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The role of difficulty in dynamic risk mitigation decisions

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Previous research suggests that individuals faced with risky choices seek ways to actively reduce their risks. The risk defusing operators (RDOs) that are identified through these searches can be used to prevent or compensate for (here, pre- and post-event RDOs, respectively) negative outcomes. Although several factors that affect RDO selection have been identified, they are limited to static decisions conducted during descriptive tasks. The factors that influence RDO selection in dynamically unfolding environments are unknown, and the relationship between task characteristics and RDO selection has yet to be mapped. We used a videogame environment to conduct two experiments to address these issues and found that experienced losses impacted risk mitigation strategy: when the task was difficult, participants experienced greater losses and were more likely to select preventive RDOs (Experiment 1). Additionally, risk mitigation behavior stabilized as participants gained experience with the task (Experiments 1 and 2) and could be shifted by making an RDO easier to use (Experiment 2). Exploratory analyses suggested that these risk mitigation choices were not driven by judgments of difficulty (JODs), even though participants' JODs were accurate and aligned with task difficulty. This research suggests that while people seek preventive RDOs when tasks are difficult and risky, risk mitigation strategy is shaped by experienced losses; decision makers do not use JODs to anticipate future risks and inform risk mitigation decisions.

Keywords: difficulty, risk mitigation, risk defusing operators, judgments of difficulty, dynamic environments

Most people brush their teeth before work in the morning. When repeated twice a day, this small preventive measure can significantly reduce the risk of cavities and improve overall oral hygiene. Despite the positive benefits of tooth brushing, more than half of Americans report forgetting to brush their teeth at least once in the past year (Delta Dental, 2014). Failing to brush your teeth invites risk but generally does not result in a negative outcome. Unless you consistently fail to brush or are particularly susceptible to cavities, you will not require a filling. This everyday decision is a simplified example of the choices that are made in high-risk medical, defense, and educational situations (to name a few) around the world: Is it better to expend time and energy on preventive measures or should we wait and minimize the costs of prevention by taking action only if a negative outcome occurs? Our research studies sought to identify factors that contribute to when and how risk mitigation strategies are chosen, specifically within dynamic environments that rapidly change and respond to peoples' actions.

Previous research involving the use of risk mitigation strategies has focused on the conditions under which people will search for risk defusing operators (RDOs), which are actions or tools that can be used to reduce the risks associated with a decision (Huber, Beutter, Montoya, & Huber, 2001). In these experiments, participants seek RDOs by asking questions about a vignette. These questions may emphasize preventive or compensatory strategies that could be employed before (pre-event RDOs) or after (post-event RDOs) a decision is made to reduce the likelihood or severity of a negative outcome (for a review see Huber, 2012). More than a decade of research with these vignette-based descriptive tasks suggests that participants' willingness to seek RDOs depends on information availability and environmental pressures. That is, risk mitigation depends not only on the environment, but also on a person's ability to detect and interpret environmental cues. While vignette-based tasks fail to capture the dynamic nature of some real-world decisions, this research illustrates an important concept: people will actively engage with the environment to reduce their risks when they perceive the opportunity to do so (Huber, Beutter, Montoya, & Huber, 2001). For this reason, we will review research that uses vignette-based tasks before exploring the implications these findings have on choices made in dynamic decision-making tasks and the current studies.

Risk Mitigation in Vignette-based Decision-making Tasks

Within the context of vignette-based tasks, individuals initiate a search for RDOs when they recognize that their desired choice is associated with an unacceptable level of risk and will discontinue this search when an acceptable RDO is found (Bär & Huber, 2008). This search hinges on their experience with a task as well as their knowledge of risks and RDO availability. When a scenario is unfamiliar and includes explicit cues about the detection of a negative event (e.g., a test that detects the negative side effects of a medication) or about RDO availability (e.g., access to an expert that may be aware of successful risk mitigation strategies), individuals are more likely to ask questions about these factors and use this information to make decisions. This search is less likely to occur when information cues are absent (Huber & Huber, 2008; Huber & Huber, 2003) and when individuals have background

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knowledge that precludes the need for additional information (Huber & Macho, 2001). Environmental pressures also appear to play a role in the search for risk mitigation strategies. Under time pressure, questions about RDOs become more strategic and focused on RDO availability (Huber & Kunz, 2007), while requiring people to justify their choices discourages them from taking risks even when RDOs are available (Huber, Bär, & Huber, 2009). To summarize, individuals use environmental cues to determine when and how to search for risk mitigation strategies in the context of vignette-based tasks.

While the factors influencing RDO search are well-studied in the context of vignette-based tasks, less is known about how RDOs are used during situations that are continuously unfolding. Although participants indicate an interest in using preventive strategies when negative outcomes are difficult to detect and severe losses are expected (e.g., a symptomless virus; Huber & Huber, 2003), these preferences may change when decisions are encountered repeatedly within a single context (e.g., Camilleri & Newell, 2013; Hau, Pleskac, Kiefer, & Hertwig, 2008; Hau, Pleskac, & Hertwig, 2010). Repeated decisions allow participants to receive feedback in the form of experienced or avoided losses, which can be used to inform future risk mitigation decisions. Thus, an RDO's role in a dynamic task can change depending on the event to which the decision-maker anchors their choice. For example, insurance is often considered a compensatory, pre-event RDO because it is purchased in advance but only pays out if a negative outcome occurs (e.g., Huber, 2012); yet some people wait to purchase insurance until after they have sustained a loss (Zaleskiewwicz, Piskorz, & Borkowska, 2002), making insurance a post-event compensatory RDO. More research is needed to determine how individuals' willingness to seek and employ RDOs is affected by the repeated choices made within dynamic environments.

Learning from Experience in Repeated-choice Tasks

Initially, repeated-choice tasks involve uncertainty (Knight, 1921) in that their risks are not yet known: new homeowners have not yet encountered a flood nor has a novice physician seen the effects of a deadly virus. As individuals gain experience in a novel environment, they sample context-specific information which can be used to estimate the probability of risk (Hertwig & Erev, 2009) and calibrate subsequent judgements (cf., Brunswick, 1952). That is, people track experienced losses and become aware of task-related cues that signal increased risks. These cues can then be used to inform subsequent risk mitigation decisions.

One class of cues that signal risk encompasses those related to task difficulty. On a broad level, difficulty correlates with risk. The more challenging the task, the more likely a person will be to make errors and experience losses. The easier the task, the more likely a person is to succeed. This relationship can be used to inform decision-making: individuals may use experienced losses to help identify and calibrate their use of cues to difficulty (e.g., visual complexity present on a radar screen), which can then be used to infer their level of risk.

