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Switch rates vary due to expected payoff but not due to individual risk tendency

Laura Broeker [a,*], Joseph G. Johnson [b], Rita F. de Oliveira [c], Harald E. Ewolds [d], Stefan Künzell [d], Markus Raab [a,c]

[a] German Sport University Cologne, Institute of Psychology, Am Sportpark Müngersdorf 5, 50933 Cologne, Germany
[b] Miami University, Department of Psychology, 100B Psychology Building Oxford, OH 45056, USA
[c] London South Bank University, School of Applied Sciences, 103 Borough Road, London SE1 0AA, United Kingdom
[d] Augsburg University, Institute of Sports Science, Universitätsstraße 3, 86135 Augsburg, Germany

ABSTRACT

When switching between different tasks, the initiation of task switches may depend on task characteristics (difficulty, salient cues, etc.) or reasons within the person performing the task (decisions, behavioral variability, etc.). The reasons for variance in switching strategies, especially in paradigms where participants are free to choose the order of tasks and the amount of switching between tasks, are not well researched. In this study, we follow up the recent discussion that variance in switching strategies might be partly explained by the characteristics of the person fulfilling the task. We examined whether risk tendency and impulsiveness differentiate individuals in their response (i.e., switch rates and time spent on tasks) to different task characteristics on a tracking-while-typing paradigm. In detail, we manipulated two aspects of loss prospect (i.e., "payoff" as the amount of points that could be lost when tracking was unattended for too long, and "cursor speed" determining the likelihood of such a loss occurring). To account for between-subject variance and within-subject variability in the data, we employed linear mixed effect analyses following the model selection procedure (Bates, Kliegl, et al., 2015). Besides, we tested whether risk tendency can be transformed into a decision parameter which could predict switching strategies when being computationally modelled. We transferred decision parameters from the Decision Field Theory to model "switching thresholds" for each individual. Results show that neither risk tendency nor impulsiveness explain between-subject variance in the paradigm, nonetheless linear mixed-effects models confirmed that within-subject variability plays a significant role for interpreting dual-task data. Our computational model yielded a good model fit, suggesting that the use of a decision threshold parameter for switching may serve as an alternative means to classify different strategies in task switching.

1. Introduction

The allure of multitasking is the (false) belief of saving time and of increasing productivity by undertaking multiple tasks and dividing attention between them. A typical way of undertaking more than one task at the same time is by interleaving independent tasks and switching back and forth between them, for instance responding to an incoming text message while watching a movie on TV. Switches to another task may be initiated by external cues (i.e., the humming phone), or by the person (i.e., boredom, attentional deficits or seeking variety; Adler & Benbunan-Fich, 2013; Gopher et al., 1982; Janssen & Brumby, 2015).

In psychological research, such behaviors have been tested in task-switching paradigms requiring participants to perform two tasks presented sequentially. Task switching includes strictly performing two tasks sequentially, selecting either task in each trial oneself (i.e., voluntary task-switching) and self-interruptions "where performance of a primary task is interrupted, either by a significant temporal break, requiring a 'restart,' or by an intervening task, so that the primary task needs to be resumed" (Koch et al., 2018, p. 560). Especially those switching paradigms, allowing participants to choose the order of tasks and/or the amount of switches between tasks without noticeable cues in the task, reveal great within-subjects variability and between-subject variance in switch rates. The majority of dual-task experiments however has ignored or subtracted out (i.e., by calculating group or condition means) any potential factors leading to variance in performance within or among individuals - rather than meaningfully explaining them. Thus, neither reasons for the emergence of changing priorities and the related decision to switch, nor the reasons why some people spend more time on a task than others, are well researched. Beyond, with the main focus being on how the sample as a whole responds to experimental manipulations and participants being replaceable, the potential interaction between individual characteristics or preferences, and task

* Corresponding author.
E-mail addresses: l.broeker@dshs-koeln.de (L. Broeker), johnsojg@miamioh.edu (J.G. Johnson), r.oliveira@lsbu.ac.uk (R.F. de Oliveira), harald.ewolds@sport.uni-augsburg.de (H.E. Ewolds), stefan.kuenzell@sport.uni-augsburg.de (S. Künzell), raab@dshs-koeln.de (M. Raab).

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characteristics remains largely unexplored (Koch et al., 2018). To examine causes of variance in switching, researchers should focus more on within-subject variability in data sets (e.g., analyzing switching from trial to trial rather than sample means) or, as it has been recommended lately, include state and trait variables that have the potential to explain variance or stability in task performance (e.g., accuracy/RT) across different experimental conditions (Goodhew & Edwards, 2019). Beyond that, it has been recommended "to use continuous measures of variables by default wherever practically possible (…) with cognitive measures" (Goodhew et al., 2015, p. 21), because they allow differentiating participants not only in dichotomous categories like responder/non-responder but in more nuanced ways.

There is some preliminary evidence for the interaction effects of individual and task characteristics on switching. For instance, the strategic-task-overload-management model by Wickens et al. (2015) posits that task difficulty, task salience, or perceived attractiveness of a task change the likelihood for switches. Furthermore, experiments by Farmer et al. (2018) investigated how payoff functions affected people's task priorities and effort division between tasks. In their dual-task setup, participants copied a string of digits that were presented on the left half of the monitor, while controlling a randomly moving cursor within a target circle which was presented on the right half of the monitor (see Fig. 1). Critically, participants were only able to see and work on one task at a time, because the unattended task was occluded. They were instructed that they could gain points for copying digits (i.e., reward prospect), but would be penalized and lose points as soon as the cursor exited the circle (i.e., loss prospect when the tracking task was unattended for too long), so they had to actively switch between tasks. The penalty varied between losing all or half of the points gained so far and losing a fixed amount of points. This way the potential payoff for switching differed. The paradigm therefore differs from other switching paradigms in terms of risk: while normally switching is considered a risky decision because it requires cognitive effort and is associated with switch costs, in this paradigm, *not* switching and ignoring the other task for too long is associated with a higher likelihood of circle exits and thus increasing loss prospects.

Farmer and colleagues hypothesized that in contrast to verbal instructions which can be subject to interpretations (e.g., "divide your attention 80:20 between tasks"), rewards and losses, and thus a payoff function, could more effectively convey how tasks should be prioritized relative to one another. Their results suggest that people can indeed adopt a near-optimal strategy after some practice, but that "the way in which people interleave tasks depends on a variety of factors" (p. 843). The authors pointed out that not only task characteristics (i.e., speed of cursor movement) but also individual characteristics like risk aversion may have affected the way participants handled the tasks. We took this as an invitation to examine whether risk tendency and impulsiveness differentiate individuals in their response to task characteristics in the same paradigm (see Fig. 1).

1.1. Risk tendency

Evidence that risk tendency explains variance in switching strategies is scarce. Driving simulation studies showed that people scoring high on risk measures hazard consequences in driving, like veering off-road, and switch more often to other tasks like cell phone use (Mizobuchi et al., 2013; Sween et al., 2017). Studies using classic switching paradigms mostly manipulated rewards and reward prospect (Braem et al., 2012; Fröber et al., 2018; Fröber & Dreisbach, 2016). Both, expected value (e.g., reward), and risk can increase the expected utility of an option, especially in risk-seeking individuals (Tobler et al., 2009), and thus the likelihood of choosing an option. Studies manipulating reward prospect have shown that, for instance when sequentially changing reward prospect, increasing reward prospect increased voluntary switch rates and reduced switch costs (Fröber & Dreisbach, 2016). Brüning and Manzey (2018) identified different processing strategies in a switching paradigm which were interpreted as a flexible adaptation to the level of risk for interference. Participants had to classify two sets of letters (A, B, C, E vs. O, U, X, Z) regarding their position in the alphabet (first half vs. second half) and their kind of sound (consonant vs. vowel) and received a preview about upcoming stimuli. Based on the results, they were able to differentiate between serial, semi-overlapping or overlapping processing of the two tasks. This means some participants switched more often between tasks using preview information to reduce switch costs, others did not use the information provided and processed the tasks strictly serially. Brüning and Manzey argued that personal preferences may have contributed to the three different ways of handling the tasks but this was not validated by separate measures. It also has to be noted that conclusions about the between-subject variance were drawn from condition means. Thus, the results represent responses to task characteristics, but ignore individuals as random effects, and thus variability between repeated measures. To address this limitation, linear mixed effect analyses should be employed accounting for both between-subject variance and within-subject variability in the data.

