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How to Improve Dynamic Decision Making: Evaluation of a Brief Training Program on Human Error

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HOW TO IMPROVE DYNAMIC DECISION MAKING: EVALUATION OF A BRIEF TRAINING PROGRAM ON HUMAN ERROR

by

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DEDICATION

In loving memory of my grandmother, Idaelia.

Your sacrifices have led me to achieve the unimaginable.

Forever in my heart.

To my partner, Gabriel.

Your love and encouragements have been my solace throughout this journey.

To my advisor, Dominik.

For your advice, patience, and guidance as a mentor.

Thank you for your support.

Finally, to caffeine and sugar.

My companion through many a long night of writing.

THESIS CERTIFICATE OF APPROVAL

The thesis of ___________________________ is approved:

____________________________________, Committee Chair   ________________ Date

____________________________________, Second Reader   ________________ Date

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Abstract

Current work environments require leaders to make effective and sound decisions in unpredictable situations. How can leaders improve their dynamic decision-making (DDM) skills? The current studies explored the effects of a training program on improving DDM in two computer-simulated tasks with different task characteristics. This study was comprised of two experiments. The first experiment included 83 undergraduate students who independently managed a computer simulated chocolate factory (ChocoFine). The second experiment included 111 students who played the role of a fire rescue chief overseeing a forest fire (WinFire). Half of the participants in each simulation group received a brief training on 15 frequent DDM errors. All the participants were later asked to select the errors they made from an error training sheet. We hypothesized that participants who received the training in DDM errors would show better performance compared to those who did not receive the error training prior to the start of the simulated tasks. Furthermore, we hypothesized that participants in the training condition would report fewer self-reported errors than those in the control, no-training condition. The results showed that the participants in the ChocoFine and WinFire training groups had better performance scores and self-reported fewer errors than the participants in the no-training group. These findings have strong implications for organizations, as they can utilize this error training to prepare future management personnel better for the challenges of novel, complex, dynamic, and uncertain situations.

Keywords: dynamic decision-making, human error, training, error management training, microworlds, self-reflection, strategies

How to Improve Dynamic Decision-Making: Evaluation of a Brief Training Program on Human Error

Dynamic decision-making (DDM) is a central and useful tool across various occupations (e.g., firefighters who make critical decisions in volatile situations with time constraints). DDM can be defined as the process of overcoming obstacles between a current state and a desired goal state via a multistep process involving an individual's cognitive, emotional, and social abilities or knowledge in a novel and ever-changing environment (Frensch & Funke, 1995; Güss et al., 2015). The daunting task of DDM is present in unstable environments, where no one decision will lead to a successful guaranteed outcome, which can be attributed to either the behavior of the decision-maker or to external factors that lie outside of one's control (Brehmer, 1992; Fischer et al., 2012). DDM is considered difficult because one cannot predict how a situation will change over time, and the consequences of one's actions are not immediately apparent in these unstable environments.

An ongoing challenge for researchers is to uncover the underlying factors that differentiate performance in DDM tasks. One possible explanation could be cognitive biases and errors. Cognitive biases and errors are common in the DDM process and hinder decision-makers' achievement of their desired goal state. These cognitive biases include inaccurate perceptions of the problem, poorly defined goals, and misinterpretation of information, among many others (Güss & Dörner, 2011).

A training program focusing on self-reflection has been shown to reduce cognitive biases and errors in DDM tasks (Donovan et al., 2015). Self-reflective strategies refer to an evaluation of one's thoughts, feelings, and behaviors (Grant et al., 2002). The use of self-reflection as a training technique in DDM tasks allows individuals to relate new information to past knowledge

and assists in the understanding of new ideas (Sanders & Mckeown, 2008; Campitelli & Labolita, 2010). The goal of these studies was to further investigate how individuals can improve their DDM skills and thus increase their performance. To this end, we presented participants with a list of errors that people typically make in dynamic tasks, allowing for self-reflection. The main goal was to investigate whether, after providing such an error list, human error decreased, and performance improved in DDM tasks.

The Dynamic Decision-Making Process

People in many occupations are confronted with environments that are unpredictable and can suddenly change. How to proceed in such situations is often unclear. Firefighters, for example, are often called to emergency fires. They approach the situation, often without knowing the scale or cause of the fire, yet they are equipped to make rapid decisions, for example, by assessing the environment to make sure it is safe to go inside and find an area from which to extinguish the growing fire. Firefighters commonly experience high stress situations in which they must make quick decisions in the face of immediate danger (Klein, 1998). Firefighters' decision-making skills ultimately decide whether a victim lives or dies.

Managers of a business organization are another example of individuals who encounter uncertain environments. Although they do not experience urgent threats, they do hold the responsibility of overseeing proper business practices that have lasting effects on the success of the company and their employees' future within their organization. DDM skills aid decision-makers in processing information, formulating flexible action plans, and balancing multiple objectives across many real-world experiences (BIBB, 2005). DDM skills are defined as a series of interdependent decisions in novel and ever-changing environments (Brehmer, 1992; Gonzalez et al., 2005; Fischer et al., 2012).

These studies were driven by the dynamic decision theory, which states that in any given dynamic task, decision-makers are expected to make a sequence of decisions. Past research has shown that in the early stages of decision-making, it is imperative for decision-makers to acquire relevant information for use in the later stages of decision-making tasks, which, in turn, produces a highly favorable payoff (Edwards, 1962). However, as previously noted, dynamic situations are ever-changing, and the acquisition of new information remains constant throughout all stages of the decision-making task, making it challenging and complex to reach an advantageous solution in DDM tasks (Edwards, 1962). The objective of the decision-maker is to make reasonable decisions with acceptable consequences (Dörner, 1996). As individuals move through the process of DDM, it is important to understand and highlight the various steps they take to reach their goals and minimize negative consequences.