Taken together, experienced losses and cues to difficulty should affect the probability with which an individual will elect to use either type of RDO. If a task is perceived to be risky, an individual may become more likely to use an RDO, especially when the magnitude of the loss associated with that risk is high (cf., Huber & Huber, 2003). Ideally, preventive strategies will be employed when risks and losses are large, such as during a challenging task (Huber, 2012); however, upfront costs (e.g., time, money, effort) may dissuade people from adopting preventive strategies (Sigurdsson, Taylor, & Wirth, 2013). This is particularly true of demanding tasks that require many resources to complete. For instance, the CHEX decision-aid, a tool intended to help air traffic controllers and tactical coordinators improve their situation awareness, does not improve performance partly because it distracts people from their primary task of monitoring the airspace. In this case, participants rarely used the preventive RDO because it occupied resources that could be used to complete the task itself (Vallières, Hodgetts, Vachon, & Tremblay, 2016). Thus, compensatory strategies may be preferred during challenging tasks because they do not require any effort unless they must be used.

Converging evidence from cognitive, comparative, and motivational literature supports the notion that people weigh the trade-offs between effort and reward when making decisions (for reviews see Mitchell, 2017; Walton, Kennerley, Bannerman, Phillips, & Rushworth, 2006; and Locke & Latham, 2002, respectively). If effort is not commensurately rewarded, people will minimize resource allocation by abandoning tasks in favor of easier or more rewarding endeavors. In this way, they strive to maximize the utility of their limited resources (Kurzban, Duckworth, Kable, & Myers, 2013) and may use the effort-reward trade-off to inform risk mitigation decisions.

The role of expertise. An individual's ability to judge task difficulty and estimate risk may be mediated by task-specific knowledge that is acquired through practice. A single task can be made difficult in many ways (e.g., the enemies in a videogame can move more quickly or more slowly; alternatively, these same enemies could take more or fewer shots to destroy). Through practice, people become sensitive to the risk-reward relationships present in their environments (Pleskac & Hertwig, 2014) and will actively exploit them by selecting strategies that maximize their successes and rewards (Lovett & Anderson, 1996). This sensitivity is particularly pronounced when cues to difficulty are easily discriminable and frequently encountered (Gaeth & Shanteau, 1984; Shanteau, 1992). When difficulty is determined by multiple task dimensions or when decision makers receive limited feedback, expertise may negatively impact decision making. Under these conditions, experts are more likely to attend to irrelevant cues and may be poorly calibrated in their estimates of difficulty and risk (for a review, see Koehler, Brenner, & Griffin, 2002). Studying risk mitigation decisions within a controlled dynamic task will allow us to determine whether people use cues to difficulty to evaluate risks and whether these relationships can be learned over time.

Judgments of Difficulty as a Measure of Resource Demands

Because difficulty, risk, and loss are closely intertwined, judgments of difficulty (JODs) should reflect peoples' awareness of changing cues to difficulty and inform the strategies they pursue as they engage in a challenging task (Kahneman 1973; Kanfer & Ackerman, 1989; for a review see Kurzban 2016), JODs should also predict the risk mitigation strategies that will allow people to achieve their goals (Kurzban et al., 2013). To be successful, people must evaluate task difficulty frequently enough to detect changes in the environment that may affect their ability to effectively allocate resources toward their goals (Brunswik, 1956). Once a task is underway, JODs can be used to reallocate resources in response to changing task demands (Flavell, 1979).

Historically, researchers interested in metacognitive evaluations of difficulty have used knowledge assessments (e.g., multiple-choice questionnaires; comprehension) to determine the degree to which people accurately estimate the disparity between their abilities and those that the situation requires (e.g., Ozuru, Kurby, & McNamara, 2012). However, JODs made in static environments differ significantly from those that must be made repeatedly as situations rapidly unfold over time. Recent research involving dynamic tasks suggests that people integrate multiple cues to difficulty when making JODs, and that the weighting of these cues can change over time (Desender, Van Opstal, & Van den Bussche, 2017; Koriat, 1997). Peoples' ability to identify, integrate, and update cues is an integral part of selecting appropriate problem-solving strategies (Lovett & Schunn, 1999); thus, JODs may be related to RDO selection in dynamic tasks. An illustration of this purported relationship can be found in Figure 1.

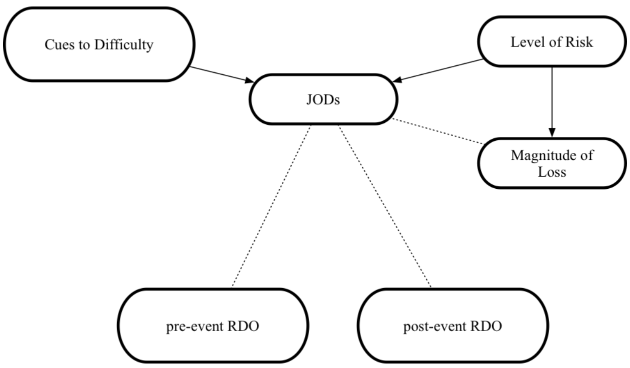

Figure 1. While it is likely that cues to difficulty, level of risk, and the magnitude of losses directly influence risk mitigation decisions, it is also possible that these factors are captured by individuals' Judgments of Difficulty (JODs). Evidence from two experiments revealed that JODs are unaffected by the magnitude of losses incurred by an individual, and that JODs do not impact risk mitigation decisions.

Studying RDOs in a Dynamic Environment

We wished to understand the influence that task difficulty and JODs have on risk mitigation strategies during a dynamic task. Our dynamic task was a third-person shooter videogame designed using the Unity game engine (Unity, 2016). Interested parties can find a video and brief description of this task at `http://youtu.be/q6AHSWfAyyY`.

Previous literature suggested competing hypotheses regarding the relationship between task difficulty and risk mitigation. If experienced losses and anticipated risks underlie RDO selection, preventive measures (pre-event RDOs) should be selected more frequently when performance is expected to worsen. In the context of this task, pre-event RDOs might be selected more often when a player's in-game losses are greater and more frequent. However, it is also possible that current resource availability dominates risk mitigation decisions. If this holds true, compensatory strategies (post-event RDOs) should be favored during difficult tasks that negatively impact performance. That is, players should allocate greater attention and working memory to improve their performance during a difficult level of the videogame rather than invest these resources in a pre-event RDO. These perspectives can be summarized in the following way:

H1a (risk estimation): participants will be more likely to select pre-event RDOs as their task performance becomes impaired.

