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Creative Cognition as a Bandit Problem*

Louis Lévy-Garboua¹ Marco Gazel² Noémi Berlin³ Jan Dul⁴ Todd Lubart⁵

Abstract

This paper draws a parallel between creative cognition and a multi-armed bandit problem involving learning from experience in an uncertain environment. Special emphasis is put on the optimal sequencing of divergent and convergent behavior by showing that divergence must be inhibited at one point to converge toward creative behavior so that excessive divergence is counterproductive. We test this hypothesis with a behavioral experiment, using measures of individual divergence and convergence components of creative potential in high school students. Results confirmed that a mix of divergence and convergence predicted high performance in a bandit task but not in a purely random task or in a simple repetitive task. These predictions are maintained after controlling for sex, personality, incentives, and other factors. As hypothesized, creative cognition was necessary for high performance under the appropriate conditions. However, it was not necessary to get high grades in a traditional school system.

Keywords: Creative cognition; Multi-armed bandit problem; Education and creativity; Individual differences in creative potential; Adolescents' behavior.

Educational Relevance Statement: Relating to the goal of educators and public policies in the 21st century to make children and adolescents more creative, and schools more receptive to creative thinking, this research focuses on the creative potential and behavior of high school students. It provides an evidence-based policy argument in support of the screening and development by the educational sector of the creative potential of students.

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1. Introduction

In popular representations, creativity is commonly attributed to exceptional thinkers, as opposed to ordinary people. However, creative cognition is now recognized as a basic mode of thinking that individuals may engage in various activities and levels (see, for example, the four-c model of creativity of Kaufman & Beghetto, 2009). Creativity is currently considered one of the four main “21st century skills”, together with critical thinking, collaboration, and communication (<http://p21.org>), and was further identified in 2020 and more recently by the World Economic Forum as one of the top three abilities for future employability.

Creativity is consensually defined as the ability to produce work that is both novel and appropriate (e.g., Runco & Jaeger, 2012; Lubart et al., 2015). This general definition implies that in creative tasks the final output and the path leading to it are imperfectly known at the start, and they emerge from a sequence of efficient decisions under uncertainty.

The creative process has been conceptualized in terms of an interplay between divergent and convergent thinking (see Lubart (2000) for a review of creativity models). The divergent phase provides an extensive search of the conceptual space, and/or an exploration of selected options. Its function is to elicit the set of possible solutions to a problem whenever solutions are unknown or imperfectly known a priori. The convergent phase involves elaboration and integration of collected information toward an appropriate solution to a problem. This process requires a synthesis of ideas but also pruning opportunities to exploit the better ideas and pursue an optimized path.

A parallel can be made between the process of creative cognition and the exploration-exploitation tradeoff, describing optimal sequential decisions from experience in uncertain environments. These sequential decision-making problems have been mainly developed in the machine learning and artificial intelligence literature. Our specific source of inspiration in this

article will be the multi-armed bandit problem, which is one of the simplest non-trivial problems that implies the exploration-exploitation trade-off. Our contribution will be to characterize creative cognition as a kind of multi-armed bandit problem encountered in novel and uncertain environments.

In the basic multi-armed bandit problem, an agent who is facing a number of slot machines (called bandits), each with an unknown distribution of rewards, must repeatedly select one machine (arm) at a time to get the maximum cumulative reward. This problem is non-trivial because the agent observes the reward for the chosen arm after each round, but not for the other arms that could have been chosen. Therefore, the agent needs to explore different arms to acquire new information, while the exploitation of the optimal decision so far would yield the highest expected rewards conditional on prior information. In essence, the agent seeks to learn which arms are best while not spending too much time exploring.

Neither complete exploration nor complete exploitation is optimal in the bandit problem. A completely exploratory agent who always selects a random arm would make no use of the information collected so far, and a completely “greedy” agent who always selects the arm with the highest expected reward would be driven to suboptimal solutions if the current estimates are inaccurate. There is no known generally optimal solution to the bandit problem in stationary (time-invariant) or changing environments, but many approximate algorithms that combine exploration and exploitation of collected data have been proposed, each with its own strengths and weaknesses.

The exploration-exploitation trade-off arises in many situations. For instance, a consumer who can purchase one good at a time will switch sometimes from familiar goods to new goods; a doctor who can prescribe one of several possible treatments to each patient who visits him or her will observe the treatment effectiveness and shift to the best experienced treatment; every scientist must engage in a research program based on one theory while

confronted to a number of competing theories, and the scientific community as a whole gradually selects the most successful programs. Hills et al. (2015) illustrate the generality of trade-offs between exploration and exploitation across diverse cognitive domains like visual search, problem solving, or social learning.

As these examples show, much creative behavior may be described as an exploration-exploitation trade-off...but not all. Our approach assumes that the menu of options is given a priori, which overlooks the role of imagination and search for ideas to explore. In spite of this limitation, we think that viewing creative cognition as a bandit problem is useful because the solution provided once options have been determined is at least necessary for attaining a good performance.

With this limitation in mind, we will associate divergence with exploration and convergence (or integration) with exploitation in the rest of the paper. The sequence of divergence-exploration followed by convergence-exploitation is an essential part of the creative process. A major, though somewhat neglected, implication of the sequential nature of creative cognition is that divergence must be inhibited at one point to converge toward creative behavior. Consequently, excessive divergence should be counterproductive, notably in a simple and well-known environment in which there is no need to search. By contrast, intensive exploration would be needed to find solutions to novel issues or to complex problems in uncertain environments; and subsequent exploitation would also be needed to adopt these innovations early.

The optimal sequencing of divergence-exploration and convergence-exploitation will be a central issue of our research that will be tested in a behavioral experiment in which the creative potential of subjects is measured and one task is a simple multi-armed bandit problem. Our measures of creative potential will be drawn from the two graphic tasks of EPoC battery recently proposed by Lubart et al. (2011), one divergent and one integrative. It departs from

popular creativity measures which emphasize divergence in the tradition of Guilford (1967) by giving an equal weight to divergent thinking and convergent thinking in the creative potential. The resolution of the bandit problem will take us one step further in assuming that an optimal trade-off between divergence and convergence is *necessary* to reach high performance in a novel and uncertain environment. This hypothesis will be tested with a new method, Necessary Condition Analysis (NCA, Dul, 2016, 2020).

Relating to the goal of educators and public policies in the 21st century to make children and adolescents more creative, and schools more receptive to creative thinking (ADOBE, 2013; Lucas et al., 2013), the current study focuses on the creative potential and behavior of high school students. The latter will be asked to solve a simple bandit problem with a well-identified solution, as well as another problem with a multiplicity of solutions and an ordinary task in which there is no need to search. This will give us a way to test whether creative potential solves the bandit problem but doesn't help with the non-creative tasks. To complete the study, we will observe the grades of our 10th grade-students at a national exam that they passed at the end of 9th grade, and relate these measures of academic achievement to their creative potential. While a meta-analysis of school achievement (Gajda et al. 2017) has found a modest correlation of .23 (s.d.=.016) with creativity tests which understate convergent thinking, it will be of interest to see whether a non-biased measure of creative potential raises this correlation.

2. Foundations and testable implications

2.1. The multi-armed bandit problem

A simple and popular algorithm which offers a first intuition of how an approximate solution to the bandit problem can be reached is “Epsilon-greedy”. The epsilon-greedy agent gives an epsilon (ϵ) chance (for example, $\epsilon = 10\%$) to random selection of an arm at any time, and makes the greedy choice of its currently most-valued arm otherwise. This rule is completed by a definition of the “value” of taking action a in the future, borrowed from the reinforcement

learning literature. If the probability distributions of rewards are stable over time, though unknown, the action-value is defined in the ϵ -greedy algorithm as the average reward on selecting arm a in the past. Action-values would then generally converge to a limit so that a rational agent following this rule would converge towards a stable strategy of exploring randomly with probability ϵ and selecting the “best” arm the rest of the time.

Constant ϵ -greedy strategies are suboptimal because, even if the agent is confident after some time that the “best” strategy dominates its alternatives, it will continue to behave randomly some ϵ -fraction of the time instead of asymptotically reaching the optimal arm. In a stationary, finite horizon environment, a decreasing ϵ -greedy would be a better strategy because it provides more exploration in the early rounds and more exploitation in the later rounds. If the horizon H is known a priori, an even superior strategy, called ϵ -first, would be to pick arms uniformly randomly during the first $\epsilon \cdot H$ plays, which form the exploration phase, and systematically choose the best empirically estimated arm in the remaining $(1 - \epsilon) \cdot H$ plays, which form the exploitation phase.

Algorithms like the ϵ -greedy and its variants should not be seen as optimal in an absolute sense. The “best” arm is the best in the long run but not always the winning arm, since rewards are stochastic. And the optimal strategy may be beaten by other “lucky” strategies for a finite number of periods. Thus, in making a parallel between creative cognition and multi-armed bandit algorithms, we wish to point out that acting creatively in an uncertain environment is necessary for attaining a good performance but not sufficient for reaching the best possible performance. Multi-armed bandit algorithms can be seen as sophisticated heuristics for limiting regret.

Burtini et al., (2015) provide a good survey of the technical literature on the stochastic multi-armed bandit problem. The common feature of all solutions is simple: it is rational to have a higher rate of exploration- i.e., acting randomly or in a non-maximizing way- first and a

higher rate of exploitation, i.e., acting greedily and reaping the rewards, when sufficient information has been gathered. In an uncertain and changing environment, some exploration is needed all the time, though often at a decreasing rate.