Researchers have agreed on the following steps encompassing DDM tasks— although they sometimes use different terminology: (1) problem identification; (2) goal definition; (3) information gathering; (4) elaboration and prediction; (5) planning, decision-making, and action; and (6) outcome evaluation and self-reflection (Edwards, 1962; Güss & Dörner, 2011; Klein, 1998; Sternberg, 1986).

As decision-makers navigate their way through a novel situation, they must first identify the problem and outline suitable problem-solving goals. These goals may include but are not limited to learning about the system or simply stating the intention to try their best. Although the main goals here may seem apparent (e.g., making profit for a company), it is imperative to develop sub-goals that help accomplish the central goal (e.g., increasing market presence and launching new products). Through the process of identifying a problem and creating goals to

reach a possible solution, decision-makers can begin to learn their strengths and weaknesses and adjust their sub-goals as they see fit (Grant et al., 2002; Sanders & McKeown, 2008).

Decision-makers, with their problems and goals in mind, are then faced with the task of gathering additional information that is relevant to their established goals. Gathering further information about their main goals allows decision-makers to determine whether causal relationships change over time and how these changes occur (Ramnarayan et al., 1997). For example, top managers must gather information about the market, target clients, potential competitors, and so on. Decision-makers are encouraged to search and explore their environment to gain insight into their current problem.

In the elaboration and prediction stage, decision-makers may begin inferring aspects of their environment and how certain variables interact (Brehmer & Dörner, 1993; Güss et al., 2011). Keeping in mind that simple heuristics may not lead to optimal results in novel and unstable environments, decision-makers begin to realize that previously successful protocols are not suitable and as a result, evade further limitations in their understanding of the problem (Dodson & Schacter, 2002). For example, decision-makers may fail to consider developments over time and may neglect to weigh their options in terms of long-term consequences when confronted with a problem situation.

As decision-makers encounter faults in their understanding of the problem, they must begin to formulate new strategies to tackle DDM tasks. Successful strategies involve those that promote situational awareness and flexibility. Individuals who enforce successful strategies evaluate their decisions in terms of their ongoing learning as they progress through the decision-making task and consequently alter their approaches based on subsequent outcomes (Donovan et al., 2015). Finally, the evaluation of outcomes is linked to error management. Decision-makers

utilize self-reflection as a means of differentiating the consequences of their actions from the outcomes that develop from the decision-making system (Schaub, 2007). This step provides insight into the decision-maker’s applied strategies and as a result, their decisions modify their mental representations of the task over time. Individuals who self-reflect more than others have a more accurate mental representation of their progress and better strategic control in pursuit of their sub-goals and hence, their central goals (Donovan et al., 2015; Locke & Latham, 2002; Osman, 2010). DDM training, in relation to the DDM process, emphasizes the importance of conducting error management training and therefore encourages decision-makers to question, gather information, elaborate, and self-reflect before implementing alternative plans (Donovan et al., 2015).

The progression of the DDM process depends largely on the characteristics of the task environment (i.e., complexity and dynamic levels) and on the objective. Decision-makers adjust their goals and time spent in each step of the DDM process (Edwards, 1962; Donovan et al., 2015). Research on DDM tasks has revealed that certain tasks are structurally complex in nature, i.e., comprising a substantial number of alternative variables, such as high time constraints and high uncertainty. Others are structurally simple, i.e., with fewer alternative variables, such as few to no time constraints and low uncertainty (Gonzalez et al., 2017). These differences highlight that the dynamics and complexity of behaviors exist and differ across situations, even in tasks that seem straightforward at first. Similarly, simple tasks have the potential to be dynamically complex because of the relationship between decision-makers’ choices and their effects across time (Sterman, 1989; Gonzalez et al., 2017).

Microworlds and DDM

Microworlds are computer-simulated problem situations, whose purpose is to immerse the participant in a specific situation, for example, the simulation of a company. Participants are expected to formulate and initiate decisions that, in turn, change the simulated environment, essentially creating an endless cycle of cause and effect influences between the participants' decisions and the targeted problem environment (Gonzalez et al., 2017). The use of microworlds as a reliable measure of DDM is based on its various characteristics that accurately depict the cognitive demands involved in dynamic situations to real-life experiences (Gonzalez et al., 2005). A microworld consists of a complex, uncertain, and dynamic problem environment, in which performance is assessed by automatically recording and saving each decision the participant makes, along with varying changes in the system (Güss et al., 2015). The use of microworld simulations to analyze DDM performance allows researchers to develop complex theories involving human thought and behavior (Dörner, 1999; Dörner & Güss, 2013). Using virtual microworld simulations also allows researchers to identify which strategies in a given DDM task are more likely to lead to success or failure (Güss et al., 2015). A major advancement in recent years in DDM research and microworlds has been to simplify the environment while maintaining the integrity of dynamic complexity (Gonzalez et al., 2017). Various types of microworld simulations exist that contain varying degrees of complexity and dynamics. We briefly discuss the two microworld simulations used in these studies.

WinFire

WinFire is a computer simulation task in which the participants' main objective is to extinguish forest fires while simultaneously saving a neighboring town as well as the forest itself (Gerdes et al., 1993). WinFire is described as moderate in complexity with few variables for the

participants to work with (e.g., the use of trucks and helicopters to extinguish fires and obstacles such as water levels, wind speed/direction, and unknown emerging fires). Although WinFire is considered moderate in complexity, the simulation is highly dynamic in nature. The situational environment in which participants find themselves in WinFire changes frequently with every decision made by the participant. For instance, the speed and direction in which the fires spread may increase based on a participant's decision to utilize fire trucks, as they are slower to extinguish fires than helicopters. WinFire is highly dynamic, even without direct intervention from the participant. Fires can start anywhere at any time. The core strategies of the DDM process one expects to detect throughout the WinFire simulation consist of assessing situations rapidly and identifying crucial situations, prioritizing, flexibility in the planning of resource allocation, situational demands, and quick long-term decision-making to evade further escalation of the problem (i.e., rapid spread of wildfire) (Güss et al., 2015).

