformed in relation to deadlines, wherein having less time to complete a task results in completing the work at a faster pace. A corollary to Parkinson’s Law, the Stock-Stanford, states: “if you wait until the last minute, it only takes a minute to do” (Pannett et al., 2013).
Researchers have categorized the degree of individual responses to deadlines and conceptualized these degrees as different pacing styles. The degree of these responses can be categorized into four modal styles according to how individual behavior is distributed over time in working towards deadlines (Gevers et al., 2015; Mohammed & Harrison, 2013). The first of these modal styles is the *early* action style, in which a person starts a task right away and finishes long before the deadline. The second is the *deadline* action style, in which a person waits until the deadline is imminent to begin and completes the bulk of the work at that time until time runs out. Third, the *steady* action style is when an individual demonstrates a constant pace by spreading their effort evenly out over the time available. The last *U-shaped* style represents high effort at the beginning, followed by low effort in the middle, and high effort again close to the deadline.

### 1.1.2. Time-Pressure Reactivity and Goal-setting theory

Goal setting, among other motivation theories, has been shown through over 40 years of empirical research to be one of the more robust, valid, and practical approaches for modeling organizational behavior (see Latham & Locke, 2007; Locke & Latham 2002; Seijts et al., 2013). Researchers define the concept of goal setting as “the object or aim of an action, for example, to attain a specific standard or proficiency, usually within
a specified time limit” (Locke & Latham, 2002). For goal-setting theory, the task condition with a “specific high goal” yielded better performance than the task condition under “do your best” (Latham & Locke, 2007). Goals improve performance through diverse mechanisms: they direct attention, mobilize effort, increase persistence, and motivate strategy development (Locke & Latham, 2002; Locke et al., 1981).

One of the determining factors of how a particular goal improves performance for individuals is the deadline, which originated from the process of scientific management developed by Frederick W. Taylor, who used time to determine work quantities. With respect to the goal-setting theory, deadlines are defined as fixed points in time when goals should be achieved (Latham & Locke, 1979). Since deadlines are known to increase motivation for the attainment of goals, work speed tends to be slower when deadlines are far-off and the available time to finish a task is longer than required to complete the task. On the other hand, work speed tends to increase when deadlines are close and the available time appears to be limited (e.g., Fried & Slowik 2004; Locke & Latham, 1990). Thus, deadline rush may be explained by goal-setting theory mediated by motivation.

1.1.3. Models Describing Individual Differences in Time-Pressure Reactivity

Models for individual differences in time-pressure reactivity enable researchers not only to quantify the phenomenon of time discounting but also to predict individual
behavior in relation to a deadline. One model for quantifying deadline rush is similar in form to the exponential distribution, as shown in Eqn. (1.1) (König & Kleinmann, 2005), where $V$ is the instantaneous work rate, $D$ is the time of the deadline, and $A$ is an upper bound on the work rate representing the pace of the worker undiscounted by the deadline rush effect (units/time). The free parameter $k$ denotes time-pressure reactivity representing the slope of the exponential function and is used as an index of the extent to which individuals discount the value of future outcomes, an individual difference variable. In other words, higher values of $k$ indicate more pronounced discounting of work pace and more reactive workers (Figure 1-1, solid line), whereas a smaller $k$ represents less reactive workers who are productive at every point in time (Figure 1-1, dashed line). More reactive workers will therefore present their behavior as consistent with Parkinson’s Law (Gutierrez & Kouvelis, 1991). Due to its simplicity, the exponential function for the explanation of time discounting has been adopted in diverse research areas such as economics (Frederick et al., 2002).

$$V = A \cdot e^{-kD} \quad (1.1)$$
Figure 1-1. Changes in work pace relative to a deadline

A second model for quantifying deadline rush uses a hyperbolic function. The hyperbolic function is used to describe time pressure reactivity originated from the study of preferences under choice tasks (Ainslie, 1992). In Eqn. (1.2), utility refers to the preference under choice, meaning that a high value of utility corresponds to high preference. Amount represents the reward for payout and Z indicates the constant for instant reward to prevent the equation from having an infinite value. (T-t) refers to a delay for the reward by subtracting the current time t from the rewarding time T. \( \Gamma \) notes individual differences in sensitivity for delay. While the exponential function demonstrates constant preferences of individuals with the benefit of simplicity of use,
the hyperbolic function in Eqn. (1.2) better describes changes of preference over time. These changes in preferences mean that preference reversal occurs as time goes by: when the reward is distant, people prefer a larger but later reward such as saving a bonus; however, as the reward is close, people choose a smaller but sooner reward such as spending a bonus. Such a preference reversal is represented by the hyperbolic function (König & Kleinmann, 2005; Steel & König, 2006).

\[
Utility = \frac{\text{Amount}}{Z+\Gamma(T-t)} 
\]  
(1.2)

The hyperbolic function under choice tasks can also be applied to time discounting. With respect to time discounting, the equation implies that a preference for time-usage changes as the time available toward a deadline varies. As a deadline approaches, a preference for urgent tasks that have instant rewards exceeds a preference for important but not urgent tasks (König & Kleinmann, 2005). The hyperbolic function, modified for the temporal discounting condition, is expressed by Eqn. (1.3), in which all the parameters are the same as those in the exponential function in Eqn. (1.1). Previous researchers found that the hyperbolic function describes real and hypothetical monetary rewards (Johnson & Bickel, 2002), job search behavior (van Huizen & Plantenga, 2014), and the phenomenon of deadline rush (König & Kleinmann, 2005) better than the exponential function.
\[ V = \frac{A}{1+kD} \]  

### 1.1.4. Time-Pressure Reactivity and Performance

The relationship between time-pressure reactivity and performance is emerging and inconsistent. A majority of the literature has demonstrated negative performance influenced by procrastination, defined as a “voluntarily delay of an intended course of action despite expecting to be worse off for the delay (Steel, 2007)”. Procrastination is known to be related to low academic performance. Academic achievement indicated by course grade and grade point average have negative correlation with procrastination (e.g., Moon & Illingworth, 2005; Van Eerde, 2003). I note that individual differences in pacing toward deadlines are not identical with procrastination in that procrastination itself implies an irrational delay of work despite the expectation of negative consequences. Most procrastinators hope to change their delaying behavior (Steel, 2007) whereas deadline action style reported that they rationally intended to do so in order to increase their motivation. Despite slight differences between the concepts of procrastination and deadline action style, rapid learning close to a deadline is more related to lower academic performance than evenly paced learning (Ariely & Wertenbroch, 2002; Perrin et al., 2011).

Some researchers, however, address whether delays of work proximate to deadlines do not always result in negative outcome. Grade point averages from active
procrastinators who deliberately suspend their pacing and chose to work under time pressure are higher than those from passive procrastinators who inevitably postpone work despite of their intention to work evenly. The inconsistent studies regarding the relationship between time-pressure reactivity and performance present future research area to be investigated in greater detail.

1.2. Research Questions

This section introduces the four broadly stated research questions discussed in this dissertation. These four questions were generated to quantitatively model and estimate individualized temporal motivation and to propose operational policies. The responses to each question or combination of questions can be found in the subsequent sections.

Question 1: Which factors are more effective in generating models for aligning time pacing in the presence of deadlines?

Question 2: How can the estimation of individual pacing styles be improved?

Question 3: How does individual pacing relate to productivity?

Question 4: Which operational policies are associated with higher productivity?
The first question was formulated to identify and understand the characteristics of individual differences in temporal motivations. Although the concept and models of temporal motivation have been investigated, the factors that significantly affect individual differences in time-pressure reactivity in industrial settings have not been adequately identified yet. The factors affecting individualized temporal motivation can be inferred from goal-setting theory. The inference is possible because goal-setting theory has close conceptual similarities with deadline setting in that individuals respond differently with respect to the proximity of the goal or deadline (described in section 1.1.2). Goal-setting theory has identified diverse attributes of goals and their relation to performance. Examples of attributes that affect performance with respect to goal-setting include goal complexity (e.g., Locke, 1996), the number of team members (e.g., Gevers et al., 2006; Waller et al., 2002), and previous experience (e.g., Fried & Slowik, 2004; Locke & Latham, 1990). Investigation of such significant factors enables researchers to produce a better estimate of individualized time-pressure reactivity by setting specific conditions for experimental environments.

The second question aims to improve the way in which researchers estimate individualized time-pressure reactivity. Despite the awareness of the importance of individual differences in pacing styles, in most research, individual pacing styles have only been conceptualized or categorized based on self-observation. Some researchers have fitted historical data into the exponential or hyperbolic models expressed in Eqn. (1.1) or (1.3) to parameterize time-pressure reactivity; however, this approach requires
enough samples to obtain reliable estimates. Thus, research Question 2 is intended to investigate the structures of measurement that convey practical information that is easily applicable to the real world. Improved qualification of estimation on individual differences in time-pressure reactivity served as a foundation for formulating research Questions 3 and Question 4.

The third question was developed to solve the inconsistency found in previous studies on the relationship between time-pressure reactivity and performance. As described in section 1.1.4, some researchers found that greater time-pressure reactivity is linked to poor performance while others did not found support for this link. Such inconsistency may be resolved by profound modeling and estimation on time-pressure reactivity, as reflected in response to Question 2.

The fourth question focuses on the issues of implementation of factors affecting measurements of time-pressure reactivity based on answers to research Questions 1, 2, and 3. Operational research has focused on the optimization of systematic performance while ignoring individual differences. Popular topics in psychological or behavioral science research, on the other hand, have emphasized individual differences in time-pressure reactivity in conceptual terms while ignoring practical applications of the individual differences. The final question therefore aims to satisfy and integrate the variables that have been noted or ignored to this point in both theory and practice. Based on a better understanding and more accurate estimates of individual differences
in time-pressure reactivity, the present research aimed to propose management policies that consider individual differences in time-pressure reactivity.

1.3. Research Purpose and Overview

This dissertation aimed to model and estimate individual behavior related to deadlines, then to propose an improved design for time management policies. To do so, this dissertation test and model the factors that affect time-pressure reactivity. Subsequently, the dissertation adopts the methodologies to measure and estimate individual time-pressure reactivity in a more quantitative and improved way. The dissertation also investigates how the quantified the time-pressure reactivity relates to performance. Finally, time management policies that consider individual differences in time-pressure reactivity are proposed.

The following five chapters include own independent research that has already been published or has been under review or in preparation for the publication. However, each chapter together answers several research questions addressed in the previous section 1.2. Chapter 2 introduces experimental research that tests factors affecting time-pressure reactivity to answer research Question 1. Two factors, group size, and task complexity were considered to study their significant effects on time-pressure reactivity using the Anti-Air Warfare Coordinator (AAWC) simulation. Chapter 3 presents more quantitative measurements of time-pressure reactivity by using online
course and AAWC simulation data to answer Question 2. In this chapter, a Bayesian approach is employed to better estimate individual differences in time-pressure reactivity. Chapter 4 aims to answer Questions 1 and 3 by considering the effect of logon times on the course website on time-pressure reactivity. It also examined the relation of time-pressure reactivity with academic performance using the structural equation model. Chapter 5 was designed to respond to Questions 3 and 4 by investigating the eye movement under time pressure and its relationship with learning performance. The chapter also tested whether the policy of giving feedback to individuals can increase learning performance. Finally, Chapter 6 addressed Question 4 by using a queueing system to propose several management policies in the queueing system while considering individual differences in time-pressure reactivity.
Table 1-1. The review of chapters in relation to four research questions

<table>
<thead>
<tr>
<th>Research Question</th>
<th>Chapter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Question 1: Which factors are more effective in generating models for aligning time pacing in the presence of deadlines?</td>
<td>2 ✓</td>
</tr>
<tr>
<td>Question 2: How can the estimation of individual pacing styles be improved?</td>
<td>3 ✓</td>
</tr>
<tr>
<td>Question 3: How does individual pacing relate to productivity?</td>
<td>4 ✓</td>
</tr>
<tr>
<td>Question 4: Which operational policies are associated with higher productivity?</td>
<td>5 ✓</td>
</tr>
</tbody>
</table>

1.4. Research Significance and Planned Contributions

The dissertation focuses on a quantitative investigation of individual differences in temporal motivation that can be applied to organizations or education. The consideration of individual differences in pacing styles in terms of modeling, estimation, and operational policies can make organizations more productive. Setting operational policies based on individualized pacing styles will also help organizations to form effective teams. Researchers have noticed that identifications of individual differences between group members are critical to team success (e.g., Mannix & Neale, 2005; Van
Knippenberg et al., 2004). Pacing style is one of the categories to be considered as an individual difference important for group success (Mohammed & Harrison, 2013). As a result of this study, improved methodologies for estimating individual differences in time-pressure reactivity will help other researchers or practitioners to calculate statistical significance even from little available data, which is common in real-world settings.

Beyond its application in the workplace, generating operational policies in consideration of individual differences in pacing styles can also be applied to educational fields. Online cyber-learning is one way to meet the growing need for distant learning because it enables education accessible to all, including learners living in remote areas or who have work or family constraints (e.g., Gunawardena & McIsaac, 2004). With an increased demand for online learning, online teaching requires moving beyond traditional pedagogy to adopt new practices associated with designing and teaching online courses. These pedagogical practices include establishing time parameters (i.e., timelines for individual group activities and project work) (Anderson, 2001; Keengwe & Kidd, 2010), which are especially important for online education. Setting time parameters in online environments is important, since time management has been described as a major factor of success in traditional educational settings (e.g., Britton & Tesser, 1991; Trueman & Hartley, 1996).
Chapter 2

Modeling Factors Affecting Time-Pressure Reactivity: Group Size and Task Complexity

Chapter 2 aims to answer Question 1: Which factors are more effective in generating models for aligning time pacing in the presence of deadlines? Among diverse factors that affect temporal motivation, this chapter examines two somewhat controversial factors affecting time-pressure reactivity – the number of team members and task complexity. I designed an experiment to address two related hypotheses: time-pressure reactivity is greater for individuals than for teams (H1); and task complexity is negatively related to time-pressure reactivity (H2). By employing a decision-making task based on an Anti-Air Warfare Coordinator (AAWC) simulator, the experiment has two task complexity levels and two group size levels. The experimental results showed that individuals are more reactive at the low task-complexity level. Also, the task complexity main effect was significant, with high-complexity tasks less reactive to the deadline than low-complexity tasks. The results of this study suggest that different task types and group sizes have potentially important impacts on production performance and that the setting of deadlines, to the degree possible, may be a relevant means towards managing or improving system performance.
2.1. Introduction

While individual differences in temporal motivation can be a fundamental component to group functioning (See section 1.1.3), the team-level in time distributions are equally valuable to examine (Blount & Janicik, 2002; Mohammed & Harrison, 2013). Gersick (1988) found that teams also follow Parkinson’s Law in the presence of a deadline. Specifically, when groups were given a specific deadline for completing a project, little progress is made on the project during the first half of the period before the deadline, subsequently major efforts were undertaken during the latter half of the period prior to the deadline. This relation appears to exist regardless of the total time for project completion.

Also, as a team-level study, time scarcity has been shown to induce lower task quality. Karau and Kelly (1992) investigated the effect of time scarcity and abundance on group performance by comparing frequencies quality contents including of originality, creativity and adequacy with their written solution for the problem. Among the conditions of time scarcity, optimal time, and time abundance, the time scarcity group performed significantly lower than the optimal time group at originality, creativity, and adequacy.

Yet most of the previous team-level research did not focus on how the time distribution related to the deadline but instead focused on performance quality, elevation, or the average amount of the temporal construct (e.g., Mohammed et al., 2008;
Souitaris & Maestro, 2010; Waller et al., 1999; 2001; West & Meyer, 1997). Also, there are no direct studies that compare individuals’ versus group’s time distribution prior to the deadline. Previous studies have shown that performance by teams is better than performance by individuals for decision making within games (Cooper & Kagel, 2005), product development (Schmidt et al., 2001), economics (Kocher & Sutter, 2005) and in problem solving (Hill, 1982). Nonetheless, the pacing of the relative efforts has not been previously evaluated. The higher performance is somewhat suggestive that teams perhaps engage in greater effort earlier, or farther from the deadline, and are less reactive than individuals. Thus, the question of how pacing compares between individuals and teams in the presence of deadlines leads to the first of our research hypotheses.

**H1: Time-pressure reactivity is greater for individuals than for teams.**

Researchers have also investigated how task complexity influences task performance. Task complexity has no single widely accepted definition; it can be defined in many ways (see Liu & Li, 2012). One approach is to view task complexity as being related to the number of elements of the task (Wood, 1986). A complex task may have many task elements that interconnect with each other. In addition, the number of goals and pathways to goals can be used to define task complexity. A complex task may have many goals and there may be many means to attaining each goal (Kelly et al., 1990;
Segal, 1982; Staw et al., 1981). The information load that must be processed for a task to be completed can also be defined as task complexity (Kelly et al., 1990). Task familiarity to the extent that they are predetermined, well understood, or well-learned procedures for performing a task may also define task complexity from the task performers’ viewpoint (Steinberg, 1983; Volkema, 1988).

Even though there is no direct research identifying the effect of task complexity on time-pressure reactivity, task complexity has been shown to be a moderator for the goal effect. Peters et al. (1984) found that the relationship between deadline length (time pressure) and performance is mediated by goal difficulty. Results showed that shorter deadlines and more difficult goals increase performance. Conversely, Wood et al. (1987) analyzed 125 goal-setting studies and found that goal-setting effects were strongest for easy tasks such as brainstorming, perceptual speed, and toy-assembly tasks, and weakest for more complex tasks. Notably, task complexity in those studies was not directly controlled. Peters et al. (1984) used the range of time pressure only from the low to mild levels, and Wood et al. (1987) used author’s task-complexity scores from 125 different studies.

