Learning from Multiple Failures: Evidence from Figure Skating Competitions[†]

Jungwon Min* and Hitoshi Mitsuhashi**

Abstracts

In diverse situations, including sports competitions, individuals execute and learn a bundle or sequence of motor tasks (i.e., multitask settings). Nevertheless, we know little about how individuals learn from failures and improve performance in multitask settings. Drawing upon the literature on individual learning and attention, we examine the conditions of multitask settings under which individuals repeat failures in the same motor task, and fail to learn from previous failures of execution. We predict that in multitask settings, individuals that experience multiple failures cannot pay equal attention to all of them; hence, they fail to learn from previous failures of the focal task if there are other failures to which they need to attend. We also argue that this tendency becomes stronger when these other failures are unpredicted. To examine our predictions, we use data on skaters who participated in major International Skating Union single figure skating competitions from 2006 to 2013. The results support our arguments and have theoretical and practical implications for the design of multitask settings from the learning perspective.

Keywords: multitask settings, performance improvement, learning from failures, attention, figure skating

I Introduction

Individuals learn from past experience and thereby perform tasks efficiently and effectively with the accumulation of experiences (Boyce & Bischak, 2010; Thornton & Thompson, 2001). In particular, past failure experiences are important for learning because experiences that have negative consequences prompt individuals to explore advanced routines. Hence, individuals should be able to learn more from failure than from success (Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001; Levinthal & March, 1981). For example, many athletes recognize skill deficits and remedy them when they have executed a task poorly in past competitions. Past failure experiences draw individuals' attention to their shortcomings, facilitating their learning processes.

Although there is much prior evidence on the effectiveness of learning from failures across diverse research areas, including education (e.g., Love, Love, & Northcraft, 2010), psychology (e.g., Ellis, Mendel, & Nir, 2006), and management (e.g., Carmeli & Gittell, 2009), this evidence is less directly applicable to learning complex motor tasks such as those in sports. This is because the prior evidence for learning from failures is based on the assumption that learning occurs in a single task setting although many complex motor tasks are learned and executed in multitask settings in which individuals either concurrently or sequentially execute multiple motor tasks as a set.

[†] This work was supported by JSPS Grant-in-Aid for Young Scientists-KAKENHI, JSPS KAKENHI Grant Number 16H03658, and JPC (Japan Productivity Center) Research Grant.

* Corresponding Author: Faculty of Economics and Management, Sophia University
E-mail: j-min-2k4@sophia.ac.jp
** Faculty of Business and Commerce, Keio University
E-mail: mitsuhashi@fbc.keio.ac.jp

Learning from failures in multitask settings should be different from that in single-task settings. Contrary to single task settings, in multitask settings, individuals execute multiple tasks, so they tend to experience multiple failures. To learn from these multiple failures, it is first necessary to pay attention to each of them before any other learning phase, such as the identification of flaws in preexisting routines, updates or revision (Levitt & March, 1988; Rerup, 2009). However, because individuals have limited attentional resources, attention to one task is likely to suffer from interference from other tasks in the same set or sequence (Monsell, 2003; Pashler, 1994), which may impair learning from unattended failures. Regardless of this possibility, prior studies on learning from failures have neglected learning in multitask settings. As a result, we know little about how the attentional interference hampers learning from failures in multitask settings or how individuals can learn effectively from multiple failures.

To fill this gap, this study examines the conditions of multitask settings in which individuals experience attentional interference and fail to learn from previous failures. Using empirical data on single figure skaters participating in major International Skating Union (ISU) competitions from 2006 to 2013, we argue that in multitask settings, individuals cannot pay equal attention to each of the multiple failures in a sequence; hence, they learn less from failures in the focal task if other tasks that they had previously failed to execute in the same sequence also required their attention. We also postulate that this propensity becomes stronger when failures in other tasks are unpredicted.

In the sections below, we introduce our empirical context. Then we propose a theory and hypotheses to test the characteristics of a multitask setting in which individuals fail to attend to a previously failed task, and consequently fail to learn from it. We then show fixed-effect analysis results for the hypothesis tests. The analysis results provide strong support for our arguments about attentional interference in the learning processes in multitask settings.

Ⅱ Research Context

Single figure skating competitions offer a setting suitable for testing learning from failures in multitask settings for the following reasons. First, a single figure skating program consists of a bundle or sequence of various tasks such as jumps, spins, and spirals. Hence, skaters (i.e., individuals) learn in multitask settings. Second, skaters participate in several annual competitions, allowing us to access not only large datasets on multiple players, but also on variations in their performance outcomes over time or across multiple competitions as a result of learning (Zitzewitz, 2014). Third, single figure skaters execute multiple tasks as individuals, not as teams or groups, which satisfies our assumption of individual learning. Finally, another advantage of this research context is the availability of data to control for various characteristics of the tasks that skaters learn. For example, the ISU assigns "base values" for each task, representing the degree of difficulty in execution. Moreover, relatedness between tasks can be inferred from information about the categories to which the tasks belong. Given these advantages, we examine our theory based on data about learning from failures in figure skating techniques by skaters who participated in the five major international competitions organized by the ISU from 2006 to 2013: the *Winter Olympic Games*, *World Championships*, *European Championships*, *Four Continents Championships*, and *Grand Prix Series*. We collected these data from the ISU website (http://www.isu.org/en/home).

In this context, skaters have four generic types of tasks (i.e., techniques), namely spins, step sequences, spirals, and jumps. Each type of task has multiple subcategories. For example, jumps have six subcategories characterized by takeoff, edging, rotating, and landing: toe loop (T), salchow (S), loop (Lo), flip (F), luz (Lz), and axel (A). These techniques can be executed independently (e.g., a triple loop, denoted by 3Lo) or jointly (a triple luz and a double loop, denoted by 3Lz + 2Lo). We view both independent and joint techniques as tasks in sequences, and include them in our sample.