1.2. Impulsiveness

It has been shown that higher levels of impulsiveness, and sensation seeking as one of its dimensions, is related to more switching between multimedia devices, to secondary tasks in driving simulations (e.g., cell phone use while driving, Sanbonmatsu et al., 2013; Schutten et al., 2017) and to frequent multitasking in general (Ophir et al., 2009). Like risk tendency, impulsiveness has been related to reward prospect. Burnett Heyes et al. (2012) demonstrated that impulsive individuals, especially those scoring high on motor impulsivity, accumulated higher reward in a task that required them to take risks under time pressure, so impulsivity was beneficial to time-sensitive risk decisions. Carver (2006) pointed out that impulsive individuals seem to be 'highly engaged in the pursuit of whatever incentives arise' (p. 107), whereas others reflect more on punishment for mistakes. Based on these findings, it seems useful to examine both risk tendency and impulsiveness, because both are related to reward prospect (see also Martin & Potts, 2004) and may explain variance in switching behavior.

1.3. Risk and impulsiveness in the typing-while-tracking paradigm

As outlined above, our aim was to examine whether risk tendency and impulsiveness differentiate individuals in their response (i.e., switch rate and time spent on the typing task ("time-on-typing")[1]) to task characteristics (i.e., "payoff" which is the amount of points that could be lost when tracking was unattended for too long, and "cursor speed" determining the likelihood of such a loss occurring) in the switching paradigm by Farmer et al. (2018). Our hypotheses are as follows:

People with a higher individual risk tendency have a lower threshold for making risky choices. The more risk-prone an individual, the better this individual will tolerate potential losses and thus is predicted to stay longer on the typing task and switch less often between tasks. It is further hypothesized that variance between risk-averse and risk-prone individuals will be more pronounced in conditions with high loss prospects, i.e., for higher cursor speed (= higher likelihood of exit) and higher penalties for circle exits (= higher penalty increasing the payoff between tasks).

The same data pattern could be predicted for impulsiveness. The more impulsive an individual, the more reward-seeking this individual will be and thus is predicted to spend more time on the typing task and switch last-minute, resulting in an overall lower switch rate. Alternatively, the more impulsive an individual, the lower the ability to capture attention which is why this individual might find switching itself

[1] Additional dependent variables in the appendix are the number of digits typed (no-of-digits-typed) and typing errors.

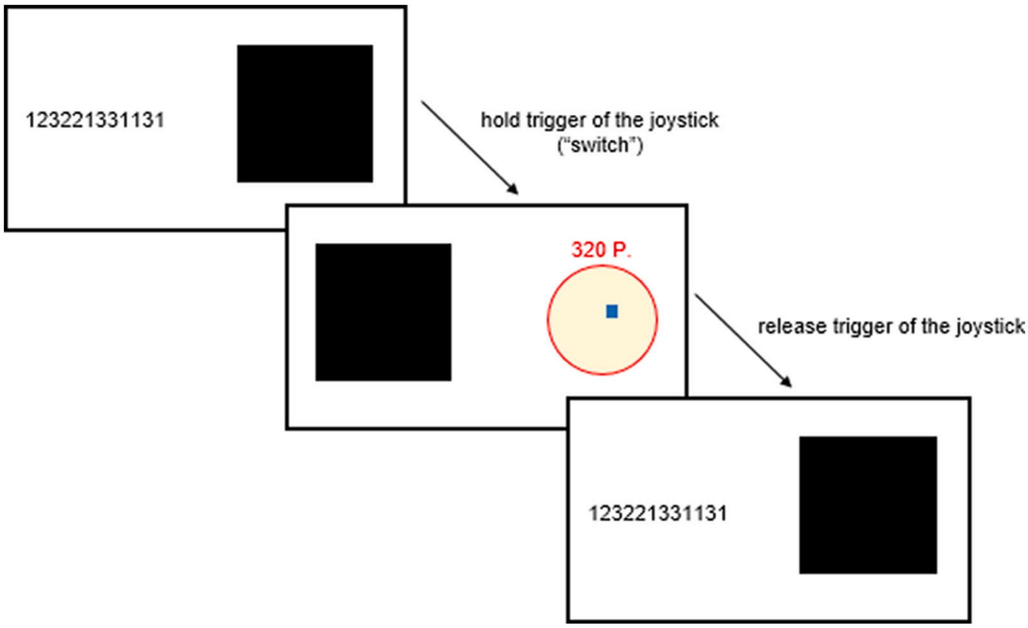

Fig. 1. Typing-while-tracking paradigm by Farmer et al. (2018)
Note: In the typing-while-tracking paradigm participants have to type as many digits as possible while ensuring the target square would not exit the circle. By default, the typing task on the left half of the monitor was visible and the tracking task was occluded. Participants could switch to the tracking task on the right half of the monitor by holding the trigger of a joystick to then control the square, and switch back by releasing the trigger to then continue typing. Participants gained points through typing (10 p per digit) and saw interim scores when switching to the tracking task (e.g., 320 p when having typed 32 digits before the switch). They were instructed that they would lose points if the target exited the circle. In this way, not switching for a longer time equaled higher risk (of losing points).

rewarding, resulting in an overall higher switch rate.

1.4. Research strategy A) conceptual replication and extension of Farmer et al. (2018)

To examine whether different penalties and cursor speed, as well as risk-tendency and impulsiveness, produce variance and variability in switch rates and/or time spent on tasks, we employed self-report questionnaires and behavioral measures of risk tendency and impulsiveness prior to or after testing participants on the typing-while-tracking paradigm. It has been recently stressed that behavioral and self-report measures often correlate weakly because they are designed to measure different response processes (Dang et al., 2020): while behavioral measures encourage people to do their best and thus include effort and willingness, "self-report measures tend to tap people's typical performance about how they usually behave" (p. 2). Apart from this issue, using both can be useful because they are sensitive to within-person experimental manipulations and "can be important for studying the processes that underlie task performance or the contexts that enhance or detract from task performance" (p. 3). In this regard, Konig et al. (2005), who measured working memory, fluid intelligence, and attention with behavioral tasks, plus polychronicity and extraversion with questionnaires, concluded that only the behavioral measures were able to predict multitasking performance. The divergence between behavioral and self-report measures in relation to the prediction of multitasking performance shows that it is important to include more objective measures when examining causes for variance in switching.

1.5. Research strategy B) exploring the modelling of switching decisions

It has been suggested that multitasking can be understood as a choice for instance by prioritizing one task over another in switching paradigms (for the full proposal see Broeker et al., 2018). If time spent on tasks and switching were understood as decisions, then it would be reasonable to examine switching decisions with the help of decision-making theory and transfer its approaches to multitasking. The idea of such a transfer was also put forward by Pashler et al. (2008), who claimed that the contribution of decision processes should not be underestimated for dual-task processing because cognitive decision models could help understanding latency effects in dual-tasking. As shown by Broeker et al. (2018), many of the constructs and model parameters employed in basic decision-making paradigms are translatable to multitasking studies. For example, the Decision Field Theory (Busemeyer & Townsend, 1993) is a probabilistic and dynamic model explaining and modelling flexible choices by utilizing several parameters. In general, it assumes that preference fluctuates back and forth between two options based on attention during a choice task, and a *threshold parameter* defines how much information, and thus time, a decision-maker needs before choosing an option. The total amount of evidence needed to reach a threshold is a random variable N and the decision time is an increasing function of N (Busemeyer & Townsend, 1993). In multitasking, the threshold would be defined as the moment in time where the person switches to the other task. This parameter could therefore model the dynamic change of preference towards either of two tasks (rather than options) over time, and predict how much time an individual needs before switching.

Thresholds depend on various external and also individual factors like personal experience with an option, or characteristics like risk tendency (Scheibehenne et al., 2009). Transferred to multitasking, switching thresholds could therefore be determined by measuring additional characteristics of the participant or by manipulating task characteristics like points or time pressure.

For the cognitive model, this would mean that the more risk-prone and/or the more impulsive an individual, the higher the switching threshold. A higher threshold implies switching later and thus less often within a predefined time window. The threshold is further predicted to be lower in *all* individuals in conditions with higher loss prospect, that is, every person is predicted to pass the threshold earlier when cursor speed and/or potential loss is high.