ChocoFine

ChocoFine is a computer simulation in which individuals assume the CEO position of a chocolate-producing factory. The participants were instructed to manage production, marketing, and sales within the company. ChocoFine is described as a top management virtual game and is considered a complex simulation. It was originally developed in 1993 as a tool for business domains (Gerdes et al., 1993) at the University of Bamberg in Germany and has been revised several times.

ChocoFine is highly complex and contains over 1,000 simulated variables. Although considered highly complex, the simulation is low in dynamics meaning that the environment changes only when participants decide to move on to the following month. ChocoFine is also low in time pressure, as participants who complete the simulation can move on to the following

month on their own accord (although they are often given a specific time to work on a specific number of months, e.g., one hour for 12 months). The level of uncertainty experienced in the ChocoFine computer simulation task is high, considering the plethora of variables participants must utilize; it is also not apparent which variable potentially causes either an increase or decrease in profit, and so on.

The use of two types of microworld simulations with different task characteristics was advantageous in these studies. Dynamic problem situations vary in their complexity, uncertainty, and dynamics; therefore, it is important to analyze how DDM differs in either condition as well as differentiate the cognitive biases specific to either task.

Human Error and DDM Training

Past research has shown the value of active exploration and error management training that aids in learning and performance; however, previous studies utilized simple tasks in their methodology, rather than designs that feature complex and dynamic characteristics, i.e., microworld simulations (Heimbeck et al., 2003). Error management training is characterized by both error encouragement (e.g., encouraging mistakes as a part of learning) and active exploration (e.g., trainees initiate, direct, and regulate their own learning while training) (Keith & Frese, 2008). Errors materialize not just as an outcome of having insufficient data, but also as a consequence of misplaced goals, interferences in decision-making or action, and inaccurate perceptions of information. Heimbeck and colleagues (2003) advocate for a positive attitude towards error training along with a guided approach in the beginning of the learning process. Positive attitudes towards errors yield long-lasting learning compared to error avoidance attitudes. According to Heimbeck and colleagues (2003), the addition of error training and

guided behaviors revealed higher performance compared to groups that did not receive error management training.

In recent years, however, researchers have identified that exposure to errors in training can improve the ability to detect them and to manage any stress associated with goal acquisition (Damm et al., 2011; Loh et al., 2013). The driving force in DDM training and error management stems from active participation and exploration by individuals with high openness to experience (Loh et al., 2013). In addition, individuals benefit from acquiring the necessary resources to manage the cognitive and affective demands of errors made during training (Loh et al., 2013). Moreover, past studies have illustrated the interactions of individual traits, as well as the emotional and cognitive processes that elucidate the effectiveness of EMT on decision-making (Brown et al., 1983; Kanfer, et al., 1996). Participants who implement EMT show an increase in self-regulatory behavior involving two components: (1) Deploying emotional control to reduce adverse emotional reactions to errors and (2) active engagement in metacognitive tasks (i.e., planning, monitoring, and self-reflection). Metacognitive tasks increase with EMT because the decision maker is forced to think through their errors and therefore thinking about the causes of those errors (Ivancic & Hekseth, 2000).

As previously noted, individuals who progress through the DDM process (e.g., from problem identification to self-reflection) may experience a rise in human error and its associated cognitive biases (Dörner, 1996; Ramnarayan et al., 1997). Some possible cognitive biases participants may face involve entrenchment under the second stage of the DDM process, which is goal definition. Individuals who experience entrenchment may spend too much time gathering all kinds of information (especially related to an irrelevant aspect of the problem) in an attempt to reach a solution. Individuals may also oversimplify or overgeneralize their conclusions in the

elaboration and prediction stages of DDM. Past research has suggested that training individuals can diminish the influences of these common human errors and biases (Hedge & Kavanagh, 1988; Gully et al., 2002; Donovan et al., 2015). The use of divergent microworld simulations allowed for the exploration of error training in more than one type of unpredictable scenario, as common errors may be apparent in one condition but not in another.

The goal of these studies was to demonstrate how error training in the DDM process can aid and facilitate performance in novel and complex environments. We investigated the effects of error management training on DDM performance across two experiments using distinct microworld simulations, WinFire and ChocoFine. We hypothesized that participants in the training conditions and across both experiments would exhibit higher performance scores than those in the control conditions. Finally, we predicted that participants in the training conditions would show fewer self-reported errors than those in the control condition across both experiments.

Experiment 1

Materials and Methods

Participants

Eighty-three undergraduate students were recruited as participants from the University of North Florida, 19 men, 63 women, and one participant identified as 'other'. Participants' ages ranged from 18 to 40 years old ($M = 21.20$, $SD = 3.67$). Regarding ethnicity, 65.1% of participants identified as White, 9.6% as Black, 13.3% as Hispanic, 7.2% as Asian, and the remaining 4.8% as 'Other'. There were 45 participants in the experimental, training group. There were 38 participants in the control, no-training group. Participants were randomly assigned to one of two conditions. No pattern of relationship was determined between gender and condition,

χ^2 (2) = 1.90, *p* = 0.39. There was also no significant effect for age, *t* (81) = 0.97, *p* = 0.33, between the control condition (*M* = 21.63, *SD* = 4.49) and the experimental condition (*M* = 20.84, *SD* = 2.80). Data collection conducted before the COVID-19 pandemic included 38 participants and 45 participants took part in the study one year after the COVID-19 pandemic—when vaccinations began and after schools and businesses had begun to slowly transition back into reopening. A total of five participants were identified as extreme outliers as having a total performance score smaller than -$1,790,000. The outlier's performance scores ranged between $-142,464.62 to $-471,908.31. Finally, data of two participants were not automatically saved properly and could therefore not be included.