In each competition, skaters are required to execute two programs: one short and one free. They execute seven tasks (i.e., techniques) over 2 minutes 50 seconds in the short program, and 14 tasks over 4 minutes 30 seconds for males and 4 minutes for females in the free program. Repeated execution of the same task in both short and free programs is permitted. Hence, one competition offers opportunities to learn and execute 21 tasks, but the total number of tasks in the programs may vary because skaters repeatedly execute the same tasks.

To investigate the failure to learn from failures requires us to specify failed tasks in the sequences in the preceding competitions. We collected data about the tasks in the sequences that a skater had failed to execute in the previous competition according to performance ratings awarded by competition judges. A panel of 8 to 12 judges rates the execution of each task on a scale from –3 to +3, a score that is called the Grade of Execution (GOE). A GOE score represents the extent to which judges perceive skaters' execution of techniques relative to standards established by the ISU. GOE is negative for a poorly executed performance relative to the ISU's standards for tasks, zero if the performance meets the ISU's standards, and positive for well-executed performances (Cinquanta & Schmid, 2014). We view negative and positive GOEs as *task failure* and *success*, respectively, and a zero GOE as neutral performance feedback that is categorized as neither failure nor success.

Ⅲ Theory and Hypotheses

1. Attentional Interference in Multitask Learning

Individuals learn and improve their performance when they change routines and behavioral patterns on the basis of performance feedback (Schultz, 2002). Successful outcomes or positive feedback suggest that current actions should be repeated and reinforce preexisting routines, whereas failures or negative feedback help individuals detect flaws in routines, generating opportunities for future performance improvement. Hence, experiences of failure trigger learning processes more than do those of success (Sitkin, 1992; Weiner, 1985). Indeed, previous research has demonstrated that individuals attend more to failures, and remember them for longer periods, which facilitates their learning (Baumeister et al., 2001; Finkenauer & Rime, 1998). Research has also shown that because individuals dislike loss and try to avoid negativity resulting from failures, they make greater efforts when perceiving their current performance to be inferior to reference points such as their own past performances (Love et al., 2010).

However, not all failures are appropriately processed for learning and result in performance improvement. Some failures cause limited or no improvement in subsequent performances. We consider that one reason for this variation in learning from failures is related to attentional interference. Attention encompasses not only visual recognition (Broadbent, 1958) but also cognitive processes such as noticing, encoding, and interpreting failure, as well as devoting time and effort to it (Ocasio, 1997). Because the allocation of attention to failures precedes any other phases of learning such as interpretation of the causes of failure and searching for or implementing new routines, inattention to failures is a primary reason for failure to learn from them (Rerup, 2009).

We argue that in multitask settings, there is a high probability that individuals cannot attend to some of the failed tasks, so they experience limited learning. Boundedly rational individuals have limited cognitive capacity and are unable to pay equal attention to every failed task when they have multiple failures (Ocasio, 1997; Starbuck & Milliken, 1988). Therefore, individuals may learn limitedly from a focal failed task when they pay attention to multiple other tasks in the same bundle. Several previous studies provide evidence to indicate such limited attention. Sullivan (2010) finds that in situations where multiple problems occur serially, decision makers adopt a rule of selective attention to specific problems in order to alleviate cognitive burdens. Piezunka and Dahlander (2015) find that managers manage information overload by limiting their attention to sets of information that meet their criteria.

This problem in limited attention is also pertinent to that in multitasking executions suggested by literature on human cognition and attention. This literature has argued that multitasking individuals need to shift their attention between two or more tasks, and suffer from a shortage of attentional resources and working memory for the effective execution of tasks (Bai, Jones, Moss, & Doane, 2014; Monsell, 2003). For example, Konig, Buhner and Murling (2005) show that the quality of performance of a task decreases in multitasking situations if people divert their attention to other tasks in which they simultaneously engage. Hambrick and his colleges (2010) find that people adopt cognitive shortcuts to reduce the burden of simultaneously coping with multiple tasks, and that these shortcuts account for performance differences. These previous findings support our view that individuals learn to a limited extent from failed tasks if they pay more attention to other tasks in the same bundle.

2. Other Failures in Multitask Settings

Our baseline hypothesis is that in multitask settings, individuals may not learn from the failure of the focal task at time t–1 and not experience performance improvement at time t if there are more failed nonfocal tasks in the sequences at time t–1 that distract their attention. In our empirical context, a figure skater learns from failures when s/he successfully performs the task in the sequence that s/he failed to do in the previous competition. The failure in the previous competition triggers a search for alternative ways (i.e., learning) of executing tasks that may generate more positive outcomes. However, with an increase in the number of failures in nonfocal tasks from which the skater must learn, the aforementioned attentional interference is more likely, limiting attention to some of the failures. This biased attention causes no performance improvement in the unattended or less attended focal task in the subsequent competition. In contrast, if the skater failed only a focal task in the sequence in the preceding competition, s/he is able to use all attentional resources for the improvement of this task, increasing the likelihood of successful learning.

More specifically, suppose that an individual's overall performance, *OP*, in a multimotor task setting at time *t* is a function of how well s/he performs each task, e_n:

[1] $OP_t = \mathrm{f}\ (e_1, e_2, e_3, \ldots, e_n)$.

The literature on learning from failures suggests that performance of the focal task e_n at time *t*, $Pe_{n.}t$, is a function of learning or performance improvement from failure in e_n at time *t–1*, which is denoted as $\mathrm{LF}e_{n.t-1}$ and nonlearning factors, α (e.g., individuals' inherent skills):

[2] $Pe_{n.t} = \mathrm{f}\ (\mathrm{LF}e_{n.t-1}) + \alpha$.

With this assumption, we predict that individuals fail to learn from failure in a focal task at time *t–1* ($\mathrm{LF}e_{n.t-1}$) with an increase in the number of nonfocal task failures at time *t–1* ($AT!e_{n.t-1}$), which distracts attention from failure in the focal task ($ATe_{n.t-1}$):

[3] $LFe_{n.t-1} = \mathrm{f}\,(ATe_{n.t-1})$,
[4] $ATe_{n.t-1} = \mathrm{f}\,(AT!e_{n.t-1})$.
These arguments lead to the following hypothesis:

Hypothesis 1: Performance improvement in a focal task that an individual previously failed to perform decreases with an increase in the number of previous failures of nonfocal tasks.