One way to measure how performance is influenced by task complexity is to compare task completion times. High-complexity tasks are known to increase the time required to complete tasks compared with low-complexity tasks in various domains, including decision making, goal-setting, auditing, human computer interaction, and material learning (Liu & Li, 2011). For example, Xu et al. (2008) compared participants’
operation time in high-complexity and low-complexity tasks in the execution of computerized Emergency Operating Procedures (EOPs) of nuclear power plants using a simulated system. In that setting, the high-complexity task led to a longer average operation time than the low-complexity task. However, no research that tracks time distributions to task complexities prior to deadlines is currently available. Thus, the second hypothesis I will examine is based on these implicit suggestions from the literature, noting that high reactivity means greater discounting of work pace.

\[
H2: \text{Task complexity is negatively related to time-pressure reactivity.}
\]

In this chapter, an experiment was designed to address two related hypotheses: time-pressure reactivity is greater for individuals than for teams (H1); and task complexity is negatively related to time-pressure reactivity (H2). By employing a decision-making task based on an Anti-Air Warfare Coordinator (AAWC) simulator, the experiment has two task complexity levels and two group size levels. The experimental results showed that individuals are more reactive at the low task-complexity level \((p = 0.045)\). Also, the task complexity main effect was significant \((p = 0.0026)\), with high-complexity tasks less reactive to the deadline than low-complexity tasks. The results of this chapter suggest that different task types and group sizes have potentially important impacts on production performance and that the setting of deadlines, to the degree possible, may be a relevant means towards managing or improving system performance.
2.2. Methodology

2.2.1. Task Setting

I employed a decision-making task based on an Anti-Air Warfare Coordinator (AAWC) simulator to measure participants’ performance (Kim et al, 2011; Macht et al., 2014; Thiruvengada et al, 2004). Figure 2-1 illustrates the main user interface, including a radar screen with the center point representing the user’s ship. On the radar section of the user interface, three different types of aircraft (air, surface, and subsurface) and three different identifications (unknown, friendly, and hostile), resulting in nine different icons, were displayed (Table 2-1). On the left side, the hooked aircraft data present specific information about surrounding ships, aircraft, and landmarks. The user menu at the bottom of the screen control various options for the operator, depending on the operator’s role requirements.

Tasks for individual participants were called rules of engagement (ROE), which corresponded to 1) identifying unknown aircraft tracks and 2) defending the ship against those aircrafts by issuing warnings. The identification task required two tasks, one for identifying the type of craft and another for identifying whether it was friendly, hostile, or assumed hostile. The defense task required participants to warn hostile or assumed-hostile aircraft by issuing three levels of warning, according to distance in natural miles (NM) from the user’s ship: Level 1 for 50NM, Level 2 for 40 NM, and Level
3 for 30NM. If a hostile or assumed-hostile aircraft was within 30NM of the user’s ship (Level 3), the rules of engagement defended the ship by targeting the aircraft with weaponry. Team participants had two different roles to complete the task: the Defense Counter Aircraft (DCA) and the ROE. DCA identified unknown aircraft and sent updated information back to the ROE in a timely manner. Meanwhile, the ROE defended the ship by warning targeted aircraft within 30NM of the user's ship (Level 3). ROE could defend the aircraft whether or not DCA identified it.

In the Anti-Air Warfare Coordinator Simulation, deadlines are defined as the time remaining before one of the nine icons representing targeted aircrafts passes a threshold that is a certain distance from the users’ ship within the ROE. Every task in the experiment has a deadline, and each deadline differs, due to the range of vectors that each target track takes relative to the radar. Considering that deadlines are defined as fixed points in time when goals should be achieved (Latham & Locke, 1979), the static boundary of the radar screen represents a deadline for icons passing in and out of boundaries on the screen. That is, deadlines are based on the time that was available to perform the tasks. For example, in the case of ROE’s defense tasks, participants need to issue the corresponding warning before the aircraft passes the next warning level threshold.
Figure 2-1. Anti-Air Warfare Coordinator simulation (Kim et al., 2011; Macht et al., 2014)

Table 2-1. Nine different icons in AAWC user interface. (Kim et al, 2011; Macht et al., 2014)

<table>
<thead>
<tr>
<th>Type</th>
<th>Unknown</th>
<th>Friendly</th>
<th>Hostile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Air</td>
<td><img src="Image" alt="Air Icon" /></td>
<td><img src="Image" alt="Friendly Icon" /></td>
<td><img src="Image" alt="Hostile Icon" /></td>
</tr>
<tr>
<td>Surface</td>
<td><img src="Image" alt="Surface Icon" /></td>
<td><img src="Image" alt="Surface Icon" /></td>
<td><img src="Image" alt="Surface Icon" /></td>
</tr>
<tr>
<td>Subsurface</td>
<td><img src="Image" alt="Subsurface Icon" /></td>
<td><img src="Image" alt="Subsurface Icon" /></td>
<td><img src="Image" alt="Subsurface Icon" /></td>
</tr>
</tbody>
</table>
2.2.2. Procedure

The experiment consisted of two sessions: a 60-minute training session on day 1, and a 75-minute main experimental session on day 2. During the day 1 initial training, a practice scenario lasting approximately 5 minutes is performed three times. The remaining 45 minutes are used to introduce the tasks and give participants feedback before, during, and after each 5-minute scenario. The practice scenario was designed to be representative of the actual experimental session.

During day 2, the main experimental session was conducted after a 5-minute refresher trial. Four different scenarios were presented in randomized order for both the individuals and team pairs. Each scenario is 15 minutes in duration, with the actual participant time taking roughly 75 minutes. Fatigue was mitigated by limiting the actual experiment time to 60 minutes, and by giving a 3-minute rest period between scenarios. I noted consistent error rates when comparing early scenarios to later scenarios in the experiment, supporting the assumption that participant fatigue was negligible.

Participants performed tasks in a quiet room, while team members were in two separate enclosed rooms. Team members could only communicate verbally through a speakerphone.

Within each scenario, there were identification actions and warning actions. The identification actions, including identification of aircraft type and friend or foe designation, are considered high-complexity tasks. The warning actions, including first,
second, and third warnings according to Level 1, 2, and 3 based on distance in nautical miles (NM) from the users’ ship, are considered low-complexity tasks. I remark that this distinction follows the definition of task complexity in which more complex tasks involve a greater number of steps and take longer periods of time. Thus, the experiment had four treatments, having two group size levels and two task complexity levels (Table 2-2). Those treatments were: the low-complexity task for individuals (Low, 1), the high-complexity task for individuals (High, 1), the low-complexity task for teams (Low, 2), and the high-complexity task for teams (High, 2). In each treatment, the undiscounted work rate, \( A \), and time-pressure reactivity, \( k \) were measured as dependent parameters. Task proportion late, \( L \) is also considered dependent parameter from post-hoc analyses. In section 2.4., I describe the analytical approach in detail.

Table 2-2. Experimental design

<table>
<thead>
<tr>
<th>Factors</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group size</td>
<td>(1, 2)</td>
</tr>
<tr>
<td>Complexity</td>
<td>(High, Low)</td>
</tr>
<tr>
<td>Dependent parameters</td>
<td>(A, k, L)</td>
</tr>
</tbody>
</table>

2.2.3. Participants

Twenty-two participants were randomly assigned to two experimental groups, with ten individuals, and six teams of two. Team members had little or no previously
established relationships. Participants were chosen to be male engineering graduate students in order to minimize variance of gender and age differences and to avoid potential gender interactions that would add additional sources of variation to our data. Participants were screened for previous experience of AAWC simulation using a skills survey and those who had no experience were included for this study. Participants were paid at the end of the experiment according to total time they spent in training and conducting the tasks. The total number of data points from ten individuals and six teams of two includes 1617 observations representing 1617 different deadlines.

2.2.4. Analysis

Work rates were calculated based on the speed of completion from the time at which the task was first available to start. For example, the ROE required identification of aircraft on screen; thus, the time when the aircrafts were identified was used to calculate work rates as the reciprocal of the time used. Deadlines were based on the time that was available to perform the tasks. For example, in defensive tasks, participants needed to issue a warning before the aircraft passed into the next warning level boundary. I remark that because aircraft could approach the participant’s location at a variety of angles and speeds, the effective deadlines formed a wide range of values. The total number of data points from ten individuals and six teams of two includes 1617 observations representing 1617 different deadlines. It is these two values, work rate, \( V \),
and deadline, $D$, that were used to fit the time-pressure reactivity model given in Eqn. (1.3).

2.2.4.1. Undiscounted work rate, $A$ and Time-pressure reactivity (quantitative data), $k$

Considering Eqn. (1.3) as a model of time-pressure reactivity, values for the undiscounted work rate, $A$, are estimated by the maximum value of work rate, $V$ for each treatment. The rationale for the estimation of $A$ from the maximum work rate is that $A$ represents the fastest speed at which the worker can perform the task and that the participants were likely to approach the fastest rate at some point, especially for very close deadlines. Values for $k$ under each treatment were fitted based on Eqn. (1.3) with calculated $A$ and the data with $V$ for each specific treatment. The extent to which this equation accounted for variance in choice patterns was also calculated by determining $R^2$ values. I used Wilcoxon Signed-Ranks tests to determine whether $A$ and $k$ values varied within the individual and team groups, (Low, 1) vs. (High, 1) and (Low, 2) vs. (High, 2). I used Mann-Whitney nonparametric tests to compare the values for $A$ and $k$ between individuals and teams (Low, 1) vs. (Low, 2) and (High, 1) vs. (High, 2). Also, a type III ANOVA was used to determine potential interactions between task complexity and the group size.
2.2.4.2. Task proportion late (qualitative data), $L$

A late response was indicated when participants could not identify an aircraft during the time available for the given track (within the deadline), whereas the response was on-time when the deadline was met. Thus, the task proportion late, $L$, was calculated from the ratio of the number of late responses to the total number of responses. Nonparametric Mann-Whitney, Wilcoxon Signed-Ranks, and ANOVA were used to examine this variable. I note that post-hoc analyses may be conducted on relationships of significant factors on the proportion late.

2.3. Results

Before directly evaluating the hypotheses posited above, for completeness I present a summary of the statistical results from the study to provide context. The descriptive results, statistics, and confidence intervals for each treatment are presented in Table 2-3. From Eqn. (1.3), $A$, the undiscounted work rate and, $k$, the time-pressure reactivity, represent the bound and the slope of the hyperbolic function, respectively. The undiscounted work rate, $A$, which was estimated from the maximum work rate, for the low-complexity task is greater than that for the high-complexity task both in individual and team conditions. The difference indicates that the interpretation of $A$ and
its relation to common definitions of task complexity, greater work speed for low-complexity task, is measurably effective.

Table 2-3. Parameter estimate comparisons between four treatments.

<table>
<thead>
<tr>
<th>Treatment (Task complexity, Group size)</th>
<th>N</th>
<th>Median</th>
<th>95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Lower Bound</td>
</tr>
<tr>
<td>(Low, 1)</td>
<td>A</td>
<td>10</td>
<td>126.90</td>
</tr>
<tr>
<td></td>
<td>k</td>
<td>10</td>
<td>9.57</td>
</tr>
<tr>
<td></td>
<td>$R^2$</td>
<td>10</td>
<td>0.24</td>
</tr>
<tr>
<td>(High, 1)</td>
<td>A</td>
<td>10</td>
<td>46.03</td>
</tr>
<tr>
<td></td>
<td>k</td>
<td>10</td>
<td>6.03</td>
</tr>
<tr>
<td></td>
<td>$R^2$</td>
<td>10</td>
<td>0.16</td>
</tr>
<tr>
<td>(Low, 2)</td>
<td>A</td>
<td>6</td>
<td>170.35</td>
</tr>
<tr>
<td></td>
<td>k</td>
<td>6</td>
<td>7.12</td>
</tr>
<tr>
<td></td>
<td>$R^2$</td>
<td>6</td>
<td>0.23</td>
</tr>
<tr>
<td>(High, 2)</td>
<td>A</td>
<td>6</td>
<td>41.61</td>
</tr>
<tr>
<td></td>
<td>k</td>
<td>6</td>
<td>4.38</td>
</tr>
<tr>
<td></td>
<td>$R^2$</td>
<td>6</td>
<td>0.13</td>
</tr>
</tbody>
</table>

Table 2-4 illustrates the results of the nonparametric analyses examining the $A$, $k$, and $L$ among treatments. Several significant differences exist among the treatment contrasts. Among individuals, the undiscounted work rate, and time-pressure reactivity are significantly higher for the low-complexity task (Wilcoxon Signed Ranks; $p=0.005$, and $p=0.028$, respectively). The same relative relationships are significant for teams (Wilcoxon Signed Ranks; $p=0.028$, and $p=0.028$, respectively). It should be noted that higher reactivity for less complex tasks represents a manifestation of the deadline rush
effect, wherein like Parkinson’s Law, where there is greater time freedom, the work rate has a steeper discounting.

For the low-complexity tasks, the undiscounted work rate is significantly higher for teams than for individuals (Mann-Whitney; $p=0.008$), and the time-pressure reactivity is greater for the individuals (Mann-Whitney; $p=0.045$). Thus, the dyads are either more capable of working faster than the individuals or more readily demonstrate their full capabilities. For the high-complexity tasks, neither $A$ nor $k$ exhibited significant differences (Mann-Whitney; $p=0.175$, $p=0.143$).

Table 2-4. Results of nonparametric treatment comparisons

<table>
<thead>
<tr>
<th>Treatment Contrasts (Task complexity, Group size)</th>
<th>Dependent Variables</th>
<th>$p$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Low, 1) vs. (High, 1)</td>
<td>$A$</td>
<td>0.005**1</td>
</tr>
<tr>
<td></td>
<td>$k$</td>
<td>0.028*1</td>
</tr>
<tr>
<td></td>
<td>$L$</td>
<td>0.3331</td>
</tr>
<tr>
<td>(Low, 2) vs. (High, 2)</td>
<td>$A$</td>
<td>0.028*1</td>
</tr>
<tr>
<td></td>
<td>$k$</td>
<td>0.028*1</td>
</tr>
<tr>
<td></td>
<td>$L$</td>
<td>0.4631</td>
</tr>
<tr>
<td>(Low, 1) vs. (Low, 2)</td>
<td>$A$</td>
<td>0.008**2</td>
</tr>
<tr>
<td></td>
<td>$k$</td>
<td>0.045*2</td>
</tr>
<tr>
<td></td>
<td>$L$</td>
<td>0.6262</td>
</tr>
<tr>
<td>(High, 1) vs. (High, 2)</td>
<td>$A$</td>
<td>0.1752</td>
</tr>
<tr>
<td></td>
<td>$k$</td>
<td>0.1432</td>
</tr>
<tr>
<td></td>
<td>$L$</td>
<td>0.015*2</td>
</tr>
</tbody>
</table>

1Results from Wilcoxon Signed-Ranks test
2Results from Mann-Whitney U test
* $p < 0.05$, ** $p < 0.01$
2.3.1. Undiscounted Work Rate, \( A \)

Table 2-5 and Figure 2-2 summarize results in evaluating \( A \) as a dependent variable using two-way analysis of variance (ANOVA with Type III Sum of Squares), (i.e., two factors: group size and complexity). Again, the group size main effect for \( A \) is significant, with teams’ maximum work velocity significantly faster than that for individuals. This also aligns well with prior studies indicating the superior performance of teams (e.g., Cooper & Kagel, 2005; Hill, 1982). Further, the low-complexity task is associated with greater work pace, which is consistent with previous research showing that low-complexity tasks take less time than high-complexity tasks (e.g., Xu et al., 2008).

The interaction between group size and task complexity is also significant, wherein, as Figure 2-2 illustrates, teams are capable of faster paces than individuals only for the low-complexity task. On the other hand, individuals can pace faster than teams for high-complexity tasks. While at first counterintuitive, this may be a manifestation of the greater overhead with respect to communication that is required to coordinate the high-complexity tasks.

Table 2-5. ANOVA for \( A \) as dependent variable

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>Type III SS</th>
<th>MS</th>
<th>( F )</th>
<th>( p )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Complexity</td>
<td>1</td>
<td>85293.338</td>
<td>85293.338</td>
<td>283.07</td>
<td>&lt; 0.0001***</td>
</tr>
<tr>
<td>Group size</td>
<td>1</td>
<td>1577.2375</td>
<td>1577.2375</td>
<td>5.23</td>
<td>0.0299*</td>
</tr>
<tr>
<td>Group size x Complexity</td>
<td>1</td>
<td>4737.0050</td>
<td>4737.0050</td>
<td>15.72</td>
<td>0.0005**</td>
</tr>
</tbody>
</table>

*\( p < 0.05 \), **\( p < 0.01 \), ***\( p < 0.001 \)
2.3.2. Time-Pressure Reactivity, $k$

Table 2-6 and Figure 2-3 present the results from a two-way ANOVA for dependent variable $k$, the time-pressure reactivity. The task-complexity main effect is significant, with high-complexity tasks less reactive to the deadline than low-complexity tasks. Figure 2-3 illustrates that this is the case for both individuals and teams. Deadlines have been identified as an important motivational factor that strongly influences the patterns and intensities of goal-directed behaviors for both individuals (e.g. Fried & Slowik, 2004; Mitchell et al, 2004; Moon & Illingworth, 2005; Schmidt et al., 2009, Steel & König, 2006; Van Eerde, 2000) and teams or collectives (e.g. Gersick, 1988, 1989; Seers & Woodruff, 1997; Waller et al., 2001). The result is consistent with goal-setting research.
(e.g., review by Locke & Latham, 1990), wherein specific and difficult, yet realistically obtainable, goals generally lead to increased performance quantity.

Table 2-6. ANOVA for $k$ as dependent variable

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>Type III SS</th>
<th>MS</th>
<th>F</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Complexity</td>
<td>1</td>
<td>92.9280</td>
<td>92.9280</td>
<td>10.94</td>
<td>0.0026 **</td>
</tr>
<tr>
<td>Group size</td>
<td>1</td>
<td>33.3908</td>
<td>33.3908</td>
<td>3.93</td>
<td>0.0573</td>
</tr>
<tr>
<td>Group size x Complexity</td>
<td>1</td>
<td>7.6508</td>
<td>7.6508</td>
<td>0.90</td>
<td>0.3507</td>
</tr>
</tbody>
</table>

*p < 0.05, **p < 0.01, ***p < 0.001

Figure 2-3. Interaction plot (Group size x Task complexity) and dependent variable $k$. Error bars denote standard errors.

2.4. Discussion

The aim was to investigate whether group size and task complexity are related to time-pressure reactivity, and whether the deadline rush effect can be found for tasks as
short as six minutes or less. I found that as a main effect, both individuals and teams are more reactive for the lower-complexity tasks than that for the higher-complexity tasks (Table 2-6, Figure 2-3). The result that lower task complexity is related to greater work speed is consistent with definitions of task complexity in the literature. The main effect for the undiscounted rate, A (Table 2-5, Figure 2-2) supports our choice of the two task complexities to correspond to identification and warning actions. That is, low-complexity tasks should take less actual performance time to complete, noting that more reactive individuals will spread this performance time out over a longer duration of clock time. I discuss the outcomes related to our research hypotheses below.

