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Managerial Cognition, Search and Strategy: Essays on Microfoundations

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presented by

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because of you. My little sister, no matter where you are in the world, you are always with me.

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SUMMARY

Search is a fundamental aspect of decision-making, strategy and innovation. Despite a strong focus on search at the organizational level, the individual level has been under-explored – despite the fact that search is ultimately a human endeavour. To overcome this gap, the main research question guiding my dissertation is: How do selected individual abilities influence search behaviour, and ultimately performance? In each of the included papers, I highlight the role of a specific cognitive capability as a driver of search behaviour and ultimately performance. I interact individual abilities with environmental factors to better understand organizational-level outcomes.

Paper 1 examines temporal focus. Temporal focus can be described as the degree of attention devoted to the dimensions of past, present and future, respectively. Our results reaffirm past findings: that temporal attention does indeed impact strategic performance, controlling for the environment. We also find that temporal focus has a different impact on strategic performance depending on the dimension of temporal focus under investigation. Paper 2 focuses on how emotions and work-life concerns affect the likelihood of becoming an entrepreneur. Paper 3 looks at working memory. While controlling for the setting, we find that heterogeneous strategies emerge, and show that differences in working memory affect people's propensity to explore, which in turn explains performance. Finally, in paper 4, we examine persistence. Our results support the findings that individual search is indeed adaptive and driven by performance feedback. Our findings show that persistent individuals perform more exploitative search, and that persistence is an important moderator in the relationship between performance feedback and search behaviour.

Overall, this dissertation serves to enrich the literature on the microfoundations of search and strategy. I rely on multiple methods, including experiments, interviews and linguistic

analysis, and show that temporal focus, working memory and persistence are important drivers of search behaviour, strategy and ultimately performance. Through this dissertation, I open up the "black box" of search behaviour to reveal the capabilities of entrepreneurs, managers and decision-makers in general that contribute to organizational-level performance.

ZUSAMMENFASSUNG

Die Suche und die damit einhergehende Mechanismen sind ein fundamentaler Teil des Entscheidungsfindungsprozesses, der Strategiefindung und letztlich der Innovationsleistung. Trotz des starken Fokus der Forschung bezüglich Suchverhalten und damit verbundener Maßnahmen auf Organisationsebene, und obwohl Suche ein sehr intuitives, menschliches Verhalten darstellt, ist das Verhalten auf individueller Ebene kaum erforscht, obwohl Suche ein sehr intuitives, menschliches Verhalten darstellt. Um die Management-Forschung dahingehend zu erweitern, befasst sich die vorliegende Arbeit mit der zentralen Fragestellung, wie bestimmte individuelle Fähigkeiten und Faktoren das Suchverhalten und letztlich das Suchergebnis beeinflussen. In den einzelnen Artikeln wird jeweils eine spezifische kognitive Fähigkeit hervorgehoben und bezüglich Suchverhalten und Potential als Treiber dessen analysiert. Zudem werden Randbedingungen und individuelle Fähigkeiten als Korrelate getestet, um Auswirkungen auf die Organisationsebene zu veranschaulichen.

Der erste Artikel prüft die „zeitliche Ausrichtung". Zeitliche Ausrichtung beschreibt den Schwerpunkt, den Individuen bezüglich der Dimensionen Vergangenheit, Gegenwart und Zukunft setzen. Unsere Ergebnisse in diesem Forschungsbereich bekräftigen vergangene Ergebnisse: Zeitliche Ausrichtung beeinflusst die strategische Leistung unabhängig von gegebenen Randbedingungen. Unsere Ergebnisse zeigen auch, dass der Grad des Einflusses auf die Strategiefindung Rückschlüsse auf die zeitliche Dimension zulässt. Der zweite Artikel untersucht inwieweit Emotionen und Work-Life-Präferenzen die Wahrscheinlichkeit beeinflussen berufliche Selbständigkeit anzustreben. Der dritte Artikel befasst sich mit dem Faktor Arbeitsgedächtnis. Unsere Ergebnisse zeigen, dass Individuen verschiedenartige Strategien und Suchverhalten in Abhängigkeit dieser spezifischen kognitiven Disposition entwickeln, welche wiederum die Leistungsfähigkeit beeinflussen. Im vierten Artikel untersuchen

wir Beständigkeit. Unsere Ergebnisse veranschaulichen, dass das individuelle Sucherverhalten anpassungsfähig ist und durch Rückmeldung über vergangene Leistung beeinflusst werden kann. Menschen mit einer ausgeprägteren Tendenz zu Beständigkeit zeigen vermehrt explorative Aktivität; zudem fungiert Beständigkeit als Moderator für die Beziehung zwischen Leistungs-Rückmeldung und dem entsprechenden Suchverhalten.

Die vorliegende Arbeit befasst sich mit der Weiterentwicklung des Suchverhaltens und Strategiefindungs-Grundlagen. Hierfür werden verschiedene Methoden der Datenerhebung und –analyse verwendet; unter anderem Experimente, Interviews und linguistische Methoden. Die genannten Vorgehensweisen erlauben einen tiefen Einblick in Suchverhalten und verwandte Korrelate, wie Beständigkeit, Arbeitsgedächtnis und zeitlichem Fokus. Der Zusammenhang zwischen Suchverhalten und unternehmerischen Fähigkeiten, als auch die Vernetzung von Suchfunktion mit Management-Kompetenzen und den Befähigungen wichtiger Entscheidungsträger trägt dazu bei, bestimmte Entwicklungen auf Organisationsebene nachvollziehbar zu machen.

INTRODUCTION

"Nothing is more fundamental in setting our research agenda and informing our research methods than our view of the nature of the human beings whose behavior we are studying. It makes a difference, a very large difference, to our research strategy whether we are studying the nearly omniscient Homo economicus of rational choice theory or the boundedly rational Homo psychologicus of cognitive psychology. It makes a difference to research." —Simon (1985, page 303)

Explaining performance differences among firms is central to management research (Nelson and Winter 2009), and the key to that is understanding differences in strategic choices. Bukszar and Connolly (1988) note that strategic decision-makers regularly engage in cognitively demanding activities including assimilating copious information about their own organization, the environments in which they operate (or might do), and the possible actions of competitors, allies and regulators. Yet, few studies have focused on where performance heterogeneity comes from, or the abilities and processes involved (Aggarwal et al. 2015). Filling this gap can enable us to better understand the source of differences in strategic choices and, ultimately, performance.

In order to better understand strategic performance, I focus on search, which is a fundamental building block of organizational learning and behavioural theories of the firm (Huber 1991; March and Simon 1958). In search processes, individuals look for information, gather knowledge, adjust aspirations, take decisions and discover new opportunities (Maggitti et al. 2013).

While we know a great deal about search at the organization level, our knowledge about the individual level is limited (Li et al. 2013). But understanding search at the individual level is vital, since it captures a central theme of behavioural strategy. Specifically, to understand the psychological underpinnings of strategic choice, we need a model that mirrors the actual psychology of rational actors (Gavetti et al. 2012), since regularities in individual-level behaviour have consequences at the organization level (Laureiro-Martinez 2014). In recent theoretical work, (Gavetti 2012) explored the behavioural theory of superior performance. He claimed that since individuals are boundedly rational, "intelligent action is confined to the neighbourhood of current activities, and superior performance comes from a **superior ability** to manage the cognitive processes that underlie the intelligence of local action" (Gavetti 2012, page 268, emphasis mine). From this perspective, superior performance is the consequence of a superior ability that makes it hard to identify and pursue distant opportunities.

Hence, the research question guiding this dissertation is: *How do selected individual abilities influence search behaviour and ultimately performance?*

The individual abilities I select are those that guide focus of attention. As we know, superior opportunities tend to require cognitively distant search. Certain individual abilities can guide actors' attention to help them make the leap to such distant opportunities (Gavetti and Levinthal 2000). March and Simon (1958) proposed key factors that guide the focus of attention at organization level; at the individual level, these were temporal dimensions and cues, the span of attention and persistence in pursuing goals. I focus on each of these individual-level abilities separately to understand its relationship with search behaviour.

Paper 1 examines *temporal focus*: the degree of attention devoted to the dimensions of past, present and future respectively. An individual's temporal focus serves as the filter through which certain information is perceived and evaluated. Temporal focus is a pivotal concept in advancing our understanding of how decision-makers notice, encode and interpret both the issues they face and the possible solutions that surround them (Ocasio, 1997, page 189). The results of this paper affirm the findings of past work: that temporal focus does indeed impact strategic performance, controlling for the environment. We also find that temporal focus impacts strategic performance in different ways depending on the dimension under investigation.

Paper 2 examines the role of emotions and work-life concerns in entrepreneurship. Emotions capture the general phenomena of subjective feelings of pleasure or displeasure (Cardon et al. 2012). Studies in psychology and entrepreneurship have shown that emotions play an important role in individual attention, behaviour and cognition (Garcia et al. 2013; Grégoire et al. 2015; Hancock et al. 2008; Huy 2012; Shepherd 2003). Emotions can be determinants of, simultaneous with and/or consequences of strategic outcomes (Cardon et al. 2012). In this paper, we examine how emotions affect the likelihood of becoming an entrepreneur, but also how performance feedback changes entrepreneurs' emotions. We find that entrepreneurs display more positive and fewer negative emotions than the general population. Interestingly, after receiving positive performance feedback, entrepreneurs' positive emotions and work concerns increase, while their negative emotions and life concerns decrease.

Papers 1 and 2 observe the outcome of search behaviour – namely, performance – rather than the link between attention/emotion and behaviour. Paper 3 addresses this limitation by conducting a laboratory study that zooms in on individuals' micro processes. The aim is to understand the relationship between an individual's attention span and performance. To capture individual span of attention, we focus on a heavily studied concept in psychology: *working memory*. Working memory is what allows an individual to retain and manipulate information (Baddeley 2012; Houben et al. 2011). This can guide the individual's search and help them learn from feedback (Helfat and Peteraf 2015). While controlling for the environment, we observe the emergence of heterogeneous strategies and show that natural (i.e. non-manipulated) differences in working memory affect people's propensity to explore, which in turn explains performance.

Finally, Paper 4 links micro and macro factors by conducting an experimental study in which the environment is manipulated. The focus here is on *task persistence*, defined as the ability to sustain goal-directed action despite obstacles or failure (Gusnard et al. 2003). Search processes are characterized by frequent failure, and persistence is the key individual ability that explains behaviour in response to such failure (Cloninger et al. 2012). In this study, we use a between-subjects design and expose participants to search landscapes with a varying likelihood of failure. We find that search behaviour differs depending on the environment, and that persistence is an important antecedent of exploitative behaviour. We also contribute to the performance feedback literature, which has neglected individual disposition as a moderator of the relationship between performance feedback and search behaviour. We find that an individual's tendency to persist moderates the relationship between performance feedback and distant search.

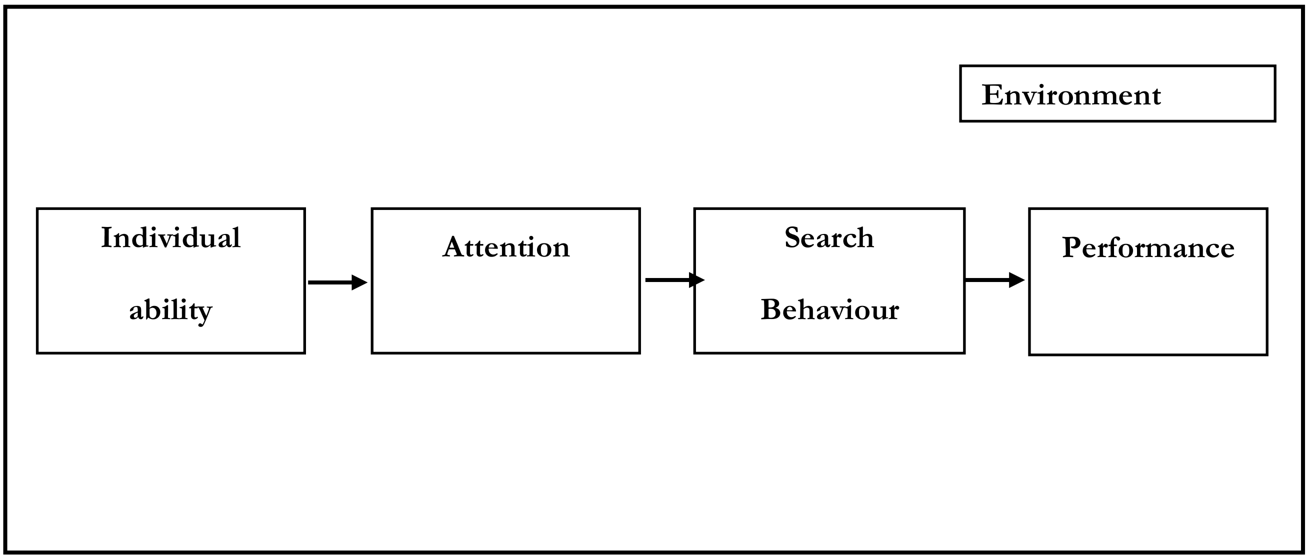
All four papers aim to contribute to the cognitive and behavioural origins of strategy. As argued by Levinthal (2011), if competitive advantage is behavioural, psychologically informed research will bring new insights. This is indeed the case and in the following sections, I first summarize the theoretical motivation of each paper and its findings, and second I summarize the overall contributions of this dissertation to theory and practice.

SUMMARY OF PAPERS

In my dissertation, I focus on the individual level as my unit of analysis. By interacting individual abilities with environmental factors, I hope to contribute to the understanding of organization-level outcomes. The underlying motivation is to understand the abilities that determine individuals' focus of attention.

Figure 1 shows a simplified model motivated by the one proposed by March and Simon (1958). Each of the individual abilities examined in this dissertation – temporal focus, emotion, working memory and persistence – can drive a decision-maker's attention. Given that decision-makers have limited information-processing capabilities, decisions are typically made on incomplete and imperfect perceptions of the environment (Knudsen and Levinthal 2007). Such limitations hold individuals back from achieving strong performance. Certain key abilities help decision-makers focus their attention so they can reach cognitively challenging or distant outcomes. The four key abilities covered in the thesis help individuals focus attention by: balancing forward- or backward-looking aspects of search (temporal focus); balancing attention towards negative or positive information (emotion); balancing multiple options or scenarios (working memory) or balancing satisficing versus optimizing behaviour (persistence). The following sections summarize all four papers with reference to the model in Figure 1. The main papers in this dissertation are papers 1, 3 and 4.

Figure 1: Process model unifying the four papers in this dissertation



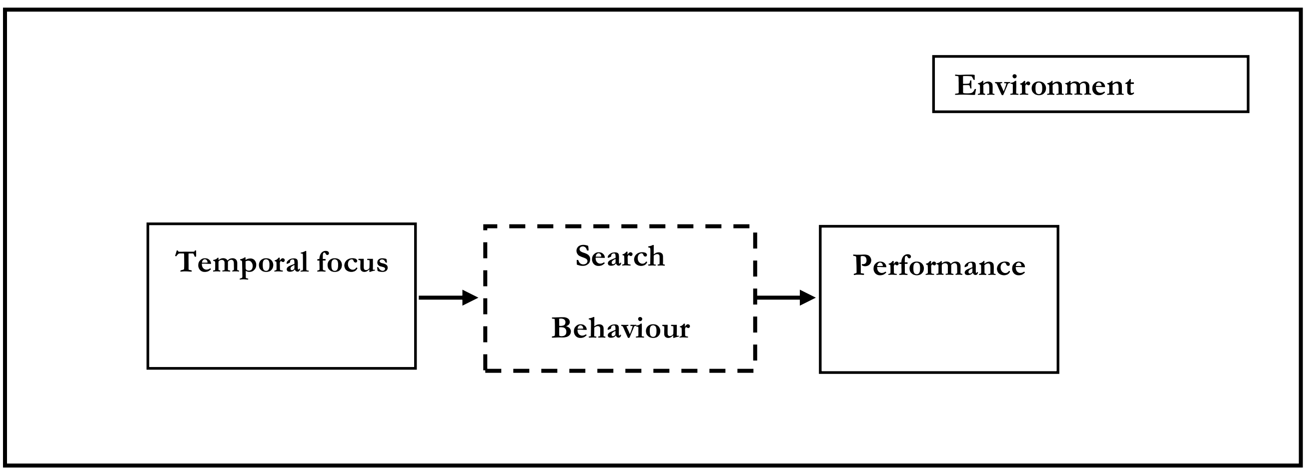
Summary of Paper 1

"The future is ours": The effect of temporal focus on startup funding

"Since these consequences lie in the future, imagination must supply the lack of experienced feeling in attaching value to them." — Simon (1947, p. 81)

In this paper, we focus on the trait-like construct of *temporal focus* to better understand heterogeneity in search outcomes. Individuals have attentional filters with regard to different dimensions of time. These can result in forward-looking capabilities in generating novel solutions, imagining distant outcomes or theorizing the future. However, they can also bring backward-looking, experiential facets of behaviour to the fore, which can sometimes lead to myopic search (Gavetti and Levinthal 2000). As shown in Figure 2, we capture the attention that an individual decision-maker pays to degrees of the past, present or future through temporal focus. We focus on the outcome of search behaviour rather than the behaviour itself – namely, funding performance.