Summing up, this study aimed at extending findings by Farmer et al. (2018) and examine whether specific characteristics of different people may explain variance in switching strategies. Second, the study aimed to follow-up an earlier proposal and implemented exploratory analyses testing the hypothesis that switching thresholds as decision parameters in computational models represent a useful extension to the field of dual-task research. By exploring and applying computational models, we could formalize individual behavior, allowing us to generalize findings to new tasks, environments, and situations, beyond simply interpreting main effects of experimental manipulations.

2. Method A (main analyses)

2.1. Participants

Following the original study, the sample size was based on Farmer et al. (2018; Exp. 2) who tested and modelled data with 30 participants. We recruited 33 participants on campus. Participants were excluded from data analysis if they violated the instruction to switch between tasks in three or more of the nine dual-task trials. Three participants were excluded, yielding a total sample of 30 participants (11 male and 19 female; aged between 19 and 29 years, $M = 22.47$ years, $SD = 2.40$).

Participants gave written informed consent before the experiment and received a small remuneration or course credit for taking part. The experiments were approved by the local ethics committee and conformed to the principles of the Declaration of Helsinki 2008.

2.2. Setup

Participants completed three computer tasks (typing-while-tracking paradigm, one computerized risk measure, one computerized impulsiveness measure) and four pen-and-paper questionnaires (order counterbalanced: two risk questionnaires, two impulsiveness questionnaires). For the computerized tasks, participants were seated at a table with a viewing distance of 60 cm from a 24-in computer screen (144 Hz, 1920 × 1080 pixel resolution). We used a Windows 10, 64-bit system with a GTX750 graphics card. The keyboard's numeric pad and participant's left hand were concentered to the left half of the monitor; a spring-loaded joystick (SpeedLink Dark Tornado, max. sampling rate 60 Hz) and participant's right hand were concentered on the right half of the monitor. For the questionnaires participants were seated at a separate small table. The experimenter sat behind an opaque divider to monitor compliance with the task.

2.3. Tasks

2.3.1. Typing-while-tracking paradigm

The dual-task paradigm was based on Farmer et al. (2018). Participants controlled a typing and a tracking task in parallel but actively switched between them as only one task could be worked on at a time. The typing task (digits) was presented on the left side of the monitor, and participants had to copy a never-ending 27-digit-string of the numbers 1–3 with their left hand using a numeric keypad (see Fig. 1). The tracking task was presented on the right side of the monitor, and participants had to control a randomly moving target square within a circular target area with a joystick. Each task was practiced as a single task before each dual-task block.

In dual-task conditions, the tracking task was occluded by default, so participants had to press the trigger of the joystick to switch from typing to tracking. Releasing the trigger enabled switching back to typing. For each digit correctly copied, participants were rewarded with 10 points; incorrectly copied digits led to a deduction of 5 points. As soon as each digit was typed in correctly, it disappeared automatically. If an incorrect entry was made, the digit remained until it was typed in correctly. To see the sum of points participants had gained during their visit to the typing window, they had to switch to the tracking task because the interim sum was displayed above the circular area (see Fig. 1). Crucially, participants had to judge how long they could leave the tracking task unattended because a cursor drift outside the circular target area made participants lose points. The penalty for a circle exit varied between "losing half of the points," "losing all points," and "losing a fixed amount of 500 points" (within-subjects factor "Payoff"). These were assumed to ordinally vary risk and losing 500 points was considered the highest risk because participants' points could become negative.[2] Further, the target cursor's movement was more or less variable thus moved at different cursor speeds (low: 3 pixels standard deviation vs. high: 5 pixels standard deviation; within-subjects factor "Cursor Speed"). The higher the cursor speed, the higher the probability that the target square would exit the circle. For instance, an 80% probability of exit was reached after 20 s in high cursor speed conditions, and only after 50 s in low speed conditions (for the formula see Farmer et al., 2018). Overall, the study had a 3 (Payoff, half vs. all vs. 500) × 2 (Cursor Speed, low vs. high), within-subjects design. At the beginning of the experiment, participants completed six familiarization trials (high cursor-speed tracking for two trials of 10 s each and typing for two trials of 20 s each, dual task for two trials of 90 s each). These were followed by six blocks, one for each condition, randomized across participants. A block consisted of one single-task typing trial (10 s), one single-task tracking trial in the respective cursor speed (20 s) and three dual-task trials (90 s). Overall, the paradigm took 30 min to complete. Target dependent variables (DVs; see Farmer et al., 2018) of the typing-while-tracking paradigm are switch rate and time-on-typing.[3]

After completing a pilot study, two changes from the original study have been implemented to potentially produce variance in switching strategies and be better able to differentiate between participants: a) explicit instructions and b) longer trial length. In contrast to Farmer et al. we explicitly instructed participants about gains in the typing task and penalties in the tracking task, so they did not have to infer penalties from feedback scores above the circular area themselves. In addition, the trial length was extended from 20 s to 90 s.

2.3.2. Risk measures

2.3.2.1. Balloon-Analogue-Risk Task (BART). We chose the BART (Lejuez et al., 2003) as a behavioral measure for risk tendency. Participants had to pump up a virtual balloon on a computer screen. Each click was accompanied by an inflation sound and an optically growing balloon. In accordance with Lejuez et al., participants were instructed that every pump would bring 5 cents, saved in a temporary reserve, and that they could collect the sum by clicking the "collect" button. An exploding balloon made them lose the temporary reserve and every balloon had an individual explosion point (randomized, ranging from 1 to 128 pumps; unbeknownst to participants). After each explosion or money collection, a new balloon appeared until a total of 20 balloons were completed. DVs are the adjusted number of pumps (non-exploded balloons only), number of explosions and total earnings. The relationship between monetary earnings and risk tendency was unclear, but individuals with lower scores on adjusted number of pumps and explosions were considered to be lower in risk tendency (Lejuez et al., 2003).

2.3.2.2. Risk Propensity Scale (RPS). We chose the RPS as a self-report measure for risk tendency (Cronbach's $\alpha = 0.77$, average 4.46 in the validation sample, Meertens & Lion, 2008). Participants rated general risk-taking tendency across 7 items on a 9-point scale (1: totally disagree – 9: totally agree, e.g., "I take risks regularly"), so risk-averse individuals would score lower than risk-seeking individuals.

2.3.2.3. Domain-specific risk-taking scale (DOSPERT). We chose DOSPERT as a second self-report measure, because research has shown that people can differ in risk-tendency depending on the risk matter. The DOSPERT covers the content domains financial investment/gambling

[2] Post-hoc analyses confirm that in 84% of the "lose-half"-trials, participants typed less than 50 digits per visit to the typing window, which means they achieved less than 500 points and indeed risked to go into minus.

[3] Additional DVs in the appendix: no-of-digits-typed and typing errors.

decisions (e.g., "Betting a day's income at the horse races"), health/safety (e.g., "Engaging in unprotected sex"), recreational (e.g., "Taking a skydiving class"), ethical (e.g., "Revealing a friend's secret to someone else") and social (e.g., "Starting a new career in your mid-thirties") decisions (internal consistency estimates range from 0.71 to 0.86, Betz et al., 2002). The questionnaire consisted of three parts with the same 30 items (6 items per domain): in part one, participants rated the likelihood of engaging in the described activities (1: extremely unlikely – 7: extremely likely), in part two they gave a gut assessment of how risky each behavior was (1: not at all risky – 7: extremely risky), and in part three they rated the benefits resulting from engaging in the specific behavior (1: no benefits at all– 7: great benefits). For our experiment, we used the mean score of the likelihood of engaging in gambling behavior since that was most similar to dealing with potential gains/losses in the typing-while-tracking task. Individuals with lower scores were considered lower in risk tendency.

2.3.3. *Impulsiveness measures*

2.3.3.1. Delay-Discounting Task (DDT). We chose the DDT as a behavioral measure of impulsiveness. Delay discounting refers to a decline in the value of a delayed reward relative to the value of immediate rewards (Frye et al., 2016). Participants had to place a cursor on a grey button and were presented with two amounts of money with different delays: a delayed amount (e.g., 100 EUR in 1 year) and an immediate amount (e.g., 80 EUR now). They then had to make a choice by clicking on one of the two options. Seven different delays (6 h, 1 day, 1 week, 1 month, 3 months, 1 year, and 5 years) were tested, and each delay was tested with 6 trials. Depending on the participant's choice, the immediate amount was adjusted up (when delayed amount was selected) or down (when immediate amount was chosen). For each individual, we created a diagram with the seven delays on the x-axis, and the total number of "delayed amount chosen" on the y-axis. Given that each participant was presented 6 trials per delay, each value could range between 0 and 6. We then analyzed the area under the curve resulting from connecting the 7 data points in the diagram. Individuals with smaller values were considered less impulsive.