2.4.1. Evaluation of H1

Hypothesis H1 states that time-pressure reactivity is greater for individuals than for teams. When considering the group size factor in the two-way ANOVA (Table 2-6, \( p=0.057 \)), the main effect is marginally non-significant at \( \alpha=5\% \). However, as the interaction plot suggests, individuals are more reactive than teams at the low task-complexity level (Figure 2-3, \( p = 0.045 \)), but not at the high-complexity level (Table 2-4, \( p = 0.143 \)). In the case of high-complexity, it may be that the workload does not allow as much reactivity, which is evidenced by the relatively low variance in the (High, 1) treatment in Figure 2-3. Thus, there is support for H1, that time-pressure reactivity is greater for individuals than for teams, and remark that this greater reactivity for
individuals may be contingent on the level of task complexity; I will attempt to address this question further in the following *post hoc* analysis.

**Post-hoc analysis of Proportion of late responses, L**

I consider an additional quality related variable, $L$, representing the proportion of late responses. Table 2-7 and Figure 2-4 summarize the results using $L$ as the dependent variable in a two-way ANOVA. The group size is the only significant main effect, showing that individuals made more errors than teams. However, the only significant contrast in Table 2-4 compares (High, 1) vs. (High, 2), ($p = 0.015$). That is, among the four treatments, only (High, 1) differs from the others statistically. Since this is the case in question from $H1$, I remark that these results together suggest that the treatment is at or near the limits of individual capability for this task type. That is, individuals are working at the same rate as teams despite the high-complexity task setting, and the elevated lateness rate is consistent with this interpretation. A number of studies indicate that individuals working under time pressure work at a faster rate, often with a cost to quality of performance (e.g., Kelly, 1988; Mohammad & Harrison, 2013; Smith et al., 1982; Yukl et al., 1976). Thus, there may be a speed-accuracy tradeoff that is partially observable (e.g., Beersma et al., 2003; Karau & Kelly, 2004; Perlow et al., 2002). Also, it should be noted that individuals, compared to teams, showed higher time-pressure reactivity, and made more errors, suggesting that higher time-pressure reactivity may be related to higher error rates.
Table 2-7. ANOVA for L as dependent Variable

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>Type III SS</th>
<th>MS</th>
<th>F</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Complexity</td>
<td>1</td>
<td>0.0202</td>
<td>0.0202</td>
<td>0.39</td>
<td>0.5382</td>
</tr>
<tr>
<td>Group size</td>
<td>1</td>
<td>0.2615</td>
<td>0.2615</td>
<td>5.02</td>
<td>0.0332*</td>
</tr>
<tr>
<td>Group size x Complexity</td>
<td>1</td>
<td>0.0620</td>
<td>0.0620</td>
<td>1.19</td>
<td>0.2845</td>
</tr>
</tbody>
</table>

*p < 0.05, **p < 0.01, ***p < 0.001

Figure 2-4. Interaction plot (Group size x Task complexity) and dependent variable L. Error bars denote standard errors.

2.4.2. Evaluation of H2

Hypothesis H2 stated that task complexity is negatively related to time-pressure reactivity. The ANOVA for dependent variable k indicates the significant main effect of task complexity on time-pressure reactivity (Table 2-6, \(p=0.0026\)). This main effect is negative, in that higher task complexities are associated with lower time-pressure
reactivity. Thus, for high-complexity tasks, the participants are capable of slower work rates generally, yet they tend to work closer to this slower pace than participants do for the low-complexity tasks. The pure contrasts associated with this hypothesis in Table 2-4, (Low, 1) vs. (High, 1) and (Low, 2) vs. (High, 2), are also both significant ($p=0.028$, $p=0.028$, respectively). Thus, I find support for $H2$, that task complexity is negatively related to time-pressure reactivity.

In this study, the lengths of deadlines for single Anti-Air Warfare Coordinator task took 6 minutes on average. That is, it was implicitly tested whether deadlines as short as 6 minutes, can generate the deadline rush effect. The extension of the range of this phenomenon in the literature is an important contribution of the current study. Under a short-term deadline, it may be difficult for researchers to identify the phenomenon of deadline rush because the proportion of “down time” for short task durations may be small relative to the task durations. If I have a month-long deadline, one may take a higher proportion of breaks; and, if I have shorter deadlines, idle time may be compressed. Despite this, there was a significant deadline rush even when deadline lengths are short (an average of six minutes). This is the first finding of the time-pressure reactivity phenomenon for less than nine minutes to our knowledge.

Although I demonstrated that task complexity was a significant effect, by showing lower task complexity in relation to greater work speed (Table 2-5), one may note the possible influence of task-prioritization. Certain tasks may have varying
priorities among participants. However, task complexity, of which there are two types in
the current study, identification and warning actions, have a potential relationship with
the notion of importance. That is, task priority and task complexity may be associated. I
posit that prioritization may be one of the reasons that complexities have differential
results. Claessens et al. (2010) studied how task priority influence task completion by
using daily diaries on planning and completion. When participants ranked priority of
their planned tasks at start of a working day and demonstrate the task-completion
proportion of the planned tasks at the end of a working day, high priority tasks were
completed more at the end of the workday. The result is in line with the concept of time
discounting. Additional study will be required to determine whether some portion of
the reactivity differences between task complexities is due to task prioritization.

The current study can inform managers, workers, and educators about the
influence of group size and task complexity on pacing performance. For instance,
graphical displays might be designed to account for these effects and reduce time-
pressure reactivity. It can also illustrate the role of individual differences in pacing
styles. This has the potential to improve organizational performance and reduce
conflicts between group members by acknowledging differences in time-pressure
reactivity between task difficulties and group sizes.
2.5. Conclusions

The focus of this chapter was to investigate the influence of group size and task complexity on time-pressure reactivity in a command and control decision-making environment. I designed an experiment to address two related hypotheses: *time-pressure reactivity is greater for individuals than for teams; and task complexity is negatively related to time-pressure reactivity.* The experimental results support both hypotheses, though time-pressure reactivity was greater for individuals than for teams only in the lower complexity case. I considered a post-hoc analysis to further investigate the non-significant high-complexity case and found the deadlines in that case were probably close to the limits of participant capability. Thus, there was less opportunity to be reactive, or slow down, since there was not much available slack time in that case.

The results of this study suggest that different task types and group sizes have potentially important impacts on production performance and that the setting of deadlines, to the degree possible, may be a relevant means towards managing or improving system performance. Deadlines are known as an important motivational factor that strongly influences goal-directed behavior for both individuals and collectives. On the other hand, time pressure has been shown to inhibit the creative thinking necessary for problem-solving tasks by causing workers to avoid critical probing and by inducing shallow rather than thorough, systematic processing of information (Andrews & Smith, 1996; Kruglanski & Freund, 1983). Organizations and
managers may orient themselves more towards innovations that consider the setting of deadlines to enable faster work rates.

I remark that this research focuses on an empirical study to analyze differences among the two factors—group size and task complexity resulting in four treatments. Clearly, numerous other variables may have impacts on performance in the current setting. These might include other task types, motivations, individual personality, and emotional intelligence. Also, for teams, the type and amount of coordinating communication may help to explain current findings. Research on time-pressure reactivity in learning processes, such as in education, is of considerable interest for future work.
Chapter 3


Chapter 3 aims to answer the Question 2: How can the estimation of individual pacing styles be improved? Although researchers have studied from various perspectives how individuals work toward deadlines, the measurement of individual differences in pacing styles has been based mostly on self-report questionnaire instruments. In other cases of the continuous parametric measurement of pacing styles, the historical evidence employed has been based on frequentist estimation, which often relies on sparse data in practice. Thus, the purpose of this chapter is to estimate distributions of individuals’ time-pressure reactivity using a Parametric Empirical Bayesian Estimation (PEB) approach. The use of this approach was motivated by the varied nature of sample sizes across individuals and task types. In this study, two datasets were used, one from an online course and another from an Anti-Air Warfare Coordinator (AAWC) task. From this data, I generated informative individualized posterior distributions for time-pressure activity and compared them with point estimates for time-pressure reactivity. I found that 18-40% of the original number of samples were sufficient to estimate posterior distributions to within 10% error. This study demonstrates the effectiveness of
Bayesian estimation in determining individual differences in time-pressure reactivity to deadlines by using individualized posterior distributions rather than point estimates.

3.1. Introduction

To measure individual differences in pacing style, many researchers have developed and used self-report questionnaires (e.g., Gevers et al., 2006; 2015; He, 2011; Tuckman, 1991; Van Eerde et al., 2016). For example, Gevers et al. (2006) generated a pacing style scale by using five graphs that illustrate the relationship between time to deadline and activities with short describing sentences. Examples of these sentences include the following: “I start right away and finish the work long before the deadline (early action style)”; “I work steadily on the task, spreading it out evenly over time (constant action style)”; or “I do most of the work in a relatively short time before the deadline (deadline action style)”. Based on the three basic types of pacing styles, two more graphs were modified from the early action and the deadline action to represent intermediate levels of pacing styles. Individuals were then asked to select the graph that best describes their time activity near the deadlines.

Some researchers employ more observation-based measurement, rather than using self-report questionnaires. For example, Fulton et al. (2013) measured the degree of “cramming” by calculating the difference of mean time in days between starting time of studying and the completion time. The ratio level data of the difference are then
compared based on discretely generated three different conditions of deadline length; weekly deadlines, monthly deadlines, and end-of-course deadlines. König and Kleinmann (2005) presented more continuous and parametric measurement of pacing style using hits and/or times at which students logged on to four computer-based Web courses. Subsequently, they fit individual historical data into Exponential and Hyperbolic models that parametrically estimate individualized time-pressure reactivity. The Exponential model they used for deadline rush is expressed in Eqn. (1.1). In the equation, \( x \) is the time of the deadline and \( f(x; k) \) is the current work rate. \( A \) is the undiscounted work rate, which indicates the amount of reward that is received on payout. Essentially, \( A \) indicates the magnitude of the incentive (Steel & Konig, 2006), thus it can be calculated as an upper bound on the work rate. The parameter \( k \) is the slope of the Exponential curve, the extent to which individuals discount the value of future outcomes. A higher \( k \) value represents more reactive individual who discounts future outcomes more; a smaller \( k \) value represents a less reactive individual.

Emerging studies on individualized time-pressure reactivity showed empirical evidence of changes of work rate as deadline approaches (Shipp & Cole, 2015). However, given that the measurement of human behavior toward the deadlines in previous research has employed mostly self-reported questionnaire/observations or historical data, more observable measurements are required to obtain informative and objective details of individuals’ time-pressure reactivity. Although the validity, dimension, or stability of the self-reported questionnaires on pacing styles have been
questioned and addressed (Gevers et al., 2015), self-reported questionnaires in nature can contain self-reporting biases. That is, if some individuals hope to change their pacing behavior (Steel, 2007), the value and intention that individuals want can be included in the questionnaire, instead of their observed behaviors. In other cases of continuous parametric measurement of pacing style, historical data has been employed based on the frequentist estimation, which is not always practical with real world-data due to small sample sizes. This is because such an approach using historical data requires a sufficiently large number of samples in order to obtain fixed data-generating models and to make reliable estimates.

Thus, a Bayesian approach may be advantageous because it can jointly use both pooled knowledge of the population and knowledge from individual specific samples. A Bayesian approach employs \textit{a priori} information, which reflects both knowledge and uncertainty about possible values of information before individual specific data are available. \textit{A posteriori} results are represented by a probability distribution. Moreover, the Bayesian approach uses the parameters of probability distributions to model uncertainty. Thus, a Bayesian approach is more flexible and general in that it can be applied in complex problems with relatively small sample sizes (Gelman et al., 2014; Wilks, 2011). The traditional Bayesian approach for continuous models can be expressed as in Eqn. (3.1).

\[
f(\theta|x) = \frac{f(x|\theta)f(\theta)}{\int f(x|\theta)f(\theta)d\theta}
\] (3.1)
In Eqn. (3.1), $\theta$ is the parameter representing the unknown state of nature, and $x$ represents the available data. A continuous prior distribution based on the existing data is expressed as $f(\theta)$, and the quantitative effect of different values of $\theta$ on the prior distribution in the process of the data-generation is expressed by the likelihood, $f(x|\theta)$. I note that while there are many potentially specific implementations of Bayesian estimation, I will employ a Parametric Empirical Bayes (PEB) methodology. In the PEB approach I will pool the data from all individuals to develop the prior distribution, and the individual-specific data will be used to update the prior distribution in order to provide a more robust estimate. The use of PEB for all individuals is especially helpful when there are relatively small sample sizes for some individuals. Posterior probabilities of the Bayesian statistical approach, $f(\theta|x)$, form optimal estimates based on the prior probabilities and the available data with respect to the parameter $\theta$. Thus, the posterior probabilities can be used to test research hypotheses by determining a Bayesian model, regardless of sample size (Ellison, 1996; Wilks, 2011).

The primary purpose of this chapter is to estimate distributions of individual’s time-pressure reactivity by using the PEB estimation approach, especially when sample sizes can vary considerably across individuals. Increasing the quality of estimates of individuals’ time-pressure reactivity with regard to deadlines will be beneficial for understanding differences in behavior across a diverse population. At an organizational level, the estimates can help predict individuals’ work rates over time, and for group
work can utilize the prediction of different pacing styles of each individual, such as in team formation or group work scheduling. Secondarily, I aim to suggest adequate sample sizes to estimate individuals’ pacing reactivity by using the Bayesian approach. The proposed sample size would be advantageous in practice where collecting large sets of data may be time consuming or expensive.

3.2. Methodology

3.2.1. Data Sets

I employed two distinct sets of data to show that the Bayesian approach is effective. For the first data set, I collected data from 59 undergraduate students enrolled in an advanced engineering class at The Pennsylvania State University. Students were relatively homogeneous in age (21-26) and educational background (engineering majors). During the semester, there were four assignments in which students were asked to apply discrete event simulation modeling for decision support. Each assignment consisted of between two and five questions pertaining to basic concepts and calculations that the students had been required to master. The questions for each assignment were posted on the course website eight days prior to the deadline. With submissions on the deadline, the course website automatically recorded the log-on times for when students first clicked on each question. This sampling specifically measured
the start of activity for each question; thus, actual performance time naturally occurred sometime afterwards. In this manner, I may view subsequent results as conservative estimates of time-pressure reactivity. That is, individuals or a subset therein may be even more reactive than estimated here. Nonetheless, this data both motivate and illustrates the proposed approach. For the second data set, I examined data from an Anti-Air Warfare Coordinator (AAWC) decision-making task (Kim et al. 2016; Macht et al. 2014) introduced in Chapter 2. The AAWC task employs a user-interface simulation of a radar screen. I note that the relative time to complete each AAWC task is given in hours rather than in days as it is for the first dataset.

3.2.2. Data-Only-Fit to the Exponential Model

I use the time-pressure reactivity model in Eqn. (1.1) as the basis of modeling this behavior for individual point estimates. Without loss of generality, I use a simplification as shown in Eqn. (3.2) for the online course dataset.

\[ f(x; k) = ke^{-kx} \] (3.2)

Of the 59 individuals from whom I collected online course data, 48 passed the Kolmogorov-Smirnov goodness-of-fit test with an exponential distribution at \( \alpha = 0.01 \). For the AAWC data, the exponential distribution appeared to have an acceptable fit to
the time-to-deadline data by showing a reliable $R^2$ of 0.421 on average with a 0.06 SE across 10 individuals.

To illustrate the usefulness of simplifying the two-parameter time-pressure reactivity model (Eqn. (1.1)) into the one-parameter model (Eqn. (3.2)) that was used for the online course data, I consider the log-on time data of the 59 individuals fitted into Eqn. (1.1) and Eqn. (3.2). I note that that Eqn. (1.1) is a mathematical model developed by König and Kleinmann (2005) to describe the phenomenon of deadline rush. In Eqn. (1.1), there are two parameters, $A$ and $k$, that I fit from empirical data. Compared with Eqn. (1.1), I set parameter $A$ equal to $k$ in Eqn. (3.2), meaning that the equation included only one parameter, $k$. I provided Eqn. (3.2), which is a one-parameter time-pressure reactivity model, because: 1) it represents an original exponential distribution that enables the straightforward construction of the Bayesian estimation process, and 2) the data follows both Eqn. (1.1) and Eqn. (3.2) with no significant differences between the usage of the two.

Table 3-1 summarizes the descriptive results of the parameters when using Eqn. (1.1) and (3.2) for the online course data. Here, I called $k$ ‘$k_{Data\ Only}$’ in order to distinguish it from $k$ parameters used in likelihood or posterior distributions, as described in the following sections. When using Eqn. (1.1), the average value of the fitted $A$ out of the 59 individuals was 1.737 with a 0.388 standard error (SE). The average value of the fitted $k_{Data\ Only}$ using Eqn. (1.1) was 1.853 with a 0.421 SE. The average mean squared error (MSE) of the 59 individuals was 0.017 with a 0.001 SE, for the fitting log-on times into
Eqn. (1.1). Similarly, when using Eqn. (3.2), the average values of the fitted \( k_{\text{Data Only}} \) out of the 59 individuals was 1.566 with a 0.370 SE. The average \( \text{MSE} \) of the 59 individuals was 0.019 and the SE of \( \text{MSE} \) was 0.002, for the fitting log-on times data into Eqn. (3.2). The paired \( t \)-test determining the difference between Eqn. (1.1) and Eqn. (3.2) in \( k_{\text{Data Only}} \) showed that the two values were not significantly different \((t(58)=1.86, p>0.05)\). The difference between \( k_{\text{Data Only}} \) and \( A \) in Eqn. (1.1) was also not significantly different \((t(58)=1.88, p>0.05)\). Since there were no significant differences in output when using Eqn. (1.1) or Eqn. (3.2), I used Eqn. (3.2), which represents an exponential distribution form for the online course data. The use of Eqn. (3.2) also enabled a straightforward construction of the Bayesian estimation process.