Instruments

Simulation instructions. In both conditions (training vs. no-training) participants received a typed handout with in-depth instructions highlighting key commands for the ChocoFine simulation, alongside screenshots for easier visual comprehension.

Error training handout. Participants received an error training handout itemizing the six identified DDM steps with each DDM step containing two to five possible errors (e.g., "Elaboration and Prediction: Not considering time developments: We think in the here and now and do not consider time developments and situational changes happening over time"; or "Evaluation of Outcome and Self-Reflection: No monitoring and self-reflection: We think sometimes that if something is going well then it does not deserve further reflection", see Appendix A for complete list of errors"). There was a total of 16 possible errors across all DDM stages. The experimenter discussed and expanded on the common human errors associated with each of the DDM steps before the start of the simulation in the experimental, training group. The

control, no-training condition, only received the handout and explanation of the error training handout after the conclusion of the simulation game.

ChocoFine simulation. The ChocoFine micro-world simulation used in the current study is both highly complex and dynamic, with over a thousand variables. The main interface of the program consists of three screens: (1) the main screen, (2) the production screen, and (3) the marketing screen (see Figure 1).

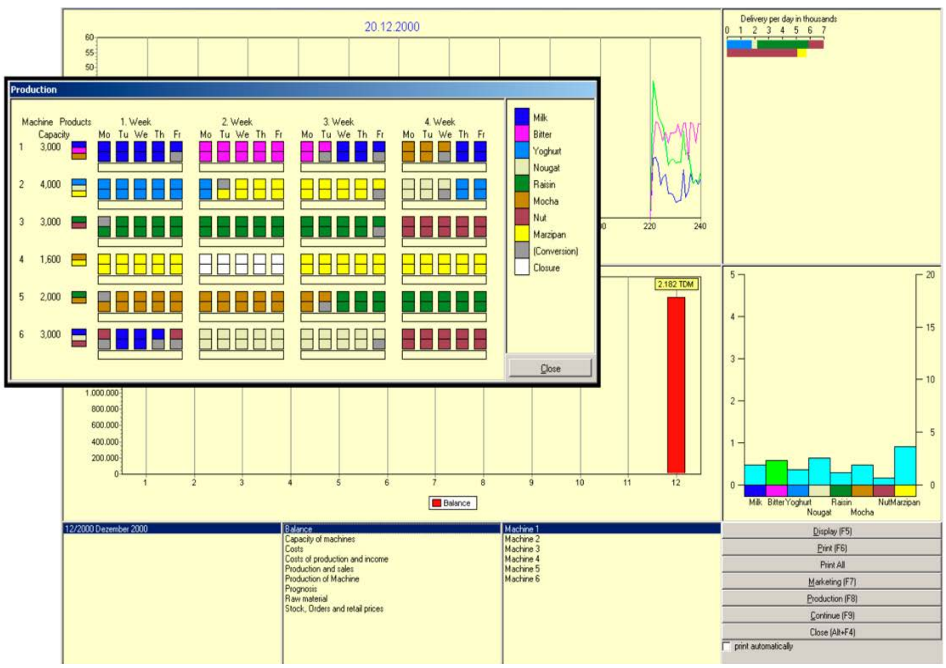

Figure 1. *Screenshot of ChocoFine: Main Screen (Back) and Production Screen (Front).*

In the micro-world, ChocoFine, participants are tasked with assuming the role of a CEO of a small chocolate company. As a CEO, participants must make decisions in the fields related to advertisement, marketing, production, and hiring/firing personnel. The complexity and uncertainty involved in ChocoFine requires participants to pick and choose from a multitude of decisions in each of these domains for each proceeding month. Performance was assessed as the

total capital decision-makers accrued in month 12 of the ChocoFine simulation. Although there are no limits for capital earnings, performance scores ranged between $-4,719,08.31 to $3,086,692.93 in the current sample. The overall mean was $1,132,355.35 (*SD* = 770800.25), the median for the sample was $11,157,057.62.

Demographic survey. Participants in both conditions received a demographic questionnaire after concluding the simulation assessing age, gender, and ethnicity (see Appendix C).

Procedure

Participants were first instructed to sign an informed consent handout upon entering the computer lab. Participants in both conditions were given a detailed handout of the simulation instructions that illustrated the goal of the simulation as well as the different types of commands or screens they can use. Participants in the training, experimental condition were given the handout detailing the DDM errors before beginning the trial version of the simulation. The training condition included a 10-minute experimental led training where each error was highlighted for every DDM step. The experimenter then verbally clarified the simulation instructions and answered any questions the participants had before beginning the trial version of ChocoFine to elucidate any uncertainty. In both conditions, participants were given a one-month trial version to complete for approximately 10 minutes. After the trial month, participants were given approximately 5 minutes to ask questions about the commands or troubleshooting the program before beginning the true analyzed version of ChocoFine. The true version of the simulation.

The experimental condition however, consisted of a 10-minute experimenter led training after receiving a detailed handout on the instructions of the ChocoFine simulation. Both

experimental and control condition received the detailed list of errors also upon completing the true simulation to identify potential errors made during the simulation task. The remaining participants in the ChocoFine control condition did not initially receive the training error handout and immediately began working on the true version of the simulation, whereas the control condition only received the list of errors after the completion of the simulation. Those participants in the experimental condition received the list of errors before the simulation in an effort to identify whether or not receiving training beforehand will have a positive influence or reduce the number of identified errors on their performance compared to the control condition.

Across all conditions, participants were then asked to complete the training sheet after concluding the simulation. Participants were asked to circle the number next to the errors for each DDM step they thought to have performed throughout the course of the simulation (see Appendix A and B). The ChocoFine simulation for both the training and no-training conditions took a total of 60-minutes to complete. Upon concluding the study, all participants completed the demographic questionnaire (see Appendix C).