2.3.3.2. Barrat Impulsiveness Scale (BIS). We chose the BIS as a self-report measure of impulsiveness because it is the most widely cited instrument for the assessment of impulsiveness (Cronbach's alpha = 0.80, average item inter-correlation r = 0.13, M = 59.18 (SD = 9.54), Reise et al., 2013). Participants rated 30 items, describing common impulsive or non-impulsive behaviors and preferences, on a 4-point scale (1: rarely/never - 4: almost always/always). Individuals with lower scores were considered less impulsive.

2.3.3.3. Arnett Inventory of Sensation Seeking (AISS). We chose the AISS as a second self-report measure of impulsiveness, because the facet sensation seeking may contribute to risk preferences (Lauriola et al., 2014). Sensation seeking is divided into the two sub-dimensions novelty and intensity, which are openness to novel situations and the need for intense stimulations (Cronbach's alpha novelty = 0.49, intensity = 0.53, Roth, 2003). Participants rate 20 items using a 4-point scale (1 = describes me very well - 4 = does not describe me at all). Individuals with lower scores were considered higher in sensation seeking, so possibly higher in impulsiveness and risk tendency.

2.4. *Procedure*

Upon arrival, participants received overview information of the different tasks and signed informed consent. The typing-while-tracking paradigm, the computerized tasks (BART, DDT) and the questionnaires (RPS, DOSPERT, BIS-11, AISS) were each counted as an experimental block. All experimental blocks were randomized across participants, and also tasks within one block were pseudo-randomized so that each participant completed the experiment in a different order. In total, the typing-while-tracking paradigm took about 30 min, the two computerized tasks took about 10 min, and the questionnaires took around 25 min to complete, yielding a total testing time of approximately 65 min.

2.5. *Data analysis*

Performance on the typing-while-tracking paradigm (DVs: switch rate, time-on-typing) with the factors Payoff (3: lose half, lose all, lose 500) and Cursor Speed (2: low, high) was analyzed in a linear mixed model (LMM) using the lmer package (Bates, Mächler, et al., 2015) in the R system for statistical computing (Version 1.2.1335) under the GNU General Public License (Version 3, November 2019). The LMM analysis included each dual-task trial of each participant (N = 270, 9 trials from 30 participants) and not the averaged performance for every condition. Participants were further specified as random factors. We followed the model selection procedure (iterative reduction of model complexity) as suggested by Bates et al. (2015). We first analyzed a maximum LMM by performing random-effects principal component analysis (rePCA) to determine the number of dimensions supported by the data. We then analyzed a zero-correlation parameter LMM removing correlations between random effects. If at least one component was close to zero, we continued by dropping variance components (i.e., random effects) until the rePCA no longer suggested over-identification (no component close to zero). After that, non-significant variance components were removed stepwise to a reduced model. Finally, the reduced zero-correlation-parameter-model was compared against the reduced correlation-parameter-model and checked for goodness of fit. If the rePCA indicated components being close to zero, the correlation parameters were left out. The full procedure will be reported for switch rates and time-on-typing; analyses for number of digits typed and typing errors can be taken from the Appendix A.

From 540 data points (270 × switch rate; 270 × time-on-typing), four missing values were identified, most likely because of a premature termination of the paradigm for two participants due to unknown technical errors, so each value was replaced by the condition mean per participant.

We further analyzed performance on the computerized tasks and answers in the questionnaires. An overview of the different variables can be seen in Table 1. As we have outlined earlier, there is some debate about whether risk and impulsiveness overlap, so we analyzed correlations between measures, too. To examine whether there is a relationship between risk tendency and/or impulsiveness and switching strategies, we further correlated the performance scores of the typing-while-tracking paradigm (switch rate, time-on-typing) with scores obtained in the separate measures.

3. Results A (main analyses)

3.1. *Typing-while-tracking paradigm/switch rate*

Descriptive analyses showed that the average visit time on the

Table 1
Average visit time on the tracking paradigm in s and total visit time in percentage for the 90 s dual-task trials.

	High cursor speed			Low cursor speed		
	Lose half	Lose all	Lose 500	Lose all	Lose half	Lose 500
M (s)	1.71	1.50	2.98	1.77	2.18	2.68
SD	2.69	1.05	7.57	2.65	4.92	7.14
Total time %	11.50%	14.97%	15.29%	10.58%	11.52%	10.38%

tracking paradigm, i.e., the time interval between the switch from typing to tracking and back from tracking to typing, took between 1.5 and 3 s (see Table 1).

Switch rates were measured by the number of trigger presses when switching from typing to tracking (counting only one direction). Mean switch rates for the six experimental conditions can be taken from Fig. 2. The fixed-effects model yielded a main effect of Cursor Speed, $F(1, 534) = 9.38$, $p = .002$, $\eta_p^2 = 0.02$, because all participants switched more often to the tracking task when the cursor moved at higher speeds. There was no significant main effect of Payoff, $F(2, 534) = 0.74$, $p = .478$, $\eta_p^2 < 0.01$, and no significant Cursor Speed × Payoff interaction, $F(2, 534) = 2.64$, $p = .072$, $\eta_p^2 < 0.01$ (see Fig. 2).

In order to better understand within-subject effects, a model with subject as random effect was analyzed. The maximal linear mixed model with all variance components (switchrate ~1 + Cursor Speed * Payoff (Cursor Speed * Payoff | Subject)), failed to converge and was thus overparameterized, which was substantiated by the sixth component being close to zero in the rePCA. A comparison between a zero-correlation-parameter LMM and stepwise reduced models showed that our data was best described by a model keeping all uncorrelated random effects (switchrate ~1 + Cursor Speed * Payoff (Cursor Speed * Payoff || Subject)). This suggests that participants showed some variability between trials. Testing main effects and interaction of the best-fit model (dummy coded) revealed no significant main effect of Cursor Speed, $F(1, 32.59) = 0.01$, $p = .920$, a significant main effect of Payoff, $F(2, 41.58) = 4.96$, $p = .012$, and a significant Cursor Speed × Payoff interaction, $F(2, 33.64) = 5.62$, $p = .008$ (for an illustration of the between- and within-subject variance see also Fig. 3).

3.2. *Typing-while-tracking paradigm/time-on-typing*

Switch rates and time-on-typing were significantly negatively correlated. The more time participants spent on typing, the less often they switched to the other task. This effect was overall more pronounced for high cursor speed conditions (see Table 2).

For time-on-typing there was both a main effect of Cursor Speed $F(1, 502.08) = 21.00$, $p < .001$, $\eta_p^2 = 0.04$, because all participants spent less time on the typing task when the cursor moved at higher speeds, and a significant effect of Payoff, $F(2, 502.07) = 3.50$, $p = .031$, $\eta_p^2 < 0.01$, because participants spent most time typing in lose half and least in lose 500 conditions for high cursor speed. There was no significant Cursor Speed × Payoff interaction, $F(2, 502.12) = 2.36$, $p = .096$, $\eta_p^2 < 0.01$, as there were no differences for time-on-typing in low cursor speed conditions (see Fig. 4).

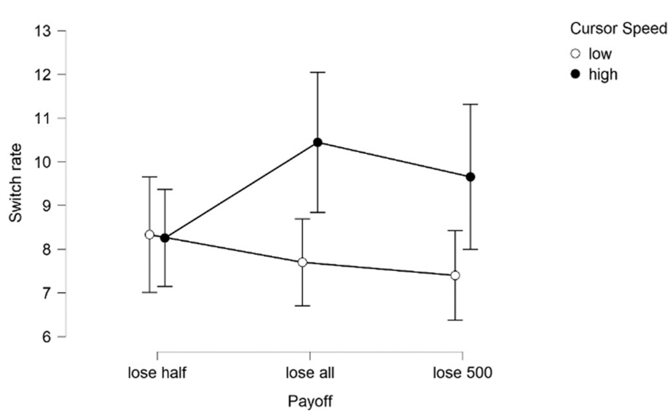

Fig. 2. Analyses of switch rates.
Note: Switch rates display how often participants switched from the typing to the tracking task window. Cursor Speed related to the movement of the random cursor inside the circle (low: 3 pixel vs. high: 5 pixel) and Payoff described how many points participants would lose as soon as the random cursor exits the circle (lose half of their points, lose all their points or lose 500 points). Error bars show the 95% confidence interval.