Table 3-1. Descriptive results of \( A, k_{\text{Data Only}} \), and MSE for each individual in the online course \((n=59)\)

<table>
<thead>
<tr>
<th></th>
<th>Eqn. (1.1): ( f(x; k) = Ae^{-kx} )</th>
<th>Eqn. (3.2): ( f(x; k) = ke^{-kx} )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( A )</td>
<td>( k_{\text{Data Only}} )</td>
</tr>
<tr>
<td>Average</td>
<td>1.737</td>
<td>1.853</td>
</tr>
<tr>
<td>Median</td>
<td>0.587</td>
<td>0.536</td>
</tr>
<tr>
<td>SE</td>
<td>0.388</td>
<td>0.421</td>
</tr>
<tr>
<td>95% CI</td>
<td>(0.960, 2.515)</td>
<td>(1.010, 2.695)</td>
</tr>
</tbody>
</table>

For the AAWC dataset, I fit the individual AAWC data into the exponential model in Eqn. (1.1). In this case, I used the two-parameter time-pressure reactivity model, Eqn. (1.1), as having an additional parameter in the model provided a better fit. When using Eqn. (1.1) to the AAWC data in hours, the average of \( k_{\text{Data Only}} \) was 21.863 with a 2.115 SE. The average of \( A \) was 193.32 with a 19.24 SE.
3.2.3. Estimation of Likelihood

In the Bayesian process in Eqn. (3.1), the data, \( x \) is used to estimate the posterior distribution via the likelihood function, \( f(x|\theta) \), considered as a function of \( x \) for given \( \theta \). The likelihood function can assume a particular underlying distribution. In checking likelihood model assumptions, the sampling distribution plays a key role. The sampling distribution of the Exponential distribution that the data follow is proportional to a Gamma distribution (e.g., El-Sayyad, 1969; Gelman et al., 2014). Thus, I assume that the sampling distribution of individuals’ time-pressure reactivity follows the Gamma \((n, k)\) distribution as represented in Eqn. (3.3).

\[
f(\mu|n, k) = \frac{k^n \mu^{n-1} e^{-k\mu}}{(n-1)!} \quad (3.3)
\]

In Eqn. (3.3), the mean \( \mu \) is the summed time to the deadline in days, \( n \) is individual data sample size (the number of deadlines), and \( k \) represents time-pressure reactivity. Here, the sample size represented by \( n \) is the number of data points per individual. Since each individual may in general have a different pattern and timing for his or her work and effort, the sample size, or number of observations, is different for each participant. On a practical note, the current case refers to the Erlang distribution, a special case of the Gamma distribution because shape parameter \( n \) in the Gamma \((n, k)\) is
a positive integer representing the sample size. However, I maintain the use of the Gamma distribution for generality.

3.2.4. Estimation of Prior Parameters $\alpha$ and $\beta$

The prior distribution represents the degree of belief about the state of nature before individual-specific data is available. In general, the form of the prior distribution is not pre-determined, but rather it depends upon context and the availability of related knowledge. However, for certain specific prior forms (conjugate priors), Bayesian estimation can be done analytically in closed form rather than numerically. The conjugate prior is a parametric distribution that is mathematically similar to the likelihood, and it yields a form parametrically similar to the posterior distribution (Wilks, 2011). For the gamma likelihood, as used in this study, the conjugate prior is also a gamma distribution (Bolstad, 2010; Luo & Altman, 2013). The conjugate prior for $k$ is known as $\text{Gamma}(\alpha, \beta)$, as shown in Eqn. (3.4). In Eqn. (3.4), $k$ represents the time-pressure reactivity that was used in Eqn. (3.1), meaning the degree to which an individual discounts the utility of effort prior to a deadline (König and Kleinmann, 2005). $\alpha$ is a shape parameter of the prior gamma distribution, and $\beta$ is the reciprocal of the scale parameter.

$$g(k) = \frac{k^{\alpha-1} \beta^\alpha e^{-\beta k}}{\Gamma(\alpha)}$$ (3.4)
To compare performance using the gamma conjugate prior to other forms, I considered the gamma, exponential, normal, and empirical distributions (Miller, 1980; Damsleth, 1975). The cumulative probabilities of these priors are given in Figure 3-1. For the course data (Figure 3-1, top), the goodness-of-fit test shows that the gamma, exponential, and normal distributions each provide a good fit to the data (Kolmogorov-Smirnov tests: $D = 0.118, 0.151, 0.176$, respectively; $p > 0.05$). The prior data follows Gamma (1.258, 1.548), Exponential (1.131), and Normal (0.686, 0.609$^2$). The AAWC dataset (Figure 3-1, bottom) similarly follows the gamma, exponential, and normal distributions significantly (Kolmogorov-Smirnov tests: $D = 0.153, 0.350, 0.162$, respectively; $p > 0.1$). Specifically, the prior AAWC dataset follows Gamma (20.098, 1.000), Exponential (0.038), and Normal (19.850, 4.414$^2$). For both data sets, the sum of squared error (SSE) to data was the smallest with Gamma (0.140 for the course website data and 0.020 for the AAWC data), followed by Exponential (0.178 and 0.416) and Normal (0.337 and 0.023). Thus, I used a gamma prior distribution for two reasons: 1) the gamma distribution shows the lowest value of SSE, and 2) the conjugate prior of gamma likelihood is a gamma prior. The similarity between the gamma distribution and the empirical distribution for the prior verifies our use of a gamma prior.
Figure 3-1. Cumulative probabilities of candidate prior distributions and empirical prior distributions from course website data (top) and AAWC data (bottom)
3.2.5. Posterior Distribution

The posterior distribution is the result of statistical estimation using a Bayesian approach. As shown in Eqn. (3.1), the posterior distribution is calculated as the combination of the prior pooled information and the likelihood function. The posterior distribution \( g(k|\mu) \) used in this study was calculated based on the conjugate prior relationship of the gamma prior and the gamma likelihood function, yielding the gamma posterior distribution, as shown in Eqn. (3.5).

\[
g(k|\mu) = \frac{\beta^\alpha k^{\alpha-1} e^{-\beta k}}{\Gamma(\alpha)} \cdot \frac{k^n \mu^{n-1} e^{-k\mu}}{\Gamma(n)} \cdot \frac{1}{g(\mu)} \quad (3.5)
\]

The hyperparameters of the posterior distribution make it convenient to communicate the degree of belief or uncertainty in relation to the data (Wilks, 2011). To obtain the hyperparameters for the gamma posterior, parameters from Eqn. (3.5) were grouped and associated with parameter \( k \) and the exponential function to obtain the corresponding gamma distributional form seen in Eqn. (3.6).

\[
g(k|\mu) = k^{\alpha-1+n} e^{-(\beta+\mu)k} \cdot \left( \frac{\beta^\alpha \cdot \mu^{n-1}}{\Gamma(\alpha) \cdot \Gamma(n) \cdot g(\mu)} \right) \quad (3.6)
\]
Then, I determine \( \alpha' \) and \( \beta' \) as Gamma hyperparameters denoted by \( \alpha' = \alpha + n \) and \( \beta' = \beta + \mu \) in Eqn. (3.7), forming a Gamma distribution with parameters \( \alpha' \) and \( \beta' \).

\[
\alpha' = \alpha + n, \quad \beta' = \beta + \mu \quad (3.7)
\]

\[
g(k|\mu) = k^{n-1}e^{-k\beta'} \cdot \left( \frac{\beta^n \cdot \mu^{n-1}}{\Gamma(n) \cdot g(\mu)} \right) \quad (3.8)
\]

I note that the posterior distribution \( g(k|\mu) \) is proportional to the Gamma \((\alpha', \beta')\) distribution, as shown in Eqn. (3.8). I can use the hyperparameters of the gamma distributions to represent the posterior (Bolstad, 2010). I used MATLAB to analyze the Bayes estimation for individual likelihood and posterior distributions.

3.3. Results

3.3.1. Estimating Prior and Posterior Distributions

Figure 3-2 illustrates the gamma prior distributions as well as each of the individual gamma posterior distributions for the online course data (Figure 3-2, top) and AAWC data (Figure 3-2, bottom). The gamma prior distribution is indicated in Figure 3-2 by a dashed black line. For the course data (Figure 3-2, top), the mode of the prior distribution was used to relate the maximum-likelihood estimates (MLE), 0.168. Since
the shape parameter $\alpha$ in the gamma prior was relatively small (1.258) in the Gamma $(1.258, 1.548)$ distribution, the shape of the distribution in Figure 3-2 at top is close to triangular, with the mode close to the origin. Thus, the prior distribution for the course data is somewhat informative about the general deadline-rush behavior of the subject population. I note that non-informative priors are often represented by a uniform distribution, which indicates that any value within the range of possible values is equally likely. The gamma prior for the course website data suggests that lower values of $k$ are more likely than higher values. I note that when $\alpha=1.0$, the gamma distribution is equivalent to an exponential distribution.
Each of the individual gamma posterior distributions for the online course data and AAWC data is also presented in Figure 3-2. For the online course data (Figure 3-2, top), three representative posterior distributions from Individuals 1 (bold black line), 2 (black dot), and 3 (wide gray line) are highlighted. The posterior distributions of the
remaining 56 individuals are illustrated by thin lines. To analyze the shape of the posterior distributions for each individual, the MLEs were estimated from the modes of the posterior distributions, while the SDs indicating posterior risk were calculated based on the hyperparameters. The spread in the posteriors represents the amount of uncertainty in each individual’s estimated $k$ value. When I examine the relationship between the MLE values and the shapes of the distributions (SD), I find that lower MLEs of $k$ values are related to accurate estimations (small SD), and large MLEs of $k$ values represent greater uncertainty in the estimations (large SD). For example, the posterior distribution of Individual 1 ($n = 28, \alpha' = 29.258, \beta' = 145.141$) estimates a small $k$ value (MLE: 0.194). The posterior distribution of Individual 1 has the least variance, indicating the robust estimation of actual pacing reactivity (SD = 0.037). The posterior distribution of Individual 2 ($n = 41, \alpha' = 42.258, \beta' = 78.308$) estimates a moderate $k$ value (MLE: 0.526) and indicates a reasonable estimate of pacing reactivity (SD = 0.083). The posterior distribution of Individual 3 ($n = 38, \alpha' = 39.258, \beta' = 37.008$) estimates a higher $k$ value (MLE: 1.034), and the relatively high variance represents some uncertainty in the estimation of pacing reactivity (SD = 0.169).

For the AAWC data, 10 individual posterior distributions (gray line) were calculated with prior distribution (dashed black line) (Figure 3-2, bottom). I found that 10 individuals follow distributions with MLEs ranging from 9.80 to 14.80. I note that the
MLE of the prior distribution (19.100) tended to be greater than the individual posterior MLEs for the AAWC data, the opposite of the relationship observed in the course data.

Descriptive results comparing the individual point estimates from the exponential distribution (kData Only) and the MLEs of posterior distributions (kPosterior) are summarized in Table 3-2. In all cases, regardless of the different types of priors used, the posterior MLEs are smaller than the classical intervals (kData Only) represented by the average, median, standard error, and 95% CI. Additionally, Table 3-2 reveals comparisons of MLEs of posterior distributions when using four different priors: gamma, exponential, normal, and empirical prior distributions, as described in Section 3.2.4. I used numerical calculations to obtain MLEs from the exponential, normal, and empirical priors. Numerical calculations are distinct from analytic calculations using a gamma conjugate prior with hyperparameters (\(\alpha'\) and \(\beta'\) in Eqn. (3.5)) for the posterior distributions. I note that the posterior MLEs are not significantly different when using different prior forms for either the course website data (\(F(3,232) = 0.32, p = 0.81\)) or the AAWC data (\(F(3,36) = 0.90, p = 0.45\)). The finding that different conjugate and non-
conjugate priors produce similar posterior MLEs supports our approach using a gamma prior distribution as a conjugate prior.

Table 3-2. Descriptive results of $k$ in data only and MLEs of $k$ in posterior distributions for each individual using gamma, exponential, normal, and empirical priors

<table>
<thead>
<tr>
<th></th>
<th>Data Only</th>
<th>MLEs of $k$ Posterior</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Gamma</td>
<td>Exponential</td>
<td>Normal</td>
<td>Empirical</td>
</tr>
<tr>
<td>Course</td>
<td>Average</td>
<td>1.565</td>
<td>0.755</td>
<td>0.834</td>
<td>0.686</td>
</tr>
<tr>
<td>Website</td>
<td>Median</td>
<td>0.657</td>
<td>0.430</td>
<td>0.438</td>
<td>0.452</td>
</tr>
<tr>
<td>Data</td>
<td>SE</td>
<td>0.370</td>
<td>0.126</td>
<td>0.160</td>
<td>0.072</td>
</tr>
<tr>
<td></td>
<td>95% CI</td>
<td>(0.824, 2.307)</td>
<td>(0.503, 1.007)</td>
<td>(0.514, 1.154)</td>
<td>(0.543, 0.829)</td>
</tr>
<tr>
<td>Data</td>
<td>Median</td>
<td>20.155</td>
<td>11.950</td>
<td>10.350</td>
<td>11.250</td>
</tr>
<tr>
<td></td>
<td>SE</td>
<td>2.115</td>
<td>0.541</td>
<td>0.592</td>
<td>0.594</td>
</tr>
</tbody>
</table>

To better understand the effect of selecting appropriate parameters for prior distributions, I added a sensitivity analysis wherein I examined $\alpha$ in the gamma prior distribution to observe the corresponding effects on the posterior distribution MLE and SD. I focused on the $\alpha$ parameter because it has the characteristic shape of the gamma prior distribution. Based on the empirically fit gamma prior, the $\alpha$ parameter of the gamma prior was adjusted across a range of values. In Table 3-3, for the course website data, the $\alpha$ parameter of the empirical Gamma prior (1.3, 1.5) has a range of 0.7, 2.0, and 5.0, and for the AAWC data, the $\alpha$ parameter of the empirical Gamma prior (20.1, 1.5) has a range of 5.1, 10.1, and 30.1. Table 3-3 shows that for both the course website and
the AAWC data, changes in $\alpha$ have little effect on the posterior MLEs and posterior risk $SD$, which are averaged from individuals.

Table 3-3. Sensitivity of the posterior distribution of $k$

<table>
<thead>
<tr>
<th>$\alpha$</th>
<th>$\beta$</th>
<th>Posterior MLE</th>
<th>Posterior Risk, SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.7</td>
<td>1.5</td>
<td>0.764</td>
<td>0.170</td>
</tr>
<tr>
<td>1.3</td>
<td>1.5</td>
<td>0.781</td>
<td>0.171</td>
</tr>
<tr>
<td><strong>Course</strong></td>
<td><strong>Website Data</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2.0</td>
<td>1.5</td>
<td>0.812</td>
<td>0.175</td>
</tr>
<tr>
<td>5.0</td>
<td>1.5</td>
<td>0.925</td>
<td>0.187</td>
</tr>
<tr>
<td>5.1</td>
<td>1.0</td>
<td>9.45</td>
<td>1.254</td>
</tr>
<tr>
<td>10.1</td>
<td>1.0</td>
<td>10.29</td>
<td>1.312</td>
</tr>
<tr>
<td>20.1</td>
<td>1.0</td>
<td>12.02</td>
<td>1.420</td>
</tr>
<tr>
<td>30.1</td>
<td>1.0</td>
<td>13.71</td>
<td>1.520</td>
</tr>
</tbody>
</table>

**AAWC Data**

3.3.2. Determining Adequate Sample Sizes for Estimation

Given the robustness of posterior distributions in the Bayesian approach, I estimated the number of samples required from each of the datasets to arrive at reliable posterior distributions. Figure 3-3 illustrates the dynamic updating of the MLEs for the posteriors as the sample size increases for both the course data (top) and the AAWC data (bottom), wherein each line represents the results from 59 individuals (top) and 10 individuals (bottom). Changes in $MLE$ were estimated based on posterior gamma parameters in Eqn. (3.7). In Figure 3-3, I can see that for most individuals in the datasets, the posterior $MLE$ can be estimated relatively accurately with only a few samples by showing how changes in the $MLE$ of the posterior tend to converge with a smaller
sample size than the actual sample size. Table 3-4 quantifies the convergence behavior of MLEs with respect to sample size and shows that a small number of samples is required to estimate the posterior MLE. In Table 3-4, I show the required sample sizes needed to approach 10% and 5%, errors based on the MLEs of the posterior distributions for both the course website and the AAWC data. I note that the original data is based on an average sample size of 26 for the course data and 58 for the AAWC data (Column “Original” in Table 3-4). The resulting average number of samples required is 5 for a 10% error and 8 for a 5% error based on the posterior MLEs for the course website data. In the case of AAWC data, the average number of samples required is 23 for a 10% error and 35. The result shows that as few as 5-8 samples from the course data and 23-35 from the AAWC data are enough to provide reasonable estimates of the posterior MLEs to within a 5-10% margin of error relative to estimates based on the full sets of available data. The patterns of convergence differ for the two datasets; the course data shows increasing patterns of posterior MLE as the sample size increases, whereas the AAWC data shows decreasing patterns of posterior MLE. This difference is likely due to the relationship between the prior MLE and the individual data; the MLE of prior from the course data was smaller than many individuals’ posterior MLEs, whereas the MLE of the prior from the AAWC data tended to be greater than individuals’ posterior MLEs. I found overall convergence as the sample sizes increased for both datasets. In both datasets, I concluded that 18-40% of the original number of samples is sufficient to
estimate posterior distributions compared to the original number of samples within 10% error.

Figure 3-3. Expected dynamic updates of MLEs of posterior distribution for the course website data (top) and the AAWC data (down) as sample size increases.
Table 3-4. **MLEs of posterior with required sample sizes**

<table>
<thead>
<tr>
<th></th>
<th>Original</th>
<th>10% error</th>
<th>5% error</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Course Data</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td>26</td>
<td>5</td>
<td>8</td>
</tr>
<tr>
<td><strong>Median</strong></td>
<td>25</td>
<td>4</td>
<td>7</td>
</tr>
<tr>
<td><strong>Standard error</strong></td>
<td>1.41</td>
<td>0.47</td>
<td>0.63</td>
</tr>
<tr>
<td><strong>95% CI</strong></td>
<td>(23.53, 29.18)</td>
<td>(4.07, 5.93)</td>
<td>(6.45, 8.97)</td>
</tr>
<tr>
<td><strong>Proportion to original sample size</strong></td>
<td>18.4 %</td>
<td>28.9 %</td>
<td></td>
</tr>
<tr>
<td><strong>AAWC Data</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td>58</td>
<td>23</td>
<td>35</td>
</tr>
<tr>
<td><strong>Median</strong></td>
<td>62</td>
<td>26</td>
<td>38</td>
</tr>
<tr>
<td><strong>Standard error</strong></td>
<td>5.65</td>
<td>3.19</td>
<td>3.37</td>
</tr>
<tr>
<td><strong>95% CI</strong></td>
<td>(44.93, 70.47)</td>
<td>(15.98, 30.42)</td>
<td>(27.48, 42.72)</td>
</tr>
<tr>
<td><strong>Proportion to original sample size</strong></td>
<td>40.0 %</td>
<td>60.8 %</td>
<td></td>
</tr>
</tbody>
</table>

### 3.4. Discussion

This chapter demonstrates the effectiveness of a Bayesian estimation process based on PEB for determining individual differences in time-pressure reactivity to deadlines. By using the distribution of individuals’ posterior distributions rather than point estimates, I am able to show that there is a more informative, flexible, and robust estimation process based on the parameters of the gamma conjugate prior, gamma likelihoods, and gamma posterior distributions. I also show that 18-40% of the original number of samples are sufficient to estimate posterior distributions to within 10%.
The effectiveness of using a Bayesian estimation for informative generation of individuals’ posterior distributions and the sufficiency of a small sample size were supported by using two different sets of data – course website data and an AAWC task. There are four ways by which the AAWC experiment setting is different from the academic setting I originally used. First, the task type is different. The course website data represent students’ activities for coursework, whereas the AAWC task is a decision-making task using a user interface simulation of a radar screen. Second, the relative time to complete each task is different: the deadline on average for the course website data is eight days and that for the AAWC is about six minutes. Third, the place to conduct each task is different. Participants in the course website research completed assignments wherever they chose, while the participants conducted the AAWC task in a quiet room. Last, regarding the demographic information, 59 undergraduate students of both genders enrolled in an advanced engineering class participated in the course online research, whereas 10 male graduate students performed AAWC simulation. Despite the difference in nature in the two datasets, two different datasets showed the similar usefulness of Bayesian estimation.