2.2. Neuroscientific observations of creative cognition

Cohen et al. (2007) discuss how the human brain manages the exploration-exploitation trade-off. Navarro et al. (2015) designed an experiment in which subjects had to decide when to “observe”, i.e., get information with no reward, and when to “bet”, i.e., receive a reward with no immediate information on this reward. By separating information from reward, this task offers a way to compare the exploration-exploitation trade-off in environments that are known to be either stationary or changing. An important lesson from their experiment is that people’s behavior is close to being optimal and most people adopt the optimal strategy after minimal experience.

How is the trade-off between exploration and exploitation of the information, depicted by the multi-armed bandit problem, implemented in the brain? There is clear evidence that divergent thinking and convergent thinking respond to different, and sometimes conflicting, cognitive processes. Radel et al. (2015) examined the role of impaired frontal-executive functioning on the enhancement of some types of creativity through a reduced capacity to exert inhibition. They tested this effect by exhausting inhibition efficiency through prolonged and intensive practice of either the Simon or the Eriksen Flanker task. Subsequent creativity tests revealed that the impairment of inhibition enhanced fluency in a divergent thinking task (Alternate Uses Task (AUT), Guilford, 1967), but no such changes occurred in a convergent task (Remote Associate Task (RAT), Mednick, 1962). In another study using the same tasks (AUT and RAT), Chermahini and Hommel (2010) examined the effect of dopamine on divergent and convergent thinking by exploiting the fact that spontaneous eye blink rate (EBR) is a clinical marker of dopaminergic functioning. EBR predicted flexibility in divergent

thinking and convergent thinking, but in different ways. The relationship with flexibility was independent of intelligence and followed an inverted U-shape function with medium EBR being associated with greatest flexibility. Convergent thinking was positively correlated with intelligence but negatively correlated with EBR, suggesting that higher dopamine levels impair convergent thinking. Beaty et al. (2016) contend that creative cognition involves dynamic interaction of two networks located in different sets of brain regions: a default network that activates during the generation of candidate ideas, and an executive control network that activates when people need to focus or control their thought processes. These two networks typically do not work together but get connected during creative cognition thanks to a third player, the salience network. Creative people are more able to connect these distinct and somehow antagonistic networks (Beaty et al., 2018).

2.3 Testable implications of representing creative cognition as a bandit problem

The neuroscientific studies reported above support the view that creativity emerges from the interaction of two mutually exclusive cognitive processes, implying a sequence of divergent and convergent behavior which requires some inhibition of the divergence-exploration process at one point to let the convergence-exploitation process operate efficiently.

There is a clear parallel between this description of creative cognition by neuroscientific observations and the way a multi-armed bandit problem would be solved efficiently; and people with a creative potential are those who have the capacity to behave like this. In the sequel, we use a behavioral experiment to test the following implications of representing creative cognition as a bandit problem, namely:

Hypothesis 1: High exploration (or luck) in combination with subsequent high exploitation increases the probability of good performance in a bandit task with an emerging best solution;

Hypothesis 2: Controlling exploration is necessary for each individual to attain good performance in a bandit task with an emerging best solution;

Hypothesis 3: Individuals with a high creative potential are also able to solve a multi-armed bandit problem efficiently;

Hypothesis 4: Individuals with a high creative potential do not perform better than average in tasks which are believed to have no unknown best solution to be discovered.

3. Method

3.1. Participants

The sample comprises 169 tenth-grade students who attended a one-day educational conference about economics, including participation in a laboratory experiment. The latter took place with the informed consent of participants with school and parental authorization at the LEEP (Laboratoire d'Economie Expérimentale de Paris). The protocol was designed with respect to the Helsinki convention and the French national research center (CNRS) ethical committee guidelines. Among the participants, 46% are girls. The average age of the participants is 15.18 years old (s.d. = 0.57). Participants came from nine mixed classes of high school students from all academic districts of the Paris region (Paris, Créteil, and Versailles, i.e., Paris and suburbs), thereby enhancing its representative nature. See Table A1 in the Appendix for descriptive statistics about the sample and variables' description.

3.2. Procedures

Nine research sessions over three days (one day per academic district supplying three sessions each) were conducted in the LEEP, each lasting 90 minutes. Participants completed first two creativity tasks, drawn from the EPoC battery, to determine the creative potential of a student, then two types of real-effort tasks. The latter were composed of two sorts of bandit problems, called the buttons tasks, and a simple repetitive task, called the typing task. They also completed: (a) a questionnaire for Big 5 personality traits (French version of Ten Item Personality Inventory, developed and validated by Storme et al., 2016); (b) the risk propensity assessment, responding to the question "How willing are you to take risks, in general?", on a

scale from 0 to 10, shown by Dohmen et al. (2011) to be a reliable predictor of real-life risk-taking behaviors; and (c) a self-report of grades obtained on the *Brevet*- a nationwide exam taken after 9th grade. 113 students (out of 169) remembered and reported all their grades from this exam that they had passed a few months ago.

All tasks and assessments were conducted within a single session and all participants performed both real-effort tasks. Candies or chocolate were used as incentives. Some of the students won an entire bag of candies or chocolates, whereas others did not win anything.

3.3. Evaluation of Creative Potential (EPoC)

A recent approach to measuring creative potential with children, adolescents, or young adults, inspired by the multivariate model of creativity (Sternberg & Lubart, 1995), was formalized in the Evaluation of Potential Creativity battery (EPoC, Lubart et al., 2011). The measurement approach adopted in the EPoC battery is to solicit creative thinking in simulated situations (verbal creation, graphic creation). The individual is thus invited to engage in creative work, and an estimate of a child's or adolescent's potential is obtained by comparing an individual's performance to others in the same task.

EPoC is composed of two tasks in each creative domain. Both modes of creative thinking are evaluated in a given domain, notably the graphic/visual and verbal/literary domains. In our study, due to time constraints, we only assessed creative potential in the graphic domain. In the graphic-visual field, we present a simple graphic stimulus (such as a banana shape) from which the participant must generate many drawings using the stimulus in ten minutes. This task requires divergent-exploratory thinking. The scoring focuses on the number of ideas, called fluency. It has been shown that fluency is closely related to flexibility and originality of ideas in the divergent-exploratory mode (Acar et al., 2023).

Also, in the graphic-visual domain, the convergent-integrative process task involves presenting a series of photographs of objects from which the participant must produce a single

integrated drawing using at least four of the eight objects presented. Participants have fifteen minutes to accomplish this task. For convergent-integrative tasks, the scoring relies on judges, adults who are instructed through guidelines and examples in the test manual on the convergent-integrative quality of a work. The interrater reliability is consistently high, usually greater than .80 (Cronbach's alpha) (Lubart, Besançon & Barbot, 2011; Storme et al., 2014). This part of EPoC focuses on creative synthesis, and two main aspects serve as the basis for scoring. First, the production must combine and truly synthesize the various elements provided. The second criterion for convergent-integrative quality is the extent to which the synthesis is original, novel, and meaningful. This novelty ranges from very typical, banal ideas to highly unique ones. Judges evaluate independently the productions on a 7-point scale, and the mean score for each production is used in the data analyses. The three judges show good inter-judge agreement (Cronbach's alpha =0.92).

The two graphical subtests of creativity from the EPoC battery were used in our study for two main reasons. First, drawing is less culturally dependent than writing and not a high-school-relevant skill; thus, it may be considered fair and exogenous. Second, drawing is unexpected and generally engaging for middle-school and high-school students. The two selected scores of creative potential are graphical divergent thinking and graphical integrative thinking. The correlation between them ($r=.130$; $p=0.093$) is not significant and the only significant correlations with the Big Five personality traits are for convergence with extraversion ($r=0.161$; $p=0.036$), and, marginally so, for divergence with openness ($r=0.150$; $p=0.052$).

3.4. Buttons task: a multi-armed bandit problem

The buttons task operationalizes a stochastic and stationary multi-armed bandit problem with a finite and known horizon. As discussed in sub-section 2.1, the ϵ -first algorithm is then

an optimal strategy. This task consists of two series of a hundred clicks on four or eight buttons¹. Each click and each button yield a number of points that can be positive, null, or negative; each button holds a hidden pre-set distribution of values, the same for all participants. The goal assigned to players in this task is to obtain the highest cumulative number of points.

One of the series is randomly selected at the end of the session, and its outcome determines the reward for this part of the experiment. Since incentive differences might influence creative behavior (Lipshitz & Strauss, 1997, Charness & Grieco, 2019), in the same session participants were randomly assigned to two incentive conditions: “performance” and “competition”. Players get one candy for 30 points in the performance condition². In the competition condition, the two players with the highest scores in the session receive a pack of 39 candies each, whereas the other players get nothing. Expected rewards are approximately the same in the two incentive conditions.

In the first series, called “Equal Solution”, the same score can be reached with any of the four buttons and, approximately so, with a random choice of buttons. No unique optimal strategy should be observed here, as any button combination over 100 clicks will lead to the same expected score. Since any behavior is approximately optimal, there should be no creativity premium in this task.

In contrast, the second series, called “Best Button”, was designed as a bandit problem with a well-identified best solution to reveal a link between the two facets of creative behavior. There are eight buttons to explore, and one is the *best*, but it takes time to discover and integrate this truth, and eventually win the jackpot. We introduced eight buttons instead of four to make this task more complex and search more valuable. The 96th click on the best button yielded a

¹ To control for button order effects, the ordering of buttons is counterbalanced across participants. A third buttons task was also considered but we will not refer to it in this paper.