H1b (resource minimization): participants will be less likely to select pre-event RDOs as their task performance becomes impaired.

If risk estimation underlies RDO selection, then people should be cognizant of the relationship between difficulty and risk and can track this relationship through repeated decisions. Support for this hypothesis would suggest that risk mitigation in dynamic tasks mirrors that of vignette-based tasks and can be conceptualized as a form of problem-solving. If resource minimization underlies RDO selection, then individuals should be less capable of minimizing the risks they encounter due to task difficulty. This finding would provide a simple explanation for peoples' tendency to violate workplace safety precautions when tasks are difficult (e.g., Sigurdsson, Taylor, & Wirth, 2013), even though such behavior is suboptimal. However, such behavior could also be explained by H1a if risk estimation is driven by experienced losses and cannot be anticipated; an exploratory model comparison will address this issue if H1a is supported.

Because the cues to difficulty within our environment were relatively straightforward and varied along a single dimension, we anticipated that previous videogame experience would change the way in which these strategies were adopted. Namely, if expertise enhances participants' ability to identify and use cues to difficulty and informs the selection of RDOs, participants who report significant experience with videogame tasks should display early risk mitigation preferences and be less likely to sample alternative strategies at the onset of the task (H2). In other words, participants with previous videogame experience should have adopted the RDO strategies outlined by H1a and H1b more quickly. We also believed that risk mitigation behavior would stabilize as time-on-task increased, regardless of participants' previous experience with videogame tasks (H3). If these hypotheses are supported, it would suggest that expertise improves the calibration of risk mitigation activities.

Experiment 1

Participants

Seventy-nine participants (43 female) from the General Psychology pool at Kansas State University completed the experimental task and received 1 hr of research credit compensation to fulfill a course requirement. One participant experienced a computer malfunction and needed to restart the videogame. The remaining data from this participant is included in the analyses.

Design and Procedure

Participants completed a 40-min session of a third-person shooter videogame in which they controlled the avatar of a young boy who had shrunk to miniature size and was pursued by stuffed-animal zombies inside his bedroom. During each level, stuffed-animal zombies appeared at semi-random locations and pursued the boy throughout the room. Participants guided their avatar across the bedroom floor using the arrow/ASWD keys and eliminated enemies with a laser cap gun that was controlled by moving and clicking with the computer mouse. The goal of the videogame was to successfully pass through as many levels as possible before the session was finished. Experimenters encouraged participants to pursue this goal by stating that "most participants clear eight levels before the session ends."

Successful completion of this goal required participants to prioritize their performance in the game because death was a time-costly event that occurred once the avatar's health was fully depleted by enemy attacks, which occurred each time a stuffed-animal zombie touched the avatar. Each enemy attack depleted 20 hit points of the avatar's 100 hit points of health. When the avatar's hit points dropped below 0, the avatar died and the game was paused for 30 s while a loading screen appeared. The purpose of this waiting period was to serve as an aversive consequence that discouraged players from using death as a gameplay strategy to avoid enemy characters. Following this delay, the avatar was restored to full health and placed at a random location within the game space.

Participants advanced to a new level by eliminating enemies. Each enemy elimination earned the player 1 point. Once participants eliminated 30 enemies from the game space (raised their score from 0 to 30 points), their score reset and the game advanced to a new level with an identical layout that could be easier or harder than the last (how this was accomplished is detailed later): unlike a traditional video game, the degree of difficulty was randomly assigned at the beginning of each level. Participants' ability to track changes in task difficulty was assessed using a pop-up window that appeared at the beginning of each level and every 2 minutes during the game. This pop-up window contained two buttons that allowed participants to indicate whether the videogame was "easier" or "harder" than it was before. This format allowed participants to make comparative assessments without interpreting scale anchors and without making assumptions about the scaling of JODs (for additional information, see Böckenholt, 2004). Once participants selected an option with the computer mouse, the pop-up window disappeared from the screen. Gameplay remained paused for 3 s before and after the pop-up window appeared to reduce the performance costs associated with task interruption (Altmann & Trafton, 2007).

After 40 mins of gameplay, the videogame ended and participants completed a demographic questionnaire that included questions about sex and videogame experience. Participants also completed a modified version of the Game Engagement Questionnaire (Brockmyer et al., 2009).

RDO selection. In an effort to ensure that all participants anchored their risk mitigation actions to the same event, RDOs were made available at the beginning of each level and every subsequent 5 mins. At these times, a pop-up window invited participants to "select a tool" that they could use to improve their performance during the game. Participants could select one of two tools, a shield (a pre-event RDO) or a health pack (a post-event RDO). Either tool could be used to mitigate 20 hit points of damage from an enemy character by preventing an enemy attack (shield) or restoring the avatar's health (health pack). Additionally, these tools differed in how difficult they were to use. While post-event RDOs could be used at any point following an enemy attack, pre-event RDOs needed to be timed to the enemy attack because they only shielded the avatar for up to 5 s and needed to be redeployed once an enemy character touched the shield.

Selecting a tool placed five of these items into the avatar's inventory, which was indicated by a set of icons in the lower left corner of the screen. Although participants received an opportunity to restore their inventory every 5 mins, they could neither stockpile items nor could they hold items of more than one type. Thus, participants needed to use their experiences in the game to develop a risk mitigation strategy that considered the strengths and weaknesses of both the tools and themselves.

Participants could use these tools at their discretion by pressing the F key on the keyboard. Each time participants used a tool, they received notification by visual and auditory cues: a 250-ms sound and a 3-D bubble accompanied each RDO use. Both the sound and the bubble were specific to the tool and could be used to differentiate tool choice. After a tool restored hit points or deflected an enemy attack, one of the five icons disappeared from the bottom of the screen. For a screenshot of the videogame task, see Figure 2.