The maximal linear mixed model with all variance components (time-on-typing ~1 + Cursor Speed * Payoff (Cursor Speed * Payoff | Subject)), failed to converge and was thus overparameterized. A comparison between a zero-correlation-parameter LMM and stepwise reduced models showed that our data was best described by a model keeping all (uncorrelated) random effects (time-on-typing ~1 + Cursor Speed * Payoff (Cursor Speed * Payoff || Subject)). Testing main effects and interaction of the best-fit model (dummy coded) revealed no significant main effect of Cursor Speed, $F(1, 58.09) < 1$, $p = .450$, a significant main effect of Payoff, $F(2, 72.30) = 5.73$, $p = .005$, and no significant Cursor Speed × Payoff interaction, $F(2, 62.74) = 3.01$, $p = .057$.

3.3. *Separate measures of risk and impulsiveness*

Variance between participants on both risk and impulsiveness questionnaires and behavioral measures (see Table 3) resembled norm tables, and previous studies applying the measures (Beck & Triplett, 2009; Lejuez et al., 2003; Meertens & Lion, 2008; Roth, 2003; Shamosh et al., 2008; Spinella, 2007; Weber et al., 2002).

Overall, there were few significant correlations between measures within one domain, i.e., behavioral risk measure and self-report risk measure (see Fig. 5). Especially participants who reported to have a higher risk tendency in the RPS, also tended to act riskier on the behavioral risk measure. As it has been argued that risk tendency and impulsiveness might not be independent (Nigg, 2017), we also checked correlations across separate measures. We found that participants who reported a higher risk tendency also report more motor impulsiveness and a higher self-reported need for stimulation. For the dependent variables on the tracking-while-typing paradigm, a significant correlation between RPS score and switch rates in three out of six conditions were found (see Fig. 5), yet none between any separate measure and time-on-typing.

4. Method B (exploratory analyses)

As it has been outlined by Broeker et al. (2018), computational modelling techniques as used in judgment and decision-making research could be useful to understand how and why participants divide effort between tasks (measured by when and how often they switch). One particularly successful model that has been used to explain a number of classic phenomena in typical judgment-and-decision-making tasks is the Decision Field Theory (DFT; Busemeyer & Townsend, 1993; for an overview see Johnson & Busemeyer, 2010). Here, we follow an earlier claim and transfer this approach to our task-switching paradigm. We intended to present exploratory analyses modelling participants' behavior by assuming that the relevant decision is whether to switch tasks.

DFT assumes that at each moment while executing a task, a person focuses on a particular feature (e.g., probability that the tracking cursor is near the edge of the circle) of the choice alternatives (e.g., switch vs. continue typing). As a participant's focus shifts between the features over time, the tendency towards either option continues to shift accordingly; increasing when a feature suggests to favor the alternative, or decreasing when the focal feature presents a relative disadvantage. The more important a feature is the more likely it is to receive attention at each moment. As this shift in attention drives fluctuations in preference over time, a stopping rule must determine when a choice is made. DFT assumes that there is some sufficient level of preference, or "decision *threshold*", which warrants choice of the (first) alternative to reach it (for neurophysiological data see also Cisek & Kalaska, 2010).

In this study, the "choice" is not between two presented options, or even an expression of preference for one task over the other, but rather represents some accumulating evidence or tendency to switch (vs. continue on the typing task). In this context, we use the threshold

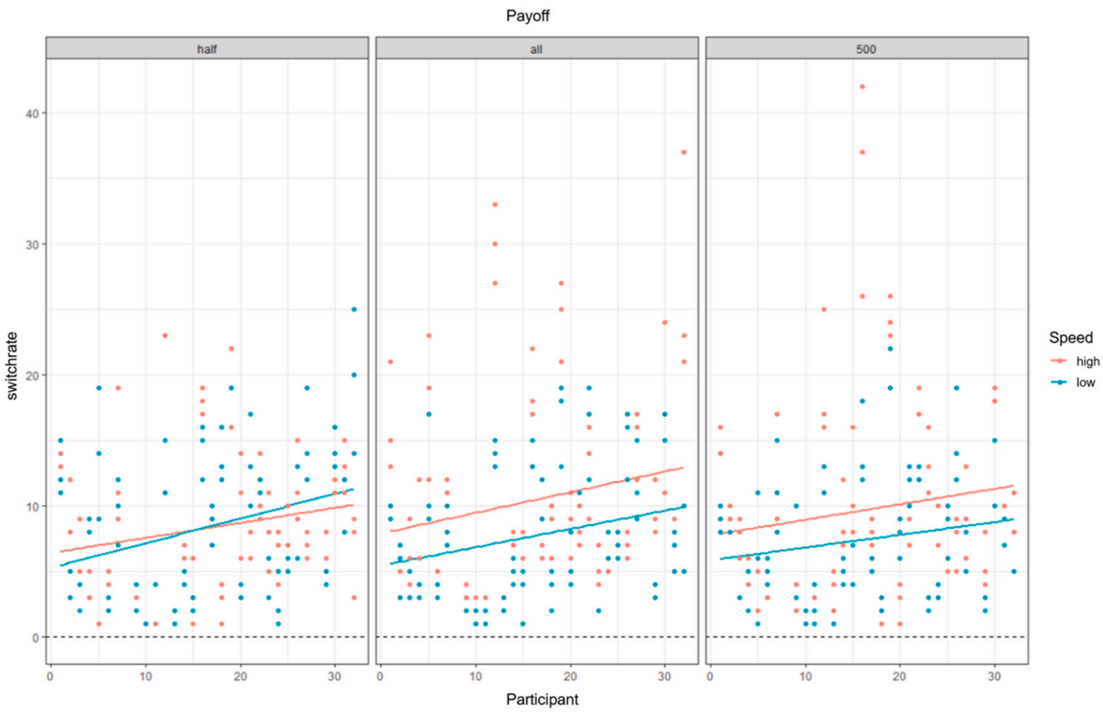

Fig. 3. Switch rates across all trials for each participant separated by Payoff conditions.
Note: Data are ordered by participant number. The left panel represents the condition “losing half of the points”, the middle panel represents “losing all points” and the right panel shows data points from the condition “losing 500 points”. Red data points are from high-speed conditions, green data points are from low-speed conditions. Lines represent y-intercepts. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 2
Correlations for dependent variables on the tracking-while-typing paradigm.

Variable		Switch rate high cursor speed			Switch rate low cursor speed		
		Lose half	Lose all	Lose 500	Lose half	Lose all	Lose 500
Time-on-typing lose half	Pearson’s r	−0.538***			−0.484***		
Time-on-typing lose all	Pearson’s r		0.574***			−0.427***	
Time-on-typing lose 500	Pearson’s r			−0.322 **			−0.250*

* $p < .05$.
** $p < .01$.
*** $p < .001$.

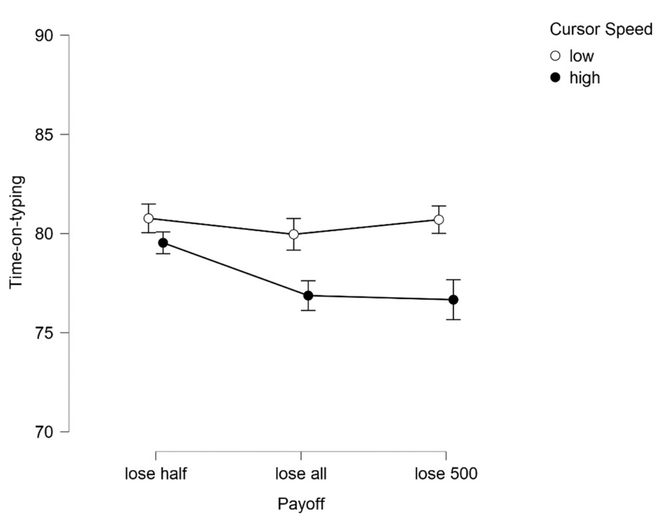

Fig. 4. Time-on-typing across all trials for each participant separated by Payoff conditions.

parameter as a means to describe the switching behavior of individuals, indicative of their strategies based on risk preferences and/or impulsivity. Because the threshold parameter represents how much information a decision maker needs before choosing an option, both task characteristics and individual characteristics can determine how high or low a threshold is set, and thus how early it is hit. For example, the higher the risk through penalty or cursor speed, the lower the threshold in general (i.e., regardless of individual differences). In addition, individual risk tendency and impulsiveness would determine how early in time the individual passes the threshold, regardless of task characteristics. A risk-averse individual would try to avoid losing points more strongly compared to risk-prone individuals, so we would expect their decision threshold to be lower, indicating an earlier moment in time to switch (see Fig. 6).