The use of gamma conjugate priors in this study to obtain hyper-parameters of gamma posterior distributions for both course website and AAWC data performed well. The goodness-of-fit for both datasets showed the best fit for the gamma distribution, followed by exponential and normal distributions. The empirical prior distribution representing the probabilities of the data was not markedly different from the gamma
conjugate prior, exponential, and normal prior distributions (e.g., Fig. 3-1). Moreover, the use of the gamma conjugate prior did not have any significant effects on posterior MLEs. The use of different conjugate (i.e., exponential and normal prior distributions) and non-conjugate priors (i.e., empirical prior distribution) showed similar posterior MLEs in Table 3-2. In addition to the comparison with other prior distributions, the gamma prior itself also did not change the posterior MLEs from the result of the sensitivity analyses provided in Table 3-3. Changes in shape parameters, $\alpha$, of the gamma conjugate prior have little effect on the posterior MLEs. These three points demonstrate that a gamma conjugate prior may be a useful choice for its quality of fit, as well as the convenience of using straightforward calculations of the hyper-parameters, rather than using numerical integration of direct empirical distributions. This facility makes implementation by a manager or technical researcher more likely and time efficient. I remark that an initial motivation for the current study was to facilitate obtaining robust estimates for a wider range of behaviors. For example, if an individual in a course has few recorded engagements with the course website, this individual’s records are no less interesting from a behavioral perspective, given that I am measuring effort distributed over time. While it is common statistical practice to remove observations with poor fits, in this case that would have the potential to significantly skew the results. Thus, the current approach is intended to leverage the bulk of the data overall to improve our ability to estimate and widen the range of individual behavioral responses. Such an approach
provides researchers and practitioners a fuller picture of these responses to time pressures.

The results of the study were analyzed based on the assumption that time distributions as deadlines approach follow an exponential distribution. I used an exponential distribution because of its significant fit (Section 3.2.2) and its natural relationship to the exponential time-pressure reactivity model in the literature. I note, however, that the hyperbolic functional form may provide an alternative estimation (see König and Kleinmann, 2005). Applying the hyperbolic function during the process of Bayesian estimation by calculating the corresponding sampling distribution may provide additional insights. I remark that the theory with respect to the exponential and hyperbolic models of time-pressure reactivity is somewhat unsettled. That is, it is not clear which model is generally most appropriate. Nonetheless, the proposed approach might be modified to incorporate either the hyperbolic model or other specific behavioral models.

For the online course data, I found that the posterior MLEs of three individuals out of 59 did not converge as quickly as most (Figure 3-3, left), which is likely due to the smaller individual sample sizes from these individuals. Specifically, these three individuals had small sample sizes (Average: 17.000, SE: 3.055) with greater posterior MLEs (Average: 4.296, SE:0.932), compared with the other 56 individuals’ sample sizes (Average: 26.857, SE: 1.452) and posterior MLEs (Average: 0.593, SE: 0.054). I note that all
of these posteriors were ultimately convergent. This implies that individuals who have both small sample sizes and greater MLEs may not converge as quickly.

3.5. Contributions and Conclusions

The use of PEB is distinct from self-reported questionnaires on pacing styles, which are widely used to measure individual pacing behavior toward deadlines (e.g. Salvendy, 1982). In addition, the theoretical novelty of the proposed methodology, using PEB to generate individual posterior distributions, is both a move towards qualitative estimation, and towards robust estimation, wherein we are able to make estimates using relatively small sample sizes for individuals. This is the first use PEB to estimate individual behavior in relation to deadline while comparing previous approaches to model individual time-pressure reactivity using points estimates. This contributes to the literature on the measurement and estimation of pacing under time pressure, and is useful for improving the effectiveness of many methods and approaches that rely upon reliable work rate estimation (e.g., Freiheit & Li, 2017; Chun & Bidanda, 2013).

The current research is potentially useful for both engineers and managers. The findings can provide engineers with more informative and robust individual work-time distributions rather than using point estimates, and the informative distribution on work-time can help researchers to estimate further relationships between the distributions of work-time and performance. We note that many work-time studies in
the presence of deadlines have been focused on point estimates rather than Bayesian estimation. Informative individuals’ work-time distributions can provide managers with data that are more inclusive of extremal behaviors, thereby leading to better decision making. One such managerial question is to decide on and calibrate deadlines for organizational personnel. The application of the current approach to improve on managerial decision making is of interest for future research.

In conclusion, I posit that Bayesian estimation is a useful tool for measuring time-pressure reactivity and is especially helpful in situations where it may be difficult to collect large amounts of data. This study presents a Bayesian approach to estimating individual time-pressure reactivity, as represented by the nominal time-pressure reactivity parameter from the corresponding behavioral model. Specifically, I employed a PEB approach wherein prior knowledge from the population as a whole was used to provide a priori estimates that were subsequently updated with individual data to arrive at a robust estimate using the course website data and the AAWC data. A distributional form of Bayesian estimation of individual time-pressure reactivity thus conveys more complete information than point estimation, in that the former distribution provides variance in addition to MLE information. A consideration of alternative models, such as the hyperbolic model, is of interest for future research.
Chapter 4

Modeling and Estimating Academic Performance from Time-Pressure Reactivity: A Structural Equation Approach

Chapter 4 aims to estimate academic performance based on the estimation of individualized time-pressure reactivity, by extending and answering Question 1: Which factors are more effective in generating models for aligning time pacing in the presence of deadlines? and Question 3: How does individual pacing relate to productivity? Predicting academic performance is of key interest to higher education. Researchers have extensively studied performance in order to identify significant factors affecting it. One factor known to affect academic performance is the individual differences in behavioral patterns of procrastination, mostly measured from self-reported questionnaires. In this study, I measured students’ degree of procrastination with their academic performance on an online course website. To model academic performance, a structural equation approach was considered. The result showed that the time students designate to studying prior to a deadline, called early activity, negatively affected the degree of procrastination, with the degree of procrastination negatively mediating academic performance. That is, the degree of procrastination has a mediating effect on the relationship between the early activity and academic performance. The model to predict
performance in consideration of individual differences in procrastination may be useful in class scheduling and course design.

4.1. Introduction

As the pace of technological development increases, the continued growth of Internet use influences trends in higher education as well. This increase in Internet usage enables students to learn whenever and whatever they want outside of the classroom. This means that students can personalize and pace their own learning. The online system also enables educators and education-researchers to access data about students’ learning styles or performances (OECD, 2016). Based on a large number of datasets, big data analytics have been used in education to predict academic performance in order to help students complete their classes and degree successfully (Vandamme et al., 2007).

Predicting students’ or trainees’ individualized performance based on monitoring is critical to educate students to meet the high demands of globalized and competitive markets. Recently, several universities in the U.S. installed early warning systems to alarm individual students if they are expected to perform poorly in a class. The early warning systems can encourage students to raise their grades and attendance in a personalized manner. However, existing predictive systems have mostly been based on students’ grades and rates of attendance or dropping out, which cannot predict and
tell the differences between detailed individualized behaviors, such as temporal
motivation or time management habits.

Being able to measure students’ work habits helps researchers predict the
likelihood of their academic success. One individualized behavior that can be observed
in an online system is a student’s work pacing habits leading up to deadlines. Students
usually work less when a deadline is far in the future and work more right before
academic deadlines whether they are preparing for homework or examination (Ariely &
Wertenbroch, 2002; König & Kleinmann, 2005). Previous research has shown that
procrastination was related to poor performance (Balkis, 2013; Richardson et al., 2012;
Steel, 2007). Procrastination in the academic field is defined as “an irrational tendency to
delay at the beginning or completion of an academic task” (Senécal et al., 2003).
Researchers measured the procrastination of college students’ majoring in Mathematics
using the self-reported 35-Likert scale. Authors found a strong negative correlation
between students’ levels of procrastination and their cumulative grade points averages
(GPA) in mathematics. The less students procrastinated, the greater mathematical GPAs
they can obtain (Akinsola et al., 2007). Also, students’ procrastination in writing,
studying, and reading, measured from 5-point self-reported scale, was negatively
correlated with cumulative GPA and course grade (Fritzsche et al., 2003). Referring to
time-pressure reactivity, I can infer that greater value of time-pressure reactivity may be
related to lower academic performance.
Though studies have consistently found a strong relationship between procrastination and lower academic performance, they have largely measured the degree of procrastination using self-reported questionnaires, which produce self-report bias. This bias can affect the quality of a given study’s estimation of academic achievement. Thus, in this study, I develop a model to predict academic performance from students’ online behavior, and in particular, their time-pressure reactivity. Students’ records on a course website were used as the study’s dataset. With our proposed model, I can predict both short-term and long-term academic performance based on sample observations, thereby enabling educators to guide students and give feedback during class.

4.2. Methodology

4.2.1. Data Collection

A secondary dataset from Chapter 3 using undergraduate students’ online records in a simulation modeling class at the Pennsylvania State University was employ. 59 undergraduate engineering students taking Discrete Event Simulation voluntarily participated. At four different points in the semester, students were asked to answer two to five simple questions, some of which asked them to define concepts learned during class and some of which asked them to perform calculations using those concepts. The
instructor posted each a set of questionnaires through the course website eight days prior to their due dates when students were asked to upload their completed assignments to the website. The course website automatically recorded students’ logon times and the frequencies with which they clicked each question. The logon times and frequencies were used to calculate students’ time-pressure reactivity. Students’ class grades and GPAs were also recorded through the website.

4.2.2. Definition and Measurement of Variables

I generated four constructs with their definitions and measurements summarized in Table 4-1. Early activity is defined as the time students dedicated to studying prior to a deadline, and early activity is calculated as the average amount of days students studied prior to the deadline. For example, if early activity is 2 (days), a student on average is studying 2 days prior to a deadline. Thus, a greater value of early activity represents that students on average are spending more time studying far in advance of the deadline, whereas a small value of early activity represents that students are spending more time studying right before the deadline. Early activity is measured by \( \frac{\mu}{n} \), the summed time to the deadline in days (\( \mu \)) divided by the frequency of log-ons (\( n \)). Here, \( n \) is different for each individual, showing an average of 26.36 and a standard error of 1.41 with a 95% confidence interval of (23.53, 29.18). Time-pressure reactivity is defined as the degree of procrastination, represented by \( k \). I used 59 \( k \) values from the 59 individuals using
parametric empirical Bayes estimation. The maximum likelihood of the posterior distributions from Bayes estimation was used because it produces more reliable estimates, and is intended to improve the quality of structural equation modeling. Underlying performance represents students’ long-term academic performance and is measured by students’ GPA. GPA is the most widely expressed and studied variable for measuring academic performance in education and education psychology research, and it has been used widely as a criterion for employment as well (Richardson et al., 2012). Task performance represents short-term academic performance and is quantified by the overall score of the class I observed.

Table 4-1. Definition and measurement of the constructs

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Measurement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Early Activity</td>
<td>The time designated to studying prior to a deadline</td>
<td>$\mu/n$</td>
</tr>
<tr>
<td>Time-Pressure Reactivity</td>
<td>The degree of procrastination</td>
<td>$k$</td>
</tr>
<tr>
<td>Underlying Performance</td>
<td>Long-term academic performance</td>
<td>GPA</td>
</tr>
<tr>
<td>Task Performance</td>
<td>Short-term academic performance</td>
<td>Class Grade</td>
</tr>
</tbody>
</table>

4.2.3. Structural Equation Modeling

Structural equation modeling (SEM) is a popular technique because it enables researchers to analyze multiple interrelated dependent relationships at one time (Vinodh & Joy, 2012; Kline, 2015). Because SEM shows relationships between multiple variables,
it is advantageous when researchers are interested in the direct, indirect, or mediating effects among multiple variables. The conceptual model illustrated in Figure 4-1 was tested in order to predict academic performance from early activity mediated by individualized time-pressure reactivity. I hypothesized that early activity is a predictor of time-pressure reactivity because early activity was used to estimate time-pressure reactivity by employing Bayes estimation. Given previous research showing a strong negative relationship between procrastination and GPA, I hypothesize that time-pressure reactivity is a predictor of underlying performance that mediates task performance, a variable measuring short-term academic performance. This relationship emerged out of previous research showing students’ GPAs are positive estimators for predicting students’ final grades in the class, as evaluated across assignments, projects, quizzes, and exams (Devadoss & Foltz, 1996).

Figure 4-1. Conceptual model for predicting academic performance
4.3. Results

4.3.1. Descriptive Statistics

Four variables—early activity, time-pressure reactivity, underlying performance, and task performance—were measured, from 59 participating students. Table 4-2 shows the descriptive statistics for the four variables. Early activity, which was calculated using \( \mu / n \), averaged out at 2.302 days, meaning that on average, students allot study times 2.302 days prior to deadlines. Time-pressure reactivity, represented by \( k \), produced an average of 0.781, meaning that the slope of exponential distributions illustrating the degree of procrastination was 0.781. I note that time-pressure reactivity was determined based on the maximum likelihood of individuals’ posterior distributions using a Bayesian estimation. Underlying performance resulted in an average GPA of 3.172 on a 4.000 scale, as obtained from students’ cumulative scores at various points of observation during the semester. Task performance had an average value of 85.311 percent out of 100 percent at the times I observed students’ activities.

Table 4-2. Descriptive statistics for variables

<table>
<thead>
<tr>
<th></th>
<th>Early Activity</th>
<th>Time-Pressure Reactivity</th>
<th>Underlying Performance</th>
<th>Task Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Average</strong></td>
<td>2.302</td>
<td>0.781</td>
<td>3.172</td>
<td>85.311</td>
</tr>
<tr>
<td><strong>Median</strong></td>
<td>2.272</td>
<td>0.438</td>
<td>3.210</td>
<td>86.140</td>
</tr>
<tr>
<td><strong>SE</strong></td>
<td>0.176</td>
<td>0.125</td>
<td>0.060</td>
<td>0.763</td>
</tr>
<tr>
<td><strong>95% CI</strong></td>
<td>(1.950, 2.654)</td>
<td>(0.531, 1.031)</td>
<td>(3.053, 3.292)</td>
<td>(83.784, 86.838)</td>
</tr>
</tbody>
</table>
4.3.2. Correlation Analysis

In order to construct a reliable structural equation model, correlations among early activity, time-pressure reactivity, underlying performance, and task performance were tested. The raw data described in Table 4-2 was standardized to range from -1 to 1. *Eqn. (4.1)* was used to scale different ranges of data. This standardization was to minimize the variance between different kinds of raw data.

\[
x_{\text{normalized}} = 2 \cdot \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} - 1
\]  

(4.1)

Table 4-3 provides a matrix of normalized data including Pearson’s correlation coefficients, averages, medians, standard errors, and 95% confidence intervals. Early activity showed a significant negative correlation with time-pressure reactivity and a positive correlation with underlying performance. Time-pressure reactivity was significantly negatively correlated with underlying performance. Finally, underlying performance and task performance were highly positively correlated. Pearson’s correlation coefficients were useful in inferring and confirming the relationships of the variables to one another in the structural equation model.
Table 4.3. Correlations among variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Early activity</td>
<td></td>
<td>-</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Time-Pressure reactivity</td>
<td>-0.499***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Underlying performance</td>
<td>0.297*</td>
<td>-0.294*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Task performance</td>
<td>0.010</td>
<td>-0.109</td>
<td>0.599***</td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>-0.194</td>
<td>-0.794</td>
<td>0.132</td>
<td>0.068</td>
</tr>
<tr>
<td>Median</td>
<td>-0.205</td>
<td>-0.912</td>
<td>0.172</td>
<td>0.135</td>
</tr>
<tr>
<td>SE</td>
<td>0.064</td>
<td>0.043</td>
<td>0.064</td>
<td>0.062</td>
</tr>
<tr>
<td>95% CI</td>
<td>(-0.323, -0.066)</td>
<td>(-0.880, -0.709)</td>
<td>(0.003, 0.260)</td>
<td>(-0.055, 0.191)</td>
</tr>
</tbody>
</table>

*p < 0.05, **p < 0.01, ***p < 0.001

4.3.3. The Structural Equation Model

The structural equation model in Figure 4-1 was tested to examine the hypothesized mediating relationships. Figure 4-2 illustrates the significant results of the structural equation model, including the mediating effect of time-pressure reactivity on the relationship between early activity and academic performance. More specifically, early activity—i.e., the time allocated to studying prior to a deadline—was shown to negatively predict time-pressure reactivity that represents the degree of procrastination ($\beta = -0.333, p < 0.001$). Noting that time-pressure reactivity is greater with more procrastination, the negative sign is in the intuitive direction. Time-pressure reactivity was found to negatively predict underlying performance, i.e., long-term academic performance ($\beta = -0.442, p < 0.05$), which subsequently had a positive effect on task performance, i.e., short-term academic performance ($\beta = 0.625, p < 0.001$), thus providing...
support for the hypothesized mediating relationship. However, early activity and time-pressure reactivity did not directly predict task performance \((p > 0.05)\). That is, the model suggests full mediation of time-pressure reactivity. Goodness-of-fit indices supported our proposed model: \(\chi^2 = 1.934\) with \(p > 0.1\). The ratio of \(\chi^2\) to degree of freedom was 1.934 (=1.934/1), which is less than the recommended 2.0 (Tabachnick & Fidell, 1996). The CFI was 0.980, which is greater than the recommended 0.96, and the SRMR was 0.058, which is lower than the recommended 0.09 (Hooper et al., 2008). I note that statistically significant paths in the structural equation model shifted from the significant correlations summarized in Table 4-3. For example, early activity and underlying performance were shown to have significant bivariate correlations in Table 4-3, whereas early activity was found to be unable to predict underlying performance in the structural equation model.