3. Other Unpredicted Failures in Multitask Settings

While the aforementioned hypothesis suggests that any kind of failure of nonfocal tasks causes an equal attentional interference and does not differentiate between the effects of failures of different types of nonfocal tasks, previous research suggests that nonfocal tasks that are more salient and noticeable should more severely distract individuals' attention. This is because individuals pay selective attention to the salient, develop a belief that failed tasks that are more salient constrain overall performance more seriously, and therefore expect greater returns if they learn successfully (e.g., Haas, Criscuolo, & George, 2015). This study conceptualizes salience by focusing on whether the experience of failing to perform tasks is unpredicted, unexpected, or surprising (Cyert & March, 1963), and argues that unexpected failures in nonfocal tasks garner more attention and cause the attentional interference.

Nonfocal task failures are unpredicted, unexpected, or surprising if individuals expect to perform such tasks well or if they fail when they had expected success (Bies, 2013). We propose that such unpredicted failures of nonfocal tasks have three characteristics. First, if failed nonfocal tasks should have been performed relatively easily, such failures are not predicted (i.e., *failures of easy nonfocal tasks*). Nonfocal tasks are difficult when they require greater skill. Individuals expect to be better able to perform easy nonfocal tasks than difficult ones. If they experience such failures, individuals consider the outcome to be below their expectations and contrary to their predictions.

Second, if nonfocal tasks have been repeatedly performed on different occasions, and individuals fail to perform them well, such failures may be unexpected or unpredicted (i.e., *failures of repeated nonfocal tasks*). Nonfocal tasks that have been repeatedly executed over time should be performed more successfully than nonrepeated ones because repetition allows individuals to accumulate experience for learning. Individuals may consider failures of nonrepeated tasks to be reasonable and understandable if they can attribute the failure to a lack of experience.

Third, if nonfocal tasks have been successfully performed in the past but are now performed poorly, such failures may be considered surprising or unpredicted (i.e., *failures of previously successful nonfocal tasks*). Individuals form an expectation that nonfocal tasks that they had once successfully performed should be performed well because of the belief that they have already acquired the required skills.

These unpredicted failures garner more attention from individuals for three reasons. First, prior to performing tasks, individuals have aspiration levels and form expectations for their performance. If the actual performance is beyond their expectations, they are satisfied and take no remedial action. However, performances below expectations require a search for alternative routines (i.e., a problemistic search) (Cyert & March, 1963; Holmes, 2011). Unpredicted failures are perceived to be those significantly below expectations, so individuals preferentially allocate more attentional resources to remedying these failures. Second, unpredicted failures may stimulate a high degree of unpleasantness and discomfort (Kolb, 1984), generating strong emotional responses to avoid repeating such uncomfortable situations and prompting learning from the failures (Ellis, Mendel, & Nir, 2006; Louis & Sutton, 1991). Third, because individuals have a stronger preference for immediate small gains over remote large gains (i.e., temporal discounting) (Doyle, 2013; Kirby & Marakovic, 1995), they tend to react to failures that can be corrected with relative ease, such as failures that were supposed to be successful and to defer work on more serious problems.

To summarize, individuals perceive nonfocal failed tasks in the sequence to be unpredictable and salient if they require lower levels of skill for execution than the focal task, have been performed repeatedly, or were once successfully executed. The attentional interference for nonfocal failed tasks is more likely if there are the greater number of nonfocal failed tasks with these characteristics. Hence, we propose the following hypotheses:

Hypothesis 2a: The negative association between performance improvement in a previously failed focal task and the number of previous failures in nonfocal tasks is stronger if the nonfocal tasks are easier to perform than the focal task.

Hypothesis 2b: The negative association between performance improvement in a previously failed focal task and the number of previous failures in nonfocal tasks is stronger if the nonfocal tasks are repeated rather than unique.

Hypothesis 2c: The negative association between performance improvement in a previously failed focal task and the number of previous failures in nonfocal tasks is stronger if the nonfocal tasks have previously been performed successfully.

We summarize the proposed hypotheses in **Figure 1**.

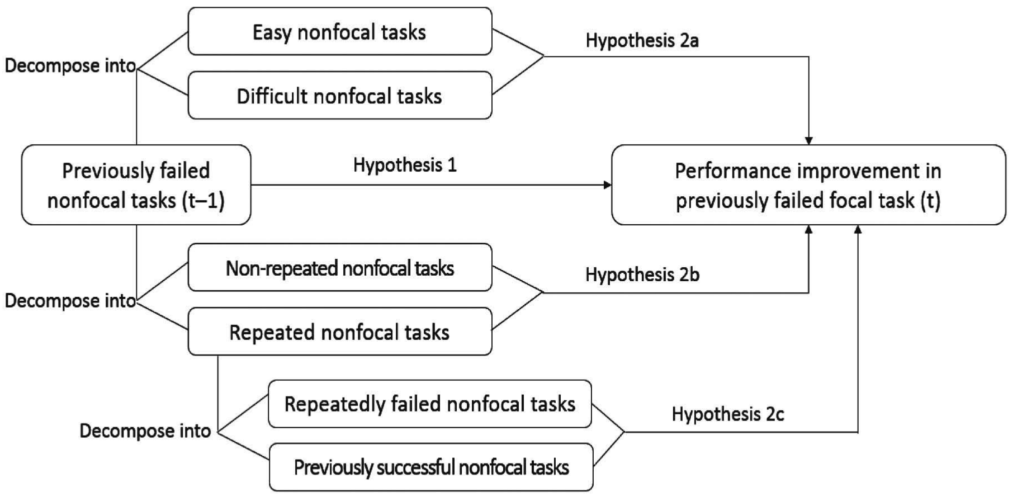

Figure 1: Summary of Hypotheses

Ⅳ Methods

1. Data Setting

Following previous findings on learning from failures, our hypotheses presume that an individual learns a task and improves his/her performance at time t if s/he fails to execute the task at time t–1. Based on this assumption, we developed our dataset, which consists of failed tasks of individuals at time t–1, and examined the conditions in which they do not learn from failures at time t. Before we developed the dataset and test hypotheses, we checked the validity of this premise by regressing task failures at time t–1 (i.e., a dummy variable coded as 1 if the GOE is below zero) on the GOE change at time t. In this analysis, we found that the subsequent performance improvement from time t–1 to time t is greater for tasks that skaters failed to perform at time t–1 ($p < .001$) than those that they successfully executed at time t–1.