Results

Comparison of Training vs. No Training

An independent samples t-test was conducted to compare performance in ChocoFine between the experimental and control condition. Five participants were identified as extreme outliers and excluded from the performance analysis and for two participants no data were saved. The results revealed a marginal significant difference between both conditions. Participants who received error training (M = 1270133.20, SD = 829475.75) compared to those who did not receive error training (M = 962159.17, SD = 699701.03) acquired more capital and thus, showed better total performance across all 12 months of ChocoFine, $t(74) = 1.76$, $p = .083$, $d = .40$.

An independent samples t-test was also conducted to compare total self-reported errors in ChocoFine between the experimental and control conditions. The results revealed a significant difference between training and no-training groups. Participants who received error training (M = 4.89, SD = 2.01) reported fewer errors compared to the participants in the no-training group (M = 6.21, SD = 2.68), $t(81) = 2.56$, $p < .05$, $d = 0.56$ (see Table 1). Significance of the .05 level p-value was Bonferroni adjusted to minimize Type 1 error to .002.

To identify which condition (training vs. no-training) identified more errors between the main six self-reported errors in DDM: Problem identification, goal definition, elaboration and prediction, planning, DM, and action, and self-reflection, independent samples t-tests were conducted. The results revealed a significant difference between condition and the total self-reported errors in the first step of the DDM process: Problem identification. Participants in the no training group (M = .89, SD = .45) identified more errors related to problem identification than the training group (M = .58, SD = .54), $t(81) = 2.86$, $p < .001$. Significance of the .05 level p-value was Bonferroni adjusted to minimize Type 1 error to .00083. Therefore some of the initial findings for a p-value of .05 were not significant anymore.

Participants in the no-training condition (M = .68, SD = .44) identified more errors for goal definition compared to individuals who received error training (M = .44, SD = .55), $t(81) = 2.02$, $p = .046$. Participants in the no-training condition (M = .84, SD = .55) reported more information gathering errors than the training condition (M = .76, SD = .65), $t(81) = .65$, $p = .082$. Lastly, participants in the no-training group (M = .79, SD = .47) reported more errors related to evaluation of outcome and self-reflection compared to the training group (M = .47, SD = .55), $t(1, 81) = 2.84$, $p < .05$.

However, no significant difference was found between the no training group (*M* = 1.30, *SD* = .80) and training groups (*M* = 1.02, *SD* = .84) and self-reported errors related to elaboration and prediction, $t(81) = 1.48$, $p = .144$. Finally, no significant difference was found between no training groups (*M* = 1.62, *SD* = .78) and training groups (*M* = 1.71, *SD* = 1.04) and the self-reported error related to planning, decision-making, and action, $t(81) = .44$, $p = .659$ (see Table 1).

Table 1. *Results of ChocoFine T-tests and Descriptive Statistics*

Outcome	Training group *M*	Training group *SD*	No-training group *M*	No-training group *SD*	95% CI for difference	*d*
Performance	1270133.2	699701.03	962159.17	829475.75	[-657471.5, 41523.44]	.4
Self-reported errors:						
Problem identification	.58	.54	.89	.45	[.1, .54]	.62
Goal definition	.44	.55	.68	.53	[.004, .47]	.44
Information gathering	.76	.65	.84	.55	[-.18, .35]	.13
Elaboration and prediction	1.02	.84	1.29	.8	[-.09, .63]	.33
Planning, DDM, and action	1.62	.78	1.71	1.04	[-.31, .49]	.10
Evaluation of outcomes and self-reflection	.47	.55	.79	.47	[.1, .55]	.63
Total SR errors	4.89	2.01	6.21	2.68	[.29, 2.35]	.56

p-value was Bonferroni adjusted to $< .0083$.

A Pearson correlation was conducted to assess total capital in month 12 and overall self-reported errors in the ChocoFine simulation across both training and no-training conditions. Preliminary analyses were performed to ensure no violation of the assumption of normality, linearity, and homoscedasticity. Five outliers were excluded from the analysis and two participants did not contain sufficient data. The results revealed no significant difference

between total self-reported errors ($M = 5.49$, $SD = 2.42$) and total ChocoFine performance ($M = 1132355.35$, $SD = 770800.252$), $r(74) = -.18$, $p = .127$.

Comparison of COVID-19 and Training on Performance

A two-way analysis of variance was conducted to explore the impact of training and COVID-19 on performance, as measured by total capital in month 12 of ChocoFine. Participants were divided based on the time they participated during COVID-19 (Group 1: Before COVID-19 and Group 2: One year after the start of COVID-19). The interaction effect between training and COVID-19 on performance was not statistically significant, $F(1, 72) = .09$, $p = .762$. There was a marginally significant main effect for training conditions, $F(1, 72) = 2.98$, $p = .089$; with a medium effect size (partial eta squared = .04). The main effect for COVID-19, $F(1, 72) = .05$, $p = .819$, did not reach statistical significance.

Experiment 2

Materials and Methods

Participants

A total of 111 participants were recruited from the University of North Florida, consisting of undergraduate students, 21 men, 88 women, and two participants identified as ‘other’. Participant’s ages ranged from 18 to 49 years old ($M = 21.54$, $SD = 5.05$). Participant’s ethnicities were identified as 64.9% White, 12.6% as Black, 15.5% as Hispanic, 4.5% as Asian, and the remaining 2.7% as ‘Other’. There were 59 participants in the experimental, training group. There were 52 participants in the control, no-training group. Participants were randomly assigned to either condition. No pattern of relationship was determined between gender and condition, $\chi^2 (2) = 0.80$, $p = 0.67$, signifying there was a similar distribution in gender across both conditions. There was also no significant effect for age, $t(109) = -0.45$, $p = 0.66$, between

the control condition (*M* = 21.77, *SD* = 5.12) and the experimental condition (*M* = 21.34, *SD* = 5.02). Data collection conducted before the COVID-19 pandemic included 50 participants and 61 participants took part in the study one year after the start of the COVID-19 pandemic in March 2021. A total of 12 participants were excluded from analysis as these log file cases only contained partial or extensive missing data regarding total performance measures perhaps due to accidentally exiting the simulation before the time was over.