Figure 2: Process model of Paper 1



Our empirical context is early venture performance. Previous work in large organizations has found that temporal focus can have an impact on deadlines, new product launches, goal-setting and innovativeness (Fried and Slowik 2004; Mohammed and Nadkarni 2011; Nadkarni and Chen 2014; Waller et al. 2001). Given this key role in established firms, we expect it to be even more salient in new ones. Additionally, these start-up's operate in turbulent environments where keeping pace with environmental change is extremely crucial (Reger and Palmer 1996). In a study of 730 startup teams, we examined the attentional biases pertaining to time in uncertain environments, and their effect on two variables that are crucial to new ventures: the amount of first-funds raised and the likelihood of a successful second round. We contribute to the strategy literature in two ways. Firstly, our study is one of the first to analyze the impact of temporal focus at the team level. We use primary, longitudinal data generated directly by the team members themselves – in contrast to previous studies, which have generally relied on secondary sources such as official company documents (e.g. letters to shareholders).

Secondly, our results extend and complement earlier findings. We disentangle the effects of temporal focus on two distinct dependent variables, related to two phases of the new venture process: amount of first-stage funding and second round likelihood. We find that these two variables are affected by different dimensions of temporal focus. Theoretically, our results help not only to account for new ventures' success, but also to identify boundary conditions between our findings and those of prior work on temporal focus in established organizations.

Our results that a high future focus increases the likelihood of venture success, while high past and present focus are detrimental to venture success. These results not only advance the behavioural theory of strategy and the attention-based view of the firm, but also have important implications for startup managers, who should recognize how their temporal focus might affect their ways of working and ultimately the performance of their firms.

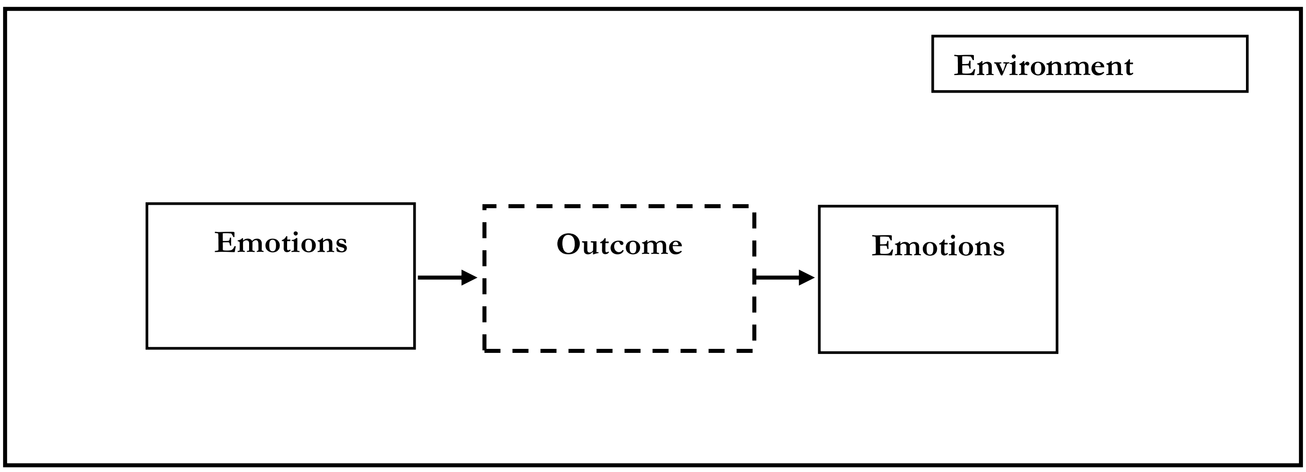
Summary of Paper 2

The psycholinguistics of entrepreneurship

"The greatest asset of the university has been its capacity for innovation. That capacity, in turn, rests partly on its traditions of small size, weak interdepartmental boundaries, and solid administrative support (or at least hunting licenses) for entrepreneurial undertakings." — Simon (1996a pg. 331)

This study supplements the three main papers by studying emotions. Research has suggested that emotions impact attention and decision-making in tasks that are complex (Rauch and Frese 2007). We study differences in emotions among entrepreneurs and non-entrepreneurs, and how performance feedback changes emotions (see Figure 3). To do so, we compare data across entrepreneurs and the general population. Overall, entrepreneurs display positive emotions 2.26 times more than the general population, and also manifest lower negative emotions. A first-round fundraising led to more positive emotions and fewer negative emotions among entrepreneurs.

Figure 3: Process model of Paper 2



Summary of Paper 3

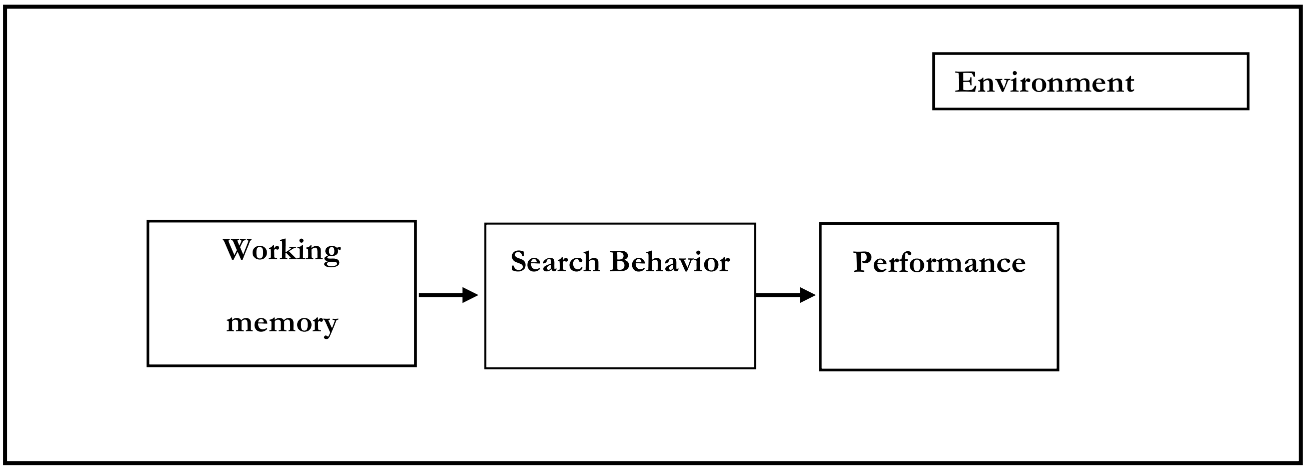
The Managers' Note-Pad: Working Memory, Exploration and Performance

"In an information-rich world, the wealth of information means a dearth of something else: a scarcity of whatever it is that information consumes. What information consumes is rather obvious: it consumes the attention of its recipients. Hence a wealth of information creates a poverty of attention and a need to allocate that attention efficiently among the overabundance of information sources that might consume it." —Simon (1971 pg. 41)

Working memory is a key individual ability that allows decision-makers to hold and manipulate information at the front of their minds (Houben et al. 2011). In this study, we focus on working memory as the ability that guides the span of attention and hence influences search behaviour and ultimately performance (see Figure 4). A higher working memory is correlated with the ability to take in and process a broader set of cues or inputs. Additionally, working memory is a trainable individual ability, and training in certain working memory tasks has been shown to lead to spillover effects in other tasks (Baddeley 2012; Houben et al. 2011; Klingberg et al. 2002).

In this paper, we study the emergence of individual choice strategies in sequential choice tasks under uncertainty using the "four-armed bandit" model. We find that in three different samples, individuals with different levels of working memory do develop different search behaviour, and that such differences are associated with more appropriate exploration rates. This helps us overcome the main limitation of Papers 1 and 2, since we can observe the direct relationship between working memory and search behaviour.

Figure 4: Process model of paper 3



Summary of paper 4

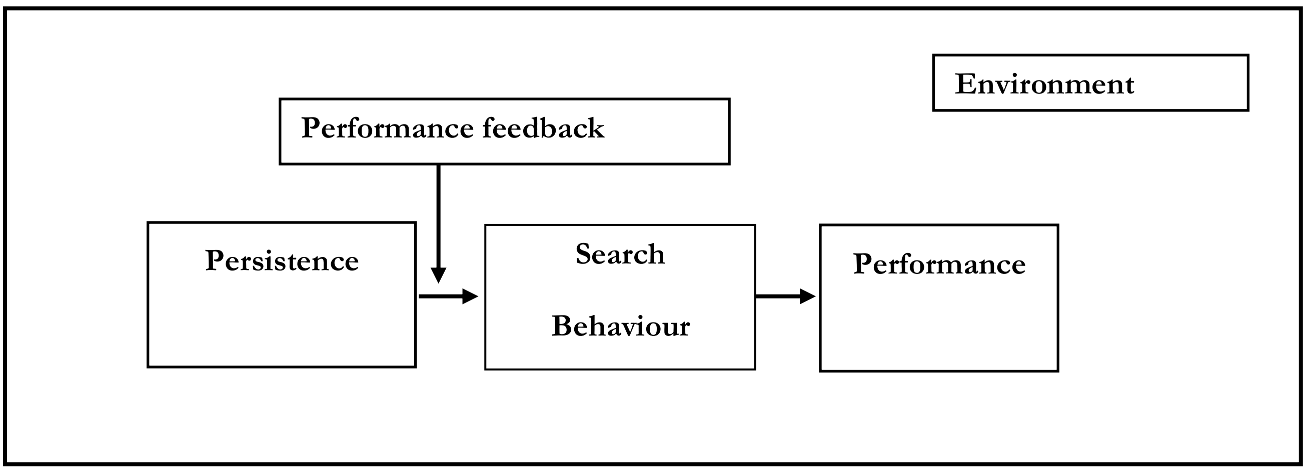
When the going gets tough, should the tough get going? The role of individual persistence in search behaviour

"Human beings, viewed as behaving systems, are quite simple. The apparent complexity of our behaviour over time is largely a reflection of the complexity of the environment in which we find ourselves." — Simon (1996b pg. 110)

When individuals search in unfamiliar and complex terrains, they often encounter failure due to the increased frequency of local peaks, which makes it harder to improve performance (Baumann 2010; Frenken et al. 1999). Task persistence has emerged has the primary construct to explain individual behaviours in response to failure (Lucas et al. 2015). In this study, we examine how adaptive search is influenced by one's tendency to persist. We also manipulate the environment using key organization-level variables – namely, the number of decision elements (scope) and the duration of the search (slack) – to help connect individual-level processes to organization-level factors (see Figure 5). Billinger et al. (2014) found that humans search adaptively, i.e. negative feedback leads to distant search, while positive feedback leads to more local search. We build on this by performing a stepwise quasi-replication of the study by Billinger et al. (2014) (Bettis et al. 2016). In the first step, we exactly replicate the study done by Billinger et al. (2014) on a population in Switzerland. However, we then go further, by measuring task persistence to better understand its role in search behaviour. In an additional step, we manipulate the search scope and search duration while continuing to measure task persistence.

Our results do support the findings that individual search is adaptive and driven by performance feedback. We also find that persistent individuals perform more exploratory search, and that persistence is a moderator in the relationship between performance feedback and search behaviour. Interestingly, while search scope does not have a direct influence on search behaviour, increasing search duration promotes more exploratory behaviours. These findings contribute to a deeper understanding of individual search and its relationship with organizational factors (Cyert and March 1963; Gavetti and Levinthal 2000)

Figure 5: Process model of Paper 4



OVERVIEW OF THE PAPERS[1]

Paper	Title	Authors	Key individual ability	Method	Contribution by Amulya Tata	Status
1	"The Future is Ours": The role of temporal focus in startup funding	**Amulya Tata**, Daniella Laureiro Martínez & Stefano Brusoni	Temporal focus	Quantitative analysis of archival and twitter data	Conception and design of the study; acquisition of data; analysis and interpretation of data; drafting and revising the paper	Reject and Resubmit: *Strategic Management Journal*
2	The psycholinguistics of entrepreneurship	**Amulya Tata**, Daniella Laureiro Martínez, David Garcia, Adrian Oesch & Stefano Brusoni	Emotions	Quantitative analysis of archival and twitter data	Conception and design of the study; acquisition of data; analysis and interpretation of data; drafting and revising the paper	Published: *Journal of Business Venturing Insights*
3	The manager's notepad: Working memory, Exploration and Performance	Daniella Laureiro Martínez, Stefano Brusoni, **Amulya Tata** & Maurizio Zollo	Working memory	Laboratory study	Analysis and interpretation of data, drafting parts of the paper	Submitted: *Journal of Management Studies*
4	When the going gets tough, should the tough get going? The role of individual persistence in search behaviour	**Amulya Tata**, Daniella Laureiro Martínez & Stefano Brusoni	Persistence	Laboratory study	Conception and design of the study; acquisition of data; analysis and interpretation of data; drafting and revising the paper	To be submitted: *Organization Science*

[1] Two other projects were carried out during my dissertation. They are related but do not directly pertain to the main research question. The first looks at the role of investors and entrepreneurs in evaluating linguistic cues, and has been submitted to the *Journal of Technological Forecasting and Social Change*. The second examines the evolution of frames in the 3D printing industry, and is being prepared for submission to *Research Policy* in collaboration with coauthors Axel Zeijen, Daniella Laureiro-Martínez and Stefano Brusoni.

CONTRIBUTIONS OF THE THESIS

Search has long been acknowledged as a key managerial function (Cyert and March 1963; Li et al. 2013). Yet, most work has focused on how organizations search, rather than examining the search processes of individual decision-makers (Maggitti et al. 2013). This gap is important, as search is essentially a human capability. The search environment can guide search processes, but it is the human who has the capability of searching. As suggested by Gavetti and Levinthal (2000), search is cognitive, and the search literature benefits by incorporating research from cognitive sciences. Research from psychology can strengthen our understanding of how individuals overcome information-processing limitations and direct their attention to different, novel information rather than familiar information (Barney and Felin 2013). In this dissertation, I addressed these issues by building on key individual abilities that are known to direct human attention and develop theory on how individual search connects to organizational outcomes.

This dissertation makes three important contributions. Firstly, it answers calls from the behavioural theory of the firm to connect individual-level abilities to performance heterogeneity (Levinthal 2011). Second, it makes significant methodological advances in helping future researchers study cognitive search processes in strategy. Third, it has important managerial implications for decision-makers in helping them to be more innovative. I describe each of these three contributions in the sections below.

Theoretical contributions

Each of the papers uncovers the role of a specific cognitive capability as a driver of performance. We find that temporal focus, working memory and task persistence are important behavioural antecedents of search behaviour that leads to heterogeneous performance. Additionally, we tackle an important gap by connecting the micro and macro levels of analysis. For example, in

Paper 1, we uncover the performance heterogeneity in new ventures, relying on an attention-based view of the firm, and find that temporal attentional biases are important antecedents of startup performance. In the entrepreneurship literature, two aspects of startup performance – the amount of funding raised and the likelihood of successfully completing a fundraising – are thought to be predicated by similar factors. Our findings show that is not the case, and that in fact temporal focus is not an important driver in predicting amount of funding raised in the first round it is crucial in understanding second-round success.

In Paper 3, we find that a high working memory does help individuals choose an appropriate exploration rate and hence gain superior performance. Through this work, we are also able to explain the emergence and persistence of heterogeneity, which is an important driver of innovation. In Paper 4, we find that task persistence interacts with the environment and determines systematic differences in search behaviour. Each of these findings helps theorists to build better assumptions about the nature of humans that constitute organizations. For example, researchers can better model when exploitation is triggered, by including task persistence as a key construct guiding exploitation.

Methodological contributions

This dissertation draws on methods that are new to strategy to incorporate psychologically informed research into the field. In Papers 1 and 2, given that the psychological capabilities of founders are hard to measure, we rely on a new data source: microblogs published on Twitter. Twitter data allows us to make thousands of observations of individuals over a long period of time. This informal, conversational content allows us to get a clear picture of a decision-maker's individual traits. We suggest that social media sources, when available, offer excellent opportunities for researchers to study the emotions, cognitions and personalities of individuals over time. Hence, we enrich the content analysis field by incorporating a newer and richer source of information into cognition research (Duriau et al. 2007). In Papers 3 and 4, we observe search in the laboratory setting. We demonstrate that laboratory settings are a great tool for carefully constructing manipulated and non-manipulated search environments that can be used to study model predictions and real-world problems. While experiments have been a very common tool to study theoretical assumptions from models in game theory, the approach is still its infancy within the strategy field (Puranam et al. 2015). In both these papers, we provide clear research designs by incorporating search tasks, behavioural tasks (e.g. "N-back", "anagram") and self-reported measures that can easily be built upon by future researchers looking to study search processes in individuals or teams.