Given the validity of our premise, we identified failed tasks at time t–1 and developed a dataset that only contains the failed tasks, namely tasks with GOEs below zero. We also excluded tasks from our dataset that were not consecutively performed over time that, by definition, exhibited no improvement or learning effects. These systematic exclusions of some parts of the data may cause a sample selection problem. To alleviate this problem, we employed a recursive two-stage approach in the estimation process (Heckman, 1979). We estimated a probit model to obtain the probabilities of a skater failing to perform a task in a competition, and then include the inverse Mills ratios obtained in regression models for hypothesis testing. The final dataset contains 3,186 observations, consisting of 107 skating techniques executed by 192 skaters. The unit of analysis in this study is skater–competition–task.

2. Variables

Dependent variables. In measuring *performance improvements*, we use changes in GOE scores for a focal task at time t, namely GOE scores at time t minus ones at time t–1.

Independent variables. Our independent variables capture the number of previously failed nonfocal tasks that the focal skater performed at time t–1 in the same sequences with the focal task. Nonfocal tasks are coded as failed if rewarded GOE scores below zero at time t–1. Because our hypothesis 1 suggests that the focal failed task experiences the attentional interference if competing against more nonfocal failed tasks in the same sequence for skaters' attention, we create a variable that counts the number of the nonfocal failed tasks (*failures in nonfocal tasks*). We expect that with an increase in the number of previously failed nonfocal tasks, an improved GOE score for the focal task is less likely.

We test hypothesis 2a with a variable that counts the number of previously failed nonfocal tasks that are easier than the previously failed focal task. To test this hypothesis, we decompose previously failed nonfocal tasks into two groups: those with higher base values (*failures in difficult nonfocal tasks*) and those with lower values (*failures in easy nonfocal tasks*) than the focal task. We then count the number of previously failed nonfocal tasks in each of the groups.

We test hypothesis 2b by counting the number of previously failed repeated nonfocal tasks (*failures in repeated nonfocal tasks*), namely nonfocal tasks that skaters failed at time t–1 and also performed, either successfully or poorly, at time t–2. Similarly, we count the number of previously failed nonrepeated nonfocal tasks (*failures in nonrepeated nonfocal task*), which skaters failed to perform well at time t–1 and did not include as part of the bundles at time t–2.

To test hypothesis 2c, we count the number of nonfocal tasks that skaters failed to perform at time t–1 but succeeded in performing at time t–2 with the premise that failure at time t–1 is unpredicted because of successful execution at time t–2. We consider the execution of a task to be successful if the GOE is greater than zero (*failures in previously successful nonfocal tasks*). We also count the number of nonfocal tasks that skaters failed to perform at both times t–1 and t–2 (*failures in repeatedly failed nonfocal tasks*).

Control variables. To eliminate the possibility of alternative explanations, we incorporate control variables at several levels: competition, skater, focal and nonfocal tasks. First, we control for the effects of competition characteristics at time t with three variables. Of the ISU competitions that we include in our sample, only competitions or events that are part of the *Grand Prix Series* have series structures such as the Grand Prix in the US, Canada, and China. In other words, the Grand Prix Series is composed of multiple competitions, so it is different from other competitions such as the Winter Olympics. Hence, we include a dummy variable that we code as 1 if the focal competition at time t when skaters' learning effects are observed is part of the Grand Prix Series and 0 otherwise. To capture home advantages (Carmichael & Thomas, 2005), we include a dummy variable that we code as 1 if the focal competition at time t is held in the focal skater's *home country* and 0 otherwise. To measure time intervals between the focal competition at time t and the preceding competition at time t–1, we enter log-transformed *elapsed days* between them.

Second, to control for the performers' characteristics, we include skaters' log-transformed *age* at time t. We also incorporate ranking at time t–2 by using a ratio of skaters' performance ranking to the total number of participants in the competition at time t–2, because past performance prior to time t–1 may influence the rates of performance improvements from time t–1 to t.

Third, we control for the characteristics of a focal task using three variables. We code a dummy variable as 1 if at time t, skaters perform the focal task in the *short program* and 0 otherwise. Because skaters may perform the same task in both the short and free programs, we also control for this possibility with a dummy variable, *both programs*, that we code as 1 if the focal skater performs the focal task in both of the programs and 0 otherwise at time t. Because the degree of failure in the focal task at time t–1 may affect performance improvement, we incorporate GOE for the focal task at time t–1 (*GOE at time t–1*). Fatigued skaters typically perform poorly in the later parts of the programs. Hence, we include the log-transformed number that indicates the order in which the focal tasks are performed in the *sequences* of tasks in the entire programs at time t. Finally, expecting skaters' performance to improve if the focal task is less difficult and was performed well in the past, we control for focal task difficulty by including its log-transformed *base values*, and enter a dummy variable that we code as 1 if the GOE of the focal task is greater than zero at time t–2 and 0 otherwise (*successful execution at time t–2*).

Fourth, we control for the characteristics of the nonfocal tasks using two variables. Different tasks in the same categories such as spins, spirals, step sequences, and jumps may have fundamental technical commonalities that allow skaters to transfer earned skills between them (Posen & Chen, 2013; Schilling, Vidal, Ployhart, & Marangoni, 2003). Thus, we control for the number of previously failed nonfocal tasks in the same category as the focal task at time t (*nonfocal tasks in the same categories*). Although we do not consider nonfocal tasks with zero GOE to be either failures or successes, their interpretation for performance improvement may differ between skaters. Hence, we enter the number of *nonfocal tasks with zero GOE*.