² The number of candies was rounded up at the moment of reward distribution.

"jackpot" of 200 points. The latter was unpredictable, but a participant who recognized the best button and its permanence would increase chances to win this prize. It is important to note that the best button is still the best if the player misses the jackpot. This task allows us to test whether most successful adolescents in solving a bandit problem are those with a higher creative potential (hypothesis 3).

3.5. Typing task: a simple repetitive task

In the typing task, participants must retype as many codes as possible in three minutes. A code consists of five random letters that do not form a word. Once correctly typed, the code is highlighted in the list displayed on the participant's screen. The typing task was performed four times per participant, under a 2x2 factorial within-subject design (alone, pair) x (performance, competition). In the "pair" conditions, participants were matched with a randomly assigned partner from the same session with whom they could not communicate. The "performance" condition is a piece-rate scheme whereas the "competition" condition is a tournament. Both competition and performance conditions serve as incentives for effort. Whereas the pair condition may generate free-riding, competition should encourage individual effort. Due to technical issues, the typing task could not be performed on the first day, resulting in a sample of 6 sessions and 109 participants for this task.

The detailed experimental protocol, including all the details for replicating the experiment, can be found in the supplementary material.

4. Results

Definitions and descriptive statistics for dependent and control variables are presented in Tables A1 and A2 in the Appendix.

The four implications of representing creative cognition as a bandit problem which are reported in sub-section 2.3 will now be tested. Hypothesis 1 will be tested in Tables 1-5 and

Figure 1, hypothesis 2 in Figures 2 and 3, hypothesis 3 in Tables 4-5, and Hypothesis 4 in Tables 2, 3, and 6.

4.1 Optimal strategies in the buttons task

4.1.1. Finding the best solution in bandit tasks

Table 1 displays correlations between exploratory behavior, described by the number of switches in five successive 20-click periods, and performance measures in the best button task, including the number of points, late clicks on the best button, and finding the jackpot. The number of points is the cumulative outcome of the task, while late clicks on the best button and finding the jackpot are measures of convergence toward the optimal strategy and good performance.

The aim of Table 1 is to empirically test the expected theoretical solution of the bandit problem represented by the best button task, namely, the ϵ -first optimal strategy of *early exploration-subsequent convergence*, with $\epsilon = 0.2$.

Table 1 Correlation between exploration behavior over 5 successive 20-click periods and performance in the best button task.

Exploration behavior	Performance indicator		
	Number of points	Late clicks on the best button	Find the jackpot
<i>click period: 1 to 20</i>	0.176*	0.147	0.144
<i>click period: 21 to 40</i>	-0.054	-0.049	-0.0015
<i>click period: 41 to 60</i>	-0.234**	-0.227**	-0.181*
<i>click period: 61 to 80</i>	-0.275***	-0.267***	-0.213**
<i>click period: 81 to 100</i>	-0.307***	-0.352***	-0.299***
Observations	169	169	169

Notes: Pearson's correlation coefficient. Significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Late clicks on the best button are defined as the number of clicks registered on the best-performing button during the final 20-click period, between the 81st and 100th button choices.

The number of switches is positively and significantly correlated at 5% level with the number of points that is to be maximized ($p=0.022$), and at 10% with the other performance indicators ($p=0.057$ and $p=0.061$), when switches occur in the first period of the sequence.

However, this correlation becomes negative and significant as the task progresses, and correlation coefficients become increasingly negative over time. Thus, switching a lot at the beginning of the task and switching less in the last part increase the probability of a good performance in the task. The pursuit of exploration in later periods is counterproductive. These results are consistent with hypothesis 1.

In contrast, the correlation coefficient between exploration behavior and the number of points on the equal solution task is close to zero and does not reach statistical significance at conventional levels (see Table A3 in the Appendix). This observation is consistent across all five distinct 20-click periods, confirming hypothesis 4 that exploration and convergence are not useful in this task.

The optimal strategies radically differ in the “equal solution” and the “best button” tasks. No unique best behavior emerges in the “equal solution” task because the expected performance is the same whether one switches constantly or does not switch at all. Because there is no unique optimal behavior, there should be no creativity premium in this task (hypothesis 4). In sharp contrast, a unique optimal strategy exists in the “best button” task: ϵ -first, that is, search for the best button at the beginning of the task and stick to the best button once it has been found (hypothesis 1).

4.1.2. Testing the complementarity of exploration and exploitation in bandit tasks

It is noteworthy in Table 1 that the number of switches in all periods correlates almost identically with the first two performance indicators and reasonably well with the third one. This recalls that clicking frequently on the best button in the last period is the way to obtain a high cumulated score in this task and, obviously, to find the jackpot. It is a measure of successful exploitation.

A stronger test of creative cognition as a bandit problem consists in testing hypotheses 1 and 4 with a weaker and more general measure of convergence-exploitation that does not

presume that the best button was found. In Table 2, we empirically define convergence-exploitation as the opposite of exploration, that is, more precisely, switching less frequently versus more frequently than the median.

Poisson regressions with fixed effects by experimental sessions were selected for their suitability in analyzing count data, such as the number of points and the number of switches in Tables 2-6. A likelihood-ratio test conducted after estimation demonstrated a superior fit for the Poisson model when compared to the Negative Binomial model. As part of our robustness checks, Negative Binomial and OLS models were also employed, yielding results that align with the patterns presented in this analysis.

“High early explorers” are defined in Table 2 as individuals who switch between buttons more frequently than the median value (11 clicks) during the *initial* 20 clicks in the best button task. Similarly, “high late convergers” switch less frequently than the median (3 clicks) during the *final* 20 clicks (between the 81st and 100th button choices). Table 2 uses a multiple regression framework to predict the performance of high early exploration and late exploitation so defined in the two buttons tasks. These two variables are introduced in Table 2 as dummy variables, taking value 1 for high exploration or high exploitation and zero otherwise. An interaction term is also introduced in an alternative formulation of the model (columns 2, 4, and 6). We provide incidence rate ratios (IRR) as coefficients for ease of interpretation (with significance tests for coefficients being different from 1). The controls added in Table 2 to check the robustness of the effect of early exploration-late convergence on the performance in the task are sex, above normal age, risk-seeking, Big five personality traits, competition or performance condition, and comprehension errors. Notably, none of these controls exhibited statistical significance. Their description and descriptive statistics can be found in Table A1.

Table 2 Performance in the buttons tasks considering the exploration and convergence behavior.

Poisson regression (IRR)	Equal solution task		Best Button task			
	Number of points	Number of points	Number of points	Number of points	Points excluding the jackpot	Points excluding the jackpot
High early explorer	0.989 (0.0173)	1.014 (0.0231)	1.299** (0.122)	0.904 (0.107)	1.264** (0.0931)	0.964 (0.0773)
High late converger	0.978 (0.0153)	1.002 (0.0165)	1.461*** (0.131)	1.031 (0.133)	1.379*** (0.0979)	1.061 (0.102)
High early explorer x High late converger		0.946 (0.0322)		1.858*** (0.278)		1.607*** (0.184)
<i>Control variables</i>						
Girl	0.990 (0.0151)	0.992 (0.0150)	0.952 (0.0833)	0.925 (0.0799)	0.923 (0.0637)	0.904 (0.0609)
Above normal age	0.980 (0.0197)	0.981 (0.0191)	1.128 (0.0986)	1.117 (0.0987)	1.108 (0.0761)	1.099 (0.0779)
Risk seeking	1.004 (0.00423)	1.004 (0.00421)	1.006 (0.0236)	1.002 (0.0233)	1.009 (0.0188)	1.006 (0.0184)
Competition condition	0.968 (0.0204)	0.968 (0.0203)	0.961 (0.103)	0.986 (0.105)	0.984 (0.0862)	1.001 (0.0866)
Comprehension error	0.978 (0.0208)	0.979 (0.0208)	0.954 (0.109)	0.958 (0.107)	0.929 (0.0877)	0.929 (0.0861)
<i>Personality traits</i>						
Openness	0.990 (0.00724)	0.991 (0.00731)	1.048 (0.0371)	1.036 (0.0345)	1.033 (0.0287)	1.024 (0.0274)
Conscientiousness	1.005 (0.00648)	1.005 (0.00647)	1.007 (0.0411)	1.008 (0.0373)	1.006 (0.0331)	1.006 (0.0299)
Extraversion	0.994 (0.00648)	0.994 (0.00647)	0.985 (0.0356)	0.987 (0.0350)	0.978 (0.0286)	0.980 (0.0280)
Agreeableness	1.002 (0.00629)	1.002 (0.00647)	0.996 (0.0468)	0.988 (0.0442)	0.992 (0.0374)	0.986 (0.0354)
Emotional Stability	0.989 (0.00561)	0.989* (0.00559)	0.945 (0.0347)	0.948 (0.0334)	0.948+ (0.0276)	0.951+ (0.0265)
Constant	465.9*** (29.82)	454.2*** (29.74)	259.5*** (94.79)	362.2*** (133.8)	226.2*** (64.32)	291.7*** (82.72)
Observations	169	169	169	169	169	169
Chi2	24.60	26.00	71.96	126.1	82.88	122.3
p(Chi2)	0.217	0.206	<0.001	<0.001	<0.001	<0.001
Log-likelihood	-969.6	-964.9	-9655.1	-9067.9	-4929.7	-4671.7

Notes: Poisson regressions with fixed effects by experimental sessions. IRR: incidence rate ratios as coefficients. Robust standard errors are in parentheses. Significance level: * p<0.05, ** p<0.01, *** p<0.001. The descriptions of variables and statistics are in Tables A1 and A2 in the appendix.