Managerial contributions

Our findings also have important implications for practitioners. Research from cognitive sciences suggests that each of the individual abilities studied in this dissertation can be trained. With respect to the findings in Paper 1, if entrepreneurs and managers understand their temporal focus better, they can make tweaks to change this and improve their balance of temporal perspective. There are no panaceas, but past research has shown how adding small tasks and habits to our daily routines – for example, phoning an old friend if one is low on past focus, or planning future events in detail if one is low on future focus – might rebalance our time perspective and have knock-on effects on our decision-making styles (Boyd and Zimbardo 2012). Incubators and coaches can help startup founders identify their own temporal focus and proactively engage in tasks aimed at increasing one dimension or diminishing another.

Previous research has found that training working memory in one task leads to improvements in working memory in other cognitive tasks too (Jaeggi et al. 2008; Klingberg 2010). For example, Klingberg et al. (2002) trained visuospatial working memory and found that individuals improved in other cognitive tasks, including standardized measures of intelligence.

Another alternative to improve working memory is to shield oneself from distractions and be aware of how multitasking can erode attention (Rosen 2008). Task persistence is also impacted by multitasking, as progress towards the goal becomes fuzzy (Rosen 2008). Individuals can also establish strict turning-back points when engaging in complex search tasks, so they can cut their losses early rather than soldiering on in the hope of recovering their investments. Since the environment also plays a role in determining behaviour, organizations can relax time pressures to promote exploratory innovations, but at the same time remain mindful of clear stop points.

Finally, I hope this dissertation can help advance research in behavioural strategy by providing a basis for future research. The next step would be to understand the aggregation processes of these constructs by incorporating social processes, teams and the organizational environment.

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FULL PAPERS

PAPER 1

"The Future is Ours":

The Effect of Temporal Focus on Startup Funding

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Reject and Resubmit at Strategic Management Journal

“The Future is Ours”:

The Effect of Temporal Focus on Startup Funding

“The present is theirs; the future, for which I really worked, is mine.”

—Nikola Tesla

ABSTRACT

We study 1,570 early-stage startup founders temporal focus (i.e. the degree to which individuals devote attention to perceptions of the past, present, or future) and the extent to which this individual trait affects two key performance milestones: the amount of first-round funding raised, and the achievement of a second round of funding. We find that the temporal focus of the startup teams affects their venture performance. Interestingly, we find no correlation between temporal focus and amounts raised in the first-round. A high future focus is instead advantageous for a higher likelihood of second round, and high past and present focus is detrimental to the chances of raising a second-round. These results demonstrate the importance of temporal attentional biases in startup performance.

INTRODUCTION

Strategy scholars have stressed the importance of understanding temporal attention, since time constitutes an elementary dimension of strategy-making (Ancona *et al.*, 2001; Das, 2004; Kaplan *et al.*, 2013; Mohammed *et al.*, 2011; Nadkarni *et al.*, 2014; Nadkarni *et al.*, 2015; Seshadri *et al.*, 2001; Souitaris *et al.*, 2010). For example, Brown *et al.* (1997) discussed how future orientation of managers helped companies in high-tech sectors develop and maintain successful product portfolios. Understanding how individuals and teams focus on temporal dimensions helps us understand attentional biases that contribute to representations, cognition, and ultimately performance.

How much attention people pay to the past, present, and future can be described by an individual difference construct: *temporal focus* (Bluedorn *et al.*, 2008; Shipp *et al.*, 2009). Previous studies in established organizations have shown that temporal focus can have an impact on deadlines, new product introduction, goal-setting and innovativeness (Fried *et al.*, 2004; Mohammed *et al.*, 2011; Nadkarni *et al.*, 2014; Waller *et al.*, 2001). Literature on executives' time orientation suggests that it forms the basis for strategic behaviors (Ancona *et al.*, 2001). Temporal focus is shown to play a role in large organizations, and it is likely to play an even greater role in young and small firms. Startup teams have a greater opportunity to shape the course of their firms than executives of large, established firms (Eisenhardt, 2013). Hence, startup teams are a very suitable empirical context to explore to what extent, and what kind of, time focus affects performance over time.

Since most startups are founded by teams, according to venture capitalists, early venture growth is largely determined by the characteristics of the founding team (Shepherd *et al.*, 1999). Indeed, several researchers have tried to understand differences in the performance of entrepreneurial ventures on the basis of individual-level characteristics and team compositions (Aldrich *et al.*, 2001; Baron, 2004;

Shane *et al.*, 2000). For example, characteristics which have been studied in relation to new venture success are prior startup experience (e.g. Delmar *et al.*, 2006; Klepper, 2001), social capital (e.g. Vissa *et al.*, 2009), personality traits (e.g. Ciavarella *et al.*, 2004) and mental models (e.g. Ensley *et al.*, 2001).

Besides its general relevance to the discussion about strategic decision-making, temporal focus is also an underexplored area in understanding new venture success. This concept is crucial, because it reflects how startup teams incorporate perceptions of experiences, current situations, and future expectations into their attitudes, cognitions, and finally, decisions that later on translate into the performance of their actions. Research has found that startup teams' goals and the visions they communicate have a direct effect on venture growth (Baum *et al.*, 2004), and their temporal focus influences how instruments such as business plans, presentations, pitches, etc. are created (Boyd *et al.*, 2012; Pennebaker *et al.*, 2015). Temporal focus is very relevant for startup teams because past knowledge and experiences, real-time information, and future speculations are all considered to be important in strategic decision-making (Nadkarni *et al.*, 2014). Hence, the research question this paper addresses is, how does the temporal focus of startup teams impact early venture success?

To foster the discussion about time focus, we build on two steps. First, we use language to derive data and direct measures of entrepreneurs' time orientation. "Language is the most common and reliable way for people to translate their internal thoughts and emotions into a form that others can understand" (Tausczik *et al.*, 2010). Empirically, we build on an original database of Twitter messages to capture the time perceptions of entrepreneurs (personal accounts) in the Bay Area. Second, we analyze the role that temporal focus plays in achieving two crucial entrepreneurial milestones. We do this since "there is a lack of research that has longitudinally examined the characteristics of new venture teams across all stages of the entrepreneurial process" (Klotz *et al.*, 2014 pg. 246). Most research in this domain has only looked at individual traits at distinct points in the entrepreneurship process. We aim to overcome this limitation because team characteristics can play a different role depending on the milestone. While some milestones are about meeting present needs, others pertain to anticipating future events.

The first preliminary milestone in our study is the amount of funding raised in the first-round, which signals the attractiveness of the venture (Delmar *et al.*, 2003). It is important because high-tech startups need to burn large amounts of capital to sustain growth before becoming self-sufficient. Previous research has used this measure to capture venture success (Alexy *et al.*, 2012). This early decision (amount of first funding raised) can have a long-lasting impact on the new organizations' future outcomes.

Secondly, our ultimate goal is to understand the relationship between temporal focus and venture success, which we capture by observing if firms managed to raise a second round or not. As argued by ter Wal et al. (2016), the achievement of second-round investments is important because high-tech startups need several rounds of funding in order to be successful. A successful second-round requires startups to show clear signals of venture quality and potential growth. This milestone, which has been used in previous studies to capture venture success, indicates either initial investors are satisfied with the startup's progress and that the startup has gained more investors on board (ter Wal *et al.*, 2016).

We build upon findings from computational linguistics, where researchers have found that microblogs are excellent sources for capturing individual attentional biases (Pennebaker *et al.*, 2003; Tausczik *et al.*, 2010) and contribute to strategy with this novel data source. We capture startup founders' attentional biases by relying on longitudinal data from Twitter. Strikingly, in the case of startups, we find temporal focus does not correlate with the amount of funds raised in the first-round. A high future focus leads to higher likelihood of venture success, and high past and present focus are detrimental to venture success. This is interesting for two reasons. Firstly, lacking group-level theories on time focus, we base several of our arguments on individual level findings in the time literature and find similar results at the team level. Secondly, in the strategy literature our two dependent variables have been assumed to be predicted by similar factors, but our findings and interviews with entrepreneurs show us that this is not the case.

Our study contributes by extending research into the micro-foundations of strategy and entrepreneurship (Barney et al., 2013; Gavetti et al., 2012; Gavetti et al., 2000). Despite the importance of subjective perception, few studies have looked at time focus. More importantly, even fewer have tried to understand the association of these variables with entrepreneurial performance, which is our aim. By doing so, we contribute to the field of entrepreneurship by understanding the role of temporal attentional biases in startup funding performance (Baron et al., 2004; Bluedorn, 2002; Fischer et al., 1997; Hayward et al., 2006; Markman et al., 2003; Rauch et al., 2007; West et al., 1997).

BACKGROUND AND HYPOTHESIS DEVELOPMENT

Early venture-success

New ventures grow by seeking investments in rounds (Byers, Dorf, & Nelson, 2010). The amount of funds raised in the first round typically provides capital to reach the next round and can include several investors (Byers, Dorf, & Nelson, 2010). The amount raised in the first round is a very important variable, since if too little is raised, it is not sufficient to meet targets to reach a successful subsequent round. Additionally, this measure captures realized rather than intended investment (Alexy et al., 2012). Most startups typically add new investors in their next rounds (Hallen et al., 2012). Subsequent round fund raising is crucial, as this influences survival (Stuart et al., 1990). When raising subsequent rounds, it is the startup founders, not the first round investors, that take primary responsibility (Hallen et al., 2012). Signals of quality such as firm progress are crucial in successfully raising a second round. Work by Hallen et al. (2012) has shown that to gain a successful round of fundraising, the startup needs to meet a ‘proofpoint’. A proofpoint is defined “as a positive signal of substantial venture accomplishment of a critical milestone that is confirmed by key external (not internal) actors" (Hallen et al., 2012 page 46). External validation is crucial to mitigate uncertainty while fund raising. Proofpoints serve as an important signal of venture quality. For example, to raise a successful second round, an app company will need to show it has gained a large percentage of new users. Proofpoints also help startups attract larger first-round funding. Timing around proof points is of strategic importance. Ventures can choose acceleration (entering the fundraising process before funds are needed), preemptive structuring (raise enough funds early to meet next proofpoint), or delaying (despite lack of funds waiting till proofpoint is achieved) (Hallen et al., 2012).

Temporal focus

The behavioral theory of the firm and the neo-Carnegie School have emphasized the importance of understanding decision-makers' attention (Cyert et al., 1963; Ocasio, 1997, 2011). Due to constraints of bounded rationality, individuals can attend to only a small fraction of their decision environment. Work by Teece (2007) has pointed out that decision-maker's perceptions and biases lead to certain information being filtered out. According to the attention based view, temporal attention serves as the filter through which stimuli are perceived and strategic options evaluated (Ocasio, 1997). Yadav and colleagues' study was one of the first to show how the timeframe that organizational leaders pay attention to influences organizational innovation outcomes. Yadav et al. (2007) used stakeholders' reports to analyze how inter-individual differences in the temporal focus of CEOs correlated to their organizations' innovation outcomes. In particular, the authors measured variables related to how quickly organizations detected new technological opportunities, developed new products, and deployed them. They found a positive correlation between the amount of attention individuals paid to the future and the innovativeness of their organizations. Temporal focus is a pivotal concept in advancing our understanding of how decision-makers notice, encode, and interpret both the issues and the possible solutions that surround them (Ocasio, 1997, page 189).

Temporal focus describes the extent to which people characteristically devote their attention to perceptions of the past, present, and future (Bluedorn, 2002; Shipp et al., 2009). These focuses are found to be independent in previous work; i.e. past, present, and future focus are "distinct dimensions rather than opposite ends of a continuum" (Nadkarni et al., 2014, p.g. 1812). Temporal focus is one element of an individual's broader time orientation (Berends & Antonacopoulou, 2014).

Temporal focus should not be confused with another temporal trait namely 'temporal depth'. Temporal depth can be distinguished from temporal focus, as the first is related to the horizon one looks into in the past or future. For example, an individual can have a very high future horizon, but this does not preclude them from having a high present focus. Work by Shipp and colleagues (2009) has shown that temporal focus and temporal depth are independent and measure different aspects of time perspective. Additionally, temporal focus captures the present dimension, which is ignored in temporal depth. In this study, we focus on temporal focus.

Crucially, temporal focus has also been shown to be a trait-like construct—that is, it is stable over time among individuals (Nadkarni et al., 2014; Shipp et al., 2009; Shipp et al., 2011). Previous research has shown high test and retest reliabilities on individuals' overemphasis or underemphasis on time frames (Mohammed et al., 2013; Zimbardo et al., 1999). According to Chen et al. (2016 page 2), "one's temporal orientation constitutes an innate and stable personality trait that, like fingerprints, is unique to each individual." A high past focus is associated with an emphasis on learning but is also associated with the tendency to overgeneralize (McDonald et al., 2015). Another danger of extreme reliance on the past is that it can lead to rumination on mistakes and regrets (Holman et al., 1998). Rumination has been associated with low motivation to meet goals. A high present focus is about "the here and now" and associated with spontaneity, risk-taking and addictive behaviors (Zimbardo et al., 1997). A high present focus has also been linked to neuroticism and pessimism (Boyd et al., 2012). Future-focused teams are usually high in motivation and ambition and engage in long-term planning (Shipp et al., 2009).

High future focus has been associated with a healthy life style, pro-environmental attitudes and conscientiousness (Daugherty et al., 2010; Milfont et al., 2006; Zimbardo et al., 1999).

Nadkarni and Chen (2014) found that temporal focus of CEOs interacts with environmental dynamism to predict the company's rate of new product introduction (NPI). They focused on 221 large manufacturing firms and found that depending on whether the environment was stable or dynamic, CEOs' temporal focus predicted the rate of NPI. They triangulated their findings by relying on various secondary data sources such as letters to stakeholders and interviews with the press. Nadkarni *et al.* (2014) study of CEOs shows that those executives in uncertain environments, with higher future focus, lead more innovative organizations. Thus, we expect temporal focus to be manifested in nascent organizations as well.

Early venture-success and temporal focus

Temporal attentional biases have been linked to information processing, planning and decision making (Mohammed *et al.*, 2011). Despite the relative importance of time, traits related to time are underexplored in the early stages of new ventures. This is important because temporal biases affect new ventures, since planning, information processing and decision-making are key elements in shaping the trajectory of a startup. Meeting proofpoints and successful fund-raising are impacted by the temporal focus of the startup founders. Especially since new ventures have few established norms and processes, founders have greater managerial discretion and wider latitude of action than established organizations (Klotz *et al.*, 2014). Thus, attentional biases related to time should play an even greater role in startups compared to established organizations. By looking at the relationship of temporal focus and two milestones for a nascent startup we can better understand when a greater degree of emphasis on the past, present or future is more suitable. Bluedorn and Martin (2008) find that the depth of past and future focus is positively related to variables important for the management of startups, such as the ability to adhere to plans and meet deadlines. Can we also expect a positive relation between a certain temporal focus and our two entrepreneurial milestones?

Past focus

Startup teams which are high in past focus are interested in maintaining the status quo and take fewer risks (Zimbardo *et al.*, 1999). They can be suspicious of things new and different (Boyd *et al.*, 2012). But more importantly, in early stages of new high-tech ventures, there is high dynamism. Opportunities for feedback-learning and opportunities for identification of new markets or products are fleeting. High past focused teams engage in retrospective sensemaking (which is about drawing upon past knowledge to use in current situations (Bluedorn, 2002; Weick, 1995)). In dynamic environments this leads to filtering out inputs which do fit with their past experience (Nadkarni *et al.*, 2014). Hence, high past-focused individuals fail in the detection of new ideas, opportunities and markets (Eisenhardt *et al.*, 1995). In uncertain environments, a strong dependence on the past has shown a failure to detect suitable markets and product opportunities (Nadkarni *et al.*, 2014). Startup teams with high past focus rely on historical events when making decisions (Pennebaker *et al.*, 1999). Extreme reliance on the past also leads to an overgeneralization bias, which causes tunnel vision, leading teams to fail (Bluedorn, 2002). In order for teams to meet the criteria to be successful in fund-raising, increased reliance on the past will not be fruitful, since in dynamic environments, recipes from the past corrode away very quickly (Atuahene-Gima *et al.*, 2004).

Hypothesis 1a. The higher the past focus of a startup team, the less first-round funding it will raise.

Hypothesis 1b. The higher the past focus of a startup team, the less likely is second-round fund raising.