Instruments

Simulation instructions. In both conditions (training vs. no-training) participants received a typed handout with in-depth instructions highlighting key commands for the WinFire simulation, alongside screenshots for easier visual comprehension.

Error training handout. Participants received an error training handout that discussed and expanded on the common human errors associated with each of the DDM steps discussed previously in Experiment 1 (e.g., "Elaboration and Prediction: Not considering time developments: We think in the here and now and do not consider time developments and situational changes happening over time"; or "Evaluation of Outcome and Self-Reflection: No monitoring and self-reflection: We think sometimes that if something is going well then it does not deserve further reflection", see Appendix A for a complete list of errors).

Figure 2. *Main Screen of the WinFire Simulation.*

WinFire simulation. The microworld used in Experiment 2 is titled, WinFire (Schaub, 2007). Participants completing the WinFire simulation assume the role of commander in chief of a fire department to protect the village and the forest from approaching fires (see Figure 2). Participants have the option to dictate a series of commands to several fire trucks and helicopters in their effort to save the village as well as the forest. Quick decisions and multitasking are a necessary component of WinFire to avoid fires from spreading. Performance was assessed as the total percentage of the saved forest fire at the end of the simulation. Performance scores ranged from 0% to 100%.

Demographic survey. Finally, participants in both conditions received a demographic questionnaire after concluding the simulation assessing age, gender, and ethnicity (see Appendix C).

Procedure

Participants in Experiment 2 followed the same procedures as Experiment 1. Participants were first instructed to complete an informed consent handout before receiving the simulation instructions. Participants in the experimental condition were given the error training handout before beginning the trial version of the simulation. Participants in the control condition only received the error training handout at the end of the simulation.

The major difference in Experiment 2 was using the quick action computer simulation, WinFire. Participants completing the WinFire simulation were instructed to complete a separate trial version of the game which lasted for approximately five minutes. The "true" analyzed version of the simulation was then completed for ten minutes. Participants across both conditions circled their errors on the error training handout immediately following the end of the simulation. Participants in the training and no-training group completed the WinFire simulation which took a total of ten minutes. Upon concluding the study, all participants were asked to fill out a brief demographic questionnaire.

Results

Training vs. No Training Comparison

At first, we compared performance in WinFire between the experimental and control group. Since the performance variable was skewed and not normally distributed the non-parametric Mann-Whitney U test was conducted. The Mann-Whitney U test result revealed that WinFire performance was significantly lower in the control, no-training condition (Mdn = 84.09, n = 43) compared to the experimental, training condition (Mdn = 97.40, n = 56), U = 566.50, z = -4.52, $p < .001$, r = -.45. These results reveal a large effect size between training groups and total WinFire performance. An independent samples t-test was also conducted to analyze total self-

reported errors between the experimental and control conditions. Results revealed no significant difference between training or no-training groups on total self-reported errors. Participants in the training condition (*M* = 4.73, *SD* = 2.18) indicated no difference in self-reported errors compared to the no-training group (*M* = 4.83, *SD* = 2.18), *t*(109) = .24, *p* = .814 (see Table 3).

To identify which condition (training vs. no-training) identified more errors between the main six self-reported errors in DDM (i.e., problem identification, goal definition, elaboration and prediction, planning, DM, and action, and self-reflection) an independent samples t-test was conducted. Significance of the .05 p-value was Bonferroni adjusted for the six t-tests to minimize Type 1 error to .00083. The results revealed no significant difference between the no training group (*M* = .62, *SD* = .53) and the training group (*M* = .63, *SD*= .55) and total self-reported errors in problem identification, *t(*109) = -.11, *p* = .910. Next, the results indicated no difference between the no training group (*M* = .52, *SD* = .58) and training group (*M* = .46, *SD* = .54) on total self-reported errors in goal definition, *t*(109) = .58, *p* = .561. The results also revealed no significant difference between no training group (*M* = .71, *SD* = .61) and the training group (*M* = .71, *SD* = .67) on total self-reported errors in information gathering, *t*(109) = -.003, *p* = .998. Similarly, no significant difference was found between those in the no training group (M = 1.19, *SD* = .86) and those in the training group (*M* = 1.10, *SD* = .84) on total self-reported errors in elaboration and prediction, *t*(109) = .56, *p* = .578. Results also showed no significant difference between the no training group (*M* = 1.25, *SD* = .74) and the training group (*M* = 1.36, *SD* = .91) on total self-reported errors in planning, DM, and action, *t*(109) = -.67, *p* = .504. Finally, results demonstrated no significant difference between the no training group (*M* = .54, *SD* = .54) and the training group (*M* = .47, *SD* = .54) and total self-reported errors in evaluation of outcome and self-reflection, *t*(109) = .62, *p* = .534. The results indicated that there was no significant

difference between condition (training vs. no training) and self-reported errors on any of the six DDM stages (see Table 3).