Table 2 allows a comparison of the effect of early exploration-late convergence on performance in the equal solution task and in the best button task. The first two columns show that high early exploration and late exploitation have no impact on the outcome of the equal solution task, in conformity with hypothesis 4. The third column shows that, in the best button task, high early explorers achieved 29.9% more points than their counterparts (p=.005), whereas

high late convergers garnered 46.1% more points ($p < 0.001$). However, when an interaction term is introduced in the fourth column, this term alone captures the overall effect, with an 85.8% increase in points ($p < 0.001$) which is about the sum of those two partial effects. This result suggests that the *combined presence* of early exploration and late convergence, i.e., their complementarity in producing points, is pivotal for maximizing performance in the best button task. A similar result is observed in the last two columns that exclude the jackpot's influence, providing confidence that the overall effect is not entirely driven by luck, thereby underscoring the robustness of our findings.

Do adolescents adopt an optimal strategy? Figure 1 shows that they do on average. In line with expectations, the frequency of switches is maintained around 40% during the equal solution series over the 100 clicks. Participants search for a solution until the end of the task, not knowing with certainty that there is, in fact, no single best solution. On the other hand, in the best button task, the frequency of switches falls monotonously from 50% to 33% from the beginning to the end. This occurs because some participants eventually identify the best button and then keep clicking on it frequently. The frequency of clicks on the best button is multiplied by three on average between the task's beginning and end.

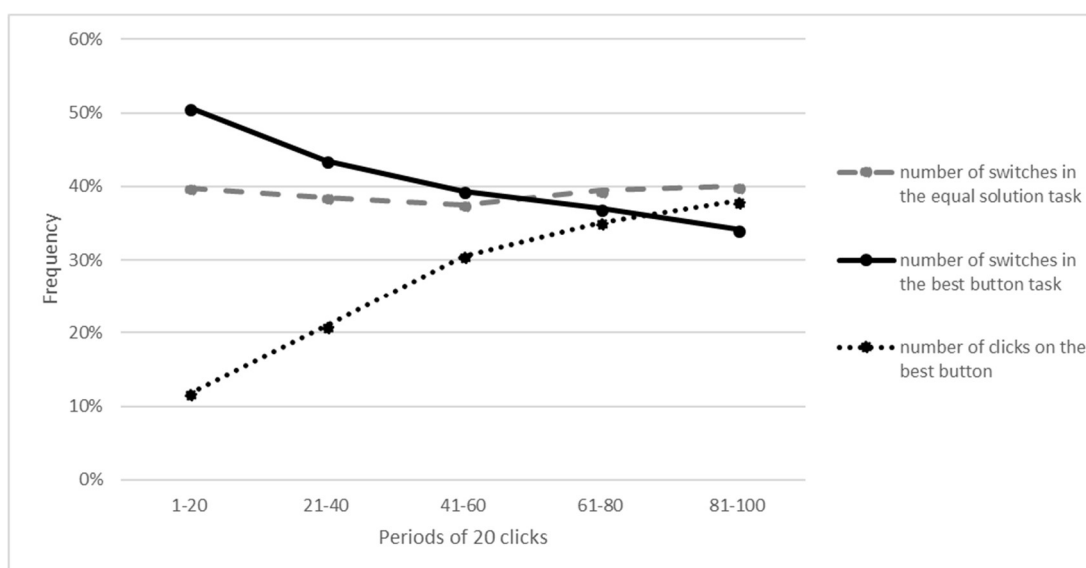
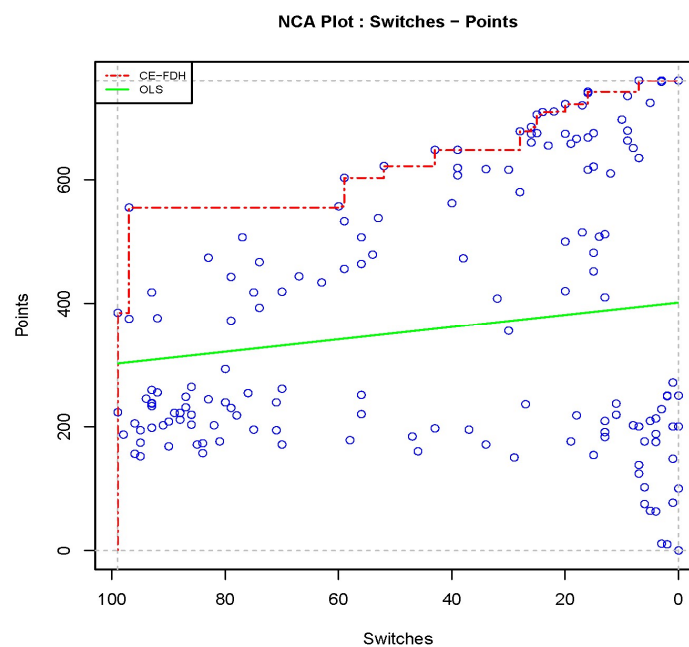


Figure 1 Exploration and convergence in the two buttons tasks

4.2 Is creativity necessary for high performance in the best button task?

To test hypothesis 2, we perform a Necessary Condition Analysis (NCA, Dul, 2016) to find out if early exploration and subsequent convergence are *necessary*, hence required for *each* individual to obtain high performance. NCA is based on necessity logic and has been applied in several disciplines, including the psychology of academic success (Tynan et al., 2020) and the psychology of creativity (Dul et al., 2020). For example, scholars demonstrated with NCA that intelligence is a necessary condition for creativity (Karwowski et al., 2016, 2017; Shi et al., 2017).



Note: The line through the middle is the OLS regression line for comparison, which shows the *average* outcome in the best button task as a function of the total number of switches.

Figure 2. Necessary Condition Analysis (NCA) showing the *maximum* outcome in the best button task as a function of the number of switches

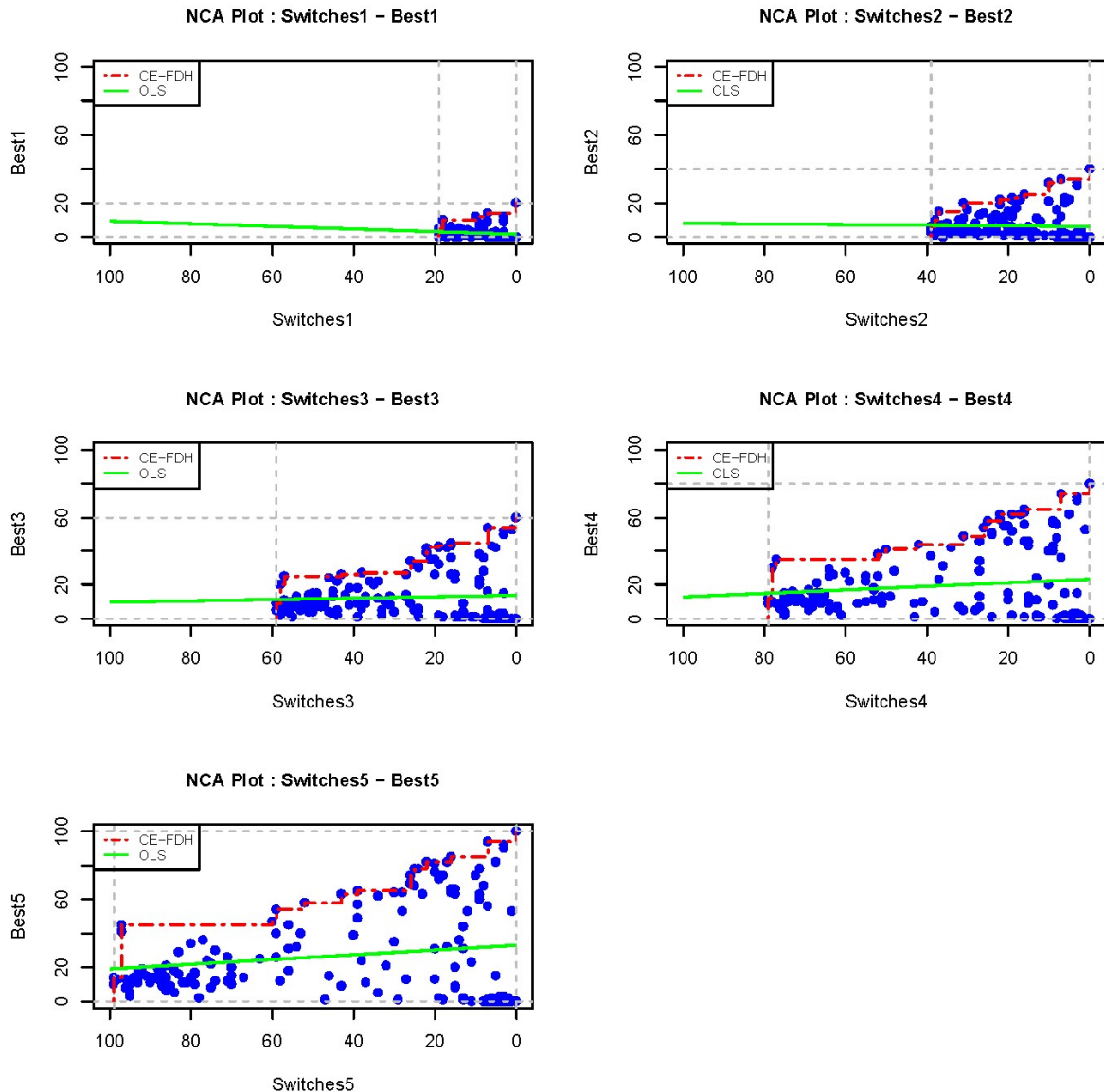
In Figure 2, the horizontal axis represents the number of switches during a session of 100 clicks (note that the horizontal axis is reversed and runs from left to right: from 100 to 0). The vertical axis represents performance, i.e., the number of points in the best button task after