Present focus

Startup founders typically need to undertake several hardships (e.g. forego salaries) when they have not met a proofpoint or goal. When startups delay fundraising to meet a proofpoint, they usually undergo adversities financially and/or personally (Hallen *et al.*, 2012). A strong present focus has been correlated in several studies with lack of delayed gratification (see Metcalfe *et al.* (1999) for complete list). High present focused individuals like to savor the moment (Shipp *et al.*, 2009). For example, high present perspectives are associated with risky driving and substance use (Boyd *et al.*, 2012; Zimbardo *et al.*, 1999; Zimbardo *et al.*, 1997). A startup team high in present focus will easily give into temptation and can be distracted from task performance (Boyd *et al.*, 2012). This is detrimental for startups, where success revolves around meeting proofpoints. It is shown in previous studies that teams high in present focus are less motivated for future deadlines (Waller *et al.*, 2001). For example, in Brown *et al.* (1997) study, managers who had less successful portfolios operated in the present with little awareness of future and future deadlines. The teams in their study who were high on present focus reacted rather than anticipated future goals and deadlines. Startups require tight controls on finances, hiring and anticipation of risks. Startup teams might also be more likely to abandon their startups to avoid undergoing severe difficulties. Also, based on individual level evidence we expect startup teams with strong present focus to pay more attention to the 'here and now'. (Zimbardo *et al.*, 1999; Zimbardo *et al.*, 1997). Startup teams with very high present focus might be so immersed in the here and now that they lose sight of the big picture. Losing sight of the big picture, i.e. being only in the here and now, will negatively affect raising large amounts of money.

Startup teams need to delay gratification to persevere in trying to reach their goals and focus on the big picture be successful in fund-raising. Hence, we hypothesize that,

Hypothesis 2a. The higher the present focus of a startup team, the less first-round funding it will raise.

Hypothesis 2b. The higher the present focus of a startup team, the less likely is second-round fund raising

Future focus

Startup founders live in a world of opportunities. In particular, as proposed by Gavetti (2011), they have to deal with "cognitively distant" opportunities and events. Entrepreneurs need to be "acting in advance "with foresight about future events before they occur" (Grant *et al.*, 2008 p. 9). High future focused individuals make decisions based on imaginings of the future and alternative courses of action (Boyd *et al.*, 2012). They are also goal-oriented and are willing to work hard for distant payoffs (Boyd *et al.*, 2012). To achieve a high amount of first-fund, startup teams need a very high quality idea, which manifests in the future. Entrepreneurs need to engage in tasks beyond what is immediately required. For instance, highly innovative technologies take time to be ready for market. Second-round fund raising requires entrepreneurs to meet certain proofpoints to gain successful second round fundraising. Planning and goal setting play an important role in meeting these targets. Hallen *et al.* (2012) point out that strategies such as acceleration and preemptive structuring require foresight. They found that anticipating resource needs, venture accomplishments are required to have a good timing of reaching a proofpoint. One of the main characteristics of having high future focus is being able to engage in planning (Zimbardo *et al.*, 1999). In rapidly changing environments firms with better planning were more successful. Bourgeois III *et al.* (1988) showed that ventures that engaged in planning in greater detail were more successful (Roure *et al.*, 1990). High future focused individuals make to-do lists, and take the time to anticipate future risks, markets, competitors, and technologies (Nadkarni *et al.*, 2014). Managers who focus on the future have been shown to avoid obsolete investments and facilitate the rapid development of new products (Brown *et al.*, 1997). Additionally, a forward-looking perspective has been shown to drive important strategic changes (Ocasio, 2011). For example, West *et al.* (1997) study on entrepreneurial teams found that teams high in future focus made more strategic changes than their counterparts. High future focus helps startup teams with better timing of proofpoints as they make the necessary strategic changes and planning.

Hypothesis 3a. The higher the future focus of a startup team, the more first-round funding it will raise.

Hypothesis 3b. The higher the future focus of a startup team, the more likely is second-round fund raising

METHODS

Sample

Our sample consists of 730 startup teams from the San Francisco Bay area who raised first round funding between 2006 and 2013. The average team size is 2.15 and the average amount raised in the first round is $3,088,535.29.

Data source for entrepreneurial milestones

Our startup and personnel data were drawn from Crunchbase, a public-domain database. Crunchbase began as a simple crowdsourced database to track startups on TechCrunch, and now claims to have more than 50,000 active contributors. Crunchbase provides a complete overview of funding for many startups, with data on the firms, their founders, teams and investors. The startups on Crunchbase are typically tech startups, extremely innovative and seeking to raise funding. Companies in Crunchbase are active in diverse high-tech industries (e.g. analytics, finance, education, security etc.). Databases such as Crunchbase and Zoominfo are steadily gaining credibility among strategy researchers (Arora *et al.*, 2012; ter Wal *et al.*, 2016). In particular, previous studies (Adcock *et al.*, 2013; Block *et al.*, 2011; Xiang *et al.*, 2012) show that Crunchbase data correlates well with VC data from other sources such as the national US National Venture Capital Association (Alexy *et al.*, 2012; Block *et al.*, 2009).

In order to allow for homogeneity in the environment (which has proven to cause many differences in temporal perspective; see Levine (2008)), and to select for an environment where many tech startups are founded, we focused on startups and entrepreneurs in the San Francisco Bay Area. In

2013, this area received 46% of all nationwide VC funding (Delevett, 2013). In 2002, when a *USA Today* study asked the National Venture Capital Association to rank the top 10 cities for startups, the Bay Area was #1 (Graham, 2012). The main reasons for this are the availability of talent, relatively low costs, and the possibility to raise money (Graham, 2012).

We downloaded the data on 6th June 2014 using Crunchbase's *Excel* exports (Crunchbase, 2014). We focused on organizations that were founded between June 2006 and December 2013, which is the date Twitter was founded (Arceneaux *et al.*, 2010). For each startup, we collected the list of founders, date first funded, funding raised, funding rounds, and markets served. We excluded records with missing data. Crunchbase does not distinguish between firms that did not raise funding and firms that did not disclose funding. Despite reliance on other datasets, we were unable to disentangle the two. Thus, we excluded these firms from our analysis. Our regression analysis was conducted on this reduced sample. We ran independent samples t-tests to compare differences in dependent and independent variables, in the sample with and without missing variables. Our analysis indicated no differences. These criteria yielded a sample of 730 startups. They had raised $30.88m each on average, with a median of $14.45m. The majority of firms are active in sectors related to curated web, software, analytics and games.

Data source for startup founders' temporal attention

Nadkarni *et al.* (2014) have noted that it is not easy to find reliable sources to measure temporal focus. They point out that surveys and interviews can result in low response rates, and create biases due to social desirability, reactivity etc. Berends *et al.* (2014) claim that studying temporal variables is extremely difficult: inquiry relying on retrospection alone is not a good measure, because it is retrospection itself that is in question.

One important limitation of previous studies on attention, acknowledged by their authors, is that they do not use direct measures, but instead rely on the temporal focus reported to third parties (e.g. stakeholders' reports in Yadav et al.'s study (2014)), or the time depth reported in questionnaires (e.g. the self-reported index in Bluedorn and Martin's study (2007)). While the focus and perception of time could be accurately self-reported, such measures should be complemented with methods that allow individuals to spontaneously record their thoughts in real time. In addition, rather than relying on a single report, it would be optimal to obtain longitudinal data from multiple data points relevant to each individual. This would generate data that are more representative of living, thinking individuals, rather than a "snapshot" at a single point in time. Microblogging data from sites such as Twitter, Facebook, and Tumblr, where millions of brief updates are posted every day, provide longitudinal conversational content that can overcome most of the issues encountered in survey research (Java *et al.*, 2007). Due to their easy accessibility and simple message format (unlike traditional blogs or mailing lists), microblogging services are used by more and more internet users (Pak *et al.*, 2010). Typically, authors of microblogs write about their own lives, share opinions on a variety of topics, and discuss current issues (Pak *et al.*, 2010).

The informal, immediate nature of conversational content means it is closer to the author's cognitive processes and spontaneous views. This makes Twitter a useful source of individual perceptions of ongoing events. Fischer and Reuber's study (2011) confirms that Twitter data are a reliable source of entrepreneurs' spontaneous thoughts—and should an entrepreneur be a particularly avid Twitter user, their Tweets will be an abundant source of fine-grained longitudinal data on their thinking. Based on interviews, the authors find that entrepreneurs prefer Twitter to other social-media platforms (e.g. Facebook), and use it to express their thoughts and interact with others. Importantly, entrepreneurs report Tweeting in the same way as they would approach a conversation, and feel they have freedom to share their "thoughts" and "voice" with those who follow them or their companies. Recent work by Lee *et al.* (2016) has shown that "CEO tweets also provide a relatively uncensored and, consequently, clean picture of a CEO's personal traits". Twitter data are generally spontaneous—although Twitter users might "self-censor" to some extent, their content is undoubtedly less filtered than, for example, stakeholders' reports. Finally, Twitter data are available over time, enabling multiple observations for each individual. Twitter has been used in research on a range of topics. For example, individuals' aggregated Tweets have been used to successfully gauge the mood of the stock market (Bollen *et al.*, 2011), to manage crises in organizations (Schultz *et al.*, 2011), to predict election results (Tumasjan *et al.*, 2010), and to assess users' views of an organization (Tan *et al.*, 2011).

We used Twitter data to collect startup founders' expressed thoughts over time. We then analyzed inter-individual differences between their expressions, and correlated those differences with the performance of their startups. For every organization in our dataset, we collected publicly available Twitter data related to both the startup's company account and the founder's personal account. In total, we found 2880 company accounts, of which around 80% had personal Twitter accounts for the founder(s). We only focused on the personal Twitter accounts of the founders to have a clear measure of their expressed thoughts. Due to restrictions on the Twitter API, we were able to collect a maximum of 3200 Tweets per person. In addition, we were able to obtain each person's total number of Tweets since joining Twitter, which is controlled for in the later analysis.

Measures and controls

Dependent variables

Milestone 1: Amount of first-round funding raised

Crunchbase is a web-based platform that mostly attracts innovative startups who want to gain funding and showcase their ideas to potential investors (Crunchbase, 2014). The amount of first-round funding raised, signals about the attractiveness of the venture (Delmar *et al.*, 2003). Previous research indicates that this amount typically reflects either the initial conditions of the startup, the perceived quality of the idea, the social capital or a combination of these factors (ter Wal *et al.*, 2016). The amount of first-round capital raised has been used a proxy for venture success. It can also reflect the value of the firm at the time of the funding round (Alexy *et al.*, 2012). The amount of first funding raised can also reflect the dilution founders are willing to undergo in their startups (Alexy *et al.*, 2012). Funding can be obtained through venture funding, angel investors, seed investors, private equity, grants debt financing, equity crowdfunding, or a combination of these. These types encompass a significant volume of startup financing. We focused on startups that raised a first-round between 2006 and 2013. For these startups, we collected the amount of first funding raised. As this distribution is left skewed we used the log amount of first funding in all analysis.

We understand that by looking at firms which successfully raised a first-round we encounter a sample selection bias. We counteract this step in two ways. First, we treat startups whose first-fund amounts raised are in the lowest decile (amounts less than 50,000 $) as zeros (not-raised any funding) since, it is difficult to get information on those who were unsuccessful in raising a first round. We then utilized the Heckman selection model which is widely used to control for selection bias (Certo *et al.*, 2016). The first step in our selection model was to predict whether or not a startup gets funding, followed by a second round where we predict the amount of first-funding received. To meet the exclusion restrictions of a Heckman model, two attention variables namely how much attention a person receives (Number of times they get retweeted) and the how much attention they give to others (Number of twitter mentions) were included as instruments only in the selection model. The rationale behind these variables is that they would influences likelihood of getting funding, but not necessarily the amount (Hallen *et al.*, 2012). We find the Heckman model to be highly significant and hence include the inverse mills ratio (lambda) as a control variable when predicting amount of first fund raised in our analysis.

Second, our main dependent variable of interest is second-round likelihood. Here we have information on those startups that failed to raise a second round. Hence do not encounter a sample selection bias at this stage.

Milestone 2: Second-round raised (yes/no)

Firms in our sample are active in the high-tech sector. These firms need to raise several rounds of funding in short periods of time to sustain growth. Previous research has indicated that second-round success is an excellent proxy for venture success and is a clear signal that initial investors are happy with the startup's progress. We rely on the procedure used by ter Wal *et al.* (2016) to set the timeframes and measure venture success. We measured first-round investment between 2006-2013. For each of these firms we collected the amount raised and who funded them. We then looked between 2006-mid-2016 to check if they had raised a second-round or not. Consistent with previous research this time window was more than sufficient for startups to raise a second-round. And if they did not raise money in this time period it indicates that they failed to do so.

Independent variables

Founders' temporal focus

In order to analyze our Twitter data to obtain representative values for temporal focus, we used a robust and well-established psycholinguistic tool: Linguistic Inquiry and Word Count (LIWC) (Tausczik *et al.*, 2010). This tool, which has been refined using data collected over 25 years, codes across different cognitive and emotional categories and is available in over 70 languages. The LIWC software calculates the extent to which certain cognitions and emotions are present in a text, based on the frequency of words and phrases related to a category. For instance, future focus would include words and phrases such as "will," "may," "going to," etc. It is important to note that words are counted and then normalized by the length of the text, so all reported measures are in proportion to the total number of Tweets we analyzed. This prevents our measures from being distorted by the frequency with which a person Tweets, or the length of their Tweets. In this study, we look at "how" startup founders tweet rather than "what" they tweet. Importantly, the attentional biases in our study have been shown to be content-neutral in previous work (Nadkarni *et al.*, 2014). Recent work by Nadkarni and Chen (2014) relied on the categories in LIWC to code CEOs' temporal focus. They found high reliability of the LIWC across different sources of text for measuring temporal focus, and also demonstrated very strong convergent and discriminant validity for temporal measures using LIWC in a validation study. Thus, we relied on LIWC to measure our various variables of interest.

One of the primary aims of our study is to analyze *how* startup founders converse, rather than the content of their conversations. Thus, we excluded Retweets, #hashtags, and @mentions, to include only the original, spontaneous content written by each founder. IBM researchers found that 250 tweets were enough to derive personality profiles encompassing 52 different personality traits, and found excellent correlations with psychometric tests (Takahashi, 2013). Nadkarni and Chen (2014) found that a three-page student essay was enough to correlate very highly with a temporal-focus questionnaire. We excluded Twitter accounts containing fewer than 2000 words in total, in order to exceed the minimum volume of content that past studies have found adequate to measure entrepreneurial sentiments. We also ignored the accounts of founders of firms that had missing or undisclosed data. We only focused on startup founders that met the criteria. Only teams where founders had greater than 2000 words were included[2]. We ultimately arrived at 1,570 startup founders' accounts that resulted in 730 startup teams.

Table 1 gives illustrative examples of Tweets for past, present and future focus. Additionally, in table 1 we list some examples of words that are assigned to each of these categories by LIWC.

INSERT TABLE 1 ABOUT HERE

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[2] All analyses reported in the text are with partial teams; i.e. for some teams, a founder can be missing (n=228). Separate analysis with teams where all founders have twitter accounts greater than 2000 words reveals similar results.

Aggregation: from individuals to teams

Our data consists of individuals nested in teams. To calculate the temporal focus of these teams we relied on aggregation measures following the procedures by different authors (Beckman *et al.*, 2007; Bird *et al.*, 2007; Mohammed *et al.*, 2013; Mohammed *et al.*, 2011; Nadkarni *et al.*, 2014; Souitaris *et al.*, 2010; Waller *et al.*, 2001; West *et al.*, 1997; Woolley *et al.*, 2010). Since traditional multilevel modeling requires outcomes and mediators to be measured at level 1, and our dependent variables are at level 2, we opted for methods used previously in aggregation of time research (Mohammed *et al.*, 2011). The analysis which is currently reported in the paper was done to capture methods used in previous research (Nadkarni *et al.*, 2014). We carried out a median split for each of our time variables, past present and future focus. The median split was done on the entire sample of entrepreneurs (solo founders, other missing data, current sample) as long as they had greater than 2000 words.

Thus, an individual could be either high or low on past, present, or future focus. Then we simply aggregated this value by counting the number of members in a team who are high on past, present and future focus, respectively. This measure captures the team temporal orientation better. Consider, for example, if one founder is high on past focus and one is low, it indicates there is a past orientation present in the team, so in such a case the mean would not capture anyone's orientation. We also checked this value divided by the team size and saw the same results. For the sake of brevity, we do not report these. We ran checks with other aggregation measures such as the mean, maximum, standard deviation and coefficient of variance which are explained in detail in the robustness checks.

Validation study: Construct validity

In order to explore what drives funding more deeply, we carried out interviews with a subsample of startup founders from our initial dataset, selected to maximize variability in the study variables. We interviewed 19 entrepreneurs from our sample. The interviews were semi-structured (typically an hour long) and included the founders filing in the TFS Questionnaire (Shipp *et al.*, 2009).