Figure 4-2. Mediating time-pressure reactivity’s ability to predict academic performance in a structural equation model
4.4. Discussion and Conclusion

This chapter shows that the time students allot to studying prior to a given deadline, here called early activity, negatively affects the students' degree of procrastination, with the degree of procrastination negatively mediating academic performance. That is, the degree of procrastination has a mediating effect on the relationship between early activity and academic performance. In practice, this result implies that the measurement of students' time logged on to access course website material can help researchers to estimate students' short-term and long-term academic performance, as mediated through individualized time-pressure reactivity.

The results also indicate that students' engagement inferred from time logged on to a given course website can be a predictor of students' GPAs. This is in line with previous research that has shown that behavioral school engagement, which refers to “the actions and practices that students direct toward school and learning,” is positively associated with students' GPAs (Wang et al., 2011). Wang et al. (2011) measured school participation as an indicator of behavioral engagement using a five-point scale questionnaire and found that decreases in school participation are related to decreases in GPA. In this chapter, early activity, which was obtained by calculating the average number of days students spent studying prior to a given deadline ($\mu/n$), had a reciprocal relationship to the frequency of log-ons ($n$) that is considered to represent school
engagement. Future studies should further investigate school engagement using structural equation modeling.

As in other studies, the study has some limitations. First, the study used a modest sample size (59 participants) to construct a structural equation model. However, given that the structural equation model has only four variables, this sample size is appropriate. That is, “the ratio of appropriate sample size \(N\) to numbers of parameters to be estimated \(q\)” can be 10:1 (“10 observations per one estimated parameter”) (Jackson, 2003). Second, this study’s sample was particularly homogeneous, given that it was made up of 59 undergraduate engineering students who are similar in age (21-26) and have relatively equal levels of academic preparation. Data collected from different settings should be used in future studies to increase the reliability of the conclusions.

The finding that students’ class grades and GPA can be estimated from students’ time logged on to a given course website is applicable to online learning systems. Based on students’ log-on times, the structural model can generate individualized pacing schedules based on individualized time-pressure reactivity, which mediates students’ class grades as well as their GPAs. This means that with only students’ log-on times and the deadlines for the various tasks, systems can continually predict and inform students about their proposed pacing schedules and levels of academic achievement. Thus, this model could be applicable to online learning systems in which the interaction between the instructor and his or her students is limited; in particular, it could help students to experience adaptive learning.
Chapter 5

Modeling and Estimating Human Performance with Temporal Motivation from Eye Movement

Eye movement measurement is both non-invasive to the learner, and available at a cost that is steadily decreasing. There are currently several mainstream laptop computers on the market that ship with fully integrated eye-tracking. Eye movements will take on a role as inputs to predict individualized learning performance. In response to the increased usage of this tool, this chapter uses eye-tracking technology to answer Question 3: How does individual pacing relate to productivity? and Question 4: Which operational policies are associated with higher productivity? The approach is to track participants’ eye movement, and to relate this eye movement to human learning behaviors while participants were asked to complete online training for a Project Management task. The study measured participants’ eye-movements in response to the amount of time to deadlines and feedback updating the remaining time. Results showed that eye movement partially mediated the relationship between time to deadline and task completion time. The results of the study will be advantageous in predicting individualized learning performance based on eye movements.
5.1. Introduction

Eye tracking measures observers’ eye movements to provide information on the locations where observers are looking or the sequences as eye-movements shift from one location to another at a given time. Measurement of eye movement provides information of viewers’ mind based on “eye-mind” hypothesis which demonstrates that tracing viewers’ attention is coupled with a visual display (Just & Carpenter, 1976; Posner et al., 1980). Due to its informative characteristics on perception and cognition, eye-movement recordings have been utilized in various domains including reading (e.g., Henderson & Ferreira, 1990), consumer research (e.g., Yang, 2012), or usability studies (e.g., Yuan et al., 2014) for decades.

Measuring the smooth movements of the eyes is mainly based on fixations (Buswell, 1935; Wedel & Pieters; 2008). Fixations have been defined as the moments the eye dwells constantly for around 100-400 milliseconds (e.g., Rayner, 1998). Changes in fixation have been used as indicators of participants’ cognitive processes (Just & Carpenter, 1976). High numbers of fixations overall are believed to represent less efficient search in visual displays or interfaces for usability studies to improve interface designs (e.g., Goldberg & Kotval, 1998; Jacob & Karn, 2003). Inversely, longer fixation durations are usually known to indicate participants’ difficulty in attaining or engaging information (e.g., Just & Carpenter, 1976). Also, the number of fixations can be measured in relation to regions of interest where the eye movements falling within the areas are
analyzed. A high number of fixation per the regions of interest reflects more importance of that element than others areas (e.g., Poole et al., 2005).

Researchers found that time pressure affects eye movement for decision making tasks from diverse research areas. High time pressure showed decreased proportions of fixation durations in the regions of interest, meaning that participants accelerate information acquisition (Wedel & Pieters, 2008). In marketing research, when participants were asked to choose a brand out of six products for a maximum duration of 7 seconds (high pressure), or 20 seconds (low pressure), averaged fixation duration in the high time pressure setting was smaller than in the low time pressure setting (Pieters & Warlop, 1999). More recently, Van Herpen and Van Trijp (2011) presented cereal box images of increasing complexity—symbolic logo, coded label, or nutrition table—for 8s (high time pressure) or 16s (low time pressure) while recording participants’ eye movement. Total durations of fixations and saccades for the regions of interest were significantly shorter for the coded label (region of interest) under the high time pressure condition, which means consumers quicken information acquisition.

Also, several studies indicate that observers under high time pressure search more simplified information, by using fixation and saccadic eye movement, than those under low time pressure. In Pieters & Warlop (1999) research, in high time pressure situation, observers skipped more textual information about brands. In addition, the high time pressure situation results in the increase of the number of saccades from areas of one brand to an area of another brand out of six products compared to the low time
pressure situation, while the number of saccades from one area to another inside the same brand remains constant between two time-pressure conditions. Van Herpen and Van Trijp (2011) found that high time pressure decreased the sum of fixation and saccades on ingredients, which represents more textual information than symbolic logo or coded label. Thus, when time is limited, observers filtered information briefly by skipping detailed information.

Although several relationships between time pressure and eye movement have found, those studies mostly focused on findings from experiments. Previous studies did not generate any models to predict performances or any suggestions to improve performance. Thus, the purpose of this chapter is to investigate the effects of time pressure and feedback on changes in eye movement and then to estimate individual performance from eye movements by generating structural models. By measuring participants’ eye movements and behavioral performance while they are conducting learning tasks under time pressure and receiving feedback on remaining time, I aim to measure the relationship between time to deadline, feedback, eye movement metrics, and behavioral performance. Given different lengths of deadlines, participants are required to learn new information and answer corresponding questions while their eye movements are recorded. Relationships between eye movement under time pressure and behavioral performance will enable researchers to predict individual learning performance from eye movement metrics. The results of the study will be advantageous in predicting individualized learning performance based on eye movements. Based on
this research, eye movements will take on a role as inputs used to predict individualized learning performance.

5.2. Methodology

5.2.1. Participants

24 undergraduate and graduate students [10 females, age 22.5 ± 2.4 (SD)] from Oregon State University participated in the experiment. All participants had normal or corrected normal vision and they had no or little knowledge about Project Management. They did not take any related courses to Project Management. All participants were fluent in speaking, listening, and reading in English. Participants were compensated $10 for their participation at the end of experiment. Participants gave written informed consent forms approved by the Institutional Review Board from the Pennsylvania State University and Oregon State University.

5.2.2. Learning Task and Apparatus

For the main experiment, participants learned and answered 4-forced choice tasks regarding concepts about Project Management. The learning materials on Project
Management were from provided textbook materials; and the related questionnaires were also taken from existing test banks within the textbook (Meredith & Mantel Jr, 2011). Figure 5-1 shows an example of one trial of learning materials (top) and a corresponding questionnaire (bottom). In the learning material (Figure 5-1, top), the current numbers of questions were presented on the top right side of the display to inform participants of the number of questions they already completed and the number of questions they need to complete. The title representing the subject of the slide was presented at the upper middle of the screen; detailed text information related to the title was presented at the center of the screen. When the participants completed reading materials, they should press the “NEXT” button at the bottom right to move to the corresponding questionnaire (Figure 5-1, bottom). After completing 4-forced choice tasks, participants again should click the “NEXT” button to move to the next trial. Four learning trials that were composed of four learning materials and four corresponding questionnaires, under one deadline, make one set. Each set had different test banks. Some sets had feedback on remaining time to deadline presented in bold red at the top middle, as shown in Figure 5-1. The other set did not show remaining time to deadline, as shown in Figure 5-2. The participants’ answer and the simulation’s current time were automatically saved. The experiment was simulated using C#. While conducting the learning materials on the computer monitor (1920 × 1080 resolution), participants’ eye movement from the right and left eye were measured using eye-tracker (Tobii X2-30, 30Hz).
Project Control

- The goal of the control is to get the project back on track
- Focus of Control
  - Scope: what must be done to produce the project’s end result
  - Cost: includes: cost depends on several variables including: resources, work packages such as labor rates and mitigating or controlling influencing factors that create cost variances.
  - Time: required to produce a deliverable is estimated using several techniques.

Control is focused on three elements of a project. They are

- a. scope, quality, and customer satisfaction
- b. performance, delivery, and cost
- c. scope, cost, and time
- d. cost, time, and customer satisfaction

Figure 5-1. Example of one trial of learning material (top) and a corresponding 4-forced choice questionnaire on Project Management (bottom) with information on remaining time to deadline in bold red.
The Varieties of Project Termination

- Termination by extinction: extinction occurs in any scenario where the project goes away
- Termination by addition: when the project is successful, it is institutionalized
- Termination by integration: it is absorbed into the existing structure, the most common way to terminate a project
- Termination by starvation: involves greatly reducing the budget of a project

The four types of project terminations are __________.

- a. extinction, addition, integration, and aggravation
- b. extinction, addition, integration, and starvation
- c. extinction, inclination, integration, and starvation
- d. extinction, addition, implementation, and starvation

Figure 5-2. Example of one trial of learning material (top) and a corresponding 4-forced choice questionnaire on Project Management (bottom) with no information on remaining time to deadline.
5.2.3. Experimental Design and Procedure

Prior to measuring eye-movement for the learning task, participants filled out consent forms on the study and a background information checklist about their knowledge of Project Management. After reading written instruction about procedure of experiment, participants conducted a practice trial to become familiar with the main tasks of the experiment. The practice trial mimicked the main experiment.

For the main experiment, participants conducted eight sets, each of which were composed of four trials, thus in total they conducted 32 trials while measuring their eye movements. In each set, under a deadline, participants were asked to complete four self-paced learning trials. Table 5-1 shows the design of the experiment in this study. Time to deadline and feedback were considered as two independent factors, each of which had two levels. For the time to deadline factor, conducting one set composed of four trials under eight minutes was considered as the long time to deadline condition; whereas conducting one set under four minutes was considered as the short time to deadline condition. For the feedback factor, a set showing remaining time on the screen in bold red was considered as the feedback condition; whereas a set with no remaining time information on the screen was considered as the no feedback condition. In total, four experimental conditions – short time to deadline with feedback, short time to deadline with no feedback, long time to deadline with feedback, and long time to deadline with no feedback – were designed in this study. Each experimental condition had two sets,
and the order of the four experimental conditions (in total, eight sets) were randomized between participants. The combination between the test sets and experimental conditions were also randomized between participants to minimize learning and any nuisance effects. Before starting each set, initial calibration was performed using the Tobii software package. The entire experiment including completing practice trials and the main experiments took about an hour.

Table 5-1. Experimental design

<table>
<thead>
<tr>
<th>Factors</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time to Deadline</td>
<td>(Long, Short)</td>
</tr>
<tr>
<td>Feedback</td>
<td>(No, Yes)</td>
</tr>
<tr>
<td>Dependent Variables</td>
<td>(The Number of Fixations, The Number of Fixations in the regions of interest, Reaction Time, Correct Rates)</td>
</tr>
</tbody>
</table>

5.3. Results

5.3.1. Descriptive Statistics

Table 5-2 shows the descriptive statistics of eye movement measures and the task performance metric under the four experimental conditions—short time to deadline with no feedback, long time to deadline with feedback, short time to deadline with feedback, and long time to deadline with no feedback. Eye movement measures include the number of fixations per minute, which was calculated from the total number of
fixations divided by task duration. Thus, in the short time to deadline condition the total number of fixations was divided by four minutes, whereas in the long time to deadline condition the total number of fixations was divided by eight minutes. The total number of fixation per minute was then divided into two parts; the first half of the trial (1st Half: Number of Fixations Per Minute in Table 5-2) and the second half of trial (2nd Half: Number of Fixations Per Minute in Table 5-2). Table 5-2 indicates that the numbers of fixations in the first half part were greater than the numbers in the second half part of the trial in the four experimental conditions. Also, the short time to deadline condition showed greater number of fixations per minute than the long time to deadline 1condition. The task performance metric includes task completion time (seconds) and correct rate (%). As expected, task completion time in the long time to deadline condition was greater than completion time in the short time to deadline condition; participants spent a longer time completing the task under the low time pressure than the high time pressure. Correct rates were greater under the long time to deadline condition than under the short time to deadline condition.
### Table 5-2. Descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>Number of Fixations Per Minute</th>
<th>1st Half: Number of Fixations Per Minute</th>
<th>2nd Half: Number of Fixations Per Minute</th>
<th>Task Completion Time (sec)</th>
<th>Correct Rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Short Time to Deadline with No Feedback</strong></td>
<td>Average 122.86</td>
<td>65.14</td>
<td>57.41</td>
<td>167.31</td>
<td>0.76</td>
</tr>
<tr>
<td></td>
<td>Median 120.44</td>
<td>62.56</td>
<td>57.63</td>
<td>171.50</td>
<td>0.75</td>
</tr>
<tr>
<td></td>
<td>SE 1.21</td>
<td>0.68</td>
<td>0.57</td>
<td>1.34</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>95% CI (110.65, 135.08)</td>
<td>(51.65, 63.17)</td>
<td>(58.23, 72.06)</td>
<td>(153.77, 180.85)</td>
<td>(0.70, 0.81)</td>
</tr>
<tr>
<td><strong>Long Time to Deadline with Feedback</strong></td>
<td>Average 75.08</td>
<td>40.57</td>
<td>35.08</td>
<td>213.54</td>
<td>0.85</td>
</tr>
<tr>
<td></td>
<td>Median 71.63</td>
<td>36.94</td>
<td>33.97</td>
<td>219.75</td>
<td>0.88</td>
</tr>
<tr>
<td></td>
<td>SE 1.06</td>
<td>0.62</td>
<td>0.55</td>
<td>2.42</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>95% CI (64.35, 85.81)</td>
<td>(29.51, 40.66)</td>
<td>(34.28, 46.86)</td>
<td>(189.0, 238.1)</td>
<td>(0.80, 0.91)</td>
</tr>
<tr>
<td><strong>Short Time to Deadline with Feedback</strong></td>
<td>Average 132.03</td>
<td>67.72</td>
<td>66.56</td>
<td>181.83</td>
<td>0.77</td>
</tr>
<tr>
<td></td>
<td>Median 129.31</td>
<td>67.13</td>
<td>68.44</td>
<td>191.75</td>
<td>0.75</td>
</tr>
<tr>
<td></td>
<td>SE 1.32</td>
<td>0.71</td>
<td>0.81</td>
<td>1.56</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>95% CI (118.63, 145.42)</td>
<td>(58.31, 74.82)</td>
<td>(60.50, 74.95)</td>
<td>(165.99, 197.68)</td>
<td>(0.71, 0.83)</td>
</tr>
<tr>
<td><strong>Long Time to Deadline with No Feedback</strong></td>
<td>Average 71.68</td>
<td>38.61</td>
<td>33.43</td>
<td>202.21</td>
<td>0.81</td>
</tr>
<tr>
<td></td>
<td>Median 72.88</td>
<td>38.84</td>
<td>34.28</td>
<td>196.25</td>
<td>0.88</td>
</tr>
<tr>
<td></td>
<td>SE 0.67</td>
<td>0.49</td>
<td>0.30</td>
<td>2.04</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>95% CI (64.89, 78.47)</td>
<td>(30.35, 36.51)</td>
<td>(33.69, 43.54)</td>
<td>(181.55, 222.87)</td>
<td>(0.75, 0.87)</td>
</tr>
</tbody>
</table>

### 5.3.2. Two-Way ANOVA

In order to know how the two factors – time to deadline and feedback – significantly affect changes in eye-movement, two-way analysis of variance (ANOVA) was conducted. ANOVA for the number of fixations per minute was considered first in order to understand if individual’s eye patterns were significantly affected by the time to deadline and the feedback factors. Table 5-3 shows ANOVA for the number of fixations per minute as the dependent variable and indicates the main effect of the time
to deadline on the number of fixations that was significant \((p < 0.001)\). The short time to deadline condition represented by the black line in Figure 5-3 showed a greater number of fixations per minute than the longer time to deadline represented by the black dotted line. This main effect implies that participants moved their eyes much more frequently when there was limited time to complete the task, compared to the condition when they had enough time to complete the task. There was no main effect to be significant for the feedback and interactions between the time to deadline factor and the feedback factor.

Table 5-3. ANOVA for number of fixations per minute as dependent variable

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>SS</th>
<th>MS</th>
<th>F</th>
<th>(p)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time to deadline</td>
<td>1</td>
<td>70156.2</td>
<td>70156.2</td>
<td>102.13</td>
<td>&lt; 0.0001***</td>
</tr>
<tr>
<td>Feedback</td>
<td>1</td>
<td>946.5</td>
<td>946.5</td>
<td>1.38</td>
<td>0.243</td>
</tr>
<tr>
<td>Time to deadline x Feedback</td>
<td>1</td>
<td>199.3</td>
<td>199.3</td>
<td>0.29</td>
<td>0.591</td>
</tr>
</tbody>
</table>

\(^*p < 0.05, \^{**}p < 0.01, \^{***}p < 0.001\)

Figure 5-3. Interaction plot (Time to deadline x Feedback) and dependent variable number of fixations per minute. Error bars denote standard errors.
Based on the main effect of time to deadline for the overall fixation numbers, I went further in order to understand if there were any differences within each condition of short time to deadline versus long time to deadline. Table 5-4 and Figure 5-4 illustrate the results of ANOVA for the number of fixations per minute in the first half of each trial. Similar to previous ANOVA analysis for the overall fixation numbers, there was a main effect of time to deadline on the first half of fixation numbers ($p < 0.001$). The number of fixations in the first half of the trial was greater when participants were given a short time to deadline than when given a long time to deadline. This means that in the first half part of the experimental trial, insufficient time to deadline increased the number fixations compared to sufficient time to deadline. Again, I could not find a main effect that was significant for the feedback and interactions between the time to deadline factor and the feedback factor.
Table 5-4. ANOVA for number of fixations per minute in the first half as dependent variable

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>SS</th>
<th>MS</th>
<th>F</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time to deadline</td>
<td>1</td>
<td>17289.1</td>
<td>17289.1</td>
<td>75.26</td>
<td>&lt; 0.0001***</td>
</tr>
<tr>
<td>Feedback</td>
<td>1</td>
<td>123.6</td>
<td>123.6</td>
<td>0.54</td>
<td>0.465</td>
</tr>
<tr>
<td>Time to deadline x Feedback</td>
<td>1</td>
<td>2.4</td>
<td>2.4</td>
<td>0.01</td>
<td>0.919</td>
</tr>
</tbody>
</table>

*p < 0.05, **p < 0.01, ***p < 0.001

Figure 5-4. Interaction plot (Time to deadline x Feedback) and dependent variable number of fixations per minute in the first half.