100 clicks. NCA draws a *ceiling line* on top of the data of an XY scatter plot³. This line differs from a central line, such as the OLS regression line (also shown in Figure 2 for reference). The ceiling line represents the level of $X = X_c$ that is necessary (but not sufficient) for a given level of performance $Y = Y_c$. The necessity effect size is the empty space above the ceiling line as a fraction of the total possible space of observations, given by the minimum and maximum observed values of X and Y. The results support that a low total number of switches is necessary for high performance. The necessity effect size is 0.18 ($p < 0.001$). This means that, with a high number of switches, it is impossible to have a high-performance score. For example, when an individual switches more than 60 times, the performance score cannot be above approximately 550. For reaching a performance score of more than 700, the number of switches should not exceed 30. The highest scores are reached with a few switches only. The results also show that a few individuals reached the highest scores without switching. Apparently, these individuals were lucky that they pushed on the best button the first time without any further exploration. Thus, we can state that *early exploration or luck is necessary for high performance in conjunction with the necessity to stop exploring after the best option is discovered*. The ability to stop on time is a crucial part of performance in the best button task.

The necessity of convergence is illustrated in Figure 3, which shows the cumulative number of clicks on the best button for the five successive periods of 20 clicks. Individuals who continue exploring will not have a high number of clicks on the best button and, consequently, will not gain a high number of points⁴.

³ For all NCA analyses, we selected the CE-FDH ceiling line because of the non-linearity of the border between the empty and full area. The p-values were estimated with 10 000 permutations.

⁴ Lee et al. (2017) theorize the effect of switching on creativity by arguing that switching reduces cognitive fixation.



Note: The ceiling line represents the *maximum* number of clicks on the best button as a function of the number of switches. The line through the middle is the OLS regression line for comparison, which shows the *average* number of clicks on the best button as a function of the number of switches.

Figure 3. Necessary Condition Analysis (NCA) shows how the ceiling line (CE-FDH) develops over time in 5 successive periods of 20 clicks.

4.3 Creativity and behavior in the buttons task

Having identified the unique optimal strategy in the best button task and its non-unicity in the equal solution task, we wish to show in Tables 3, 4, and 5 below that individuals showing the right combination of divergent thinking and convergent thinking tend to behave optimally like early explorers and late exploiters. This is Hypothesis 3. Table 3 relates to the equal solution task, and Tables 4 and 5 to the best button task. Poisson regressions are used in these tables to

explain the number of switches within 20-click periods (in Tables 3 and 4) and the number of clicks on the best button (in Table 5) by scores of divergent thinking and convergent thinking with the same controls as in Table 2.

Table 3 shows that adolescents with a high score of divergent thinking switch significantly more than others in *all* 20-click periods for the equal solution task. They maintain a high exploration intensity throughout the task as if they were in search of the best move. For example, a one standard deviation increase in the divergence score corresponds to a 31.7% increase in the number of switches during the 41-60 period of clicks ($p < 0.001$). In contrast, as expected for this task, a high score of convergent thinking does not generate less switching, i.e., more exploitation, over time.

Table 3 Creativity scores and exploration behavior in the equal solution task

Poisson regression (IRR) Dep. var: Number of switches	Periods of 20 clicks				
	1-20	21-40	41-60	61-80	81-100
<i>Creativity score</i>					
Divergent thinking	1.157* (0.0661)	1.282** (0.0988)	1.317*** (0.0887)	1.243*** (0.0761)	1.176* (0.0813)
Convergent thinking	0.983 (0.0663)	0.937 (0.0698)	0.965 (0.0752)	0.978 (0.0768)	1.013 (0.0797)
<i>Control variables</i>					
Girl	0.991 (0.129)	0.840 (0.131)	0.809 (0.127)	0.811 (0.117)	0.811 (0.129)
Above normal age	0.968 (0.139)	1.026 (0.184)	0.942 (0.177)	0.969 (0.177)	1.022 (0.191)
Risk seeking	0.989 (0.0302)	0.983 (0.0337)	0.945 (0.0313)	0.970 (0.0355)	0.960 (0.0379)
Competition condition	0.933 (0.164)	0.928 (0.190)	0.974 (0.185)	1.029 (0.213)	0.841 (0.171)
Comprehension error	1.074 (0.187)	0.820 (0.171)	0.735 (0.147)	0.967 (0.200)	0.749 (0.163)
<i>Personality traits</i>					
Openness	0.944 (0.0512)	0.908 (0.0585)	0.866* (0.0533)	0.957 (0.0615)	0.937 (0.0573)
Conscientiousness	0.940 (0.0559)	0.925 (0.0653)	0.924 (0.0667)	0.939 (0.0635)	0.899 (0.0631)
Extraversion	1.025 (0.0545)	1.034 (0.0684)	1.091 (0.0693)	0.999 (0.0628)	0.987 (0.0674)
Agreeableness	1.046 (0.0722)	1.034 (0.0805)	1.063 (0.0841)	1.012 (0.0806)	0.996 (0.0785)
Emotional Stability	0.979 (0.0519)	0.991 (0.0628)	0.973 (0.0604)	1.007 (0.0580)	0.970 (0.0573)
Constant	11.98*** (6.579)	19.86*** (13.17)	24.28*** (15.00)	20.10*** (12.31)	46.14*** (30.50)
Observations	169	169	169	169	169
Chi2	51.61	37.86	53.85	33.61	30.81
p(Chi2)	<0.001	0.00921	<0.001	0.0289	0.0578

Log-likelihood	-747.5	-898.4	-872.7	-902.7	-939.5
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Notes: Poisson regressions with fixed effects by experimental sessions. IRR: incidence rate ratios as coefficients. Robust standard errors in parentheses. Significance level: * p<0.05, ** p<0.01, *** p<0.001. Description of variables and statistics in Tables A1 and A2 in the Appendix.

Table 4 reproduces Table 3 for the best button task, with a different result as hypothesized. Now, an increase of one standard deviation in the divergence score significantly increased the number of switches during the first 20-click period by 14.6% (p=0.004), but the significance level decreases regularly in subsequent periods. Thus, adolescents with a high score of divergent thinking were more eager than others to adopt the optimal strategy of exploring intensively in the early periods, which is hypotheses 1 and 3, and showed a declining propensity to explore more than others any time. The negative effect of convergent thinking on the number of switches is in the assumed direction but not significant.

Table 4 Creativity scores and exploration behavior in the best button task

Poisson regression (IRR) Dep. var: Number of switches	Periods of 20 clicks				
	1-20	21-40	41-60	61-80	81-100
<i>Creativity score</i>					
Divergent thinking	1.146** (0.0539)	1.158* (0.0769)	1.136 (0.0879)	1.164 (0.0982)	1.158 (0.0991)
Convergent thinking	0.991 (0.0570)	0.996 (0.0686)	0.964 (0.0763)	0.973 (0.0816)	0.953 (0.0818)
<i>Control variables</i>					
Girl	0.946 (0.104)	0.871 (0.127)	0.909 (0.147)	0.939 (0.164)	0.891 (0.159)
Above normal age	0.912 (0.117)	1.051 (0.163)	0.776 (0.144)	0.747 (0.153)	0.716 (0.164)
Risk seeking	0.945* (0.0215)	0.951 (0.0306)	0.942 (0.0348)	0.956 (0.0381)	0.948 (0.0407)
Competition condition	1.080 (0.159)	0.881 (0.170)	0.706 (0.158)	0.766 (0.178)	0.815 (0.207)
Comprehension error	1.146 (0.165)	1.036 (0.207)	0.861 (0.193)	0.885 (0.212)	0.990 (0.259)
<i>Personality traits</i>					
Openness	0.946 (0.0408)	0.954 (0.0529)	0.971 (0.0667)	0.981 (0.0735)	1.017 (0.0842)
Conscientiousness	0.951 (0.0444)	0.916 (0.0553)	0.939 (0.0657)	0.935 (0.0721)	0.951 (0.0792)
Extraversion	1.030 (0.0461)	1.026 (0.0541)	1.038 (0.0647)	1.007 (0.0699)	1.042 (0.0778)
Agreeableness	0.954 (0.0547)	0.972 (0.0727)	0.890 (0.0750)	0.902 (0.0855)	0.912 (0.0903)
Emotional Stability	1.034 (0.0453)	1.089 (0.0599)	1.168* (0.0770)	1.138 (0.0796)	1.122 (0.0800)
Observations	169	169	169	169	169
Chi2	36.03	45.79	37.50	31.70	23.44
p(Chi2)	0.0153	<0.001	0.0102	0.0466	0.268
Log-likelihood	-773.0	-868.3	-944.8	-994.7	-953.3

Notes: Poisson regressions with fixed effects by experimental sessions. IRR: incidence rate ratios as coefficients. Robust standard errors in parentheses. Significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Description of variables and statistics in Tables A1 and A2 in the Appendix.