To triangulate, we checked the correlations and factor loadings of our Twitter data with the TFS questionnaire completed by the interviewees. Confirmatory factor analysis displayed a poor fit for the one-factor model and a strong fit for the three-factor model. The scale items and our temporal focus variables loaded strongly on each hypothesized factor: past focus (scale items: 0.74– 0.89; Twitter: 0.83), present focus (scale items: 0.46– 0.92; Twitter: 0.76), and future focus (scale items: 0.77 – 0.83; Twitter: 0.88). Additionally, the temporal-focus measures extracted from Twitter strongly correlated ($p < 0.001$) with the corresponding scale items for each temporal dimension: past focus (0.81), present focus (0.67), and future focus (0.71).

Validation study: Stability over time

We controlled whether the main study variables (i.e. past, present and future focus) were stable over time. As in previous literature, we found them to be highly and significantly correlated over time (yearly correlations, past = 0.75, present =0.79, future =0.60). This supports previous findings stating that these variables are stable between the ages of 20 to 60, and despite some events changing them momentarily, we revert to our general tendency (Nadkarni *et al.*, 2014; Shipp *et al.*, 2009; Shipp *et al.*, 2011). This suggests to us that successfully gaining funding does not change founders' perceptional biases with respect to time focus. Additionally, we do not find any statistically significant correlation between temporal focus and age or previous venture experience.

Controls

In choosing controls we relied on work by Klotz *et al.* (2014), whose review lists important controls for new venture success.

Firm controls

We controlled for sector using the first digit of the SIC code for each startup; a separate analysis with all digits generated similar results, which have not been reported for the sake of brevity.

We controlled for the year the startup received its first investment, as this can have a significant influence on the amount of funding raised. We also checked whether the number of founders played a role. From previous research, we are aware that this plays a huge role in raising venture capital. Finally, we controlled for amount of funding raised in the first-round when predicting if the venture successfully raised a second-round or not.

First-round investor controls

Previous research has shown that the prominence of investors who fund the first-round are among the most important early ties in the life of a startup (Samila *et al.*, 2011). These ties have been positively associated with access to suppliers, customers and financial resources (Ahlers *et al.*, 2015). High status investors through their constant advice and knowledge serve as the basis for a venture's subsequent success. To measure status, we rely on measuring prominence of investors in the Bay Area through popular ranking lists (Ahlers *et al.*, 2015). Measuring status through lists is different from measuring centrality of these investors. Founders typically rely on word of mouth and such lists when deciding which investors to turn to. Our status measure is made by aggregating four famous lists in the Bay Area, mattermark.com, angel.co, business insider and entrepreneur.com (angel.co; BusinessInsider; Entpreneur.com; Mattermark). First, we extracted all the investors funding the first-round of each startup (N=1484). For each investor, she/he received a rank based on the position in the list (angel.co is an exception here as here we relied on measuring number of followers as the rank). If there were several investors funding the first-round of a startup, we averaged this value across the investors and arrived at a score for each list for each startup. Finally, we standardized the scores for each list and averaged them to arrive at a cumulative status score for the first-round. Additionally, we control for the number of investors funding this first round and the type of the first round (seed, series a or other).

Team controls

For all teams, the average of the startup founder's values for previous venture experience, word count of tweets, number of twitter followers and gender was used as a control. Below we list how we obtained these measures for each founder.

Previous venture experience was obtained through Crunchbase profiles. This was coded as a 1 if the founder had previous startup experience or 0 if not. In addition to analyzing a maximum of 3200 Tweets per individual, we also controlled for the number of words posted by each startup founder. To control for social capital, we relied on two measures: the average number of followers on twitter for a startup team and the average number of retweets the startup received. To code for gender, we matched each individual's first name with a machine-learning gender classifier (Genderize.io, 2014). Genderize matches against approximately 190558 names from sources such as US social-security databases and social-network data, and also produces a certainty value. This method has been previously used to gender-code Twitter usernames (Mislove et al., 2011), authors of research papers (Sugimoto, 2013), and the names of IBM engineers (Dahlander *et al.*, 2014). age, and education

Table 2 presents an overview of our data analysis and Table 3 presents the descriptive statistics for the variables at the team level. Our data represents 730 firms[3].

INSERT TABLE 2 ABOUT HERE

INSERT TABLE 3 ABOUT HERE

[3] Data on age and level of higher education were collected through graduation dates and Crunchbase profiles. We could not obtain this information for all individuals. We have run individual analysis comparing past, present and future focus on 985 entrepreneurs. A one-way ANOVA revealed no significant differences between the variables of the reduced sample and sample used for analysis.

RESULTS

Our main results are composed of 4 models. The first two are OLS regression models. The standard diagnostic plots in CRAN R were used to ensure that the assumptions for the (pooled) OLS model are met, and the results were satisfactory. To address biases from the potential presence of heteroscedasticity, we calculated robust standard errors and the corresponding t-ratios, but this step did not change the main findings. Additionally, for all our regression analysis we calculated the value inflation factors (VIFs) for all combinations of variables, and found that all were below 2, which is below the accepted limit of 10.0 (Kutner *et al.*, 2004). This indicates that multicollinearity is unlikely to be a concern in our analyses. The last two models employ a logit model, which is suited for discrete time events (second-round raised or not). We conducted Hosmer-Lemeshow tests to check diagnostics that were satisfactory. In the first two models, we used a logarithmic transformation on our first dependent variable, amount of first-round funding, to make the analysis more suitable for linear regression. As mentioned earlier we include inverse mills ratio (lambda) as a control in both these models since the Heckman model was highly significant. The first model reports the regression with only controls and the second model includes our independent variables. Looking at the log of the first-fund amount raised, the results demonstrate that high past focus does not have a statically significant and negative influence on the amount raised (B = - 0.04, p = 0.49). Interestingly we also do not find statistical support for the hypothesis regarding the negative relationship between present focus and amount raised (B = -0.07, p = 0.29), nor do we find support for the hypothesis of a positive relationship between future focus and amount raised (B = 0.05, p = 0.52). In the first round of fundraising, decisions are made primarily on the startup team, and less the idea. The amount of funding raised in the first round is also considered a noisy variable as it also depends on the private equity and financial status of a startup team (Hallen *et al.*, 2012). But activities such as strategic thought and planning become more salient when having to raise subsequent rounds. Thus, we do not find support for H1a, H2a and H3a.

In our final two models, we look at the relationship between second-round success and the three temporal focuses. Here we find support for all our hypothesis. Past focus (B= -0.32 p = 0.02), present focus (B= -0.25, p = 0.09) and future focus (B= 0.24, p = 0.10)[4] are related to second-round raised as theorized earlier. Interestingly, the effect sizes of temporal focus are comparable in magnitude to the effect size of number of founders. These effect sizes are larger than the overall status of first-fund investors and amount raised in the first round (B= 0.25, p = 0.007, B= 0.03 p= 0.70). A successful second round requires startup to meet a proofpoint. To meet a proofpoint, startups need to carefully anticipate resource needs, time accomplishments and fundraising. Both past and present focus are detrimental to this, but future focus, as expected, has a positive result. This shows the importance of future focus for venture success in dynamic environments for venture success.

INSERT TABLE 4 ABOUT HERE

Alternative explanations

Social capital: Previous research by Hallen *et al.* (2012) has indicated that the social capital of startup founders plays a role in fundraising success. We control for social capital in two ways, first we control for the status of the investors funding the first round and second, we control for the average social capital of the founder team. These variables are statistically significant, but when included in the regression they do not change the magnitude or direction of the effects temporal focus has on fund raising success.

Diversity in temporal focus: The main focus of our study is in understanding *elevation* (i.e. temporal focus of the team/ founder). However, we also checked for diversity in temporal foci which could be driving our results (Mohammed *et al.*, 2013). We looked at startups which are not founded by a solo founder, and operationalize diversity as the standard deviation from the mean in past, present and future focus respectively. Interestingly, we found that temporal diversity did not play a role in explaining our results (Appendix table A1, A2). We ran additional regressions where we included the coefficient of variance (Std. deviation / mean), which is a variable used to capture diversity in continuous variables. We ran regressions using the coefficient of variance on our dependent variables and found non-results. These results suggest that the elevation of team focus is important in explaining entrepreneurial outcomes. Additionally, we used several different aggregation measures for temporal focus. Measures related to the average, maximum past, present and future focus of the team yielded results consistent with our findings. We chose to use our existing measure as it takes into account the size of the team and does a more effective job in capturing the true temporal focus of the team. These results are reported in the appendix.

DISCUSSION

Attention allocation is a central influence that drives learning processes and ultimately impacts the strategic orientation of organizations (Rerup, 2009; Stevens *et al.*, 2014), entry into new markets (Eggers *et al.*, 2009), formative processes in the business strategy (Gebauer, 2009), and innovation outcomes (Laureiro‐Martínez *et al.*, 2014; Yadav *et al.*, 2007). Our study contributes to the strategy literature by connecting a psychological construct related to attention -time focus- to explain two different aspects of venture performance, as suggested by previous studies (Nadkarni and Chen 2014).

Our results reaffirm past work: temporal focus is an important variable affecting strategic performance. In addition, our results show that depending on the dependent variable of interest, the relationship between time focus and performance is nuanced. A possible reason is as startups mature, rules, norms, and processes become more rigid. Hence, our results move closer to those found in established organizations as we move further in the lifecycle of a startup. In a way, it is as if the future focus on the team has to compensate for the rigidities introduced by norms and procedures that are created over time. We ruled out alternative explanations such as social capital or diversity of temporal foci by controlling for them in the analysis. Additionally, despite previous evidence on temporal focus existing mainly on the individual level, we found these results to hold at the team level as well.

Methodologically, this paper contributes by using novel data sources to derive in a robust manner –very detailed through thousands of observations per individual through eight years- the traits of startup founders. Our data sources - Twitter and Crunchbase- have gained enormous importance not only as general media, but also as social platforms for exchanging business-related information, and are starting to gain importance as data sources informing research (Fischer *et al.*, 2014; Hellmann *et al.*, 2015). The combination of these data sources with dictionary tools allows us to analyze fine-grained variables that could not previously be measured so precisely, or that depended on self-reported measures. As in past studies, we found that attentional biases are stable over time, supporting the notion that they are trait-like constructs in teams (Nadkarni *et al.*, 2014; Shipp *et al.*, 2009; Shipp *et al.*, 2011). We used 19 interviews and established construct validity to triangulate our data.

Since entrepreneurial success can be measured with a myriad of measures (Beckman et al., 2007), one strength of our study is to disentangle the impact that founders' individual temporal focus has on different aspects of performance. Despite previous literature indicating that similar factors predict our two dependent variables, our interviewees mentioned that the amount of first-round funds raised depends mainly on the idea and team. We do not find evidence for temporal focus being correlated with such a performance indicator. In contrast, instead, for a successful second round, proofpoints, strategies, planning and foresight are crucial. We found support for past and present focus being negatively correlated with the likelihood of raising a second round, whereas a high future focus is positively correlated with second round success. Temporal dimensions had not been previously connected to entrepreneurial performance, especially not at the team level. Our study demonstrates that they are important to better understand entrepreneurial cognition and its impact on venture performance. Future research should examine what other temporal variables can help explain success in first-round funding.

Our results have some limitations. Firstly, while the CrunchBase data has several advantages, its use, in conjunction with Twitter data, limits both generalizability and the number of variables we can control for. In terms of generalizability, we could only extend to startups and founders who are technologically savvy and tend to be aged 15 to 50. Our results focus on the SF Bay area, which is known to have a high density of startups. Whether these results are a feature of the environment could be tested in future research by including other locations and countries. In addition, further work could complement funding with other variables such as growth, traction, user numbers, etc. to get a more holistic picture of entrepreneurial performance.

We understand that fundraising is only one aspect of startup performance, and we use it as a starting point to understand entrepreneurial success. Also, like other studies on firm performance, we face the issue of unobserved heterogeneity due to unobserved behavioral and personality traits. Future experimental work could control for these factors to understand the causal mechanisms. Finally, this study has uncovered how temporal focus affects performance. Future studies could build on our results to disentangle the importance of two potential mechanisms underlying our results. On the one hand, temporal focus matters because it is translated into the work the startup does (inside impact). On the other hand, temporal focus matters because it affects the way the startup is perceived by investors (outside impact).

In terms of managerial implications, our results inform practitioners about the importance of recognizing how their temporal focus might affect their ways of working, and ultimately the performance of their startups. Although temporal focus does not seem to be the main driver in achieving first-round funding, it appears to be a very important driver of performance in a second-round. As such, our results highlight the importance of explicitly considering time focus as a trait that characterizes teams and that plays a role –even though silently- in the behaviors of founders. Startup coaches could help start-up founders to first of all measure and recognize their own time focus, second, openly discuss it with other team members, and third, proactively engage in tasks that might increase one focus and diminish another. While time focus is constant and is considered a trait-like variable, there are multiple exercises that can be followed individually or as teams to enhance one focus or diminish another (Boniwell *et al.*, 2003; Hammond, 2012). In a complementary way, by gaining awareness of the existence and importance of time focus, entrepreneurs, and more generally organizational members, can take advantage of their own temporal focus on different organizational tasks. If the tasks are about learning and reflecting, perhaps a good leader is someone who has a high past-focus. In contrast, if the tasks involve a lot of future scenario thinking, someone with a future focus might be better suited to lead this.

Finally, this paper answers calls from the behavioral theory of strategy and attention-based view of the firm (Gavetti et al., 2012; Gavetti et al., 2007; Ocasio, 1997), to uncover antecedents that help explain performance heterogeneity in new ventures. From an attention-based view, an important antecedent of performance is understanding how available information is attended to in particular time and place contexts (Joseph *et al.*, 2012). Temporal focus determines the degree to which individuals devote attention to perceptions that are situated in the past, the present, or the future contexts and is, therefore, a pivotal guide of attention. Together, our results support the contention that temporal attentional biases are important antecedents of startup performance. In particular, it seems from our data that temporal focus is very important to reach second-round funding, which many would consider the real success measure for a startup. The startup teams that achieve second-round funding are those that, as the Nikola Tesla quote opening this manuscript suggested, focus on chasing the future.

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TABLES AND FIGURES

Table 1: Example of Tweets and LIWC words per construct

Construct	Example Tweet	Example word 1	Example word 2	Total number of words in construct category
Past focus	One of my great joys **was** helping @anonymized take his TED prize from idea to reality. #reflections	accepted	admitted	145
Present focus	I can't live without twitter... and **im** pretty addicted to tiny wings now!	admit	admits	169
Future focus	If the company gets bought or goes public, **will** I make any money?	may	soon	48

Table 2: Data analysis overview

	Steps to final sample	N	Tests
1	Crunchbase data, startup first funded 2006-2013 SF Bay area	3,645-startups	
2	Founder details extracted	7,940-founders	
3	Founder personal twitter accounts extracted	6,800-founders	Manual checks to distinguish founder personal accounts from company accounts, t- tests carried out to check sample differences.
4	LIWC run on founder accounts (after removal of #tags etc.) to extract temporal focus		Interviews were used to establish construct validity
5	If founder account had greater than 2000 words	4,986-founders	730 startups had at least one founder with greater than 2000 words
6	Firm, founder and funding controls extracted for teams	1,570-founders	T-tests were run with missing data on variables which were available and these indicated no significant differences.
7	Amount of first fund-extracted	814-startups	
8	Heckman selection models	730-startups	In the first stage, we treat all startups that received less than 50,000 $ in funding as those who did not receive any funding. The sample used for all analysis henceforth does not include these startups.
	Second funding extracted (We checked till mid 2016 to check if the startups received funding or not)	730-startups	
	Other robustness checks-samples		
a	Other aggregation measures for temporal focus	730-startups	More information in text-page 28
b	Teams where all founders had greater than 2000 words	348-startups	Regression results did not change
c	Interactions with team size	730-startups	No significant interactions
	Other robustness checks-controls		
a	Age and education	447-startups	Regression results did not change
b	Social capital	730-startups	Regression results did not change

Table 3: Descriptives and correlations

		Mean	Std. Dev	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Log-First round amount	6.11	0.56	1												
2	Second round success	0.68	0.47	0.033	1											
3	Year first-funding	2010.73	2.01	-.159**	-.114**	1										
4	Sector	6.04	2.09	0.022	0.049	.080*	1									
5	Status first-fund	2.06	0.96	.202**	.078*	0.041	-0.04	1								
6	No.of investors	4.38	4.16	.099**	.091*	.156**	-0.066	-0.011	1							
7	Word count	14215.79	9893.51	-0.061	-.089*	-0.051	-0.072	0.03	.138**	1						
8	Gender	0.10	0.27	-0.028	0.037	0.058	-0.059	0.043	-0.029	0.007	1					
9	Previous venture experience	0.65	0.48	0.002	-0.011	-0.035	0.002	-0.03	0.049	-0.004	0.038	1				
10	No of founders	2.15	0.91	-0.051	.104**	0.012	0.001	0.058	.076*	0.032	-0.002	.074*	1			
11	Past focus	0.80	0.81	-0.057	-0.059	0.015	-.107**	.126**	.244**	.296**	0.031	.076*	.261**	1		
12	Present focus	0.77	0.82	-.092*	-0.027	-0.006	-0.046	.130**	.164**	.221**	.108**	.117**	.271**	.510**	1	
13	Future focus	0.78	0.77	-.076*	0.013	-0.012	0.026	.076*	0.052	.228**	0.018	0.069	.266**	.408**	.568**	1

N=730. Two tailed non-parametric correlations, Spearman correlation and p values reported.