Thus, for each individual, we fit separate threshold parameters for each of the two cursor speed conditions, also illustrated in Fig. 6. Predictions from DFT were generated by using a discrete approximation to the drift diffusion process illustrated in Fig. 6 (see Busemeyer & Townsend, 1992, for derivations). That is, rather than modelling the specific attentional shifts and resulting changes in preference, one can summarize the trajectories as shown in Fig. 6 by three parameters. The drift rate, *d*, characterizes the average trajectory path, or the slope of the

Table 3
Descriptive statistics of the five questionnaires and two behavioral measures examining risk tendency and impulsiveness.

	Task	Variable of interest	Scale	No of items	Min	Max	Mean	SD
Risk	BART	Adj. tot. pump count		20	188	740	454.1	137.7
		Total earnings EUR			11.90	37.00	23.50	6.31
		No of explosions			3.00	11.00	6.67	2.51
	RPS	Mean	1–7	1	2.17	6.50	4.46	1.10
	DOSPERT	Financial risk	1–7	3	0.00	16.67	11.06	1.62
		Gambling risk		3	0.00	15.33	9.83	2.18
Impulsiveness	DDT	Area under the curve		7 × 6	−7.14	−21.4	−16.0	3.74
	BIS	Motor	1–4	8	16.00	27.00	21.70	3.48
		Attention		11	11.00	23.00	15.80	3.38
	AISS	Mean intensity	1–4	10	1.50	3.50	2.60	0.33
		Mean novelty		10	2.20	3.50	2.83	0.42

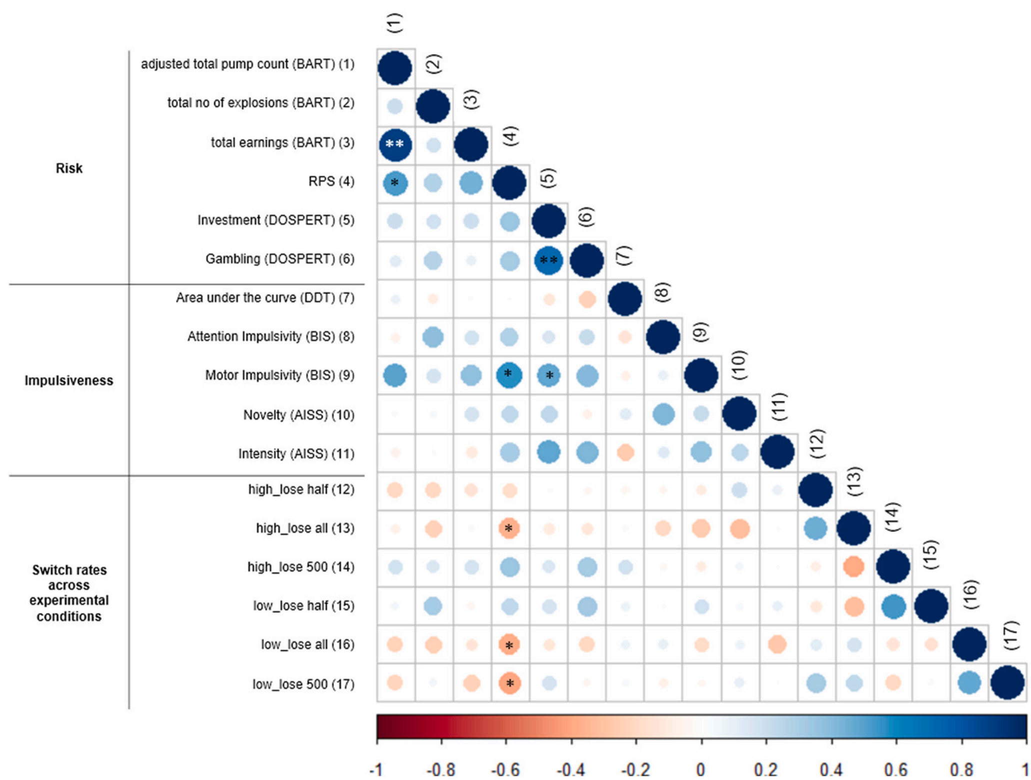

Fig. 5. Correlation plot separate measures and switch rates.
Note: Correlations of all separate measures of risk tendency/impulsiveness (1)–(11), and of switch rate in the different experimental conditions (12)–(17). Circle color contrast and size depict the strength of the correlation. Significant correlations are marked with an asterisk, $^{*}p < .05$, $^{**}p < .01$.

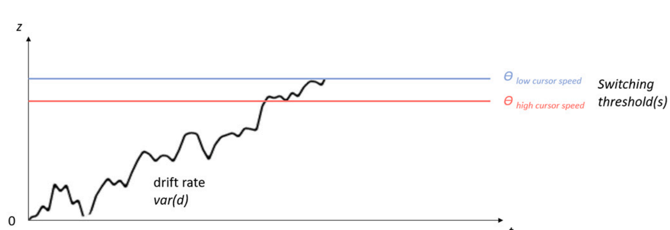

Fig. 6. Schematic visualization of the modelling approach.
Note: The switching thresholds (decision to switch from typing to tracking) are determined by the task characteristic Cursor Speed low vs. high. The drift rate is assumed to be determined by personality characteristics, so any score on separate measures, and to be subject to slight fluctuations over time.

line that would best fit the trajectory. The fluctuations around the best-fit line can be characterized by a variance parameter, var_d. In our framework, it could also be proposed that a task characteristic such as cursor speed might not affect (only) the threshold, but (also) the drift rate or accumulation of evidence itself. These are conceptually somewhat different realizations, and we prefer to adopt the former notion that the evidence threshold is impacted. We should note, however, that these competing explanations may still produce similar predictions for switching times. That is, a shallow drift rate may reach a lower threshold at the same time a steeper drift rate reaches a higher threshold. As such, both of these possible explanations cannot be simultaneously considered without more trials and/or conditions to produce reliable parameter estimates. In our exploratory analysis, we focus on the threshold parameter which represents our preferred conceptual interpretation, while holding the drift rate and variance constant. Given the relatively few trials to generate robust predictions on an individual trial and participant level, we need to further restrict our analysis scope as well. In particular, we will first focus on changes in one task characteristic only (cursor speed) collapsed across levels of the other feature (payoff). Doing so allowed us to use nine trials per participant for model estimation (rather than three or six).

The starting point for the trajectory is modelled by a third parameter, z, which can be used to indicate any initial biases or preferences that are present at the beginning of the task (prior to any task-relevant attentional focus). Recall that the two “options” modelled in our framework are switching vs. staying, and we did not hypothesize individuals to have any initial preference towards either of these, so z was set to zero. Given values of θ, d, var_d, and z, DFT generates predictions for the mean time at which the decision is made to switch. We made a few simplifying assumptions to apply DFT to the data from our specific task-switching paradigm. First, as already mentioned, we assumed that there was no initial bias in the task, such that $z = 0$ for all participants. Second, we used a constant drift rate and variance across participants; we chose $d = 1$ for simplicity and assumed some low variability with $var_d = 0.5$. This allowed us to focus solely on changes in the threshold to account for any differences across individuals.[4] DFT makes predictions for the distribution (and thus mean) time it takes for an individual to switch tasks, indicated by the time at which the trajectory hits θ in Fig. 6, rather than the switch rate directly. So, we converted the time-on-typing into an average switch time for each individual, by dividing the time-on-typing by the number of switches in that trial. As such, switch times indicate the average time between two switches. Given the switch time for each participant, we used the fminsearch routine in MATLAB to find the value for θ that produced the lowest sum of squared errors (SSE), between the observed and predicted mean switch time.