Task difficulty and risk. Task difficulty was manipulated as a between-subjects variable (difficulty type) by adjusting one characteristic of the enemy characters' behavior at the start of each level. This characteristic was automatically adjusted within-subjects by a programmed algorithm that randomly selected a value from a uniform distribution that represented a wide range of difficulty, as determined through participants' performance during pilot testing (Vangsness, 2017). This randomly selected value was held throughout the level, while all other characteristics of the enemy characters' behavior remained constant during the session. For example, participants assigned to the "speed" condition saw the enemy characters' rate of movement change between levels but did not experience changes in the enemy characters' hit points or population rate. Similarly, participants assigned

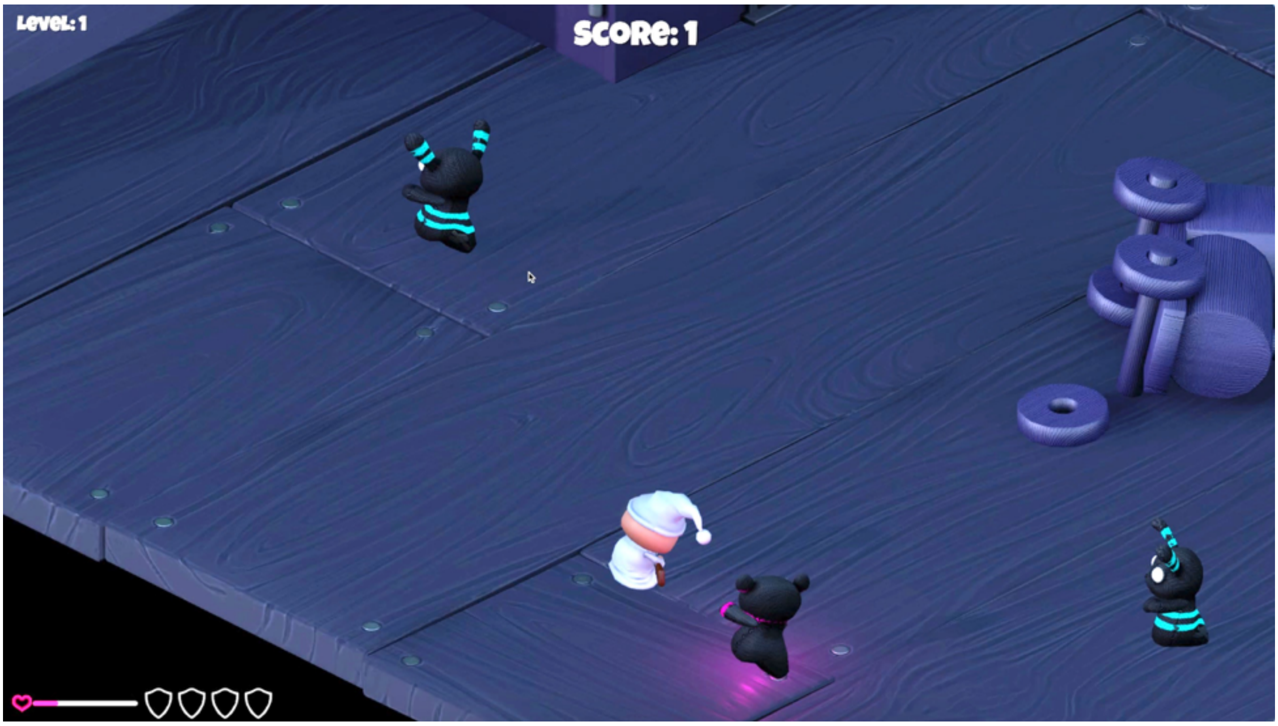

Figure 2. A screen shot from the videogame task depicts the player's avatar surrounded by three enemy characters. The player's health and remaining shields are depicted in the lower left corner.

to the "population" condition experienced changes in how quickly enemy characters appeared in the level, but did not see changes in the enemy characters' speed or hit points. A brief description of the characteristics and their sampling values can be found in Table 1.

Previous analyses of gameplay data showed that difficulty was inversely related to gameplay performance (Vangsness, 2017). That is, participants were attacked more frequently and experienced greater losses when the manipulated difficulty parameter took values near the upper limit of the range. Conversely, participants experienced fewer losses when this parameter took on smaller values. These analyses suggest that risk is higher during more difficult levels and is lower during easier levels. While it is theoretically possible to estimate the moment-by-moment risks incurred by each participant, this estimation would require knowledge of many factors (e.g., skill of the individual player; location, velocity, and enemies' expected time of arrival; etc.) that fluctuate considerably during the task. As we were interested in broad, robust patterns of behavior that transcend a single, specific context, we defined risk as it varied with task difficulty.

Tutorial level. The videogame included a tutorial level to familiarize participants with the layout and controls of the game. The tutorial level was identical to the videogame task in all respects but only contained three enemy characters which participants were required to eliminate before progressing to the first level of the game. Because the tutorial level differed significantly from the remainder of the videogame, data from this portion is excluded from subsequent analyses.

Results

Risk Mitigation Strategy. We explored the factors underlying participants' risk mitigation strategies with a multilevel logistic regression model that predicted the probability that a participant would select either tool (Health pack, Shield) using participants' game performance, time-on-task, previous videogame experience, and difficulty type (Population, Speed, Strength) in the fixed effect structure. Game performance was defined as the rate of damage from enemy characters that had elapsed since the most recent RDO selection ("total damage since last RDO choice ÷ time since last RDO choice"), videogame experience as the summed responses to relevant items from the demographic questionnaire, and time-on-task as the amount of time that had elapsed since the beginning of the first level of the videogame task. The random effect structure was selected using AIC comparisons (Akaike, 1973), which supported a structure that included the intercept, game performance slope, and time-on-task slope. This specification allowed the model to account for participant differences in overall ability, perceptions of difficulty, and rate of learning. A full disclosure of random effect comparisons can be found in the appendix.

The findings from this analysis are illustrated by Figure 3. The slope in each time-slice panel illustrates that risk mitigation strategy was significantly affected by participants' damage rate since last RDO selection, and that this relationship changed over time. Early in the game, participants had little preference for either RDO but as time-on-task increased they learned to use preventive RDO strategies to compensate for heavy losses. When participants performed well during the

Table 1. Both experiments included a between-subjects manipulation in which participants experienced different difficulty types.

condition	description	randomly selected values	constant values
Population rate (n = 26)	The rate at which enemies appeared in the game space	1 – 25 s	10s
Speed (n = 23)	The speed at which enemy characters could travel.	0.2 – 15.0 Unity units	5.0 Unity units
Strength (n = 30)	The number of hit points enemies had when they first appeared in a level.	20 – 400 hit points	115 hit points

Note. Unity units are an arbitrary measure that can be used to scale game objects with respect to one another.

later stages of the game they became increasingly likely to select post-event RDOs. This pattern of behavior aligns with our hypothesis that risk estimation underlies RDO selection (H1a). Specifically, participant selected risk mitigation strategies that would prevent losses when they were likely to occur rather than choosing to conserve resources for task completion by selecting the less-effortful post-event RDO. This relationship became more pronounced over time, suggesting that risk mitigation strategies stabilize as individuals become more familiar with available RDOs (H3). The other main effects included in the model were non-significant (p's $> .05$), suggesting that there is not a strong relationship between previous videogame experience and RDO selection (H2). All estimates and significance values are disclosed in Table 2.