Table 4: Results of regression analysis for relationship between temporal focus and two entrepreneurial milestones (Standard errors in brackets)

	Dependent variable:			
	Log(first-round amount)		Second-round (Yes/No)	
	OLS		*Logistic*	
	(1)	(2)	(3)	(4)
Year fixed effects	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes
Funding type dummies	Yes	Yes	Yes	Yes
Lambda (Heckman)	-2.543 (0.747)	-2.676 (0.802)		
	p = 0.001	p = 0.001	p = 0.77	p = 0.94
Log(first-round amount)			0.048 (0.085)	0.033 (0.085)
			p = 0.574	p = 0.700
First-round investor status	0.163 (0.040)	0.172 (0.040)	0.199 (0.092)	0.257 (0.095)
	p = 0.00005	p = 0.00003	p = 0.031	p = 0.007
Previous venture experience	-0.085 (0.079)	-0.078 (0.079)	-0.098 (0.179)	-0.054 (0.181)
	p = 0.278	p = 0.323	p = 0.585	p = 0.768
Word count	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
	p = 0.442	p = 0.658	p = 0.005	p = 0.037
No. of founders	-0.073 (0.041)	-0.060 (0.045)	0.285 (0.098)	0.383 (0.110)
	p = 0.079	p = 0.183	p = 0.004	p = 0.0005
No. of investors	0.084 (0.010)	0.087 (0.010)	0.067 (0.025)	0.088 (0.026)
	p = 0.000	p = 0.000	p = 0.008	p = 0.001
Gender	0.039 (0.158)	0.064 (0.162)	0.465 (0.332)	0.527 (0.341)
	p = 0.804	p = 0.693	p = 0.162	p = 0.122
Past focus		-0.042 (0.060)		-0.323 (0.139)
		p = 0.487		p = 0.021
Present focus		-0.068 (0.064)		-0.252 (0.147)
		p = 0.291		p = 0.087
Future focus		0.053 (0.066)		0.240 (0.147)
		p = 0.426		p = 0.102
Constant	13.300 (0.415)	13.308 (0.420)	-0.200 (1.409)	-0.063 (1.420)
	p = 0.000	p = 0.000	p = 0.887	p = 0.965
Observations	730	730	730	730
R^2	0.44	0.45		
Adjusted R^2	0.42	0.43		
Log Likelihood			-422.819	-416.453
Akaike Inf. Crit.			903.637	896.907
Residual Std. Error	0.981 (df = 701)	0.981 (df = 698)		
F Statistic	20.300^{***} (df = 28; 701)	18.400^{***} (df = 31; 698)		
Note:	*p<0.1; **p<0.05; ***p<0.01			

APPENDIX

Table A1: Results of regression analysis for relationship between temporal focus of each team obtained with different aggregation measures and amount of first fund raised (Standard errors in brackets). Model 2- average of team members, Model 3- maximum of team members, Model 4- standard deviation of team members and Model 5- coefficient of variance of team members

	Dependent variable: Amount of first fund ($)				
	Only controls	Means (TF)	Max (TF)	Std.dev (TF)	Cov (TF)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes	Yes
Funding type dummies	Yes	Yes	Yes	Yes	Yes
First-round investor status	0.18 (0.04) p = 0.0001	0.18 (0.04) p = 0.0001	0.18 (0.04) p = 0.0001	0.13 (0.06) p = 0.05	0.13 (0.06) p = 0.05
Previous venture experience	-0.04 (0.08) p = 0.58	-0.03 (0.08) p = 0.76	-0.02 (0.08) p = 0.77	0.02 (0.12) p = 0.84	0.02 (0.12) p = 0.89
Word count	0.00 (0.00) p = 0.03	0.00 (0.00) p = 0.04	0.00 (0.00) p = 0.05	0.00 (0.00) p = 0.03	0.00 (0.00) p = 0.02
No. of founders	-0.05 (0.04) p = 0.22	-0.05 (0.04) p = 0.26	-0.04 (0.04) p = 0.39	-0.003 (0.07) p = 0.97	-0.01 (0.07) p = 0.94
No. of investors	0.09 (0.01) p = 0.00	0.09 (0.01) p = 0.00	0.09 (0.01) p = 0.00	0.08 (0.01) p = 0.00	0.08 (0.01) p = 0.00
Gender	-0.20 (0.14) p = 0.16	-0.17 (0.14) p = 0.25	-0.18 (0.14) p = 0.22	0.16 (0.27) p = 0.56	0.14 (0.27) p = 0.60
past.m		0.04 (0.04) p = 0.42			
present.m		-0.09 (0.05) p = 0.08			
future.m		-0.01 (0.05) p = 0.89			
past.max			0.03 (0.04) p = 0.54		
present.max			-0.08 (0.05) p = 0.12		
future.max			-0.02 (0.05) p = 0.73		
past.sd.dev				0.01 (0.06) p = 0.88	
present.sd.dev				0.04 (0.06) p = 0.58	
future.sd.dev				-0.04 (0.06) p = 0.51	
past.cov					-0.004 (0.003) p = 0.19
present.cov					-0.0003 (0.0004) p = 0.53
future.cov					-0.002 (0.01) p = 0.75
Constant	12.89 (0.40) p = 0.00	12.80 (0.40) p = 0.00	12.78 (0.40) p = 0.00	12.56 (0.65) p = 0.00	12.57 (0.65) p = 0.00
Observations	730	730	730	368	368
R^2	0.44	0.44	0.44	0.43	0.43
Adjusted R^2	0.42	0.42	0.42	0.38	0.38
Residual Std. Error	0.99 (df = 702)	0.99 (df = 699)	0.99 (df = 699)	1.03 (df = 337)	1.02 (df = 337)
F Statistic	20.32^{***} (df = 27; 702)	18.47^{***} (df = 30; 699)	18.47^{***} (df = 30; 699)	8.41^{***} (df = 30; 337)	8.50^{***} (df = 30; 337)
Note:	*p<0.1; ** p<0.05; *** p<0.01				

Table A2: Results of regression analysis for relationship between temporal focus of each team obtained with different aggregation measures and second round likelihood raised (Standard errors in brackets). Model 2- average of team members, Model 3- maximum of team members, Model 4- standard deviation of team members and Model 5- coefficient of variance of team members

	Dependent variable: Second round (Yes/No)				
	Only controls	Means (TF)	Max (TF)	Std.dev (TF)	Cov (TF)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes	Yes
Funding type dummies	Yes	Yes	Yes	Yes	Yes
Log(First-round amount)	0.05 (0.08) p = 0.58	0.05 (0.09) p = 0.56	0.05 (0.09) p = 0.58	-0.08 (0.12) p = 0.51	-0.07 (0.12) p = 0.56
First-round investor status	0.20 (0.09) p = 0.04	0.23 (0.09) p = 0.02	0.22 (0.09) p = 0.02	0.18 (0.14) p = 0.20	0.16 (0.14) p = 0.25
Previous venture experience	-0.10 (0.18) p = 0.59	-0.09 (0.18) p = 0.61	-0.10 (0.18) p = 0.60	-0.29 (0.27) p = 0.28	-0.28 (0.27) p = 0.29
Word count	0.00 (0.00) p = 0.005	0.00 (0.00) p = 0.01	0.00 (0.00) p = 0.02	0.00 (0.00) p = 0.11	0.00 (0.00) p = 0.14
No. of founders	0.29 (0.10) p = 0.004	0.30 (0.10) p = 0.003	0.31 (0.10) p = 0.003	0.34 (0.16) p = 0.04	0.40 (0.16) p = 0.02
No. of investors	0.07 (0.02) p = 0.01	0.08 (0.03) p = 0.003	0.08 (0.03) p = 0.003	0.07 (0.03) p = 0.05	0.07 (0.03) p = 0.05
Gender	0.46 (0.33) p = 0.17	0.48 (0.34) p = 0.16	0.49 (0.34) p = 0.15	0.65 (0.61) p = 0.29	0.64 (0.63) p = 0.31
past.m		-0.20 (0.10) p = 0.05			
present.m		-0.04 (0.12) p = 0.75			
future.m		0.19 (0.11) p = 0.10			
past.max			-0.16 (0.10) p = 0.09		
present.max			-0.06 (0.12) p = 0.61		
future.max			0.17 (0.11) p = 0.15		
past.sd.dev				0.08 (0.14) p = 0.60	
present.sd.dev				-0.02 (0.14) p = 0.88	
future.sd.dev				0.05 (0.14) p = 0.72	
past.cov					0.01 (0.01) p = 0.42
present.cov					0.0000 (0.001) p = 1.00
future.cov					0.03 (0.02) p = 0.13
Constant	-0.20 (1.41) p = 0.89	-0.16 (1.42) p = 0.91	-0.18 (1.42) p = 0.90	-0.10 (2.20) p = 0.97	-0.33 (2.22) p = 0.89
Observations	730	730	730	368	368
Log Likelihood	-422.82	-419.67	-420.39	-208.23	-207.12
Akaike Inf. Crit.	903.64	903.35	904.78	480.46	478.25
Note:	*p<0.1; **p<0.05; ***p<0.01				

PAPER 2

The Psycholinguistics of Entrepreneurship

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The Psycholinguistics of Entrepreneurship

Abstract

We compare data across 24,624 Twitter users to examine differences between entrepreneurs and the general population. Analyses reveal that entrepreneurs manifest more positive and fewer negative emotions than the general population. Entrepreneurs also communicate more about work, and less about aspects related to personal life. Interestingly, during the early phases of a venture, positive emotions and work concerns increase, while negative emotions and life concerns decrease. Counterintuitively, work and negative emotions are negatively associated. Entrepreneurs express negative emotions 2.26 times less, and these negative emotions reduce by 8% after successful fundraising. We find exciting implications for future work.

INTRODUCTION

> *"When you're in a company, running a company, everything keeps you up at night. It's mainly that you're at a company that's not yet profitable, and you're stressed about everything".* [Entrepreneur from our dataset]

Entrepreneurship has been called an "emotional journey" (Cardon et al. 2012). As entrepreneurs build their companies, they face challenges including high uncertainty, work overload, managing individuals, and the need to raise capital (Baron et al. 2013). Thus it is commonly assumed that, along with the higher satisfaction they derive from their accomplishments, entrepreneurs experience higher levels of stress and negative emotions (Schneider et al. 2000). As entrepreneurship is a process of self-organizing it has been shown to be closely associated with well-being (Shir 2015). Most studies have relied on indicators such as GDP or income to capture the relationship between entrepreneurship and well-being (Wiklund et al. 2016).

Emotions and work-life concerns are important and intertwined facets of well-being. Understanding emotions and work-life concerns of entrepreneurs is important because of three reasons (Baron 2008). Firstly, research on emotions has shown that they are more salient when a task is highly relevant to an individual, such as in the case of entrepreneurs who are deeply committed to their ideas they experience emotions and concerns more intensely (Delgado-García et al. 2012). Secondly, emotions can impact decision-making when tasks are complex or atypical. Entrepreneurs work in situations that stretch the limits of their cognitive capabilities and hence emotions can serve as in important antecedent to decision-making (Rauch and Frese 2007). Thirdly, work-life concerns can decrease the likelihood of exploitation of entrepreneurial opportunities (Kirkwood and Tootell 2008).

The lack of empirical evidence probing emotions and work-life balance is a major gap in the entrepreneurship literature. The recent study by Patzelt and Shepherd (2011) is one exception, in which the authors systematically study differences in positive and negative emotions between the self-employed and other types of workers. Based on their findings, we expect entrepreneurs to have higher positive emotions and lower negative emotions than the general population, despite their poorer work-life balance. Our first research question in this study is, "Are entrepreneurs, on average, happier than the general population?"

A crucial related question (not covered by Patzelt and Shepherd (2011)) is how entrepreneurial emotions change over time. The temporal aspect is important, as the early phases of a venture are marked by a process of learning and adaptation. In particular, after entrepreneurs have successfully raised money, they enjoy the reassurance of the capital they have secured, but may also face new pressures from investors. Assuming entrepreneurs can indeed cope with the challenges of running a new venture, we would expect their negative emotions to subside over time. We would also expect entrepreneurs to be more immersed in their work, and less committed to leisure and family. Our second research question is, "How do emotions and work-life balance evolve during the fundraising cycle?" Finally, we also expect entrepreneurs to use work as a method for coping with the challenges of a new venture; thus, we expect work to be negatively associated with negative emotions.

To study the emotions and work-life balance of entrepreneurs and the general population, we rely on the language that both groups use. Previous research has shown that language is a robust means for revealing individuals' work-life concerns and emotions (Tausczik and Pennebaker 2010). We investigate our research questions with a content analysis of Twitter updates ("Tweets"). Twitter data overcomes several limitations of traditional data sources such as surveys, avoiding response and recall biases and offering a real-time window into people's thoughts over long periods (Ritter et al. 2013). Additionally, content analysis of Twitter helps us collect data on our constructs, emotions, and concerns simultaneously.

By understanding how entrepreneurs express emotions and work-life concerns differently from others, we can better understand the affective side of entrepreneurship and obtain a fine-grained view of the temporal evolution of emotions and work-life concerns during key stages of the entrepreneurial process. Our novel, extensive dataset lends itself very well to this exploratory analysis.

BACKGROUND

Emotions and work-life concerns

Studies in psychology and entrepreneurship have suggested that emotions and concerns play an important role in judgments, behaviors, and individuals' cognition (Garcia et al. 2013; Grégoire et al. 2015; Hancock et al. 2008; Huy 2012; Shepherd 2003). Emotions encompass the general phenomena of subjective feelings of pleasure or displeasure (Cardon et al. 2012). Trait emotionality (i.e. a person's tendency to feel a certain way) and emotional states (i.e. how they feel at a given moment) are the focus of our study (Schachter and Singer 1962). Emotions can be antecedents of, concurrent with, and/or consequences of the entrepreneurial process (Cardon et al. 2012). It is important to note here that positive and negative emotions are independent dimensions, and negative emotions can dominate positive ones. Work-life concerns are an important facet of most individuals' and entrepreneurs' lives; they can influence their emotions, exist simultaneously with their emotions, or constitute an outcome of their emotions. Work-life concerns have a bidirectional relationship with emotions (Kirkwood and Tootell 2008). Work-life issues related to occupation, leisure activities, and money are known to impact or trigger emotions (Bolger and Zuckerman 1995). Previous literature suggests that emotions and work-life concerns are an important part of the entrepreneurial rollercoaster (Cardon et al. 2012). Work-life concerns are an important facet of well-being. For example, the buffering hypothesis suggests that concerns related to family, friends can help decrease negative emotions during stressful times (Cohen and Wills 1985). Work-life concerns act as the 'buffers' that can dissipate negative emotions (Cohen and Wills 1985).

The lack of empirical evidence investigating differences in work-life concerns and emotions between entrepreneurs and others is an important gap in current knowledge. To fill this gap, in our study, we focus on four constructs: negative emotions, positive emotions, work concerns, and life concerns.

Entrepreneurs versus non-entrepreneurs

Entrepreneurial pursuits are marked by high levels of information overload, uncertainty, time pressures, fatigue and strong emotions (Baron 1998), and entrepreneurs "face these conditions more often and with more intensity than most other people tend to do in their respective professions or endeavors" (Grégoire et al. 2015 p. 16). These have led scholars to believe that entrepreneurs will display higher emotional changes over time than non-entrepreneurs.

The explanations for these could be either due to the fact that entrepreneurs self-select into certain pursuits due to emotional preferences or to face certain challenges. Or that entrepreneurs have certain traits and abilities that help them navigate the entrepreneurial journey. Despite the two different explanations, scholars agree that entrepreneurs will tend to exhibit notable emotional differences vis-à-vis their non-entrepreneurial counterparts (Grégoire et al. 2015).

Many entrepreneurs actively and consciously search for startup opportunities (Patel and Fiet 2009). Positive emotions such as joy are known to impact tendency to exploit entrepreneurial opportunities (Carver 2003). Positive emotions increase the likelihood of detecting new changes and opportune circumstances. Previous research has shown that entrepreneurs often experience high levels of passion, an intense positive feeling (Baum and Locke 2004). Additionally, self-employment leads to higher levels of life satisfaction which also results in more happiness and excitement. Entrepreneurs are typically more optimistic and hopeful (Patzelt and Shepherd 2011). Hope has been shown to enable goal accomplishment (Blanchflower 2001; Henry et al. 2004). Entrepreneurs have a high need for achievement, desire for autonomy and gaining financial rewards. Fulfilling these quests have been shown to allay negative emotions. Negative emotions such as grief, doubt and fear work against entrepreneurial effort (Foo 2011). Thus, we expect entrepreneurs to have higher positive and lower negative emotions than the general population.