Table 5 shows the impact of creativity scores on successfully clicking on the best button.

Table 5 Creativity scores and convergence behavior in the best button task

Poisson regression (IRR) Dep. var: Number of clicks on the best button	Periods of 20 clicks				
	1-20	21-40	41-60	61-80	81-100
<i>Creativity score</i>					
Divergent thinking	1.028 (0.0961)	1.174 (0.135)	1.200 (0.120)	1.085 (0.107)	1.127 (0.0973)
Convergent thinking	1.120 (0.140)	1.103 (0.128)	1.016 (0.0918)	1.140 (0.105)	1.209* (0.102)
<i>Control variables</i>					
Girl	0.967 (0.166)	0.999 (0.226)	0.911 (0.170)	1.008 (0.173)	1.040 (0.175)
Above normal age	1.798** (0.391)	1.594* (0.344)	1.565* (0.277)	1.371 (0.237)	1.441* (0.247)
Risk seeking	1.027 (0.0521)	0.974 (0.0573)	1.007 (0.0516)	0.988 (0.0444)	0.983 (0.0380)
Competition condition	1.596* (0.335)	1.126 (0.342)	1.387 (0.349)	1.261 (0.296)	1.008 (0.213)
Comprehension error	1.173 (0.226)	0.953 (0.290)	1.092 (0.276)	1.052 (0.246)	0.789 (0.183)
<i>Personality traits</i>					
Openness	1.062 (0.0820)	0.972 (0.0823)	0.995 (0.0686)	1.086 (0.0751)	1.030 (0.0656)
Conscientiousness	1.152 (0.107)	1.117 (0.105)	0.943 (0.0784)	0.977 (0.0748)	0.966 (0.0682)
Extraversion	0.919 (0.0678)	0.897 (0.0745)	0.958 (0.0769)	1.008 (0.0744)	1.025 (0.0650)
Agreeableness	0.912 (0.0852)	0.982 (0.0982)	1.037 (0.0999)	1.087 (0.0950)	1.057 (0.0883)
Emotional Stability	0.954 (0.0773)	0.861* (0.0647)	0.908 (0.0637)	0.919 (0.0624)	0.943 (0.0597)
Constant	1.177 (0.821)	5.062 (4.607)	5.800* (4.658)	3.081 (2.193)	6.533** (4.317)
Observations	169	169	169	169	169
Chi2	37.50	67.04	56.21	44.49	39.28
p(Chi2)	0.0102	<0.001	<0.001	0.00130	0.00615
Log-likelihood	-384.6	-656.6	-823.8	-889.8	-900.4

Notes: Poisson regressions with fixed effects by experimental sessions. IRR: incidence rate ratios as coefficients. Robust standard errors in parentheses. Significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Description of variables and statistics in Tables A1 and A2 in the Appendix.

Divergence has no significant effect on the frequency of clicks on the best button, whereas convergence has a sizable and significant effect on the latter, essentially in the last 20 clicks. During this period, an increase of one standard deviation in the convergence score increases the number of clicks on the best button by 20.9% ($p = .025$). Thus, adolescents with a

high score of convergent thinking also behave optimally. This is another confirmation of hypotheses 1 and 2.

Interestingly, Tables 4 and 5 show that students above normal age click significantly more than others on the best button in the first three 20-click periods while risk-seeking students switch significantly less than others in the first period and do not click more on the best button in later periods. Thus, older students were relatively lucky or insightful to find the best button early and kept clicking on it later on whereas risk-seeking students counted on their luck in choosing a button and holding their choice, at the risk of being disappointed.

4.4 Typing task

The typing task aims to test the hypothesis that creative individuals are no more productive than others in simple tasks bearing no uncertainty where learning is not really needed (hypothesis 4). The adolescents' productivity in the typing tasks is measured by the number of correct codes typed in three minutes.

Table 6 relates the behavior in the typing task to the two creativity scores and control variables. A dummy variable indicating that typing was done alone or in pairs was added here to the controls introduced in previous tables. The first column shows the Incidence Rate Ratios (IRR) coefficients of a Poisson regression on the number of correct codes typed by participants in each of the four typing task conditions. The second column shows odds ratios from a Probit regression on a dummy variable equal to 1 if the participant typed more correct codes than the partner and 0 otherwise. The Probit regression provides probability estimates for binary or categorical outcomes and is well-suited for quantifying the likelihood of typing more than the partner.

Table 6 Behavior in the typing task and creativity scores.

Dependent variable	Poisson regression (IRR)	Probit regression (odds ratios)
	Number of correct codes	Typing faster than partner
<i>Creativity score</i>		
Divergent thinking	0.985 (0.0283)	1.065 (0.118)
Convergent thinking	1.055 (0.0360)	1.337* (0.166)
<i>Experimental condition</i>		
Competition condition	0.968 (0.0250)	
Pair condition	0.925** (0.0235)	
Competition condition x Pair condition	1.231*** (0.0405)	
<i>Control variables</i>		
Girl	1.017 (0.0585)	2.008** (0.483)
Above normal age	0.957 (0.0849)	1.173 (0.368)
Risk seeking	1.032* (0.0126)	1.118* (0.0538)
Comprehension error	0.994 (0.0648)	0.938 (0.214)
<i>Personality traits</i>		
Openness	0.970 (0.0195)	0.789** (0.0695)
Conscientiousness	0.987 (0.0221)	0.892 (0.0854)
Extraversion	1.006 (0.0210)	0.998 (0.0712)
Agreeableness	0.999 (0.0251)	0.876 (0.0979)
Emotional Stability	1.012 (0.0210)	1.158 (0.108)
Constant	21.71*** (3.509)	1.748 (1.377)
Observations	436	218
Chi2	126.1	27.75
p(Chi2)	<0.001	0.0479
Log-likelihood	-1476.3	-134.8

Notes: IRR: incidence rate ratios as coefficients. Standard errors clustered at the participant level in parentheses. Fixed effect by experimental session. Significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The descriptions of variables and statistics in Tables A1 and A2 are in the Appendix.

Our main result, displayed in the first column, is that high creativity scores do not help typing fast, as neither divergent thinking nor convergent thinking scores show significant relationships to task performance. Thus, hypothesis 4 is once more confirmed.

The probability of typing more correct codes than the partner, displayed in the second column, shows that the convergence score increases eagerness to cooperate with partner under

the pair condition, whether competing with other pairs or not. Increasing the convergence score by one standard deviation raises probability of being the more productive partner by 33.7% ($p=0.019$). A plausible reason for more integrative thinkers being cooperative is that they are intelligent (Karwowski et al., 2017) and understand the benefits of cooperation in teamwork.

It is worth noticing in the first column that free riding occurred when the teenagers worked in pairs but competition forced them to cooperate and work harder when they formed pairs. However, if participants work alone, a tournament scheme, i.e., the competition condition, does not make the adolescents work harder than a piece-rate offering the same expected return. We may also note that risk-seekers are more successful and cooperative than others in this task. While they counted on their luck-at the risk of being disappointed- in the best button task (see Table 4), they put more effort in finding correct codes, whether alone or in pairs, because they seem to appreciate betting and playing. Other things equal, girls too appear much more cooperative than boys in Table 6.

4.5. School grades and creativity

Because a major goal of educational policy in the 21st century should be to develop the creative potential of students, we collected the grades obtained by our 10th graders at the *Brevet*, a national exam taken in France by the vast majority of students after 9th grade, to examine how the academic achievement in French middle schools correlates with the divergent and convergent components of adolescents' creative potential.

The *Brevet* contains three written tests: in Math, French literature, and History-Geography. Students also take an oral test on Arts history. Data for these grades were collected for 113 participants. It is important to note that these grades are delivered anonymously at a national level, not by the students' own teachers. We also gathered the general grade which is the average of these four tests and of a grade the students got during the school year for different topics. It hence reflects a broader level of knowledge, regular attention, and skills than the four

tests. The national grade was collected for 119 participants. All grades are delivered on a continuous 20-point scale. A general grade of 10 or more is required to pass the *Brevet*.

Following the same methodology as in Berlin et al. (2016), we regress grades in Math and French literature for the *Brevet* on individual measures of creativity, controlling for personality traits, risk-seeking, sex, age above normal. We disaggregated the five personality traits into their positive and negative components because these are not strictly opposite within the condensed Ten Item Personality Inventory (TIPI) score and do not necessarily exert opposite effects. To control for potential correlation of unobserved variables in the error terms, we will present the results through SUR (Seemingly Unrelated Regression)⁵ using one-step estimation. We also regress the general grade, using an OLS, on the same independent variables. The results are shown in Table 7.

Table 7 Seemingly unrelated and OLS regressions of school grades of 9th graders

	Seemingly unrelated regression (SUR)		OLS
	Math	French Literature	General grade
<i>Creativity score</i>			
Divergent thinking	0.227 (0.275)	0.105 (0.224)	0.125 (0.202)
Convergent thinking	0.886** (0.293)	0.519* (0.239)	0.245 (0.227)
<i>Control variables</i>			
Girl	-1.093+ (0.594)	1.803*** (0.483)	0.335 (0.400)
Above normal age	-0.188 (0.672)	0.0976 (0.547)	-0.0877 (0.488)
Risk seeking	-0.176 (0.156)	0.284* (0.127)	-0.0196 (0.108)
<i>Personality traits</i>			
Extraverted, enthusiastic	0.133 (0.229)	0.131 (0.187)	0.0788 (0.135)
Reserved, quiet	-0.0158 (0.172)	0.0653 (0.140)	-0.0146 (0.0965)
Critical, quarrelsome	0.398+ (0.221)	-0.202 (0.180)	0.142 (0.142)
Sympathetic, warm	-0.156 (0.268)	-0.398+ (0.219)	-0.300+ (0.152)
Dependable, self-disciplined	0.329 (0.259)	0.0858 (0.211)	0.275+ (0.140)
Disorganized, careless	-0.0655 (0.167)	-0.0258 (0.136)	-0.155 (0.0974)

⁵ We do not report the regressions for History/Geography and Arts history which also contribute to the general grade and are included in the SUR regression. Their results do not change the main conclusions.