Table 2. Model estimates from Experiment 1 reveal that game performance and time-on-task significantly predict participants' risk mitigation strategy during gameplay.

predictor	B	*SE*	*z*	*p*
intercept	0.77	0.28	2.74	.01
game performance	-0.34	0.16	-2.11	.04
time-on-task	0.82	0.29	2.82	.005
previous videogame experience	0.03	0.02	1.32	.19
Population	0.22	0.22	1.01	.31
Speed	-0.09	0.23	-0.39	.69
performance x time-on-task	-0.40	0.19	-2.13	.03

Note. Performance (M = 1.32, SD = 1.53) was centered around 1.17, a value halfway between the means of Experiments 1 and 2. Previous videogame experience (M = 8.93, SD = 7.40) was centered around its mean, and time-on-task (M = 1088.25, SD = 723.64) was centered around its mean and scaled by dividing by 1,000 prior to analysis. Experimental condition was effect coded, with Strength serving as the -1, -1 baseline.

To evaluate participants' ability to use JODs as a measure of resource demands, we used AIC values to compare the existing model with one that included participants' perceptions of task difficulty as a main effect. Adding this predictor did not significantly improve the predictions of our earlier model (ΔAIC = -2.87). We interpreted this finding to have one of two meanings: either participants' JODs were highly correlated with damage rate, suggesting that participants used the magnitude of their losses as a cue to game difficulty, or participants did not incorporate their JODs in risk mitigation decisions.

Exploratory analysis. To address the multiple interpretations of our model comparison, we conducted an exploratory analysis to determine whether damage rate was responsible for participants' JODs, or if perceptions of difficulty were based on additional unmeasured factors. This was accomplished by comparing two multilevel logistic regression models that included either a measure of participants' game performance (damage rate since last JOD question) or of objective game difficulty (task difficulty parameter standardized across experimental condition). Both models included time-on-task, previous videogame experience, and experimental condition (Population, Speed, Strength) in the fixed effect structure. AIC comparisons supported a random effect structure that included intercept, standardized difficulty slope, and time-on-task slope to account for participant differences in ability, experiences of difficulty, and rate of learning. A full disclosure of random effect comparisons can be found in the appendix.

Table 3. Model estimates from an exploratory analysis reveal that an objective measure of difficulty and time-on-task predict participants' JODs in Experiment 1.

predictor	B	*SE*	*z*	*p*
intercept	0.43	0.15	2.76	.01
standardized difficulty	3.50	0.37	9.41	<.001
time-on-task	-0.47	0.14	-3.33	<.001
previous videogame experience	0.01	0.02	0.48	.63
Population	0.001	0.19	0.01	.99
Speed	-0.12	0.21	-0.55	.58

Note. Standardized difficulty (M = 0.51, SD = 0.30) and previous videogame experience (M = 9.16, SD = 7.22) were centered around their means. Time-on-task (M = 1214.01, SD = 713.03) was centered around its mean and scaled by dividing by 1,000 prior to analysis. Experimental condition was effect coded, with Strength serving as the -1, -1 baseline.

Model comparisons using AIC strongly supported a model that included objective game difficulty as a fixed effect (ΔAIC = 82.95). The findings from this model (see Figure 4) suggest that cues to difficulty unrelated to the magnitude of losses (e.g., the number of enemies

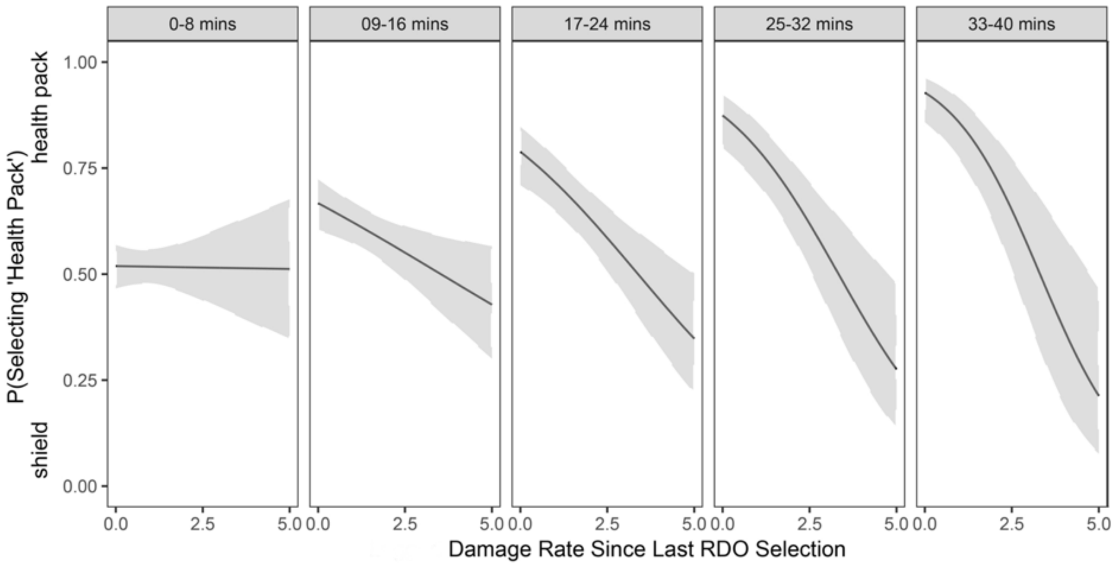

Figure 3. During Experiment 1, participants' risk mitigation strategies were not initially sensitive to changes in task difficulty. As the experimental session continued, participants began to compensate for changes in task difficulty by selecting preventive tools (i.e., the shield) when they experienced greater losses and compensatory tools (i.e., the health pack) when they experienced fewer losses. Error ribbons represent one standard error above and below the model estimates.

visible on the screen; how quickly enemy characters move) underlie participants' JODs. Despite this, the positive slope in each time-slice reveals that participants' JODs were well-calibrated to the difficulty level of the game. Participants were more likely to indicate the game was "harder than before" when they were playing levels that were objectively harder, and were more likely to indicate the game was "easier than before" when playing levels that were objectively easier. We also found that participants' JODs were influenced by time-on-task such that they became less likely to say that the game was "harder than before" later in the game; however the size of this effect was small. The other predictors included in the model were not significant (p's $> .05$). All estimates and significance values are disclosed in Table 3.