The second half for both a short time to deadline and a long time to deadline was also analyzed. Figure 5-5 and Table 5-5 summarize ANOVA for the number of fixations per minute in the second half as the dependent variable. Time to deadline was a main factor, which was similar to ANOVA for the number of fixations for the whole and the first half part of the experiment (p < 0.001). The result indicates that when participants had a short time to deadline in the second half of experiment, they frequently fixated their eye movement as they did for the whole and the first half of the experiment. Thus, the increase of eye fixation in the short time to deadline was found in all cases – the first half, the second half and the total duration of the experiment. In addition to the
significant effect of the factor time to deadline, the other factor feedback showed marginal effects on the fixation numbers in the second half of the experiment. Note that this marginal effect was not found in the first half or the overall duration of the experiment for the number of fixations. The interaction effect between the time to deadline and the feedback was not found to be significant.

Table 5-5. ANOVA for number of fixations per minute in the second half as dependent variable

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>SS</th>
<th>MS</th>
<th>F</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time to deadline</td>
<td>1</td>
<td>18455.5</td>
<td>18455.5</td>
<td>92.78</td>
<td>&lt; 0.0001***</td>
</tr>
<tr>
<td>Feedback</td>
<td>1</td>
<td>699.8</td>
<td>699.8</td>
<td>3.52</td>
<td>0.064</td>
</tr>
<tr>
<td>Time to deadline x Feedback</td>
<td>1</td>
<td>337.7</td>
<td>337.7</td>
<td>1.70</td>
<td>0.196</td>
</tr>
</tbody>
</table>

*p < 0.05, **p < 0.01, ***p < 0.001

Figure 5-5. Interaction plot (Time to deadline x Feedback) and dependent variable number of fixations per minute in the second half.

In addition to eye movement metrics, participants’ behavior performance was measured and analyzed. Table 5-6 and Figure 5-6 provide ANOVA for task completion time and indicates the main effect of the factor of the time to deadline (p < 0.01). That is,
participants completed the tasks faster when they were given a short time to deadline than when given a long time to deadline. I note that the long time to deadline conditions where participants were given 480 seconds to complete the task, they completed the task within 220 minutes on average which was even shorter than the short time to deadline condition where they were given 240 seconds. The main effect of the feedback and the interaction effect between the two factors of the time to deadline and the feedback were not significant.

Table 5-6. ANOVA for task completion time as dependent variable

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>SS</th>
<th>MS</th>
<th>F</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time to deadline</td>
<td>1</td>
<td>26616.7</td>
<td>26616.7</td>
<td>12.98</td>
<td>&lt; 0.01**</td>
</tr>
<tr>
<td>Feedback</td>
<td>1</td>
<td>4010.6</td>
<td>4010.6</td>
<td>1.96</td>
<td>0.165</td>
</tr>
<tr>
<td>Time to deadline x Feedback</td>
<td>1</td>
<td>61.0</td>
<td>61.0</td>
<td>0.03</td>
<td>0.864</td>
</tr>
</tbody>
</table>

*p < 0.05, **p < 0.01, ***p < 0.001

Figure 5-6. Interaction plot (Time to deadline x Feedback) and dependent variable task completion time.
Another behavioral performance, correct rate, was conducted for ANOVA and summarized in Table 5-7 and Figure 5-7. As the other ANOVA results for eye movement and behavioral performance, the time to deadline showed main effects for the correct rate of participants’ performance ($p < 0.05$). The main effect implies that participants made more errors when they were given a limited time to deadline compared to when given enough time to deadline. Here, I can infer a speed-accuracy trade-off from the effect of the time to deadline into the task completion time and the correct rate. That is, short time to deadline makes participants complete the task fast with the cost of making more errors compared to a long time to deadline. I could not find any main effect to be significant for the feedback and the interaction between the two factors of the time to deadline and the feedback.
Table 5-7. ANOVA for correct rate as dependent variable

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>SS</th>
<th>MS</th>
<th>F</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Time to deadline</strong></td>
<td>1</td>
<td>0.119</td>
<td>0.119</td>
<td>6.15</td>
<td>&lt; 0.05*</td>
</tr>
<tr>
<td><strong>Feedback</strong></td>
<td>1</td>
<td>0.020</td>
<td>0.020</td>
<td>1.02</td>
<td>0.315</td>
</tr>
<tr>
<td><strong>Time to deadline x Feedback</strong></td>
<td>1</td>
<td>0.004</td>
<td>0.004</td>
<td>0.21</td>
<td>0.647</td>
</tr>
</tbody>
</table>

*p < 0.05, **p < 0.01, ***p < 0.001

Figure 5-7. Interaction plot (Time to deadline x Feedback) and dependent variable correct rate.

5.3.3. Structural Equation Modeling

To construct a conceptual structural equation model that could estimate individuals’ performance, eye movement and behavioral data were normalized between 0 and 1. Table 5-8 summarizes a matrix of normalized data including Pearson’s correlation coefficients, averages, medians, standard errors, and 95% confidence intervals. The number of fixations per minute showed significant positive correlations with the number of fixations in the first half and the second half of the experiment. The number of fixations was also negatively correlated with the factor time to deadline which had binary numbers. The number of fixations in the first half and the second half...
of the experiment were positively correlated with each other, each of which was negatively correlated with the time to deadline. Finally, the task completion time and the correct rate were positively correlated with the factor time to deadline. Pearson’s correlation coefficients were used to generate conceptual structural models by providing significant relationships between variables.

Table 5-8. Correlations among variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Number of Fixations</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. 1st Half: Number of Fixations</td>
<td>0.936*</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. 2nd Half: Number of Fixations</td>
<td>0.941***</td>
<td>0.771***</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Task Completion Time</td>
<td>0.153</td>
<td>0.184</td>
<td>0.107</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Correct Rate</td>
<td>-0.081</td>
<td>-0.115</td>
<td>-0.050</td>
<td>0.003</td>
<td>-</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. Time to Deadline (Factor)</td>
<td>-0.722***</td>
<td>-0.670***</td>
<td>-0.699***</td>
<td>0.348**</td>
<td>0.249*</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>7. Feedback (Factor)</td>
<td>0.084</td>
<td>0.057</td>
<td>0.136</td>
<td>0.135</td>
<td>0.101</td>
<td>0.000</td>
<td>-</td>
</tr>
<tr>
<td>Average</td>
<td>0.411</td>
<td>0.437</td>
<td>0.404</td>
<td>0.470</td>
<td>0.677</td>
<td>0.500</td>
<td>0.500</td>
</tr>
<tr>
<td>Median</td>
<td>0.376</td>
<td>0.417</td>
<td>0.358</td>
<td>0.466</td>
<td>0.600</td>
<td>0.500</td>
<td>0.500</td>
</tr>
<tr>
<td>SE</td>
<td>0.025</td>
<td>0.024</td>
<td>0.024</td>
<td>0.021</td>
<td>0.023</td>
<td>0.051</td>
<td>0.051</td>
</tr>
<tr>
<td>95% CI</td>
<td>(0.361, 0.389, 0.356, 0.429, 0.631, 0.398, 0.398)</td>
<td>(0.460, 0.486, 0.451, 0.512, 0.723, 0.602, 0.602)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*p < 0.05, **p < 0.01, ***p < 0.001

Figure 5-8 illustrates a conceptual model for predicting behavioral performance inferred from correlations represented by Table 5-8. Two independent factors – time to deadline and feedback – are located in the first as predictors of eye movement. The number of fixations in the whole, the first half, and the second half of the experiment are then placed to see if there are any mediation effects between the relationship between independent factors and behavior performance which is located next to the eye.
movement. The task completion time and the correct rate are indicated as the predicted behavior performance.

Figure 5-8. Conceptual model for predicting performance

Figure 5-9 provides a significant structural equation model and shows the mediating effect of the number of fixations on the relationships between the time to deadline and the task completion time. The time to deadline negatively predicted the number of fixations of the whole experiment ($\beta = -0.350, p < 0.001$) implying that the less time left to deadlines, the more frequently participants fixated their eyes. The number of fixations is shown to positively estimate task completion time ($\beta = 0.711, p < 0.001$), meaning that frequent numbers of fixations predicted a longer time to complete the tasks. Since time to deadline negatively predicted the number of fixations which positively predicted the task completion time, the number of fixations had a mediating effect between the relationship between the time to deadline and the task completion time. I also note that the time to deadline positively estimated the task completion time, meaning that the longer the time left to the deadlines, the longer the time to complete
the tasks. Due to the significant relationship between the time to deadline and the task completion time, the structural equation model suggests partial mediation of the number of fixations. The other independent factor, feedback did not predict any variables in the structural equation model. Goodness-of-fit indices supported the proposed model presented in Figure 5-9: $\chi^2 = 7.496$ with $p > 0.1$. The ratio of $\chi^2$ to degree of freedom was 1.874 ($=7.496/4$), which is less than the recommended 2.0 (Tabachnick & Fidell, 1996). The CFI was 0.974, which was greater than the recommended 0.96, and the SRMR was 0.051, which was lower than the recommended 0.09 (Hooper et al., 2008).

![Figure 5-9](image.png)

Figure 5-9. Mediating number of fixations’ ability to predict task completion time in a structural equation model

5.4. Discussion and Conclusion

In this chapter, the number of fixations, one measurement of eye movement, has partially mediated the relationship between time to deadline and task completion time.

That is, insufficient time to deadline accelerated scan paths on the screens, and an
increased number of fixations increased task completion time when participants learned about Project Management. The structural equation model is inferred from correlations between variables and the 2-way ANOVA which showed significant main effects of the time to deadlines on eye movements (i.e., the number of fixations), and on behavioral performance (i.e., task completion time, and correct rate).

I found one independent factor, time to deadline, to be significant for the eye movement measures and behavioral performances, whereas the other factor, feedback, was not significant. However, the marginal effect of the feedback on the number of fixations per minute in the second half of the experiment ($p=0.064$) yields some meaningful implications. The marginal effect of the feedback was found only for the number of fixations in the second half of the experiment and was not found in the all parts or in the first half of the experiment. This tendency was different from the main effects of the time to deadline where all parts of the experiment, the first half, and the second half of the experiment were found to be significant. Unlike the effect of the time to deadline, the feedback may have affected only eye movement in the second half of the experiment in which time to the deadlines was limited. Participants checked the feedback much more frequently with approaching deadlines regardless of how much time they were given in the beginning – 240 minutes or 480 minutes. This implies that feedback in the online learning setting may play a key role in pacing their behavioral learning based on their eye movements. Besides the current eye movement and
behavioral data collected from 24 individuals, additional data may need to be gathered to determine the effect of the feedback.

Although I did not consider individual differences in pacing styles to meet the deadlines in this chapter, I could consider such individual differences in pacing styles in the future research. During the experiment, participants also answered Pacing Action Categories of Effort Distribution (PACED) self-reported questionnaire that measured conceptualized individual pacing styles with nine-items (Gevers et al., 2015). The individual difference in pacing styles showed significant differences in the region of interest – i.e., the area of the feedback on the screen. Figure 5-10 shows the difference between long time to deadline and short time to deadline in the number of fixations for the area of the feedback for all (left), deadline action (top right), and U shaped individuals (bottom right). All individuals \((n=24)\) were divided into deadline action \((n=11)\), U shaped \((n=10)\), and steady action styles \((n=3)\). The difference between the long time and short time to deadline was only found for the individuals with deadline actions style \((t (10) = -2.38, p < 0.05)\). U shaped individuals and all individuals did not differ in short or long time to deadline. Individuals with the deadline action style looked at the feedback provided on time much more frequently when they were given short time to deadline rather than enough time to deadline. The different results from different individuals suggest that further research on patterns of eye movement should be conducted in consideration of individual differences in pacing styles.
This chapter aimed to model the effect of time pressure and feedback on learning performance through the mediation of eye movement, which is a new metric measurement of time-pressure behavior. It should be noted that such eye movement measurement is both non-invasive to the learner and available at a cost that is steadily decreasing. Several mainstream laptop computers are currently on the market with fully integrated eye-tracking. The model that would be able to estimate individual learning performance through eye movement can be applied to online learning system, where
eye-tracking technique can be installed in laptops to foster adaptive learning systems with feedback.
Chapter 6

Operational Policies for Human Performance with Temporal Motivation in a Queuing System

Chapter 6 aims to mainly answer Question 4, *Which operational policies are associated with higher productivity?* Most of the current settings of job/task assignments were based on a company’s perspective to meet the demands of a schedule or to maximize workers’ productivity, ignoring the diversity in individuals’ pacing styles in different work settings. If task assignment systems instead considered the diversity in time-pressure reactivity and tried to include this information in system design, system productivity could increase. This chapter considers diversity in time-pressure reactivity and proposes job assignment policies that could be used in a queueing system. Using the reciprocal relationship between time-pressure reactivity and task complexity investigated in Chapter 2, I generated the Targeted-Complexity-Prioritization (TCP) policy by comparing performances of queueing systems. That is, when the current job had a long deadline and was more complex than the new job, the policy suggests stopping the current job and switching to the new job. Based on the generated TCP policy, performance in the queueing system was simulated and compared under six policies – First-In-First-Out, Last-In-First-Out, Earliest-Due-Date First, High-Complexity-Preempt-Priority, Low-Complexity-Preempt-Priority, and the Targeted Complexity
Prioritization Policy. The result showed that the Earliest-due-date First policy dominated other policies. These findings can contribute to further research in the fields of education, management, or systems engineering.

6.1. Introduction

Queuing theory has been adopted as an underlying framework in research on waiting lines that often uses mathematical models or simulations. Queueing structure includes entities arriving at servers, waiting in the queue, getting served, and ultimately leaving the system. Entities in the queuing system can be anything that arrives and requires servers, such as customers, patients, pallets, or vehicles. Servers in the queueing structure denote any sources that provide services, such as clerks, hospitals, order pickers, or toll gates on a highway. If information about the distribution of customer arrival and service time is given, various aspects of system performance, such as the proportion of service time or length of time spent waiting in lines, can be measured using a random process, e.g., rush hour traffic or customers in restaurants (Newell, 2013; Ross, 2013).

Industrial engineers and system designers simulate queueing systems to predict and improve the function of the system. For example, researchers can change input parameters or server demands to find the optimized server utilization. Researchers can
also compare queue discipline while considering system characteristics. Generally, policies used to manage queueing system include first-in-first-out (FIFO), last-in-first-out (LIFO), service according to priority, or shortest processing time first (e.g., Banks et al., 2000). Due dates also play a key role in job scheduling or task assignments.

Industrial and systems engineers consider deadlines as systematic due dates utilized to prioritize tasks. Psychologists or economists who investigate individual differences in human behavior have focused on the effect of deadlines on individualized performance. Most of the current settings for task assignments are however based on a company’s perspective to meet the demands of a schedule or to maximize workers’ productivity, ignoring the diversity in pacing styles among those workers. If task assignment systems considered workers’ diversity in time-pressure reactivity and tried to include that diversity in the system, system productivity could increase along with worker satisfaction.

The purpose of this chapter is to suggest assignment policies to maximize system productivity in a queueing system. To consider different time-pressure reactivity of servers, this chapter uses the findings presented in Chapter 2, which showed that time-pressure reactivity differs according to different task complexity. I employed greater time-pressure reactivity of servers’ service rates for the low-complexity tasks and smaller time-pressure reactivity of service rates for the high-complexity tasks. The percentages of deadlines met for each assignment and total work amounts have been used to compare assignment policies.
6.2. Methodology

The study employed M/G/1 queueing; Poisson process (Markovian) showed interarrival rates, service rates followed general distribution, and one server was considered in the system. The simulation model in this chapter depicted an advanced engineering class at the Pennsylvania State University. Figure 6-1 illustrates the overall process of the queueing simulation in this study. Entities (assignments in the class) were distributed to servers (students) who processed the assignments differently according to the different complexity of entities. Using the results in Chapter 2, the service rate for the low-complexity task was assumed to be greater than that for the high-complexity task. Since each server (student) was assumed to process only one entity at a time, the remaining entities that were not processed were placed in a queue. Alternative operational policies were tested to find the best policies by comparing system productivity. The length of running simulation was set to 90 days (three months). Table 6-1 summarizes experimental design and four components of designed queueing system. Four components of the queueing system – entities, service rates, system performance, and operational policies – are described in detail in the following subsections.
Table 6-1. Experimental design in the queueing system

<table>
<thead>
<tr>
<th>Components</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entities</td>
<td>(Low-complexity task, High-complexity task)</td>
</tr>
<tr>
<td>Service rates</td>
<td>(High time-pressure reactivity, Low time-pressure reactivity)</td>
</tr>
<tr>
<td>System performance</td>
<td>(Percentages of deadlines met, Total work amount)</td>
</tr>
<tr>
<td>Operational policies</td>
<td>(First-In-First-Out (FIFO), Last-In-First-Out (LIFO), Earliest-Due-Date First (EDD), High-Complexity-Preempt-Priority (HCPP), Low-Complexity-Preempt-Priority (LCPP), Targeted-Complexity-Prioritization (TCP))</td>
</tr>
</tbody>
</table>

6.2.1. Entities

The characteristics of entities in the queueing system imitate mostly two kinds of assignment in an advanced engineering class at The Pennsylvania State University in
terms of task complexity, interarrival rates, and deadlines. Two types of entities were generated and distributed to students. The first type involved class assignments in which students were required to solve the problems given during class. The class assignments were distributed on average once every two or three weeks during the semester. Here, *the first type of assignment was considered a low-complexity task* because there were only two to five short questions in each assignment that students needed to calculate by hand. In the simulation, the low-complexity task was assumed to take one day. Here, I defined the task complexity as the number of day(s) to complete the task. Thus, the low-complexity task was assigned the value of one (day).