3. Model Specifications

Our data have a panel structure of cross-sectional time series. One underlying assumption of our argument is that performance improvement at time t is likely if performers learn effectively from the t–1 failure. Such rapid improvement may be questionable if performers inherently lack the skills for the tasks, or if learning takes time and requires the accumulation of several failures. That is, skaters have time-invariant backgrounds and abilities that are substantially different, and these heterogeneities may affect their learning rates and cause biased estimation. Hence, we use fixed-effect models to control for unobserved heterogeneity across skaters. We use *xtreg* commands in Stata 13.0 with the *fe* option.

V Results

Table 1 displays the means, standard deviations, and correlations of the variables that we use in the analysis. Although some of the variables that we create through decomposition procedures have high correlations, we do not use these variables in the same models. To assess multicollinearity, we check the variance inflation factors (VIFs) for all estimated models and find that the highest VIF is 1.35. These are below the threshold of 10, so we take no remedial action to correct for multicollinearity (Belsley, Kuh, & Welsch, 1980).

Table 2 shows the results of GLS to test hypotheses 1 and 2. Model 1 includes control variables only. To test hypothesis 1, we add the number of previously failed nonfocal tasks to model 2. The coefficient of this variable is negative and significant ($p < .05$); thus, the results suggest that the GOE improvement of the failed focal tasks decreases with the number of previously failed nonfocal tasks, supporting hypothesis 1.

In model 3, we use the focal task's base values as a cutoff point and test hypothesis 2a about the effects of the difficulties of previously failed nonfocal tasks with an expectation that easy tasks are perceived as unpredicted by skaters and thus garner more attention. We find that the coefficient of the number of easy nonfocal tasks is negative and significant ($p < .05$), suggesting that the improvement in GOE for the focal tasks decreases with an increase in the number of such nonfocal tasks. In contrast, we find that the coefficient of the number of previously failed difficult nonfocal tasks is not significant in model 3. These results thus appear to support hypothesis 2a.

Hypothesis 2b posits that skaters' learning from a previously failed focal task is limited by an increase in the number of previously failed nonfocal tasks that have been repeatedly performed, whether successfully or unsuccessfully, at both times t–2 and t–1. In model 4, to which we add counts of the number of repeated and nonrepeated nonfocal tasks, we find that the coefficient of the number of repeated nonfocal tasks is negative and significant ($p < .05$), whereas that of nonrepeated nonfocal tasks is not significant. Our analysis hence supports hypothesis 2b.

We test hypothesis 2c about the effects of nonfocal tasks that skaters failed to perform well at time t–1 but had successfully performed at time t–2, and the effects of nonfocal tasks that they failed to perform well at either time. We add the two variables in model 5 and find that the coefficient of the former variable is negative and significant ($p < .05$), but that of the latter variable is not significant. The results of model 5 support hypothesis 2c, suggesting that improvement in GOE for the focal task decreases at time t with an increase in the number of nonfocal tasks that skaters succeeded in performing at time t–2 but failed at time t–1.

We conduct three additional analyses as robustness checks. First, we redefine our dependent variables as GOE at time t instead of the changes from time t–1 to t. Second, we redefine failures by counting tasks with a zero GOE as well as those with a GOE below zero as failures. Third, there is a possibility that regardless of attentional interference, highly- or poorly-skilled skaters may experience performance improvement or decline for the focal tasks because of their skill levels, so we exclude from the sample if their ranking at time t-2 is above the 80th percentile or below the 20the percentile. Columns 1, 2 and 3 in each model in Table 3 show the results of the first, second and third additional analyses, respectively, using the variables that we used in Table 2. We find the results are comparable with those that we report in Table 2.

Table 1: Descriptive Statistics and Correlations

	Variable	Mean	SD	1	2	3	4	5
1	Performance improvement	.60	1.18					
2	Grand Prix Series	.47	.49	.00				
3	Home country	.14	.35	.02	.16			
4	Ln (elapsed days)	4.47	1.14	–.03	–.07	–.01		
5	Ln (age)	3.15	.13	–.03	–.14	–.07	.11	
6	Ranking at time t–2	.43	.26	–.11	–.28	–.09	.17	.09
7	Short program	.36	.39	–.10	–.07	–.02	.00	.03
8	Both programs	.30	.46	–.04	.00	.00	–.09	–.05
9	GOE at time t–1	–.99	.86	–.50	–.05	.00	.04	.05
10	Ln (sequences)	1.54	.57	–.03	–.03	–.02	.02	.06
11	Ln (base values)	1.80	.42	.20	.05	.04	–.12	–.01
12	Successful execution at time t–2	.34	.47	.14	.08	.04	–.09	–.01
13	Nonfocal tasks in the same categories	3.02	1.77	–.06	.14	–.03	.01	–.04
14	Nonfocal tasks with GOE zero	2.21	2.04	–.10	–.06	.00	.04	.12
15	Failures in nonfocal tasks	4.14	2.02	–.08	–.04	.03	.05	.07
16	Failures in difficult nonfocal tasks	1.82	1.68	–.10	–.01	.02	.06	.02
17	Failures in easy nonfocal tasks	2.29	1.87	.00	–.03	.01	–.01	.05
18	Failures in nonrepeated nonfocal tasks	.97	1.11	–.07	–.01	.00	–.02	–.09
19	Failures in repeated nonfocal tasks	3.18	1.73	–.05	–.03	.03	.07	.14
20	Failures in repeatedly failed nonfocal tasks	1.76	1.29	–.02	–.08	–.02	.10	.04
21	Failures in previously successful nonfocal tasks	.93	.98	.00	.10	.08	–.04	.09