Discussion

Participants' risk mitigation strategies were affected by the interaction between their experienced losses and time-on-task. Initially, participants' risk mitigation strategies were unaffected by experienced losses, but over time, pre-event RDOs (i.e., the shield) were preferred following heavy losses. These results suggest that people respond to environmental changes by adopting risk mitigation strategies that reflect experienced losses (here, damage rate since last RDO question) and that these strategies change as people gain experience with a task. This behavior lends support to the hypothesis (H1a) that risk estimation drives the selection of risk mitigation strategies because participants actively compensated for their losses with a most costly pre-event RDO rather than allocating all their resources toward task completion. Participants' behavior was unaffected by their level of videogame experience (H2), but did stabilize over time lending support to hypothesis H3. Our results also demonstrated that people actively and accurately monitor the environment for cues that reflect changes in task difficulty, but that these cues are not determined by the magnitude of participants' losses and may instead focus on cues to difficulty within the videogame itself (e.g., the number of on-screen enemies). Because participants' risk mitigation strategies were predicted by experienced losses while JODs were predicted by cues to difficulty, we believe that the shifts in risk mitigation strategy are caused by individuals' awareness of experienced losses, and that the cues used to select a risk mitigation strategy differ from those used to make JODs. This would seem to suggest that individuals' risk mitigation strategies do not anticipate risks but respond to them after they have occurred.

Although our results support the risk mitigation hypothesis (H1a), they do not completely discount the resource optimization account of human behavior (e.g., Kurzban et al., 2013; Vallières, Hodgetts, Vachon, & Tremblay, 2016). While losses led participants to select resource-intensive pre-event RDOs, they did shift toward selecting post-event RDOs when losses were infrequent. Perhaps participants recognized that preventing losses, while strategic, came with inherent costs and therefore effectively navigated the trade-off between effort and reward. We reasoned that if participants engaged in trading off effort and reward, they would shift toward preventive risk mitigation strategies when this tool was made easier to use (H4a). However, if resource optimization did not underlie participants' behavior, tool selection would not be influenced by the pre-event RDO's ease-of-use (H4b). We tested these competing hypotheses in Experiment 2 by manipulating the coordination required to effectively use the shield tool and measured the impact this had on tool selection throughout the videogame task.

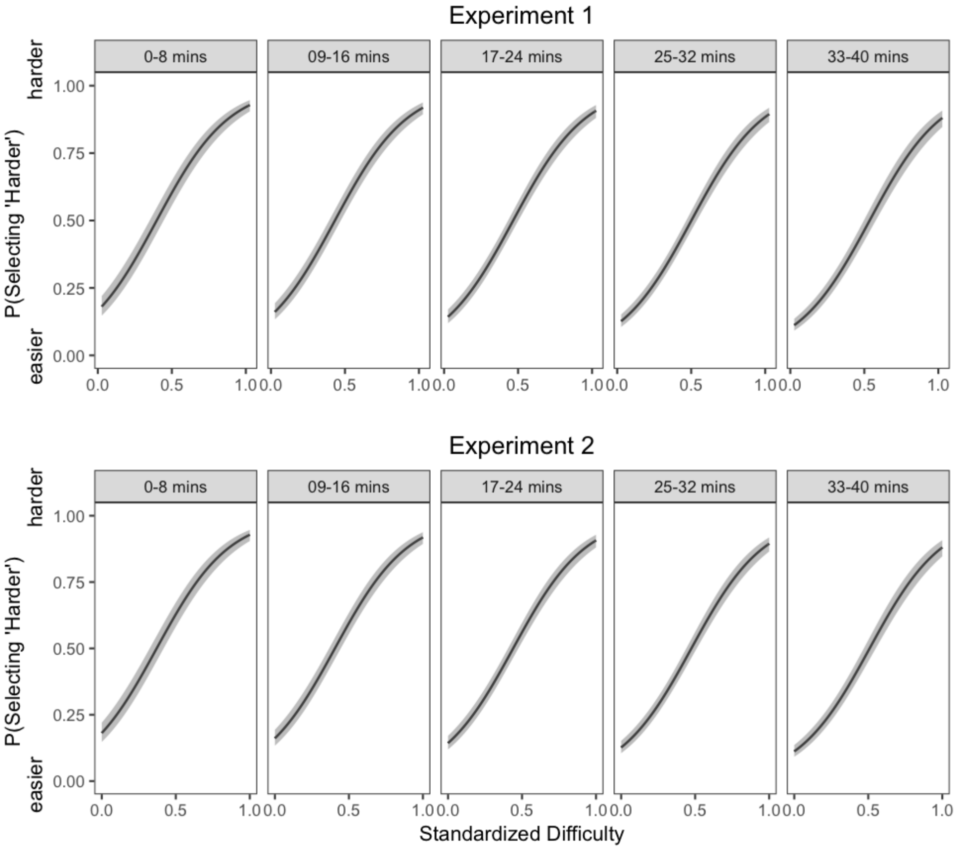

Figure 4. Participants' judgments of difficulty (JODs) were well-calibrated to the difficulty level of the videogame (parameter values standardized across difficulty types). JODs were also consistent across both experiments. Error ribbons represent one standard error above and below the model's estimates.

Experiment 2

Participants

Eighty-eight participants (41 female) from the General Psychology pool at Kansas State University completed the experimental task and received 1 hr of research credit compensation to fulfill a course requirement.

Design and Procedure

Participants completed a 40-min session of the videogame task in which we manipulated the difficulty of the shield's use as a between-subjects condition variable (RDO type), but held the reward for using this tool (avoiding an enemy attack) constant. In the Steady condition, pre-event RDOs were less costly: participants that selected the shield needed only to deploy it a single time. Once active, the shield protected the participants' avatar from five enemy attacks. In the Sporadic condition, the shield was more costly because behaved as it did in Experiment 1. That is, it remained active for five seconds and participants needed to deploy it multiple times to remain protected from enemy attacks. Furthermore, the timed activation window required participants to coordinate the shield's deployment with an anticipated attack.