The second type of entities consisted of lab reports from lab sessions. Students usually attended one lab session per week and needed to submit a lab report that included simulation models. *The lab report assignments were considered a high-complexity task* because students were required to write lab reports with simulation models that took greater time and effort to complete and required deeper levels of problem solving compared to the class homework. In the simulation model, the high-complexity task was assumed to take two days to complete, and the task complexity was assigned the value of two.

Inter-arrival rates for all entities in the simulation were assumed to follow Poisson distribution, as shown in Eqn. (6.1), with the average number of events ($\lambda$) of 3.5. This implies that all assignments were distributed randomly every 3.5 days per week on average with the range of one day to eleven days. Both the low-complexity and the high-
complexity tasks assumed to follow random Poisson distribution, with the average of 3.5
days for the simplicity of the simulation model.

\[ p(x; \lambda) = \frac{e^{-\lambda} \lambda^x}{x!} \quad x = 0, 1, 2 \ldots \quad (6.1) \]

Finally, all entities were assumed to have deadlines of seven days (one week) or
fourteen days (two weeks). Deadlines of seven or fourteen days were randomly assigned
to all entities following Uniform distribution. Fifteen entities, including both the low-
complexity and the high-complexity tasks, were generated for 90 days. In summary, the
etities were classified by two levels of task complexities (high and low), random
interarrival rates (random Poisson distribution), and two levels of deadlines (one week
and two weeks).

6.2.2. Service Rates

Apart from traditional queuing system where service rates follow random
exponential distribution, the service rate in the current study employed time-pressure
reactivity from deadline rush model (Eqn. (1.1)). I used exponential distribution with
time-pressure reactivity \( k \), as represented in Eqn. (3.2), which was modified from Eqn.
(1.1) for the simplicity. Here, the students’ time-pressure reactivity was assumed to
depend on task complexity. The assumption was based on a research finding presented
in Chapter 2, which indicates that high-complexity tasks are less reactive to the deadline compared to low-complexity tasks. Since the two task complexities, defined as number of days to complete the task, were coded one and two, as described in the section 6.2.1., I assumed that time-pressure reactivity had an inverse proportion to the task complexity. That is, if the task complexity had a value of one, meaning that it took one day to complete the task, the time-pressure reactivity was coded as two. When the task complexity had a value of two, the time-pressure reactivity was coded as one. Thus, service rates in this queueing system had an inverse relationship with the task complexities of entities.

6.2.3. System Performance

The queueing system in this study quantifies system performance using two measurements, the percentages of deadlines met and total work amount. Since each entity was randomly assigned seven or fourteen days of deadlines, whether each entity met its own deadline could be calculated after the server completed processing the entity. The percentages of deadlines met were calculated from the number of entities that met deadline divided by the total number of generated entities, which was fifteen. The total work amount was calculated by integrating the service rates in Eqn. (3.2) for the given deadlines.
6.2.4. Operational Policies

Six operational policies, including the existing policies and policies to be generated, were tested by comparing system performance under each policy. This study included three queueing policies that have been used frequently in previous research, specifically first-in-first-out (FIFO), last-in-first-out (LIFO), and earliest-due-date first (EDD). The FIFO policy processed first the first entity. The LIFO policy processed the last entity first. The EDD processed first entities with earliest deadlines.

I also generated two operational policies that considered task complexities of the entities modified from the policy service according to priority. As the policy name suggests, the High-Complexity-Preempt-Priority (HCPP) prioritized the high-complexity task. As soon as the high-complexity assignment arrived, the server switched to the high-complexity job. If the current task was a low-complexity task, the server stopped working on the current job and switched to a new high-complexity task. If the current task was a high-complexity task, the server kept working on the current high-complexity job and subsequently moved to the new assignment. Although this switching rule in the current study considered only two cases, the rules could be more diverse if the levels of complexity had multiple levels.

The Low-Complexity-Preempt-Priority (LCPP) was the same as the HCPP except that the low-complexity task was considered the high-priority job. This means that when the low-complexity task and the high-complexity task were given at the same time,
servers switched to the low-complexity tasks to conduct the high-priority job. If the current task was a high-complexity task, the server stopped working on the current job and switched to the new low-complexity task. If the current task was a low-complexity task, the server kept working on the current low-complexity job and then worked on the next assignment.

Finally, the Targeted-Complexity-Prioritization (TCP) policy was generated by focusing on a single stage where a new job came to the server. Thus, only two entities were compared in terms of the systems productivity during 30 days. Two entities had two levels of the assigned deadlines (seven days and fourteen days) and the task complexity (one day and two days), as described in the section 6.2.1. The interarrival rate was fixed to eight days to minimize the variances in determining the TCP policy, thus the second entity always came to the server on day eight.

6.3. Results

The results are presented in two sections. The first part, described in the section 6.3.1, shows the process and results of TCP policy generation. Only two entities with fixed interarrival rate during 30 days were identified to find the best TCP policy. Based on the generated policies, the second section, described in the section 6.3.2, compares performance across six operational policies, the FIFO, LIFO, EDD, HCPP, LCPP, and TCP. Fifteen entities were generated during 90 days to compare operational policies.
6.3.1. Targeted-Complexity-Prioritization (TCP) Policy Generation

To generate the TCP policy, only two entities with fixed interarrival rate of eight days were considered. The current job defined the entity that a server (student) was working while the new job defined the entity that came to the server on day eight. The entities in the current job and new job had two different levels of the length of deadline and the task complexity. In total, four combinations for each entity in terms of the length of deadline and the task complexity are provided in Table 6-2. The long deadline was fourteen days and the short deadline was seven days. For the task complexity, the high-complexity was defined as two days to complete the task and the low-complexity was defined as one day to complete the task. According to two levels of the task complexity, service rate had proportionally reciprocal relations. Service rate had the exponential distribution with the time-pressure reactivity \( (k) \) of one for the high-complexity task and two for the low-complexity task.

Table 6-2. Two by two characteristics of entities

<table>
<thead>
<tr>
<th>Deadline</th>
<th>Task Complexity</th>
<th>Expression: (Deadline, Task Complexity)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Long</td>
<td>High</td>
<td>(L, H)</td>
</tr>
<tr>
<td>Short</td>
<td>Low</td>
<td>(S, L)</td>
</tr>
<tr>
<td>Long</td>
<td>Low</td>
<td>(L, L)</td>
</tr>
<tr>
<td>Short</td>
<td>High</td>
<td>(S, H)</td>
</tr>
</tbody>
</table>
Table 6-3 summarize system performance that indicates keeping or switching the current job. In the first column of Table 6-3, sixteen combinations of entities’ characteristics are described for the current job on which the server was working and the new job that came to the server later. Subsequently, system performance in terms of deadlines met (%) and work amount (days) is illustrated for each entity under the policy to keep and the policy to switch. Finally, the resultant strategy in Table 6-3 reveals which policies produce better system performance. The resultant strategy suggests switching from the current to a new job when the percentages of deadline met or the total work amount increase when switching the current job compared to when keeping the current job. On the other hand, the resultant strategy suggests keeping the current job when the percentages of deadline met or the total work amount increase when keeping the current job compared to when switching the current job. If the system performance was the same when keeping and switching policy, the strategy suggested keeping the policy because switching the current job may take extra costs or time. As highlighted in Table 6-3, the strategy suggests that when the current job is high in complexity with long deadline while the new job is low in complexity, stopping the current job and switching to the new job resulted in greater percentages of deadlines met and greater total work amount accomplished.
### Table 6-3. System performance under the policy to keep or to change current job

<table>
<thead>
<tr>
<th>(Deadline, Task Complexity)</th>
<th>Policy: keep</th>
<th>Policy: switch</th>
<th>Resultant Strategy</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Current Job</strong></td>
<td><strong>New Job</strong></td>
<td><strong>Deadline Met (%)</strong></td>
<td><strong>Work Amount</strong></td>
</tr>
<tr>
<td>(L, H)</td>
<td>(S, L)</td>
<td>0</td>
<td>1.58</td>
</tr>
<tr>
<td>(L, H)</td>
<td>(S, H)</td>
<td>0</td>
<td>1.58</td>
</tr>
<tr>
<td>(L, H)</td>
<td>(L, L)</td>
<td>0</td>
<td>1.58</td>
</tr>
<tr>
<td>(S, H)</td>
<td>(S, L)</td>
<td>50</td>
<td>3.89</td>
</tr>
<tr>
<td>(S, H)</td>
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### 6.3.2. Comparisons of Operational Policies

Based on the generated TCP policy, system performance was simulated with fifteen entities for three months and subsequently compared under six policies. In the current queueing simulation, service rates had an inverse relationship with task complexity, which was distinguished from other simulation system. Figure 6-2
illustrates the percentages of deadlines met under six policies. Overall, the EDD dominated other policies, showing the greatest percentages of deadlines met ($F_{5,54} = 18.84, p < 0.001$). The one-way ANOVA was followed by Fisher’s post-hoc test to determine which policies were significantly different. The EDD showed significantly greater percentage of deadlines met than all other five policies ($p < 0.05$). The FIFO, LCPP and TCP policies showed the greater percentage of deadlines met than the LIFO and HCPP policies ($p < 0.05$). The LIFO and HCPP policies were smaller in the percentages of deadlines met than all other four policies – the FIFO, EDD, LCPP, and TCP ($p < 0.05$). In conclusion, the EDD policy showed the largest percentages of deadlines met, followed by the FIFO, LCPP, and TCP, while the LIFO and HCPP policies showed the smallest percentages of deadlines being met.
The total work amount illustrated similar tendency under six different policies (Figure 6-3). The EDD produced the greatest total work amount ($F_{5,54} = 11.66, p < 0.001$). The one ANOVA followed by Fisher’s post-hoc test was carried out to investigate the effectiveness of policies. The EDD showed significantly greater total work amount than all other five policies ($p < 0.05$). In comparison, the LIFO produced the smallest in terms of the total work amount out of six policies ($p < 0.05$). The LCPP and TCP policies showed greater total work amount than the LIFO policy ($p < 0.05$). The FIFO showed the greater total work amount than the LIFO and HCPP policies ($p < 0.05$).
This chapter aimed to suggest assignment policies to maximize system productivity in a queueing system by considering different time-pressure reactivity in response to different task complexities. To do so, I first generated the TCP policy through which I recommended that workers should switch to the new job when the current job are high in complexity with a long deadline, and the new job are low in complexity. In consideration of the transition between the current and new jobs, I

Figure 6-3. System performance of the total work amount under six policies

6.4. Discussion and Conclusion

This chapter aimed to suggest assignment policies to maximize system productivity in a queueing system by considering different time-pressure reactivity in response to different task complexities. To do so, I first generated the TCP policy through which I recommended that workers should switch to the new job when the current job are high in complexity with a long deadline, and the new job are low in complexity. In consideration of the transition between the current and new jobs, I
created the TCP policies. Then, I compared the TCP policy to other existing policies – the FIFO, LIFO, EDD, HCPP, and LCPP. According to my results, for both the percentages of deadlines met and the total work amount, the EDD policy showed the greatest followed by the FIFO, LCPP, and TCP, whereas the LIFO policy showed the smallest.

I note that for the percentages of deadlines met, the HCPP was the smallest, as smallest as the LIFO (Figure 6-2). However, for the total work amount, the HCPP was not the smallest out of all six policies (Figure 6-3). This difference in the performance of the HCPP suggests that the HCPP will be advantageous in terms of the total work amount; yet, it doesn’t function as advantageously in regards to the percentages of completed deadlines. This implies the percentages of deadlines met and the total work amount are two distinct factors to be considered in future research.

The current study had some limitations, which can be improved in the future study. First, overall system performance, especially when represented by the percentages of deadlines met, was about 50% from all the policies. This suggests that simulation parameters, such as inter-arrival rates and the number of entities, can be changed to increase system performance and statistics power. Secondly, the simulation model simplified all system components. More than two levels of task complexity can be considered in the real-world settings. Additionally, combining more than two queuing policies may enhance system performance. Finally, in order to simulate team performance, multiple servers in the queueing system can be designed to determine the optimal combinations of individuals.
These findings can inform future research in the fields of education, management, or systems engineering. In education or management field, the research can guide students or trainees about time management policies to increase their performance by illustrating the queueing system performance under multiple policies. Also, the findings could show educators or managers how to distribute assignments and jobs to employees and students by showing optimal inter-arrival rates of queueing system.
Chapter 7

Conclusions

The dissertation modeled and estimated human performance using temporal motivation and generated operational policies to improve that performance. Previous works on human performance with temporal motivation using mostly self-reported questionnaire have yielded only conceptual findings. This study, in contrast, uses statistical and physiological measurement to model factors affecting human performance in the presence of temporal motivation and to estimate informative distributions of pacing in the presence of deadlines. This study uses its findings to suggest operational policies that would be applicable in the real-world industrial and educational settings. The following section reviews the findings of this dissertation, discusses its limitations and suggests the contribution of this research to future works.

7.1. Review of Findings

The results of this dissertation, which focused on modeling, estimation, and operational policies for human performance with temporal motivation, answered research questions addressed in Chapter 1 using behavioral modeling, biometric, and simulation approaches. First, the current research found that several factors are effective
in generating models for aligning time pacing in the presence of deadlines. The task complexity and the group size affected individual time-pressure reactivity in an air-traffic control setting, as presented in Chapter 2. Individuals’ time-pressure reactivity was greater compared to teams’ reactivity, and greater task complexity was associated with lower time-pressure reactivity. Additionally, the time that students dedicated to studying prior to a deadline affected students’ time-pressure reactivity, as described in Chapter 4. The time-pressure reactivity was lower for students who logged on to the website earlier than for students who logged on close to deadlines. The factors that significantly affected time-pressure reactivity were found in laboratory simulation as well as in online field settings.

Second, the dissertation improved the quality of estimation of individual time-pressure reactivity by using the parametric Bayesian estimation. The Bayesian estimation of course website data produced individual posterior distributions with variances and maximum likelihood, which is more informative compared to point estimate, as described in Chapter 3.

Third, the research found close relationships between individual pacing and work productivity. Individuals with low-time pressure reactivity showed greater academic performance, according to the structural equation model presented in Chapter 4. This means that procrastination is related to low academic performance. Chapter 5 also showed that participants moved their eyes frequently as deadlines approached, which caused them to complete learning tasks more slowly. Both the quality (GPA and
class scores) and the quantity (task completion time) of performance were related to individual time pacing.

Fourth and lastly, the dissertation proposes operational policies associated with higher productivity. In Chapter 6, prioritizing tasks via early due dates increased the amount of work done and the number of assignment deadlines met. Specifically, if new tasks were assigned earlier deadlines compared to the current task, than it is better to stop the current task and switch to the new task with earlier deadlines. In addition, Chapter 5 suggested that if feedback was provided measured via eye tracking, learners paced themselves in the online learning system.

7.2. Contributions

The result of the current study contributes to the field of engineering, education, and management by considering individual differences in time-pressure reactivity that had been ignored or oversimplified in the practical application. Some factors, such as the group size, task complexity (Chapter 2), and feedback (Chapter 5), to be found to be effective can be considered when designing air-traffic control or online training systems to improve both individuals and system performance. Operational policies tested in the queueing system (Chapter 6) can guide students or workers who want to manage time efficiently.
Additionally, the current study strengthens the study of human performance with temporal motivation, using multiple research methodologies in diverse task settings. Behavioral modeling in Anti-air traffic simulation setting (Chapter 2), Bayesian estimation (Chapter 3), and the structural equation modeling using field data form the engineering classroom (Chapter 4 and 5), eye-movement measurement in laboratorial learning task settings (Chapter 5), and queueing simulation (Chapter 6) were used to analyze human performance with temporal motivation. The multiple methods of investigation of human performance with temporal motivation distinguished this study from previous research that measured temporal motivation or time-management policies using mostly self-reported questionnaire.

7.3. Limitations and Future Works

The current research had some limitations, which can be addressed in future works. Despite attempts to include applicable research settings, data in the current study may be limited to an academic setting with small sample sizes. Less than 30 individuals were included in the air-traffic and online learning simulation of the laboratory settings (Chapter 2, 3, and 5). Also, in the case of the course website data (Chapter 3 and 4), the data from 59 individuals was quite homogenous in that all participants were undergraduate or graduate students majoring in engineering. Future research may include individuals of various ages and education which could strengthen the research
by showing diversity in the analyzed data. The big data analysis for the human performance with temporal motivation may be one way ahead in future research. Also, power analysis may be investigated in future research to know the effect of sample sizes on experimental results.

The current study can also be strengthened by using much deeper statistical analyses, though the research used diverse biometric and statistical research methods and simulations. Multivariate analysis of variance (MANOVA) referring to an ANOVA with multiple dependent variables can be used when several dependent variables are designed. For example, in Chapter 2, three dependent variables – $A$, $k$, and $L$ – can be tested using MANOVA to understand any differences between dependent variables under different experimental conditions. Also, in Chapter 3, the bootstrapping technique – repeated resampling from small samples of the sample size – could be used to see the effect of the number of observations on the MLEs and SDs of posterior distributions (Efron, 1979). In Chapter 4, latent variables with increased numbers of observations can be implemented in the structural equation model. A less saturated structural equation model should also be considered.

The insufficient consideration of personality factors was another limitation in the current research, despite the close relationship between procrastination and the big five personality traits which researcher have found (e.g., Steel, 2007; Watson, 2001). In the big five personality dimensions, neuroticism, conscientiousness, agreeableness, and introversion are known to be negatively correlated with procrastination (Burka & Yuen,
In future research, the big five personality questionnaire would be distributed during the experiment, then the personality factors could be implemented in the modeling performance in relation to the time-pressure reactivity.

Additionally, future research can incorporate more than one biometric measurement, as this study included only eye-movement measurement. Additional biometrics, such as electroencephalogram (EEG), heart rate, skin conductance resistance, and electromyography, can be used to model human performance with temporal motivation and make the research much more fruitful.

Finally, various applications of modeling and estimating human behaviors into the real-world are required in the future. Present studies applied human behavior in terms of temporal motivation to the air-traffic control, education and queueing settings. Diverse industrial settings, such as medical, manufacturing, or transportation, may be possible areas. That is because people often face increased time-pressures particularly in these areas, affecting human performance in emergency room, serial production system, or traffic behavior on the road. The modeling, estimation, and operational policies in human performance with temporal motivation can be applied to numerous real-world cases.
Chapter 8

References


Curriculum Vitae

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EDUCATION
2013-2017  Ph.D. in Industrial Engineering
            The Pennsylvania State University, University Park, PA, USA
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