Anxious, easily upset	-0.442** (0.157)	-0.116 (0.128)	-0.110 (0.108)
Calm, emotionally stable	-0.0444 (0.210)	0.0804 (0.171)	0.0174 (0.130)
Open to new experiences, complex	-0.180 (0.194)	0.113 (0.158)	0.168 (0.115)
Conventional, uncreative	0.00908 (0.179)	0.361* (0.146)	0.220+ (0.118)
Constant	12.39*** (2.634)	9.152*** (2.146)	11.47*** (1.677)
Observations	113	113	119
R-squared	0.214	0.248	0.143
Adjusted R-squared	0.093	0.132	0.0188
F-Statistics	2.046	2.488	1.427
Prob > F	0.0118	0.0016	0.1488

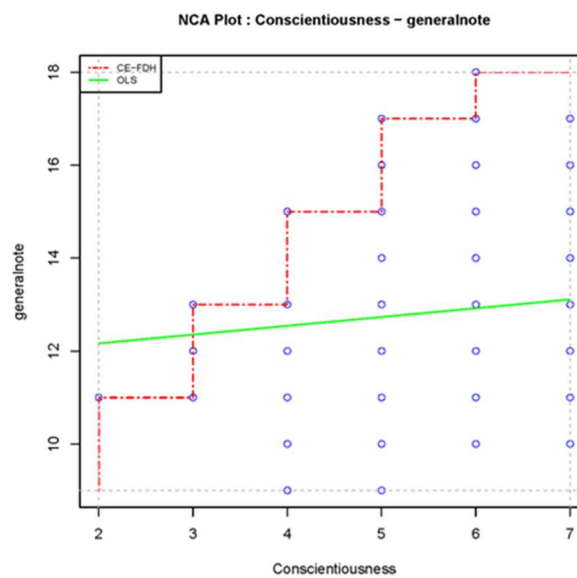
Notes: Columns (1) and (2) are the results of one-step SUR analysis. A Breusch-Pagan test of independence confirms correlations of the error terms of the different regressions ($\chi^2 = 70.135$, $p < 0.0001$). Standard errors in parentheses. Significance level: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The descriptions of variables and statistics in Tables A1 and A2 are in the Appendix.

Convergent and divergent thinking show distinct relationships to Math and French literature grades. Convergent thinking has a positive, significant relationship for both Math ($p=0.003$) and French literature ($p=0.030$). A one-unit increase in the score of convergent thinking is estimated to have an increase of 0.886 points in the Math grade. In contrast, the effect of divergent thinking on grades is never significant. However, its real effect is ambiguous in French literature because we observe at the same time that ‘conventional, uncreative’ and ‘risk-seeking’ students are better graded than others. Anxiety is negatively related ($p=0.005$), and critical thinking positively related ($p=0.073$), to mathematical ability. Finally, girls have higher grades than boys in French literature ($p < 0.001$) and marginally lower grades in Math ($p=0.066$) after controlling for the set of creativity and personality measures.

The effects of convergent and divergent thinking on the general grade are not significant, and we observe that being ‘conventional, uncreative’ even exerts a marginally significant effect on the general grade ($p=0.064$). Interestingly, the virtues of self-discipline and organization conveyed by conscientiousness have but a small effect on each specific grade, but the attention uniformly devoted to all fields makes a significant difference on the general grade ($p=0.052$). In contrast, a sympathetic, warm personality correlates negatively with

grades ($p=0.051$), probably because it is associated with a lack of discipline and seriousness at school. However, the OLS on the general grade does not pass an F-test.

We additionally performed a necessary condition analysis on these data that shows no necessity of a high creative potential for high grades. In contrast, conscientiousness is needed by a student to be successful in middle school (Figure 4), though it is not sufficient to obtain a high grade. The necessity effect size is 0.30 ($p = 0.004$).



Note: The line through the middle is the OLS regression line for comparison, which shows the *average* grade as a function of conscientiousness.

Figure 4. Necessary Condition Analysis (NCA) showing the ceiling line (CE-FDH) for general grade as a function of conscientiousness.

5. Discussion and Conclusion

5.1. What have we learned?

The goal of our study was to show that creative cognition can be partly analyzed as a bandit problem as it requires a combination of exploration of new ideas and a subsequent exploitation of the better ideas. This process of thought is both probabilistically sufficient and

individually necessary for achieving high performance in sequential decisions of experience under uncertainty. However, it is neither necessary nor sufficient to achieve the well-known or simple tasks of ordinary life. Our empirical demonstration relied on behavioral experiments including a simple bandit problem with a unique optimal strategy, the best button task, and two other tasks in which search either does not converge (the equal solution task) or is not helpful (the typing task).

We find strong evidence for the optimality of early exploration followed by exploitation of the best button after finding it and for the inefficiency of pursuing exploration when it is no longer needed (hypotheses 1 and 2). Luck may substitute for intentional exploration, but convergent-integrative thinking is still needed to exploit this luck (serendipity). Our study demonstrates that adolescents with a high creative potential can solve a multi-armed bandit problem with an emerging best solution and behave optimally as efficient explorers and exploiters (hypothesis 3). Because the best behavior is known or obvious in simple repetitive tasks like our typing task, a high creative potential is not helpful for these tasks, at least in the short run (hypothesis 4).

The returns to creative potential appear thus to be positive and high in uncertain environments where some unknown good can be discovered, but low and possibly negative in environments where it is believed that no such good can be found. They remained significant after controlling for sex, personality, incentives, and other factors.

Describing creative cognition as a bandit problem that an algorithm can solve might be seen as a limitation of the complexities of the human brain. However, if creative cognition essentially applies to novel and/or complex sequential decisions in an uncertain environment, we should not be too surprised that an algorithmic solution to a bandit problem provides a good description of the process. The recent outburst of artificial intelligence algorithms offers an illustration of the fact that the human brain works apparently like an algorithm to perform

creative tasks and recent computational approaches tend to “demystify creative cognition” (Mekern et al., 2019). Finally, it should be recalled that no general mathematical solution to the bandit problem has been found yet so that the available algorithms provide approximate solutions that may be compared with sophisticated heuristics.

Divergence has typically been emphasized in the creativity literature (Guilford, 1967), but we found that convergence is equally important in the creative process. Several models in the creative cognition approach and related work (see Mumford et al., 1991; Finke et al, 1992; Ward, 2007; Smith et al., 2009) have identified a set of micro processes, underlying divergence and convergence, which combine in dynamic sequences. And the neuroscientific models presented in sub-section 2.2 revealed that creative cognition results from the interaction of two networks located in different sets of brain regions that typically do not work together and are rarely connected. This description is confirmed by our behavioral experiment since our two dummy variables ‘high early explorer’ and ‘high late converger’ are strongly negatively correlated ($r = -0.457, p < .001$). The behavioral counterpart of the (rare) connection of two separate networks in the brain is the (rare) interaction of high early exploration and high late exploitation in the bandit task.

We observed a close correspondence in the best button task between the scores of divergent thinking and early exploration. Such correspondence was not immediate because divergent thinking measures fluency in the generation of ideas whereas early exploration merely captures random switching between different buttons at the beginning of the task. We think that this is what makes the result interesting. The link derives from our hypothesis that creative thinking is like a bandit problem and bandit problems are solved efficiently by a timely combination of random exploration and subsequent exploitation of good ideas. Thus, if our hypothesis is correct, random exploration should be a basic form of divergent thinking. This is

what we find. A similar argument can be made for the close correspondence between convergent thinking and late exploitation.

Insofar our experiment validates a theory that creative cognition works like an efficient resolution of bandit problems, the measure of creative potential by the EPoC battery giving an equal weight to divergence and convergence would also be supported. However, the two components of creative potential are used jointly in creative cognition so that the creative potential might be better captured by their product than by their sum. Even this last assertion must be tempered because, as we showed in the best button task, too much exploration would be counterproductive. This discussion suggests that scores of exploration and exploitation in a bandit problem might provide a simple, though partial, test of creative potential in experiments. Such measures would need to be completed by a measure of imagination like the one proposed by Jankowska and Karwowski (2015).

5.2. Limitations of our study and future research

The strength of our results may partly rest on the focus of our experiment which uses a simple bandit problem to describe creative cognition. Consequently, a limitation of our study is that we do not account for the role of imagination in our experiment as all options are given and just need to be explored. Due to time constraints, we only used graphical tasks, and no verbal tasks, for measuring creative potential. This may have contributed to reducing the beneficial effect of creative thinking on grades. On the other hand, we could use many controls and robust multivariate regressions to test our hypotheses. Future research will have to confirm our findings on more sophisticated bandit problems and with verbal measures of creative potential.