Table 2. *Results of T-tests and Descriptive Statistics of WinFire Analysis*

	Training group		No training group					
Outcomes	*M* (*Mdn*)	*SD* (*n*)	*M* (*Mdn*)	*SD* (*n*)	95% CI for difference	*d*	*z*	*r*
Performance***	(97.4)	(56)	(84.09)	(43)			-4.52	-.45
Self-reported errors:								
Problem identification	.63	.55	.62	.53	[-.22, .19]	.02		
Goal definition	.46	.54	.52	.58	[-.15, .27]	.12		
Information gathering	.71	.67	.71	.61	[-.24, .24]	0		
Elaboration and prediction	1.10	.84	1.19	.86	[-.23, .41]	.12		
Planning, DM, and action	1.36	.91	1.25	.74	[-.42, .21]	.13		
Evaluation of outcomes	.47	.54	.54	.54	[-.14, .27]	.13		
Total SR errors	4.73	2.18	4.83	2.18	[-.72, .92]	.05		

****Significance at the .001 level (two-tailed).*

Performance and Self-Reported Errors

The relationship between total performance and total self-reported errors after completion of the simulation was investigated using a Spearman correlation. The results indicated that there was a marginally significant weak, negative correlation between total performance in the WinFire simulation (M = 84.24, SD = 19.43) and participant's total self-reported errors after completion of the simulation (M = 4.77, SD = 2.17), $rs(97) = -.19$, $p = .065$. These results indicate that as overall performance increases in the WinFire simulation, participants numbers of total self-reported errors after the simulation decrease.

Comparison of COVID-19 and Training on Performance

A Kruskal-Wallis Test revealed a statistically significant difference between training groups and COVID-19 groups in WinFire performance (H(3) = 21.17, $p = < .001$), with a mean rank of 62.57 for training/during COVID-19, 57.82 for training/before COVID-19, 39.07 for no-training/during COVID-19, and 33.09 for no-training/before COVID-19.

General Discussion

The goal of the current study was to illustrate how an error training program could facilitate performance in dynamic decision-making environments. We conducted an in-depth analysis of dynamic decision-making changes in self-reported error strategies and investigated why training would lead to higher performance. We expected that individuals in the experimental training condition would have better performance compared to the control, no-training condition.

The results indicated that training had a significant influence on performance in both simulations. There was mixed support for our hypothesis in the ChocoFine simulation that self-reported errors were related to the training condition. However, the findings in the WinFire condition supported our hypothesis that the training condition would show fewer self-reported errors.

The findings that training involving DDM errors is a predictive factor of performance across both simulations supports the theory in that error management training (EMT) alleviates the process from one's current state to the desired goal. Participants were provided with identified cognitive errors involved in each step of the DDM process, thus equipping decision makers with the tools to manage the cognitive demands involved in either simulation (Heimbeck et al., 2003; Loh et al., 2013).

The results revealed mixed support for our hypothesis that participants in the training condition would submit fewer self-reported errors. We found partial support for our hypothesis in the ChocoFine experiment however, when accounting for Bonferroni corrections we did not find significant differences. In the WinFire experiment, we found no significant difference in self-reported errors between the training and no-training groups.

One possible explanation for the variability in our findings might be the highly complex nature of the ChocoFine simulation compared to the WinFire simulation. A possible confounding variable that was not controlled for in this study was the difference in time constraints between the WinFire and ChocoFine simulations. The self-reported errors task that participants completed at the end of the simulation necessitated that they greatly reflect on their actions compared to their goals and overall performance in the simulation. The ChocoFine simulation is more convoluted and therefore requires more time for participants to complete than the WinFire condition. The participants spent a longer amount of time completing the ChocoFine simulation mainly because it had an extensive list of behaviors and actions they could modify and change to their liking, while the WinFire condition had only a few commands to choose from. Therefore, the absence of time constraints experienced in the ChocoFine simulation allowed for more use of self-reflective strategies than the WinFire condition. On the other hand, participants who worked in the WinFire simulation were under higher time constraints and perhaps relied less on strategic methods of DDM, contrary to what was expected for the training condition, and more on simple heuristics (Gigerenzer et al. 1999). According to the instance-based model, individuals with a high variability of cognitive resources and in-time constrained tasks have a higher inventory of exemplars to apply in fast-paced settings (Gonzalez et al., 2003, Gonzalez et al., 2005).

Therefore, future studies could investigate the possible moderating effects on personal attributes, such as the high need for cognition in time-limited tasks related to dynamic environments.

Finally, at the start of this study, the COVID-19 pandemic halted data collection as college campuses and work organizations experienced temporary closure. As a result, we decided to conduct exploratory analyses on the influence of the COVID-19 pandemic on decision-making performance. Interestingly, we found a significant difference in the WinFire experiment, but we did not find a significant difference in the ChocoFine experiment. Participants in the WinFire condition who participated in the study before the pandemic showed worse performance than those who participated during the pandemic. Although there is no research concerning the impact of the global pandemic on decision-making, it can be speculated that these findings may be due to the increased use of computers and the higher dependence on technology as a means to communicate with others for class instruction or for work-related duties. Furthermore, the hasty changes following the COVID-19 outbreak primed individuals to assimilate and modify their behaviors from in-person interactions to a strictly remote access to the external world; therefore, the experiences in the WinFire condition can arguably be compared to that of the external world at the present moment. Conversely, one possible explanation for the lack of difference between training groups in the ChocoFine simulation are the highly complex and longer time constraints involved. Participants must be detail-oriented in their methodology, and the cognitive demand related to attention span could be diminished for college students by the prolonged use of technology related to online learning during the COVID-19 pandemic. Future studies could further investigate the negative effects related to cognitive demand on attention and dynamic task performance.

A major limitation of our study is the generalizability of our findings due to the large use of a college student population with a disproportionally high number of whites compared to other ethnic groups. However, the descriptive results showed a large distribution between age and gender. The use of an exclusively student-centered sample may not reflect the appropriate types of decision-making skills necessary to understand the difference between the training and no-training conditions. The ChocoFine computer simulation relies heavily on managerial experience to comprehend the simulations' overarching goal, and most students reported not holding positions beyond entry-level.