Entrepreneurship is an all-consuming career, especially in its early stages. Entrepreneurs are faced with more demands related to finances and achievement of goals than non-entrepreneurs (Delmar and Shane 2003). This time consuming pursuit also leaves less time for concerns related to leisure, friends or family (Kirkwood and Tootell 2008). We expect entrepreneurs to have higher work and lower life concerns than the general population.

The funding journey

Research on emotions and work-life concerns during ventures' early stages is mixed. On one hand, the process of fundraising is a high-stress environment. Founders must divert precious time from managing the startup, prepare pitches, plan finances, and persuade investors (Chen et al. 2009). It is a period of high stress, uncertainty, and time demands. Moreover, success in a new venture can lead to high growth, which can impose significant demands in itself (Baron et al. 2013). On the other hand, positive emotions are viewed favourably by investors (Chen et al. 2009). In the following paragraphs, we detail the changes we expect to see in the facets of well-being of entrepreneurs post successful fund-raising.

Changes in the facets of well-being after fund-raising

Positive emotions

Baron (2008) suggests that positive emotions "may contribute to capacity for responding effectively in dynamic environments" (p. 334). Strong positive emotions can help decision-makers cope with the high uncertainty, conditions typical for successful entrepreneurs. Additionally, high-tech startups must pass through several rounds of fundraising in order to succeed. Display of positive emotions such as excitement have been known to impact investor decisions favourably (Mitteness et al. 2012). Additionally, since high-tech startups must pass through several rounds of fundraising in order to succeed, we expect entrepreneurs to continue to manifest positive emotions to attract investors. The relationship of deliberate emotional displays of founders and investor outcomes is still unexplored (Cardon et al. 2012). While we do not aim to disentangle, actual emotions from displayed emotions, we expect positive emotions to increase over the course of the funding cycle.

Negative emotions

Previous research has shown that entrepreneurs who are higher in negative emotions such as anxiety tend to discontinue projects (Brundin and Gustafsson 2013). Success in fundraising can help mitigate stress and negative emotions. This is in line with previous research, which suggests that achieving key goals mitigates negative emotions (Diener 2000; Rafaeli and Sutton 1987). Also, as shown in previous research, entrepreneurs could use their passion for their startup to allay negative emotions (Patzelt and Shepherd 2011). Or reduced negative emotions could free up mental energy and thus entrepreneurs take on more work. Once a startup successfully achieves a round of funding, some uncertainty is reduced, thus reducing negative emotions related to fear, anxiety, grief and embarrassment (Foo 2011). We expect display of negative emotions to subside over the course of the entrepreneurial journey.

Work-Life concerns

Previous research has shown that for high-tech startups post successful first round fund-raising, the need to reach milestones and raise capital increases (Hallen and Eisenhardt 2012). This period is marked with extreme time-pressures and push to achieve goals. We therefore expect work demands to increase post funding and displays of life concerns to decrease.

METHODS

Sample

General population

We focused our data collection on California and used a set of 21,048 Twitter accounts from previous research (Abisheva et al. 2014; Garcia et al. 2014), extracted from a large dataset of Twitter users in the US. The accounts were selected according to their location as indicated on their profiles, using Yahoo! Placemaker to match Californian place names. The oldest Tweet in this dataset was from 2006, and the latest from mid-2013.

Entrepreneurial population

We focused on every startup listed in Crunchbase founded between 2006 and mid-2014 in the San Francisco Bay area of California. We then manually collected the personal Twitter accounts of each startup's founder(s) making sure not to collect company accounts; approximately 80% of founders had personal accounts. Our criteria yielded a sample of 3576 entrepreneurs (dataset for analysis 1). The oldest Tweet in this dataset was from 2006, and the latest from mid-2014.

Given our objective of studying entrepreneurs who were actively working on startups, we focused on those who had raised at least one round of funding. We focused on Twitter data from the single years immediately preceding and following the first year of fundraising. To ensure enough depth in the data, each of the two years had to yield a minimum of 1500 words per entrepreneur. This criterion resulted in a sample of 480 entrepreneurs (dataset for analysis 2).

From each account (of both types), we removed all hashtags, retweets, links, mentions, replies, etc., leaving only the original content spontaneously written by the user. In line with previous studies, we focused on accounts that yielded over 2000 words in total (Nadkarni and Chen 2014). Research by Lee et al. (2016) has shown that such Twitter data (founder personal accounts) provides an uncensored and complete picture of individual traits over and above other data sources,

Linguistic analysis

We analyzed all Twitter data with Linguistic Inquiry and Word Count (LIWC). LIWC counts frequencies of words and word stems and outputs the percentage of words that appear in each category; thus, scores are normalized according to text length. LIWC has been widely used, and hyper validated, in psychology and linguistics, where it has been shown to reliably detect positive and negative emotion words, and to correlate with the human judgment of emotional content (Golder and Macy 2011; Schwartz et al. 2013; Tausczik and Pennebaker 2010).

Measures

Emotions. We operationalize positive emotions by relying on LIWC's positive emotion dictionary, which comprises 407 words (e.g. "love," "nice"). The negative emotion dictionary consists of 506 words, subdivided into anger, sadness, and anxiety. The LIWC categories of positive and negative emotion have also been shown to be relatively independent (Hancock et al. 2008; Quercia et al. 2012).

Work-life concerns. To operationalize the "work" side of the work-life balance, we summed up three constructs from LIWC's "personal concerns" category: money, work, and achievement. For the "life" element we summed up the family, leisure, friends, and home categories. These categories have been validated in previous studies with self-reported measures, and have been shown to capture inter-individual differences extremely well (Schwartz et al. 2013).

RESULTS

Our results section is divided into two parts, in the first part we want to explore differences in well-being among entrepreneurs and non-entrepreneurs (population differences) and next explore the interaction between the dimensions of well-being (hierarchical linear regression).

In the second part, we first explore differences in wellbeing of entrepreneurs pre and post funding (population differences) and then run a linear regression to understand how these differences might be due to work-life concerns, industry sector, gender or size of the founding team.

Entrepreneurs vs the general population

We ran the Mann-Whitney U test to compare differences in the LIWC scores for emotions and work-life concerns between Californian entrepreneurs and the rest of the local population (Table 1). This indicated that negative emotions were significantly lower for entrepreneurs (5914.33) than the general population (13399.53); Z=-58.22, p = 5.75E-12 i.e. 2.26 times less. Also, entrepreneurs express more positive emotions than the general population. These results are consistent with the findings of (Patzelt and Shepherd 2011). In addition, we also find that entrepreneurs talk much more about work, and much less about life, than the general population.

Linear regressions with positive and negative emotions as dependent variables were also carried out, to better understand the relationship between work-life concerns, affect and entrepreneurship (Table 2). We do find confirmation of the same findings as in Table 1, additionally we find that interaction effects of work and life concerns with emotions to be statistically significant (Figures 1 and 2). For example, the relationship between entrepreneurs and positive emotions is positively correlated with work whereas for non-entrepreneurs this relationship is negative.

Entrepreneurial expressions over the funding cycle

To investigate how emotions and work-life concerns evolve during entrepreneurship, we focused on entrepreneurs one year before the year of successfully receiving funding and one year after. Correlations and descriptives are reported in table 3. We ran a Wilcoxon signed ranked test, and found that positive emotions and work concerns increased during the funding cycle, while negative emotions and life concerns decreased 8% and 11% (Table 4). As entrepreneurs progress through the development of a new venture, concerns related to home and leisure decrease the most, while concerns related to achievement increase the most. Concerns for families and friends are reduced, but not as much as leisure. Finally, concerns related to money increase. A separate analysis indicated that concerns related to money were lowest in the year before funding and highest in the year during funding, decreasing again in the year following funding.

DISCUSSION

On one hand, entrepreneurship has been linked to the need for achievement, the locus of control, passion, and excitement. On the other hand, it has also been linked to high stress, loneliness, and grief (Patzelt and Shepherd 2011). We strengthen the findings of Patzelt and Shepherd (2011) by replicating their study in a completely different context and obtaining the same result—i.e., entrepreneurs do express significantly lower negative emotions, and significantly higher positive ones, than the general population. Our results for entrepreneurs over time also are consistent with previous studies of the enhancing effect of positive emotions on entrepreneurs (Patzelt and Shepherd 2011). One possible explanation for our results is the attraction component of the ASA (attraction-selection-attrition) theory (Schneider et al. 2000). This theory suggests that individuals are attracted to specific careers—for example, "to the romance of being an entrepreneur" (Baron et al. 2013). These individuals hence have a better career fit, and experience more positive emotions and fewer negative ones.

Entrepreneurs' work-life balance can offer interesting insights into their affect. For example, concerns related to work were negatively associated with negative emotions. Despite leisure being positively correlated with positive emotions, entrepreneurs expressed significantly less about leisure as they embarked on the funding journey, which could reflect that they had entered a "flow state" as previously studied in the literature (Komisar 2000; Rai 2008). We could also conceive work concerns to be a form of coping mechanism, which helps entrepreneurs stay upbeat. Finally, achievement of key goals reduces negative emotions, which we see as entrepreneurs successfully complete their fundraisings.

Despite the richness of Twitter data, our generalizability is restricted to the age group of twitter users (which ranges between 15 and 50 years) and the Californian population. Future work can explore other geographic locations and can look at the tendency to engage in entrepreneurship by controlling for demographic factors and using emotions and work-life concerns as predictors. Additionally, since we were interested in nascent entrepreneurs who were actively working on their startups, we focused on those who had achieved first-round funding. Further studies can explore emotional differences among those who have endured unsuccessful fundraisings, or who are in the middle stages of fund-raising.

Through this study, we contribute to the entrepreneurship field both methodologically and empirically. Methodologically, we propose social media sources as excellent opportunities for researchers to study the emotions, cognition, and personalities of entrepreneurs over time. Empirically, we confirm previous findings and extend them to track emotions longitudinally, during the early stages of an entrepreneurial venture, and by doing so we offer potentially new constructs for the field. Work seems to contribute to lower negativity for entrepreneurs; perhaps it really is true that "an entrepreneur's life is their work, and their work is their life."

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FIGURES AND TABLES

Figure 1: Interaction plots of positive emotions and work-life concerns

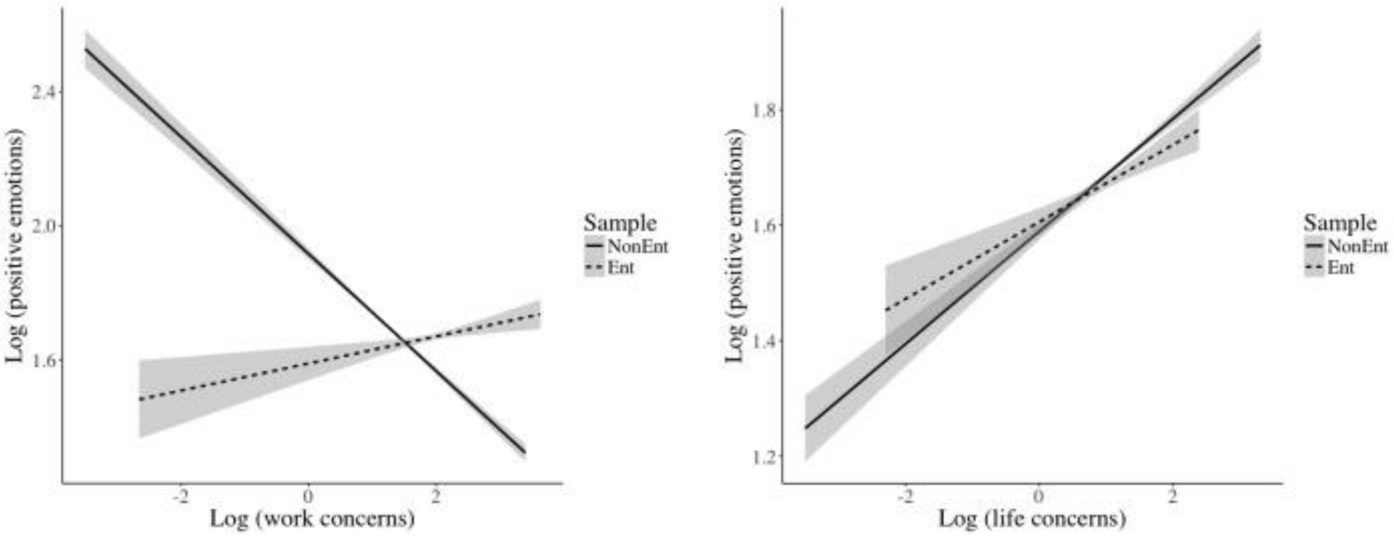

Figure 3: Interaction plots of negative emotions and work-life concerns

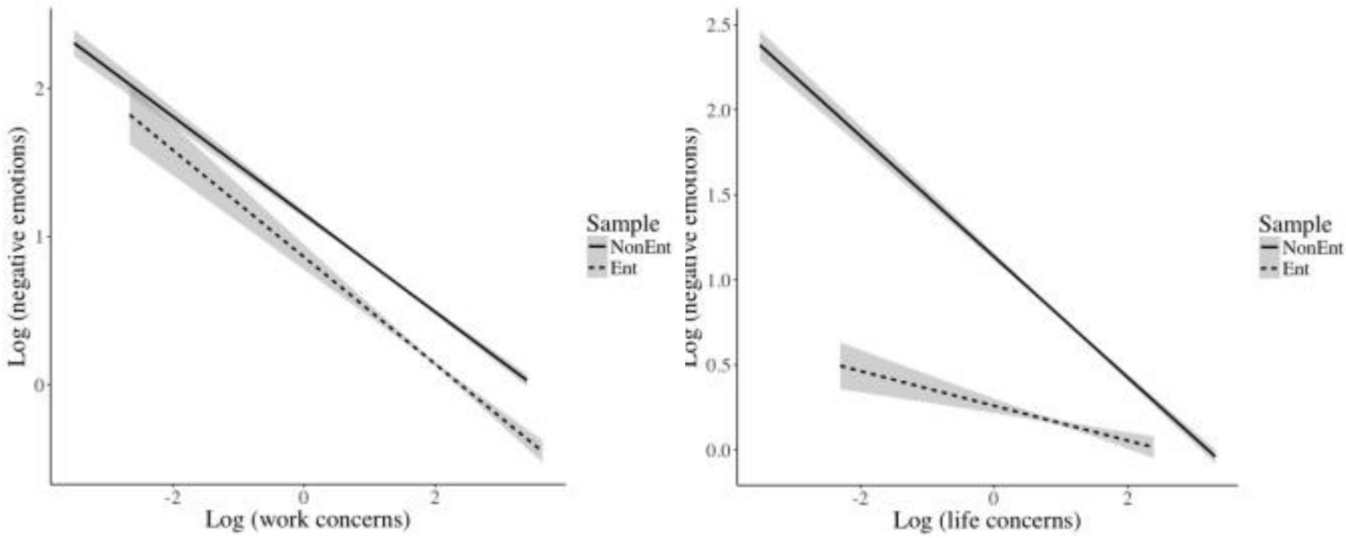

Table 1: Mann-Whitney U Test to compare differences between entrepreneurs and the general population

	Sample	N	Mean Rank	Mann Whitney U	Asymp. Sig. (2-tailed)
Positive emotions	0	21048	12183.93	34927675	0
	1	3576	13069.25		
Negative emotions	0	21048	13399.53	14753969.5	0
	1	3576	5914.33		
Work	0	21048	10821.58	6252848.5	0
	1	3576	21087.94		
Life	0	21048	12683.97	29815151.5	0
	1	3576	10126.07		

Table 2: Linear regression to predict positive and negative emotions separately

	Dependent variable:			
	Log (Positive Emotions)		Log (Negative Emotions)	
Variable	1	2	3	4
Entrepreneur (Yes=1, No=0)	0.08*** (0.01)	-0.15*** (0.02)	-0.35*** (0.01)	-0.56*** (0.03)
Work concerns	-0.03*** (0.001)	-0.04*** (0.001)	-0.08*** (0.002)	-0.09*** (0.002)
Life concerns	0.02*** (0.001)	0.02*** (0.002)	-0.10*** (0.002)	-0.10*** (0.002)
Entrepreneur * Work concerns		0.04*** (0.002)		0.03*** (0.003)
Entrepreneur * Life concerns		-0.01** (0.01)		0.005 (0.01)
Constant	1.73*** (0.01)	1.79*** (0.01)	1.36*** (0.01)	1.40*** (0.01)
Observations	24,624	24,624	24,624	24,624
R^2	0.03	0.05	0.27	0.27
Adjusted R^2	0.03	0.04	0.27	0.27
Residual Std. Error	0.32 (df = 24620)	0.32 (df = 24618)	0.48 (df = 24620)	0.48 (df = 24618)
F Statistic	255.54*** (df = 3; 24620)	232.89*** (df = 5; 24618)	2,969.79*** (df = 3; 24620)	1,807.16*** (df = 5; 24618)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3: Descriptives and correlations of entrepreneurs who received funding

		Mean	Std. D	1	2	3	4	5	6	7	8
1	Prefunding_posetiveemotions	5.27	1.31	1							
2	Prefunding_negetiveemotions	1.48	0.52	-.16**	1						
3	Postfunding_posetiveemotions	5.57	1.49	.68**	-.16**	1					
4	Postfunding_negetiveemotions	1.42	0.49	-.16**	.61**	-.22**	1				
5	Prefunding_work	6.38	2.17	0.04	-.33**	0.04	-.25**	1.00			
6	Postfunding_work	6.61	2.08	0.02	-.31**	0.03	-.23**	.76**	1.00		
7	Prefunding_life	2.71	0.91	0.01	-0.09	0.04	-.17*	-.12**	-0.07	1.00	
8	Postfunding_life	2.50	0.91	-0.01	-0.04	0.05	-.16**	-.11*	-.15**	.56**	1.00

N=480

** Correlation is significant at the 0.01 level (2-tailed).

Table 4: Wilcoxon signed ranked samples test to compare differences among entrepreneurs, pre- and post-funding

Category	Z	Asymp. Sig. (2-tailed)
Postfunding_posetiveemotions - Prefunding_posetiveemotions	-5.847b	0
Postfunding_negetiveemotions - Prefunding_negetiveemotions	-2.768c	0.006
Postfunding_work- Prefunding_work	-3.682b	0
Postfunding_life - Prefunding_life	-6.278c	0

b Based on negative ranks.

c Based on positive ranks.