5.3. Education, learning, and creativity

Our examination of grades obtained in a nation-wide exam at the end of 9th grade has confirmed the appreciation of convergent thinking, essentially in Math and French literature,

and the ambiguous status of divergent thinking at the end of middle school. Though divergent thinking is never significant in the regressions when personality traits are maintained constant, some results suggest that convergent but ‘conventional, uncreative students’ may succeed at this stage of their education.

The meta-analysis of Gajda et al. (2017) found a significant but modest correlation of grades with creativity tests, especially with the kind of graphical tests that we used. Our study confirms this impression even though convergence was given a higher weight than in much previous analysis. Taking the EPoC index of creative potential defined as the sum of scores of convergent and divergent thinking, the correlation of this index with grades is only 0.110 ($p=0.233$) for the general grade, but 0.202 ($p=0.032$) for Math and 0.175 ($p=0.064$) for French literature. This correlation would be higher for convergent thinking, that is, 0.257 ($p=0.006$) for Math, 0.194 ($p=0.040$) for French literature, but only 0.116 ($p=0.211$) for the general grade; but it would be almost null for divergent thinking.

In light of the optimism of Guilford (1967) considering that creativity and learning are essentially the same activity, defining creative cognition as a bandit problem leads to a distinction of these two activities. While creative cognition requires a strong ability to learn, education is a form of learning restricted to existing knowledge. Therefore, the lack of consideration of French middle schools toward excessively divergent students may reflect the general expectation of teachers that young adolescents should learn existing knowledge before solving novel issues. Students' divergent thinking may appear irrelevant to anonymous teachers at this stage of the child's education, while convergence would be valued. However, even convergence is not uniformly valued at the end of middle school. The significance of convergent thinking's effect in Math and in French literature, and its non-significance in History-Geography, Art history and the general grade recall that convergence is the ability to solve problems and is essentially useful in fields where problems need to be solved.

Showing, for the first time, the *necessity* of controlling divergence-exploration for successful adaptation and decision making in novel uncertain environments provides a compelling policy argument in support of the screening and development by the educational sector of the creative potential of students. Therefore, our results enable us to provide an evidence-based answer to an important question in this 21st century: Do we *need* creativity? The results suggest that the answer is no for unqualified jobs; but, yes for the growing proportion of qualified jobs and for successful adaptation to a rapidly changing world.

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Appendix

Table A1 Description of individual variables and statistics

Variables	Description	N	Mean	SD	Min	Median	Max
Divergent thinking	Score for the individual's performance in the graphic/visual divergent thinking task of the Evaluation of Potential Creativity battery of tests.	169	5.59	2.66	0	5	16
Convergent thinking	Score for the individual's performance in the graphic/visual convergent thinking task of the Evaluation of Potential Creativity battery of tests.	169	3.61	1.43	1	4	7
High early explorer	This dummy variable equals 1 if the participant switches between buttons more frequently than the median value during the initial 20 clicks (click period: 1 to 20) in the best button task and 0 otherwise.	169	0.48				
High late converger	This dummy variable equals 1 if the participant switches between buttons less frequently than the median value during the last 20 clicks (click period: 81 to 100) in the best button task and 0 otherwise.	169	0.48				
Girl	This dummy variable equals 1 if the participant is a girl, and 0 if the participant is a boy.	169	0.46				
Age	Age of the participant.	169	15.18	0.57	14	15	17
Above normal age	Instead of using the age as a continuous variable, we aim at taking into account students who are repeating, or have repeated, a year, as this seems more informative on their school level. When the study took place, the normal age of 9th graders should be 15 or 14 yo. We hence create this dummy variable =1 if the student is strictly above 15 (hence repeater), 0 otherwise.	169	0.24				
Risk seeking	Self-declared willingness to take risks rated on a scale from 0 to 10. ("How willing are you to take risks, in general?"). Higher values reflect a stronger propensity for risk.	169	6.60	2.11	0	7	10
Comprehension errors	This dummy variable takes the value 1 if a participant made at least one mistake in the comprehension questions asked after instructions on the tasks and 0 otherwise. It is important to note that participants had to answer the questions correctly to progress, and they were allowed multiple attempts to answer correctly if needed.	169	0.43	0.50	0	0	1
Session	The categorical variable, ranging from 1 to 9, serves to characterize each of the experimental sessions. Each individual experimental session is uniquely identified by three key elements: 1) an academic district, 2) the sequence of tasks involving buttons, and 3) the sequence of typing tasks.						
<i>Personality traits</i>	Big 5 personality traits scores for the French version of the Ten Item Personality Inventory.						
Openness		169	4.99	1.19	1	5	7
Conscientiousness		169	5.15	1.16	2	5.50	7
Extraversion		169	4.21	1.33	1	4	7
Agreeableness		169	5.41	1.05	1.50	5.50	7
Emotional Stability		169	4.57	1.39	1	5	7

Table A2 Description of performance variables and statistics

Variables	Description	N	Mean	SD	Min	Median	Max
Equal solution buttons task							
Number of points	The cumulative points achieved by the participant during the equal solution buttons task. The value spans a total of 100 clicks.	169	394	40.5	249	393	535
Number of switches		169	39	34.4	0	29	99
<i>click period: 1 to 20</i>	The total count of button switches occurred within the first period of 20 clicks, from clicks 1 to 20.	169	7.96	6.67	0	7	19
<i>click period: 21 to 40</i>	The total count of button switches occurred within the second period of 20 clicks, from clicks 21 to 40.	169	7.70	7.65	0	4	20
<i>click period: 41 to 60</i>	The total count of button switches occurred within the third period of 20 clicks, from clicks 41 to 60.	169	7.50	7.54	0	5	20
<i>click period: 61 to 80</i>	The total count of button switches occurred within the fourth period of 20 clicks, from clicks 61 to 80.	169	7.88	7.56	0	6	20
<i>click period: 81 to 100</i>	The total count of button switches occurred within the last 20 clicks, from clicks 81 to 100.	169	7.99	7.77	0	5	20
Best button task							
Number of points	The participant achieved cumulative points during the best button task. The value spans a total of 100 clicks.	169	361	215	0	250	760
Points excluding the jackpot	The cumulative points achieved by the participant during the best button task, excluding the jackpot value, if found. The value spans a total of 100 clicks.	169	274	132	0	237	560
Find the jackpot	This dummy variable takes the value 1 if the participant finds the jackpot hidden in the 96 th click.	169	0.43				
Number of switches		169	40.9	34.8	0	28	99
<i>click period: 1 to 20</i>	The total count of button switches occurred within the first period of 20 clicks, from clicks 1 to 20.	169	10.1	6.94	0	11	19
<i>click period: 21 to 40</i>	The total count of button switches occurred within the second period of 20 clicks, from clicks 21 to 40.	169	8.70	7.55	0	9	20
<i>click period: 41 to 60</i>	The total count of button switches occurred within the third period of 20 clicks, from clicks 41 to 60.	169	7.88	7.95	0	4	20
<i>click period: 61 to 80</i>	The total count of button switches occurred within the fourth period of 20 clicks, from clicks 61 to 80.	169	7.41	8.16	0	3	20
<i>click period: 81 to 100</i>	The total count of button switches occurred within the last period of 20 clicks, from clicks 81 to 100.	169	6.83	7.72	0	3	20
Clicks on the best button		169	27.3	27.7	0	16	100
<i>click period: 1 to 20</i>	The total count of clicks on the best button occurred within the first period of 20 clicks, from clicks 1 to 20.	169	2.36	3.12	0	2	20
<i>click period: 21 to 40</i>	The total count of clicks on the best button occurred within the second period of 20 clicks, from clicks 21 to 40.	169	4.18	5.92	0	2	20
<i>click period: 41 to 60</i>	The total count of clicks on the best button occurred within the third period of 20 clicks, from clicks 41 to 60.	169	6.11	7.36	0	3	20
<i>click period: 61 to 80</i>	The total count of clicks on the best button occurred within the fourth period of 20 clicks, from clicks 61 to 80.	169	7.01	7.92	0	3	20
<i>click period: 81 to 100 (Late clicks on the best button)</i>	The total count of clicks on the best button occurred within the last period of 20 clicks, from clicks 81 to 100.	169	7.60	7.97	0	3	20
Typing task							
Number of correct codes	The total count of correct codes typed by a participant in each of the four conditions of the typing task, resulting in four distinct values for each participant (n=109).	436	22.3	6.99	3	22	55

Type more than partner	This dummy variable takes a value of 1 if the participant typed strictly more correct codes than their partner in the two conditions they played with a pair, resulting in two distinct values for each participant (n=109).	218	0.47				
Grades		The grades obtained by the participants at the Brevet, a national exam taken in France by the vast majority of students after 9th grade.					
Math		120	10.5	3.18	3.50	10.5	19
French Literature		120	12.0	2.63	5	12	18
Arts History		125	14.9	3.33	6	15	20
History and Geography		122	13.3	2.41	7	13	18.5
General grade		119	12.7	1.93	9	12.5	18

Table A3 Correlation between exploration behavior over 5 successive 20-click periods and performance in the equal solution task.

Exploration behavior	Performance indicator
Number of switches	Number of points
<i>click period: 1 to 20</i>	<i>-0.0275</i>
<i>click period: 21 to 40</i>	<i>0.0387</i>
<i>click period: 41 to 60</i>	<i>0.0071</i>
<i>click period: 61 to 80</i>	<i>0.0282</i>
<i>click period: 81 to 100</i>	<i>0.0330</i>
Observations	169

Note: No Pearson's correlation coefficient significant at 0.05 level.