	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
7	.13														
8	.00	.23													
9	.07	.10	.03												
10	.01	–.29	–.10	.28											
11	–.17	–.04	.12	–.32	–.32										
12	–.24	–.01	.02	.05	.07	.07									
13	.03	–.14	.00	–.13	–.11	.11	.07								
14	.23	.09	.01	.05	.02	–.09	.11	–.08							
15	.22	.05	–.01	.07	.06	–.13	–.09	–.10	.06						
16	.12	–.03	–.07	.22	.33	–.48	–.13	–.05	.13	.24					
17	.13	.08	.06	–.12	–.24	.29	–.48	–.02	–.04	.09	.50				
18	.14	.07	.00	.04	–.01	–.06	.29	–.04	.18	.17	.62	–.36			
19	.17	.01	–.01	.05	.07	–.12	–.06	–.03	.04	.18	.52	.20	.37		
20	.25	.03	–.02	.04	.05	–.12	–.12	–.04	.13	.16	.83	.46	.48	–.04	
21	–.15	–.04	.00	.00	.03	.04	–.12	–.07	.13	.09	.59	.33	.33	–.01	.70

N = 3186

Table 2: Results for Predicting Performance Improvement of Previously Failed Focal Tasks

Variable	Model 1		Model 2		Model 3		Model 4		Model 5	
Grand Prix Series	–0.022		–0.03		–0.031		–0.030		–0.020	
	(0.07)		(0.07)		(0.07)		(0.07)		(0.07)	
Home country	–0.034		–0.036		–0.038		–0.035		–0.032	
	(0.24)		(0.24)		(0.24)		(0.24)		(0.24)	
Ln (elapsed days)	0.032		0.036		0.038		0.037		0.035	
	(0.17)		(0.17)		(0.17)		(0.17)		(0.17)	
Ln (age)	1.117	*	1.060	*	1.061	*	1.083	*	1.132	*
	(0.52)		(0.52)		(0.52)		(0.53)		(0.53)	
Ranking at time t–2	–0.07		–0.078		–0.077		–0.077		–0.103	
	(0.10)		(0.10)		(0.10)		(0.10)		(0.10)	
Short program	–0.433		–0.449		–0.454		–0.450		–0.442	
	(0.41)		(0.41)		(0.41)		(0.41)		(0.41)	
Both programs	–0.065		–0.062		–0.063		–0.062		–0.064	
	(0.07)		(0.07)		(0.07)		(0.07)		(0.07)	
GOE at time t–1	–1.045	***	–1.046	***	–1.045	***	–1.046	***	–1.044	***
	(0.03)		(0.03)		(0.03)		(0.03)		(0.03)	
Ln (sequences)	–0.439		–0.478		–0.489		–0.48		–0.462	
	(1.02)		(1.02)		(1.02)		(1.02)		(1.02)	
Ln (base values)	0.626	***	0.624	***	0.626	***	0.623	***	0.631	***
	(0.17)		(0.17)		(0.17)		(0.17)		(0.17)	
Successful execution at time t–2	–0.337	***	–0.335	***	–0.335	***	–0.336	***	–0.334	***
	(0.05)		(0.05)		(0.05)		(0.05)		(0.05)	
Nonfocal tasks in the same categories	–0.064	***	–0.066	***	–0.066	***	–0.066	***	–0.064	***
	(0.01)		(0.01)		(0.01)		(0.01)		(0.01)	
Nonfocal tasks with zero GOE	–0.025		–0.025		–0.025		–0.025		–0.023	
	(0.02)		(0.02)		(0.02)		(0.02)		(0.02)	
Lambda	0.651		0.738		0.765		0.741		0.695	
	(2.45)		(2.45)		(2.45)		(2.45)		(2.45)	
Failures in nonfocal tasks			–0.030	*						
			(0.01)							
Failures in difficult nonfocal tasks					–0.030					
					(0.02)					
Failures in easy nonfocal tasks					–0.029	*				
					(0.01)					
Failures in nonrepeated nonfocal tasks							–0.025		–0.019	
							(0.02)		(0.02)	
Failures in repeated nonfocal tasks							–0.032	*		
							(0.01)			
Failures in repeatedly failed nonfocal tasks									0.002	
									(0.02)	
Failures in previously successful nonfocal tasks									–0.050	*
									(0.02)	
Constant	–4.704	**	–4.436	*	–4.463	*	–4.508	*	–4.711	*
	(1.81)		(1.82)		(1.82)		(1.84)		(1.84)	
R-squared	0.418		0.420		0.420		0.420		0.420	
F	98.34	***	92.41	***	86.57	***	86.60	***	81.45	***
N	3186		3186		3186		3186		3186	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are in parentheses.

Table 3: Results of Robustness Checks

Variables	Model 6			Model 7			Model 8			Model 9		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Failures in nonfocal tasks	–0.030 *	–0.022 **	–0.056 **									
	(0.01)	(0.01)	(0.02)									
Failures in difficult nonfocal tasks				–0.030	–0.021 *	–0.032						
				(0.02)	(0.01)	(0.03)						
Failures in easy nonfocal tasks				–0.029 *	–0.023 **	–0.065 **						
				(0.01)	(0.01)	(0.02)						
Failures in nonrepeated nonfocal tasks							–0.024	–3.E–04	–0.057	–0.018	0.008	–0.050
							(0.02)	(0.01)	(0.03)	(0.02)	(0.01)	(0.03)
Failures in repeated nonfocal tasks							–0.032 *	–0.029 ***	–0.055 **			
							(0.01)	(0.01)	(0.02)			
Failures in repeatedly failed nonfocal tasks										0.002	0.004	–0.024
										(0.02)	(0.01)	(0.03)
Failures in previously successful nonfocal tasks										–0.051 *	–0.045 *	–0.065 *
										(0.02)	(0.02)	(0.03)
Constant	–4.167 **	–2.413 *	–6.317 *	–4.184 **	–2.421 *	–6.225 *	–4.254 **	–2.923 *	–6.300 *	–4.489 **	–3.673 **	–6.696 *
	(1.44)	(1.13)	(2.55)	(1.44)	(1.13)	(2.56)	(1.47)	(1.16)	(2.58)	(1.47)	(1.15)	(2.60)
Δ R-squared	0.002	0.002	0.006	0.002	0.002	0.006	0.002	0.003	0.006	0.002	0.002	0.002
N	3186	4461	1922	3186	4461	1922	3186	4461	1922	3186	4461	1922

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are in parentheses.