Beyond that, we cross-validated the model, separately for high and low conditions. The model parameters were fit using trials one and two in order to predict the third trial in each condition. This eliminates free parameters from the model and allows us to see how well the model can predict out-of-sample. Specifically, we averaged the switch times for the first two trials, and fit the model parameter θ to these data. Then, we used the fit value of θ to predict the switch times for the third trial. Finally, we determined whether fit theta values from all trials correlate with scores obtained in the risk and impulsiveness measures, in line with our hypothesis discussed above (e.g., lower thresholds for more impulsive individuals).

5. Results B (exploratory analyses)

Mean time-on-typing was used as the proxy for switch times and subjected to the fitting routine, separately for each of the cursor speed conditions. Thus, each participant had nine trials (per condition) from which mean switch times were calculated and fit using the model. The model fit the data very well in both conditions; across all participants, we obtained mean $SSE_H = 0.005$ and mean $SSE_L = 0.003$. The mean predicted switch time for low cursor speed was 17.40 s (real mean switch time = 17.41 s) and for high cursor speed 15.48 s (real mean switch time = 15.46 s). The distribution of individual θ values is shown in Fig. 7. In general, threshold values are higher for the low cursor speed condition ($M = 24.64$) compared to the high cursor speed ($M = 21.90$), as one might expect (i.e., producing longer switch times). A paired-samples t-test comparing the threshold values across conditions was not significant, however, $t(29) = 1.29$, $p = .209$.

The θ parameters with the highest fit were correlated with the scores obtained in the behavioral measures and questionnaires (separate measures). No significant correlations could have been detected.

For the cross-validation procedure, we used the same fit routine to find the values of θ that best fit the data from the average switch times across the first two trials, for each condition. The resulting distribution of θ values follows a similar trend as above, as one would expect when applying the same model to a subset of the original data. To the degree that participants behaved somewhat differently across the three trials, the model performance in subsequently predicting the switch times for the third trial, without refitting values of θ, varied as well. Prediction error increased as expected, but most participants were still fit rather well. The median SSE values were 4.22 and 4.70 for the low and high cursor speed conditions, respectively. This translates to an error of slightly over 2 s in predicting switch times on a single trial without using any free parameters, which is admirable performance for the cognitive model.

Finally, we repeated the initial fitting procedure separately for each penalty condition, rather than for each cursor speed; we thus collapsed across the latter. All other aspects of the original fit routine were the same, however now there were only six trials per participant, for each of three conditions (three trials for each of two cursor speeds). Although some caution may be warranted with relatively few trials per parameter estimate in a relatively complex model, the results show an effect of penalty condition on the estimated threshold values in the expected direction (Fig. 8). The difference between threshold values for the “lose all” ($Mdn = 35$) and “lose half” ($Mdn = 46$) conditions was significant, $t(29) = 2.24$, $p = .03$; as was the correlation between them ($r = 0.83$). As one would expect, participants had lower thresholds in order to shorten the amount of time between switches.

6. Discussion

Farmer et al. (2018) hypothesized that individual switching strategies might be not only influenced by task characteristics, but differences between persons. The aim of this study thus was to examine whether risk tendency and impulsiveness can differentiate individuals in their response, that is, switch rate and time spent on tasks, to different task characteristics (cursor speed and payoff). We were able to replicate the finding that individuals vary in switch rate and time-on-typing both for varying potential losses and across trials, but our extension shows that differences cannot be explained by differences in risk or impulsiveness measures, at least not the measures we chose. The only exception was that people high in risk propensity have lower switch times, so switching earlier and more often. If, contrary to our original idea, switching itself (rather than not switching) is considered a risky decision because one must increase cognitive effort and abandon current processes, then this correlation seems to be informative. However, considering that the majority of separate measures show no relation to switch rates and time-on-typing, it seems more likely that variance is mostly provoked by cursor speed and payoff. Furthermore, the effect of payoff was more visible for time-on-typing task than for switch rate. One cautious conclusion could be that even though these two variables correlated, participants’ attention was on gaining points and their endeavor to earn as many points as possible through typing motivated switching behavior stronger than the avoidance of potential losses, irrespective of whether the reward for typing was always equally high in each condition. This in turn makes time-on-typing a more sensitive indicator of risk-seeking behavior. Future experiments could test whether this effect would be even more pronounced if the typing score was visible above the typing task and not the tracking task. In the current version, the amount of points gained was only visible after having switched to the tracking task which could have made switches a measure of performance monitoring, too, rather than only a measure of loss avoidance motivation.

In any case, our results are in line with recent recommendations to focus more on the individual, thus within-subject variability in cognitive experiments (Goodhew & Edwards, 2019). The iterative model reduction approach showed that for both switch rates and time-on-typing it was important to account for within-subjects variability and between-subjects variance, because a model containing uncorrelated random effects terms had a higher goodness of fit than a model with fixed effects only. Models considering fixed effects only, much alike traditional

[4] We explored different values for d and var_d and they had little effect on the quality of the model predictions. Changing these values would be compensated in the model by changing the values for θ, so it becomes simply a matter of scale and thus somewhat arbitrary. That is, using a shallow slope (small d) with a lower threshold (θ) could produce predictions similar to a steeper slope (large d) and higher threshold.

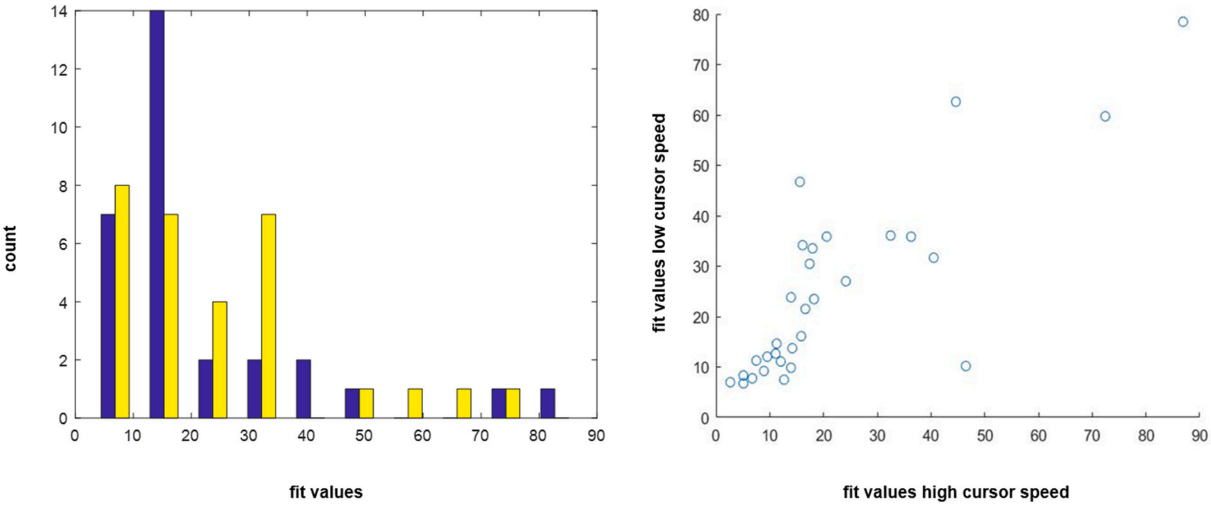

Fig. 7. Best fitting threshold values, by cursor speed. Histogram of the best fitting θ values in "high" (blue) and "low" (yellow) conditions (left panel); and a scatterplot of individual θ value pairs for "low" vs. "high" conditions (right). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