Because the between-subject difficulty manipulation (Population, Speed, Strength) was not a significant predictor in the Experiment 1 analyses, we included only two levels of the difficulty manipulation (difficulty type: Strength, Speed), in Experiment 2. We counterbalanced the four possible combinations of difficulty type and RDO type across experimental sessions. In all other respects, the videogame task was identical to that used in Experiment 1.

Results

We again used multilevel logistic regression to predict the probability that a participant would select either tool (Health pack, Shield) using participants' game performance, time-on-task, previous videogame experience, difficulty manipulation (Strength, Speed), and RDO type (Sporadic, Steady). Game performance, videogame experience, and time-on-task were included in the fixed effect structure and operationalized using the measures outlined in Experiment 1. AIC comparisons supported a random effect structure that included the intercept, game performance, and time-on-task which allowed the model to account for participant differences in overall ability, perceptions of difficulty, and rate of learning. Because we were interested in replicating the effects found in Experiment 1, we included the three-way interaction between game performance, time-on-task, and RDO type.

The results of our analysis are depicted in Figure 5. The stark difference in risk mitigation patterns between the Sporadic and Steady RDO type is clear; only RDO type and its two-way interaction with time affected participants' risk mitigation strategies during the game (see Table 4). This effect intensified as time-on-task increased and became most apparent in the final time-slice panel. Including participants' perceptions of task difficulty as a main effect again did not significantly improve our model's predictions (ΔAIC = -2.97), complementing our results from Experiment 1. The results of the two- and three-way interactions involving game performance, time, and RDO type also align with our previous analysis. Although these effects did not reach significance, the model estimates for the "Sporadic" RDO type fall within the 95% confidence intervals established in Experiment 1. As this subset of the data represents only half of that included in our previous experiment, we expect that the increasing sensitivity to damage rate observed in Experiment 1 would have replicated had we included more participants.

Table 4. Model estimates from Experiment 2 demonstrate that the ease-of-use manipulation overshadowed all other factors in predicting participants' risk mitigation strategy.

predictor	B	*SE*	*z*	*p*
game performance	-0.03	0.18	-0.19	.85
time-on-task	-0.43	0.36	-1.19	.23
previous videogame experience	0.02	0.03	0.71	.48
Sporadic	1.49	0.43	3.46	<.001
Speed	-0.28	0.19	-1.53	.13
performance × time-on-task	-0.13	0.18	-0.71	.48
performance × Sporadic	0.001	0.18	0.01	.99
time × Sporadic	1.15	0.38	3.07	.002
performance × time-on-task × Sporadic	-0.07	0.19	-0.39	.69

Note. Performance ($M = 17.53$, $SD = 34.01$) was centered around 1.17, a value halfway between the means of Experiments 1 and 2. Previous videogame experience ($M = 6.30$, $SD = 9.76$) was centered around its mean, and time-on-task ($M = 1285.87$, $SD = 846.32$) was centered around its mean and scaled by dividing by 1,000 prior to analysis. RDO type and difficulty type were effect coded, with Steady and Strength coded as -1.

Exploratory analyses. We again conducted an exploratory analysis to determine whether participants' JODs reflected changes in damage rate, or if a different factor was responsible for their perceptions of difficulty. We used AIC values to compare two multilevel logistic regressions that included either game performance (damage rate since last JOD question) or objective game difficulty (task difficulty parameter standardized across experiment condition). Both models included time-on-task, previous videogame experience, difficulty type (Speed, Strength), and RDO type (Steady, Sporadic) in the fixed effect structure. AIC comparisons supported a random effect structure that included intercept, standardized difficulty, and time-on-task slope to account for participant differences in ability, experiences of difficulty, and rate of learning. A full disclosure of random effect comparisons can be found in the appendix.

Model comparisons again supported the second model ($\Delta AIC = 171.99$), replicating our finding that the participants did not use the magnitude of losses to make JODs. As before, positive slopes across each time-slice (see Figure 4) reveal that participants' JODs were well-calibrated to the objective difficulty of the game. Time-on-task again affected participants' JODs: participants became less likely to say the game was "harder than before" as time progressed (see Table 5).

Table 5. Model estimates from an exploratory analysis reveal that an objective measure of difficulty and time-on-task predict participants' JODs in Experiment 2.

predictor	B	*SE*	*z*	*p*
intercept	0.09	0.14	0.61	.54
standardized difficulty	4.07	0.40	10.24	<.001
time-on-task	-0.29	0.11	-2.69	.01
previous videogame experience	-0.03	0.02	-1.30	.19
Sporadic	0.10	0.13	0.73	.46
Speed	0.13	0.15	0.89	.37

Note. Standardized difficulty ($M = 0.71$, $SD = 0.31$) and previous videogame experience ($M = 6.39$, $SD = 5.69$) were centered around their means. Time-on-task ($M = 1242.38$, $SD = 775.39$) was centered around its mean and scaled by dividing by 1,000 prior to analysis. RDO type and difficulty type were effect coded, with Steady and Strength coded as -1.

Discussion

The results of Experiment 2 strongly confirm the hypothesis that people attempt to balance effort and reward during challenging tasks (H4a). Indeed, when we manipulated the effort-reward trade-off and included the pre-event RDO's ease-of-use as a predictor in our model it attenuated the effects of many other predictors, including game performance. This suggests that people prioritize the immediate conservation of resources only when it does not negatively impact their performance goals: unlike the participants in Experiment 1, participants in Experiment 2 were willing to use pre-event RDOs exclusively because they were easier to use and no longer presented a resource cost. The findings from our exploratory analysis, which revealed that JODs were affected by the difficulty manipulation but not by the ease-of-use manipulation, further illustrates that the factors used to select RDOs are different from those used to make overall judgments of task difficulty.