Ⅵ Discussion

Using data on learning in a multitask setting by single figure skaters, this study examines how individuals learn from failures in multitask settings, and more specifically how the attention interference hampers learning from failures in a multitask setting. The results show that individuals learn less from past failures in a focal task if there are more nonfocal tasks that they failed to perform well and that need their attention. We also find that this propensity for ineffective learning from failures becomes stronger when the past failure of the nonfocal tasks is unpredicted; specifically, if they are less difficult than the focal task, repeatedly performed, or have been successfully performed in the past, because such failures trigger a search for alternative routines and distract attention.

These findings contribute to the preexisting literature in at least the following two ways. First, the findings apply insights on learning from failures to the investigation of learning in multitask settings. Previous research on learning from failures assumes a situation where individuals engage in a single task and learn from a single task failure, although in diverse forms of work, such as the arts, physical labor, and sports, individuals execute a bundle of multiple motor tasks and simultaneously experience multiple failures. This study shifts the focus from learning from failures in single task settings to that in multitask settings, and finds attention interference to be a determinant of learning from failures in multitask settings. Second, in the literature there are some previous studies that identify attentional interference in multitask settings on human cognition and attention. However, these studies limit the focus on attentional interference during multitasking executions, not on learning processes (Konig et al., 2005; Meyer & Kieras, 1997; Pashler, 1994). This study shows that attentional interferences are observed in learning processes of multiple tasks as well as in multitasking executions, and proposes that not only do the effects of the number of tasks distract individuals' attention but also that the characteristics of tasks further distract them from the learning processes.

In addition, our results provide several implications about learning and practices of motor tasks, which we believe to be relevant to athletes and their coaching staff. First, to increase the speed and rates of learning, athletes should be cognizant of the attentional interference and design a set or bundle of tasks that reduces the extent of attentional interference in the learning processes. If there are more tasks in a set that compete for attention, learning rates will be reduced. In particular, from the learning standpoint, athletes at an early stage of their careers should be cautious about choosing what to include in a set or sequence of practice tasks. An attempt to improve all of the failed tasks simultaneously may retard overall learning processes.

Second, our findings suggest that one of the reasons that players learn very few skills in executing difficult tasks is that they attend more to other previously failed tasks that are less difficult. Because in some cases it is difficult rather than easy tasks that actually need more attention to optimize overall performance in multitask settings, learners need to recognize this attentional pattern when formulating strategies so as to learn from their failures in multitask settings. On the basis of our findings, it may be argued that those who need to learn skills for difficult tasks in multitask settings should exclude from the bundles other tasks that they perceive to be unpredicted when they fail to perform them well. Such exclusions would increase their focus on learning from failures in difficult tasks. However, it is remarkable that our evidence does not directly indicate strategies that optimize learning rates in multitask settings, which should be one of the themes of future research.

Finally, our results offer a warning that nonfocal tasks that have characteristics and commonalities with the focal task may also exacerbate the attentional interference. The literature on skill transfers such as a study by

Darr, Argete and Epple (1995) suggest there is a positive spillover in multitask settings; individuals can transfer commonly used skills and competence across multiple tasks with high degrees of similarity, which enables them to conserve cognitive costs for execution and learning. However, we find that the coefficient of the number of nonfocal tasks in the same category as the focal task is negative and significant (see Table 2), from which we draw two alternative interpretations. One potential interpretation is that skaters may lack inherent skills for executing tasks in some specific categories such as jumps and spins, which is unlikely as we use fixed-effects models. The alternative interpretation is that different tasks, even in the same categories, require different sets of tasks, so skaters should not expect positive spillovers of skills that they develop for one task to other tasks in the same category. Moreover, with the expectation of such spurious positive spillovers, skaters may further experience a delay in skill acquisition.

This study has several other limitations, which suggest directions for future research. First, we focus exclusively on the attentional interference; consideration should be given to other time-invariant factors that could influence learning in multitask settings. One such factor may be working memory capacity (Hambrick et al., 2010), which varies across situations, such as in response to the pressure that skaters perceive as a result of interim rankings or over time as a result of routinization of task execution (Bothner, Kang, & Stuart, 2007). Second, although individuals may have different strategies for pursuing overall performance in multitask settings, we still know little about which strategies are available and which are more effective under what conditions. In addition, there may be individual differences in terms of inertia and maintaining attention or capability to switch back and forth between tasks that need attention (Ocasio & Wohlgezogen, 2010). Future research should examine how such switching occurs and the factors that enable individuals performing tasks to switch. Third, our research context of skating performances—which allows us to control for unobserved individual heterogeneity and estimate performance improvements—is also notably unique, and this may limit the generalizability of our findings. Future research should conduct both field and experimental research in other contexts to advance our understanding of the role of learning in multitask performance.

Despite any shortcomings, we believe that this study makes a substantial contribution to the literature on learning from failures by incorporating insights from the literature on multitask settings, and shows that the attentional interference is a factor that accounts for the rates of learning from failures in multitask settings. Our findings and their implications open up exciting new avenues to advance our knowledge about individuals' performance.

References

Bai, H., Jones, W.E., Moss, J., & Doane, S.M. (2014). Relating individual differences in cognitive ability and strategy consistency to interruption recovery during multitasking. *Learning and Individual Differences, 35*, 22–33.

Baumeister, R.F., Bratslavsky, E., Finkenauer, C., & Vohs, K.D. (2001). Bad is stronger than good. *Review of General Psychology*, *5*, 323–370.

Bies, R. J. (2013). The delivery of bad news in organizations: A framework for analysis. *Journal of Management, 39*, 136-162.

Bothner, M.S., Kang, J.H., & Stuart, T.E. (2007). Competitive crowding and risk taking in a tournament: Evidence from NASCAR racing. *Administrative Science Quarterly, 52*, 208–247.

Boyce, J., & Bischak. D.P. (2010). Learning by doing, knowledge spillovers, and technological and organizational change in high-altitude mountaineering. *Journal of Sports Economics, 11*, 496–532.

Broadbent, D. (1958). *Perception and Communication*. London: Pergamon Press.