Past research has demonstrated that college students typically engage in more risk taking (Salameh et al., 2014). Student participants may also not be motivated to utilize the necessary cognitive resources in a computer simulation where they are not as responsible for performance as they are in real-world situations. Since young adult brains are not fully developed until age 25 (Arain et al., 2013), students may not contribute the same cognitive load or attention they otherwise would if presented with these scenarios in real life (Güss et al., 2015; Su et al., 2018). Another possible explanation for the lack of a difference in DDM errors between the training and no-training groups is the higher likelihood of risk-taking behaviors. Future research could utilize a sample of participants outside of a college demographic to account for maturational changes in middle-aged and older adult individuals and further increase generalizability [although age (M = 21.2, SD = 3.67) did not correlate with performance (M = 1132355.35, SD = 770800.25) in neither ChocoFine, $r(74) = .07$, $p = .563$, nor did age (M = 21.54, SD = 5.05) correlate with WinFire performance (M = 84.24, SD = 19.43), $r(97) = -.14$, $p = .171$].

Due to the absence of time constraints found in ChocoFine, participants had more time to reflect on cognitive biases involving each step of the DDM process. A possible moderating

influence of performance in which future investigations may consider is need for cognition. Individuals considered to be high need for cognition are described as frequently engaged in self-reflection and cognitive tasks, whereas low need for cognition individuals are those who are less involved in thinking through their decisions. In fact, the positive influence of need for cognition on dynamic decision making and complex problem-solving performance in the Manutex business simulation was demonstrated by Nair and Ramnarayan (2000). Previous research indicates that an individual’s orientation towards self-reflection can interact with the elements of the task and shape their decision choices (McElroy et al., 2020). Future studies can investigate individual differences involving a high or low need for cognition as a possible moderating factor of time-limited tasks, such as WinFire.

In conclusion, the current study showed that a brief EMT can enhance performance in a highly complex and slow-paced task environment such as ChocoFine and in a less complex but highly dynamic and fast-paced task environment such as WinFire. We conclude that creating awareness of possible errors in these tasks can stimulate self-reflection and monitoring through EMT. The promotion of self-reflection through EMT ultimately increases the performance of dynamic decision-making outcomes. The results of the present study have practical applications for managers who make decisions in stressful, complex, and dynamic work environments. Organizations may benefit from utilizing a training program that encourages self-regulatory practices in fast-paced environments.

Appendix A

Participant Nr.: ________________ Date: ________________

17 Errors and Their Causes

Research on complex problem solving has identified several errors people make while making decisions and solving problems. We will provide you now with a list of the most common errors. When you work now on a complex problem, this list might help you to avoid making such errors.

After you completed working on the simulation we will ask you to encircle the errors on this list that you think you did fall for during the simulation.

(1) Problem identification

1.1. <u>Inaccurate perception and denial of reality</u>: We don't look at the key aspects of the problem and often deny the problem even exists.

1.2. <u>Methodism</u>: We think we can apply a successful plan in the current situation and do what we have done before, but we do not realize that the new situation is different and that the new plan will not work.

(2) Goal definition

2.1. <u>No goals</u>: We are satisfied about how the situation is right now and do not set goals.

2.2. <u>Secondary goals determine actions</u>: We try to set and achieve goals that are not really relevant.

(3) Information gathering

3.1. <u>Entrenchment</u>: Sometimes we spend too much time gathering all kinds of information.

3.2. <u>Misinterpretation of information</u>: Sometimes we do not analyze the causes and do not think about possible consequences.

3.3. <u>Conflicting information in teams</u>: Sometimes teams make decisions and then they rather stick to them even knowing that they should be changed given the change in the situation.

(4) Elaboration and prediction

4.1. <u>Oversimplification and overgeneralization of conclusions</u>: We have a tendency to make things too simple.

4.2. <u>Not considering side-effects and future developments</u>: We are often not aware that decisions have side-effects and long-term effects.

4.3. <u>Not considering time developments</u>: We think in the here and now and do not consider time developments and situational changes happening over time.

Appendix B

Participant Nr.: ________________ Date: ________________

(5) Planning, decision making, and action

5.1. Ego-enhancing decisions: One tries to show off and makes decisions more challenging than they need to be with the goal of enhancing their image.

5.2. Avoidance of making decisions: One is hesitant and avoids making decisions.

5.3. Overplanning and horizontal flight: One plans out all the details and loses sight of the actually important aspects of the problem.

5.4. Underplanning and actionism: One does not plan at all but acts right away.

5.5. Single-focus strategy and lack of holistic strategy: One only focuses on one thing at a time and does not consider all the other relevant elements.

(6) Evaluation of outcome and self-reflection

6.1. No monitoring and self-reflection: We think sometimes that if something is going well then it does not deserve further reflection.

6.2. Ballistic action: If something is not going well, we don't analyse the possible causes and put blame somewhere else or on somebody else.

Some possible causes of these errors:

- We feel under time pressure and feel we have to act right away.
- We are overwhelmed by uncertainty and/or feel we lack sufficient knowledge to deal with a situation.
- We fear we cannot control the situation and cope with the situation successfully.
- We feel team harmony is more important than thoughtful problem-related decisions.

Appendix C

Participant Nr.: _______________ Date: _______________

Demographic Questionnaire

Age: _____

Sex: Male___ Female ___ Other/do not disclose_______

English is my native language? No___ Yes___

My current major is: _____________________

What is your cumulative GPA? _____

I have employment experience in organizations/business above an entry level position? No___ Yes___

Are you? Black ___ White ___ Hispanic or Latino ___ Asian American ___ Other ___

How many hours per week do you play video games (average)? ____________________

When you play or have played video games, what type do or did you play the most?

Action/Reflex 1 ___ 2 ___ 3 ___ 4 ___ 5 ___ 6 ___ 7 ___ Strategy/Non-reflex

I have played Choco Fine before? no___ yes___

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