General Discussion

Our study provides conclusive evidence that decision-makers balance effort and reward to select appropriate risk mitigation strategies. In Experiment 1, participants developed risk mitigation preferences as the

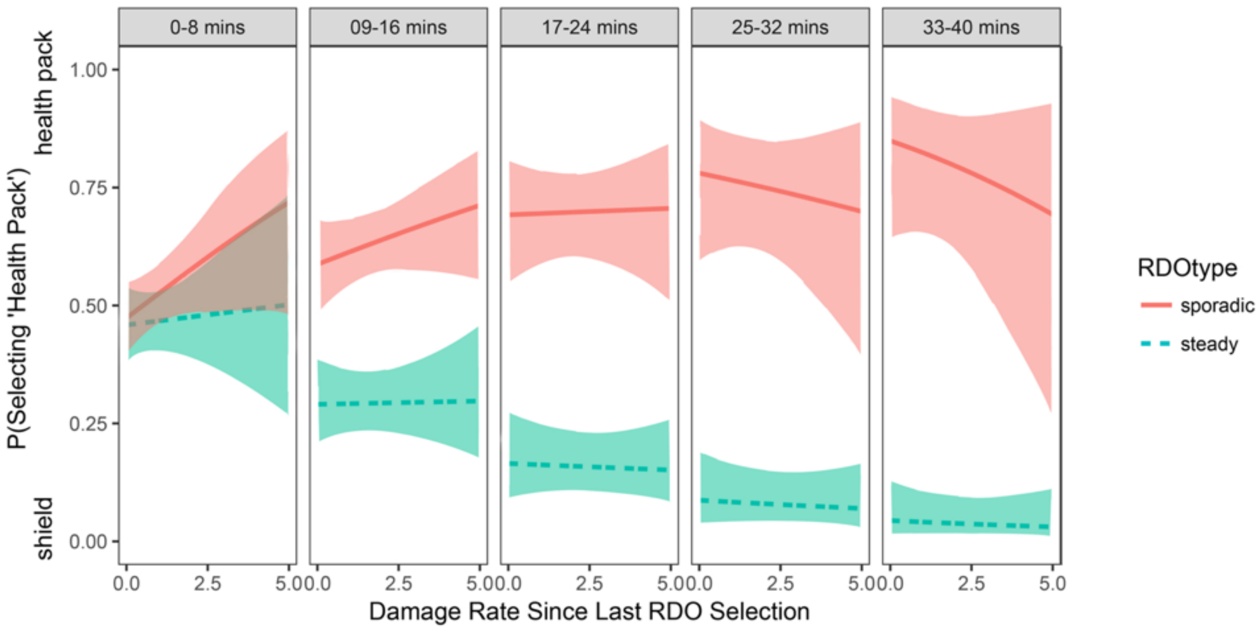

Figure 5. Participants' behavior in Experiment 2 differed as a function of RDO type. Although participants in the sporadic condition behaved similarly to those in Experiment 1 (to which it is identical), participants in the steady condition developed a strong preference for the shield which was easier to use in this condition. Error ribbons depict one standard error above and below model estimates.

task progressed. Later in the session, participants selected more resource-intensive pre-event RDOs when losses were likely and preferred easier-to-use post-event RDOs when losses occurred less frequently. This preference shifted in Experiment 2 among participants for whom pre-event RDOs were made easier to use. In both experiments, behavior stabilized over time as participants gained familiarity with each tool. Together, this evidence suggests that while experienced losses influence the risk mitigation strategy an individual pursues, preferences can also be affected by how difficult an RDO is to use.

Although people recognize and respond to elevated risks and severe consequences by adopting pre-event RDOs (c.f., Huber, 2012; Huber & Huber, 2003), they are sensitive to the effort-reward trade-off presented by the RDO's ease-of-use (c.f., Sigurdsson, Taylor, & Wirth, 2013). While JODs do not contribute to peoples' risk mitigation strategies, people are affected by how easy RDOs are to use. Harder-to-use pre-event RDOs, which require an upfront investment of effort to employ, were only favored when they are necessary to reduce experienced losses. When pre-event RDOs were made easier to use, people relied upon them more often regardless of their experienced losses. This finding supports the theoretical opinion of Kurzban et al. (2013), in that participants will avoid unnecessary risk mitigation strategies if they are difficult to use. This finding is particularly relevant to situations that involve infrequent but costly risks during which preventive actions may be undervalued with respect to the efforts they require, such as natural disaster preparedness (Douglas, Leigh, & David, 2005) and responding to variations in air traffic control workload (Desmond & Hoyes, 1996).

The specificity of cues to difficulty and JODs was further revealed in our analysis of participants' JODs. Although objective measures of task difficulty predicted JODs, damage rate (a measure of a participants' experienced losses) did not produce a good model fit. This suggests that participants used other cues to produce JODs (see the right side of Figure 1), an assertion that is supported by the difference across RDO manipulations in Experiment 2. Thus, it is likely that the magnitude of losses was responsible for or mediated the relationship between level of risk and RDO selection but did not provide a cue to task difficulty overall; however, this relationship should be explored more directly before strong claims are made.

Unlike previous research, which showed that participants discontinued their search for RDOs when they had previous experience in an area (Huber & Macho, 2001), we found that participants' behavior was unaffected by domain-specific background knowledge (videogame experience). However, participants developed a systematic adoption of risk mitigation strategies over time, supporting previous research that successful strategies are pursued once they are learned (c.f., Lovett & Anderson, 1996). This result also supports Huber and Huber's (2008) assertion that people use their expectations to determine the availability and efficacy of RDOs, as evidenced by the shifts in behavior that occurred over time and resulted in stabilization of risk mitigation strategy. Although general aspects of risk mitigation behavior appear to be consistent, behavior in experiential tasks does differ from that of descriptive tasks in important ways.

Recent research has suggests that people can be trained to attend to certain task-related cues more strongly than others when making JODs (Desender et al., 2017). It may be possible to encourage individuals to use task-related cues to select risk mitigation strategies and to down-weight the influence of an RDO's ease-of-use. Similar means might be achieved by architecting an environment that emphasizes certain task cues above others. Together, these lines of research will clarify the factors that influence risk mitigation decisions and help people mitigate risks strategically.

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Appendix

AIC comparisons suggested that the random effect structures for the models used to analyze Experiment 1 data could include intercept and time-on-task or intercept, performance, and time-on-task.

Random effect structure	AIC
Experiment 1 – RDO selection	
intercept only	706.33
intercept and performance	706.09
intercept and time-on-task	668.57
intercept, performance, and time-on-task	674.18
Experiment 1 – JODs	
intercept only	1199.64
intercept and performance	1181.73
intercept and time-on-task	1199.13
intercept, performance, and time-on-task	1180.63

Experiment 2 – RDO	
intercept only	877.10
intercept and performance	861.21
intercept and time-on-task	769.85
intercept, performance, and time-on-task	767.62
Experiment 2 – JODs	
intercept only	1767.43
intercept and performance	1755.55
intercept and time-on-task	1764.33
intercept, performance, and time-on-task	1753.60