Burgess, P. W. (2000). Real-world multitasking from a cognitive neuroscience perspective. *Attention and Performance, 18,* 465–472.

Carmeli, A., & Gittell, H.J. (2009). High-quality relationships, psychological safety and learning from failures in work organizations. *Journal of Organizational Behavior, 30*, 709–729.

Carmichael, F., & Thomas, D. (2005). Home-field effect and team performance: Evidence from English premiership football. *Journal of Sports Economics, 6*, 264–281.

Cinquanta, O., & Schmid, F. (2014). http://www.isu.org/en/single-and-pair-skating-and-ice-dance/isu-judging-system/introduction.

Cyert, R.M., & March, J.G. (1963). *A Behavioral Theory of the Firm*. Englewood

Darr, E.D., Argote, L., & Epple, D. (1995). The acquisition, transfer, and depreciation of knowledge in service organizations: Productivity in franchises. *Management Science, 41*, 1750–1762.

Doyle, J.R. (2013). Survey of time preference, delay discounting models. *Judgment and Decision Making, 8*, 116–135.

Ellis, S., Mendel, R., & Nir, M. (2006). Learning from successful and failed experience: The moderating role of kind of after-event review. *Journal of Applied Psychology, 91*, 669–80.

Finkenauer, C., & Rime, B. (1998). Socially shared emotional experiences vs. emotional experiences kept secret: Differential characteristics and consequences. *Journal of Social and Clinical Psychology, 17*, 295–318.

Haas, M.R., Criscuolo, P., & George, G. 2015. Which problems to solve? Online knowledge sharing and attention allocation in organizations. *Academy of Management Journal, 58*, 680–711.

Hambrick, D.Z., Oswald, F.L., Darowski, E.S., Rench, T.A., & Brou, R. (2010). Predictors of multitasking performance in a synthetic work paradigm. *Applied Cognitive Psychology, 24*, 1149–1167.

Heckman, J.J. (1979). Smple selection bias as a specification error. *Econometrica, 47*, 153–161.

Holmes, P. (2011). Win or go home: Why college football coaches get fired. *Journal of Sports Economics, 12*, 157–178.

Kirby, K.N., & Marakovic, N.N. (1995). Modeling myopic decisions: Evidence for hyperbolic delay discounting within subjects and amounts. *Organizational Behavior and Human Decision Processes, 64*, 22-30.

Kolb, D.A. (1984). *Experiential Learning: Experience as the Source of Learning and Development*. Englewood Cliffs, NJ: Prentice Hall.

Konig, C. J., Buhner, M., & Murling, G. (2005). Working memory, fluid intelligence, and attention are predictors of multitasking performance, but polychronicity and extraversion are not. *Human Performance, 18*, 243–266.

Levinthal, D., & March, J.G. (1981). A model of adaptive organizational search. *Journal of Economic Behavior and Organization, 2*, 307–333.

Levitt, B., & March, J.G. (1988). Organizational learning. *Annual Review of Sociology*, *14*, 319–340.

Louis, M.R., & Sutton, R.I. (1991). Switching cognitive gears: From habits of mind to active thinking. *Human Relations, 44*, 55–76.

Love, E.G., Love, W.D., & Northcraft, G.B. (2010). Is the end in sight? Student regulation of in-class and extra-credit effort in response to performance feedback. *Academy of Management Learning & Education, 9*, 81–97.

Meyer, D.E., & Kieras, D.E. (1997). A computational theory of executive cognitive processes and multiple-task performance: Part 1. Basic mechanisms. *Psychological Review, 104*, 3–65.

Monsell, S. (2003). Task switching. *Trends in Cognitive Sciences, 7*, 134–140.

Ocasio, W. (1997). Towards and attention-based view of the firm. *Strategic Management Journal, 18*, 187–206.

Ocasio, W., & Wohlgezogen, F. (2010). Attention and Control. *In Organizational Control: New Directions in Theory and Research*, edited by Sitkin, S., Cardinal, L., Bijlsma-Frankema, K.M., 343–398.

Pashler, H. (1994). Dual-task interference in simple tasks: Data and theory. *Psychological Bulletin, 16*, 220–244.

Piezunka, H., & Dahlander, L. (2015). Distant search, narrow attention: how crowding alters organizations' filtering of suggestions in crowdsourcing. *Academy of Management Journal, 58*, 856–880.

Posen, H.E. & Chen, J. S. (2013). An advantage of newness: Vicarious learning despite limited absorptive capacity. *Organization Science, 24*, 1701–1716.

Rerup, C. (2009). Attentional triangulation: Learning from unexpected rare crises. *Organization Science, 20*, 876–893.

Schilling, M.A., Vidal, P., Ployhart, R.E., & Marangoni, A. (2003). Learning by doing something else: Variation, relatedness, and the learning curve. *Management Science, 49*, 39–56.

Schultz, M. (2002). Organizational learning. In J. A. C. Baum (Ed.), *Companion to Organizations* (pp. 415-441). Oxford, UK: Blackwell Publishers.

Sitkin, S.B. (1992). Learning through failure: The strategy of small losses. *Research in Organizational Behavior*, 14, 231–266.

Starbuck, W.H., & Milliken, F.J. (1988). Executives' perceptual filters: What they notive and how they make sense. In D. Hambrick (Ed.), *The Executive Effect: Concepts and Methods for Studying Top Managers* (pp. 35-66). Greenwich, CT: JAI Press.

Sullivan, B.N. (2010). Competition and beyond: Problems and attention allocation in the organizational rulemaking process. *Organization Science, 21*, 432–450.

Thornton, R.A., & Thompson, P. (2001). Learning from experience and learning from others: An exploration of learning and spillovers in wartime shipbuilding. *American Economic Review, 91*, 1350–1368.

Weiner, B. (1985). An attributional theory of achievement motivation and emotion. *Psychological Review, 92*, 548–573.

Zitzewitz, E. (2014). Does transparency reduce favoritism and corruption? Evidence from the reform of figure skating judging. *Journal of Sports Economics, 15*, 3–30.