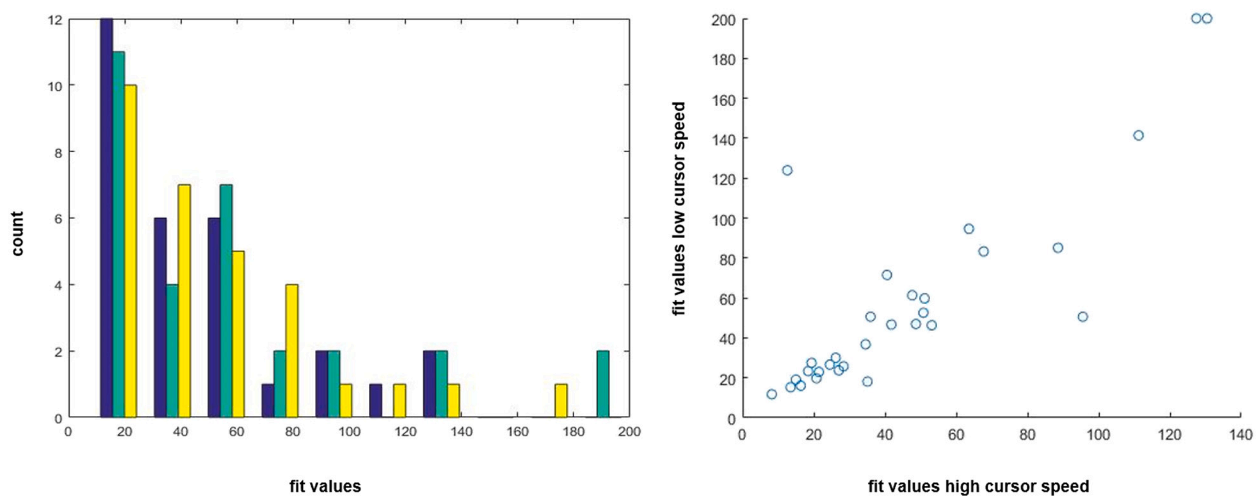

Fig. 8. Best fitting threshold values, by penalty condition. Histogram of the best fitting θ values in "all" (blue), "half" (yellow), and "500" (teal) conditions (left panel); and a scatterplot of individual θ value pairs for "all" vs. "half" conditions (right). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

rmANOVAs, would have camouflaged this, yet in order to understand why some individuals show better multitasking performance than others it is important to disentangle influence by task characteristics from individual influence. Besides the impact of random effects, our study might have lacked sufficient power to detect this result in traditional rmANOVAs, as the post-hoc power of this study was 0.652.

When analyzing the total number of digits typed and typing errors (see Appendix A), participants responded similarly to task characteristics and so a model not considering within-subject variance was appropriate to represent the data. However, switch rate is a dependent variable representing the way individuals treat two tasks, and typing quantity and errors only represent performance on one task, so this might have contributed to less variance, too. Finally, we explored the use of a threshold parameter in a model that presumes a "build-up" in the need to switch, beyond the switch rate per trial, and showed that it can be a useful extension to switching research when examining within-subject variability. That is, a higher penalty is associated with a lower threshold for determining when to switch, leading to more frequent task switching. Future research should find more robust measures like the time-on-typing suited for modelling the parameter values in order to be able to make more reliable behavioral predictions across different tasks or situations. Other changes could serve as avenues for tailoring our tasks to such modelling endeavors and they benefits they offer. By increasing the number of trials we could explore relative influence of parameters and/or interactions between them, and use more sophisticated hierarchical estimation techniques.

Relatedly, we are aware that one limitation to the study may be the sample size. With the main aim to extend research by Farmer and examine the proposed explanation that differences in characteristics contribute to the switching variance, it was based on the original study. Yet, sample size and heterogeneity of the sample may affect power when analyzing between-subject differences between the typing-while-tracking paradigm and separate measures. Likewise, the small sample prevented us from conducting analyses of co-variance, median-splits or reporting reliability scores of the separate measures and we could only infer from descriptive statistics that data obtained in our sample was comparable to norm samples.

This study represents one of the first attempts to explore reasons for different task-switching strategies in a switching paradigm entailing different payoffs. Using an experimental study and modelling approach including threshold parameters from decision-making theory provides an extension of previous research. In future research a simple DFT model testing only the threshold parameter could be extended for a systematic modelling approach testing other potential important parameters such as the drift rate. The results of our study suggest that task characteristics (i.e., reward and loss prospect) modulate behavior on this switching paradigm more than the characteristics of the person (i.e., risk tendency and impulsiveness). Yet future studies should still consider other characteristics that may have a stronger influence on task-switching strategies like the ability of relational integration or shifting as recently proposed by Himi et al. (2019).

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Availability of data and material

The data repository is Open Science Framework (osf); data is available at: https://osf.io/gup4c/?view_only=15957fa2f758409dac5668f266869cf5.

Code availability

The code is available at: https://osf.io/gup4c/?view_only=15957fa2f758409dac5668f266869cf5.

Declaration of competing interest

The authors have no competing interests to disclose.

Appendix A

Descriptive statistics of the three performance scores on the typing-while-tracking paradigm for all six experimental conditions.

	Cursor speed											
	Low						High					
	Lose half		Lose all		Lose 500		Lose half		Lose all		Lose 500	
	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
Switch rate	8.3	5.4	7.7	4.9	7.4	4.7	8.3	5.5	10.4	7.3	9.7	7.5
Total no of digits typed	196.9	41.0	199.9	34.9	194.1	35.9	196.0	33.9	189.9	40.04	179.6	38.8
Typing errors	5.6	5.0	5.6	5.9	4.9	3.9	5.6	4.7	5.1	4.9	4.5	5.0

Total no. of digits typed (per trial)

For the fixed effects, we found a main effect of Cursor Speed, $F(1, 29) = 9.19$, $p = .005$, $\eta^2 = 0.013$, because participants typed more numbers in 90 s trials when the cursor moved at lower speeds. We also found a significant main effect of Payoff, $F(2, 58) = 5.14$, $p = .009$, $\eta^2 = 0.015$, because there was a tendency to type less digits per trial the higher the expected payoff. There was no significant Cursor Speed × Payoff interaction, $F(2, 58) < 1$, $p = .448$, $\eta^2 = 0.004$.

The maximal LMM was singular, so variance components were dropped to achieve model identification. Dropping Payoff as a variance component improved goodness of fit, $\chi^2(18) = 112.63$, $p < .001$. Comparing this model against a zero-correlation-parameter LMM, shows that removing correlation parameters does not improve goodness of fit, $\chi^2(1) = 0.07$, $p = .789$. When further simplifying the random-effects structure of the identified LMM (digits typed ~ Cursor Speed * Payoff + (Cursor Speed | Subject)), we found that there was no loss of goodness of fit when removing all variance components, subsequently the data was best represented without random effects term, so there were no major inter-individual differences for the total no. of digits typed.

Analyses of the total number of digits participants typed during a 90 s trial. Cursor Speed was the speed of the random cursor inside the circle (low: 3 pixel vs. high: 5 pixel) and Payoff described how many points participants would lose as soon as the random cursor exits the circle (lose half of their points, lose all their points or lose 500 points). Error bars show the 95% confidence interval.

Correlations between number of digits typed and time-spent-on typing for all six experimental conditions to control for the potential influence of motor skill or experience.

Variable		No. of digits typed			No. of digits typed		
		High cursor speed			Low cursor speed		
		Lose all	Lose half	Lose 500	Lose all	Lose half	Lose 500
Time-on-typing Lose all	Pearson's r	0.484***			0.388***		
Time-on-typing Lose half	Pearson's r		0.190*			0.357***	
Time-on-typing Lose 500	Pearson's r			0.435**			0.362***

Note: If motor skill or experience influenced the number of digits typed, then those individuals being more skilled should type more digits in less time than less skilled individuals, leading to rather weak correlations among the sample.

* $p < .05$.

** $p < .01$.

*** $p < .001$.

Typing errors

For fixed effects only, we found a main effect of Payoff, $F(2, 58) = 4.02$, $p = .023$, $\eta^2 = 0.006$, so participants made fewer typing errors the higher the expected payoff. We neither found a significant main effect of Cursor Speed, $F(1, 29) = 1.38$, $p = .250$, $\eta^2 = 0.001$, nor a significant Cursor Speed × Payoff interaction, $F(2, 58) < 1$, $p = .836$, $\eta^2 = 0.000$. The maximal linear mixed model with all variance components (typing errors ~1 + Cursor Speed * Payoff (Cursor Speed * Payoff | Subject)), failed to converge and was thus overparameterized, which was substantiated by the fifth and sixth component being close to zero in the rePCA. When removing correlations between the variance components, we found singularity in the model, so we dropped variance components to achieve model identification. The stepwise reduction showed that the data was best represented when dropping 27 out of 36 variance components (typing error ~ 1 + Payoff * Cursor Speed + (1 + Payoff + Cursor Speed||Subject)). The identified model was then further reduced by non-significant variance components, and none of the variance components improved goodness of fit, $\chi^2(2) = 2.05$, $p < .359$. This suggests that a model without random effects term represents the data set best.

Analyses of typing errors participants made during a 90 s trial. Cursor Speed was the speed of the random cursor inside the circle (low: 3 pixel vs. high: 5 pixel) and Payoff described how many points participants would lose as soon as the random cursor exits the circle (lose half of their points, lose all their points or lose 500 points). Error bars show the 95% confidence interval.

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