PAPER 3

The Managers' Note-Pad:

Working Memory, Exploration and Performance

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Abstract

This paper builds upon March and Simon's intuition that individual level differences matter in explaining decision-making performance. We extend their discussion about the importance of decision makers' attention span to explain the emergence of heterogeneous exploration levels within the same uncertain environment. We develop and test a model of decision making under uncertainty in which attention span is operationalized as 'working memory' i.e. the amount of information one can hold under the focus of attention to actively process it. We design a laboratory study and two replications involving a total of 171 individuals. We show that working memory differences allow to identify those individuals who are more likely to choose the appropriate levels of exploration, and thus achieve higher performance. We discuss the implications of our study for management theories, and how the work of March and Simon still provides a unifying framework to generate and test managerially relevant hypotheses.

Keywords

attention, cognition, e-greedy, exploration, sequence analysis, working memory,

INTRODUCTION

Scholars have long accepted the idea that strategic heterogeneity is a key driver of learning, competition, and ultimately performance. In 1958 March and Simon put forward a decision-making model that incorporated the cognitive limits of organizational members and identified working memory, as a key antecedent of performance heterogeneity. Thirty-three years later, in 1991, March proposed exploration and exploitation as a central dilemma for organizations. In this paper, we theoretically and empirically tie these two foundational works with the objective to propose an antecedent that explains the emergence of heterogeneity in exploratory decisions.

Few studies have focused on the generation of heterogeneity in strategic choices, or uncovered the micro-processes that underpin them. These gaps are important, for both theory and practice, as understanding the origins of strategic heterogeneity could aid our understanding of the sources of performance heterogeneity. Several studies have established a relationship between individual-level cognitive characteristics and some dimension of performance (Rosenbloom 2000, Datta, Rajagopalan et al. 2003, Taylor and Helfat 2009, Herrmann and Nadkarni 2014). These studies' lens for understanding individual and organizational cognition, primarily focus on how information is organized, how knowledge is coded, and the relationships between different types of knowledge.

A different, but complementary lens was proposed by March and Simon (1958)'s model in which the emphasis is on the cognitive abilities of decision makers, and in particular, on individuals' span of attention. To operationalize and theorize how the span of attention may be related to heterogeneity and performance, we build on March and Simon (1958)'s model and complement it with recent advances in cognitive neurosciences and psychology. More specifically, we rely on ongoing work about working memory as an observable, and actionable, precursor of attention span in individuals (Conway, Kane et al. 2005). We then develop a theoretical framework and an empirical strategy to study working memory as a key individual antecedent of exploration exploitation (March, 1991).

From an empirical standpoint, we design a study to observe the emergence of strategies in a task that involved repeated exploration-exploitation decisions (i.e. the "four-armed bandit" task). We apply sequence analysis and clustering techniques to observe the emergence of heterogeneous strategies and show that differences in working memory affect people's propensity to explore, which in turn explains performance.

We focus on a cognitive mechanism (i.e. working memory) that contributes to explain the emergence of heterogeneous choice patterns (strategies) related to variations in exploration rates and hence in decision-making performance. Why is working memory so important?

Working memory allows to hold information in mind while at the same time it allows to process and manipulate it. Whereas a number of individual characteristics could help direct perception and attention more effectively, working memory is a key mechanism to overcome failures of both. It defines the span of attention and therefore is critical in selecting what information gains more processing, and what information instead falls out of the attention span, and is therefore critical in the definition, differentiation and persistence of goals (March and Simon 1958, see figure 1 taken from their book, chapter 6).

< INSERT FIGURE 1 ABOUT HERE >

Using an established metaphor, working memory can be described as the brain's note-pad that temporarily stores information and supports thinking by providing an interface between attention, perception, and action (Baddeley 1992, Baddeley 2003). Recent advances in the cognitive sciences have found that working memory acts as an "attention buffer", that relies on two key mechanisms: holds elements in mind and actively computes them (Diamond 2013). Thanks to these two mechanisms, working memory allows individuals to attend to multiple elements and to identify patterns even under conditions of uncertainty and change, make decisions, and better learn from the feedback. We thus expect individuals with higher working memory to be better at choosing how much to explore, and obtaining, in turn, superior decision-making performance.

To test this overarching hypothesis, this article proposes a two-step design. First, we rely on a widely used decision-making task that entails repeated decisions among exploitation and exploration (March 1991, Daw, O'Doherty et al. 2006). Using this task, we examine the emergence of heterogeneous choice patterns that reflect different exploration levels that in turn lead to different decision-making performance. Second, we explore whether differences in working memory can explain differences in exploration and performance, and show that higher working memory leads to more appropriate levels of exploration and to higher performance.

This paper comprises six sections. Following this introduction, the second section proposes our theory. Third, we introduce our methods. Next follows the analyses section. The fourth section presents our results. The fifth section presents two replication studies. Finally, we discuss the implications of our findings for the understanding of the emergence of heterogeneity and the performance implications of strategic decision-making in turbulent environments.

THEORY

Exploration heterogeneity and performance

Environmental uncertainty undermines beliefs about the merits of different alternatives.

Alternatives that seem promising at first glance can turn out to be worse, while other, initially disregarded alternatives may improve. The way people adapt their beliefs has been studied to explain overall organizational or team performance (Meyer and Shi 1995, Daw, O'Doherty et al. 2006, Steyvers, Lee et al. 2009). There has been interest in understanding how inter-individual differences can drive heterogeneity with most contributions appearing in related fields. Only more recently in management the study by Helfat and Peteraf (2015) proposed to understand how specific cognitive abilities can antecede heterogeneous strategies that in turn affect performance. We build on the received literature to understand performance as the result of heterogeneous strategies that in turn are rooted in differential cognitive capabilities.

When faced with repeated decisions, individuals use their sensing capabilities to develop strategies based on choice patterns that allow them to plan ahead —not only maximizing short-term gains by exploiting the alternative they perceive as being the best, but also maintaining long-term gains by exploring their environment, recognizing opportunities, and learning from the outcomes of their choices. In doing so, they aim to get maximum value not only from the choice at hand, but also from those that will come later. We can think of a *choice pattern* as a rule or routine (Cyert and March 1963, Nelson and Winter 1982) that maps someone's beliefs about the merits of different choices from a set of alternatives. A choice pattern does not determine a specific action; rather, it suggests an action that is conditional on beliefs about the state of a changing world.

Past literature has provided conflicting evidence about the relationship between the extent of exploration and performance under uncertainty. On the one side, exploration is expected to generate positive long-term results, since it allows us to update knowledge about the environment and the consequent behavioral adaptations. This is particularly true when there are diminishing performance gains over time (for example incremental gains in performance decline with the use of the existing technology). Research on learning curves demonstrates this viewpoint (Argote, Beckman et al. 1990, Argote and Epple 1990, Epple, Argote et al. 1991). However, high levels of exploration might lead to excessive costs of failed experiments and insufficient rewards from successful ones (March 1991, Levinthal and March 1993, Benner and Tushman 2003). Stieglitz, Knudsen et al. (2015) proposed to solve this tension by showing that the dimensions of environmental dynamism (frequency, direction, and variance magnitude) matter: frequent directional changes diminish the value of exploration, while variance magnitude increases it. However, in turbulent environments individuals will vary in their abilities of responding appropriately to the specific source of dynamism (e.g. frequency, vs magnitude of change. This is consistent with Helfat and Peteraf's (2015) discussion about sensing capabilities as cognitive skills. These skills most likely differ across individuals. Hence, we expect that, in turbulent environments, strategies will significantly differ along their level of exploration, because different individuals will sense and compute differently the changes they experience. In particular, we expect that individual level differences in cognition capabilities will lead to the generation and persistent of heterogeneous strategies.

Attention span and Working memory

But which specific individual level differences in cognition matter in this discussion? March and Simon's chapter 6 on their 1958 book pioneered the idea that managers' limited rationality affects not only their attention and the setting of their goals, but most importantly their behavior and therefore their performance (and hence that of the organizations they lead). Since then, many studies have empirically observed the positive (Ocasio 1997, Rosenbloom 2000, Eggers and Kaplan 2009, Taylor and Helfat 2009, Joseph and Ocasio 2012, Helfat and Peteraf 2015) and negative (Tripsas and Gavetti 2000, Helfat 2007, Danneels 2011) effects that managers' cognition has on learning, behavior, and performance. Some individuals have capabilities that help them lead their firms through exploration and strategic change (Rosenbloom 2000). However, even managers with such capabilities differ, in part due to differences in managerial cognition (Adner and Helfat 2003). Some managers are better than others at anticipating, interpreting, and responding to the demands of a changing environment (Helfat and Peteraf 2015).

What makes some individuals better at developing appropriate exploratory behaviors—luck, or learning (Denrell, Fang et al. 2014)? If it were down to luck, individuals might do well a few times, but not consistently in a setting (such as the one of interest in this study), that involves repeated choices. So, if some individuals are better at learning from their environments, what cognitive capabilities are at work?

Strategic management research has mostly focused on understanding cognition as knowledge structures and mental representations, finding that there are ample differences across managers in a given industry context (Barr, Stimpert et al. 1992, Barr 1998, Tripsas and Gavetti 2000, Gavetti and Rivkin 2007, Eggers and Kaplan 2009) . This is a very important issue. However, it begs the understanding of the sources of this individual-level heterogeneity, and, in particular, whether some of these sources can be located in specific *capabilities*, which would then influence the processes and the quality of decision outcomes (Ocasio 2011, Helfat and Peteraf 2015)

In particular, it is well established that, in conditions of high environmental change and uncertainty, when the opportunities and threats must be recognized, sensing capabilities are needed to override automatic responses and redirect behavior to explore new alternatives (Posner 1978, Norman and Shallice 1986, Posner and Rothbart 1998). This sensing managerial capability requires at least both attention –which helps selecting and holding under focused awareness the selected stimuli– and perception– which helps making connections and recognizing a pattern among the selected stimuli (Helfat and Peteraf 2015). Working memory has been associated with both the ability to focus attention on selected pieces of information and the ability to interpret and process such pieces of information. Working memory acts as an "attention buffer" relying on its two key elements: to hold information in the mind and manipulating it. In other words, working memory processes information that is no longer present.

Recent advances in neuroscience have proposed working memory as one of the most important cognitive capabilities, so much, that without working memory, reasoning is not possible at all (Diamond 2013). Working memory is necessary for making sense of written or spoken language, for doing any mental calculation in your head, and even for mentally reordering items and for translating instructions into action plans. Working memory is highly involved in multiple processes that are central to managers' decision-making as it is critical for making sense of anything that unfolds over time, decisions that require holding in mind what happened earlier and relating it to what comes later, thinking about sequential actions, for incorporating novel information and alternatives into your thinking and for updating any action plans. Finally, it is needed to "considering alternatives, and mentally relating information to derive a general principle or to see relations between items or ideas» (Diamond 2013 page 143). All of these essential tasks related to decisions that deal with exploitation of known alternatives or exploration of novel ones.

It is important to differentiate working memory from short-term memory. Working memory and short-term memory show different developmental progressions; the latter develops earlier and faster. They are linked to different neural subsystems (working memory relies more on dorsolateral prefrontal cortex)(Diamond 2013). Most importantly, for this paper, they involve different functions. While short-term memory only involves holding items in mind, working memory also involves interpreting, actively manipulating, comparing, and selecting them. In other words, working memory allows for the active manipulation of information that is held under the focus of attention, whereas short-term memory only refers to the short-term storage of information.

The *measure* of the capacity of the information that can be held in the working memory is the span. The *capability* is working memory. Information is supposed to be hold in "chunks", regardless whether the elements are digits, letters, words, or other units. The span has been associated with controversial “magic numbers” [i.] One might remember the number seven, as the magic number of attention span. It seems that the span varies depending on the type of information that is held (Hulme, Roodenrys et al. 1995). Beyond the numbers, so beyond the span, the ability seems to be a concept that is context independent: if an individual has a higher ability she should have such ability in different contexts (be it holding words, digits, images, etc.). We focus our attention on the ability, and therefore on working memory rather than on attention span.

Working memory as an antecedent of exploration and performance

Working memory allows for focusing on representations of various options and scenarios. It is essential for drawing conclusions and understanding the patterns that emerge from sequences of events that unfold both backwards and forwards in time (Fuster 1990, Baddeley 1992, Goldman-Rakic 1993, Baddeley 2003). Strategy scholars have proposed that the inability to hold the bigger picture in mind—including short- and long-run outcomes, successes and failures—is detrimental for deriving appropriate mental representations and thus affects learning and results in myopia (Levinthal and March 1993). Misspecified mental representations can have an impact on the level of exploration, and the subsequent performance that results (Martignoni, Menon et al. 2015). Appropriate mental representations will result in strategies that avoid myopia by contemplating not only immediate, short-term outcomes, but longer timeframes too [ii]. Since working memory allows to hold information in mind and manipulating it, it is responsible for the ability to discern temporal patterns and connections between seemingly unrelated things (Diamond 2013). An individual with higher working memory will be able to better hold the elements of the current situation under the focus of attention, and will be more capable of recalling past experiences to discern patterns and make connections between different pieces of information. One could expect that better working memory would be associated with superior exploration ability (i.e. knowing how much exploration is needed), which will, in turn, lead to better performance.

To theorize (and later operationalize) how the span of attention may be related to heterogeneity and performance, we build on March and Simon (1958)'s model (see figure 1) and focus on the components most directly related to individual cognition and attention (bottom part of figure 1, highlighted in yellow). We propose that having a goal in mind, and holding constant the time pressure (see (a) in figure 2), the working memory of an individual (see (1) in figure 2) will be associated with a higher attention focus (see (b) in figure 2). Recent neuroscientific findings have found that working memory and focused attention appear to be similar in many ways, including the prefrontal parietal system that support both (Gazzaley and Nobre 2012). Also, recent discoveries show that improvements in working memory can support improvements in selective attention (Stedron et al. 2005) which are helpful in filtering out alternative options and selecting the most relevant information. A higher attention focus will then lead to a better selection of alternatives, thus a more appropriate level of exploration (see (2) in figure 2) that will in turn impact performance (see (3) in figure 2).

< INSERT FIGURE 2 ABOUT HERE >

METHODS

To empirically test our model, we designed a study aimed at capturing inter-individual differences.

We relied on two different and complementary tasks. First, we drew on studies of decision-making in management and neuroscience to provide the context where sensing is needed—i.e. the non-stationary four-armed bandit task which requires participants to recognize the need to explore for potential opportunities and to exploit them (e.g. Denrell and March 2001, March 2003, Daw, O'Doherty et al. 2006, Boorman, Behrens et al. 2009, Kovach, Daw et al. 2012, Posen and Levinthal 2012, Seymour, Daw et al. 2012, Laureiro-Martínez, Canessa et al. 2013, Laureiro-Martinez 2014). Second, we turned to cognitive psychology to capture participants' attention span using a working memory task that measured participants' "real" rather than "manipulated" ability. It is important to highlight that because of our objective of capturing inter-individual differences in working memory, and studying if those affect exploration, which in turn should affect performance, we designed a study that allowed inter-individual differences to emerge "naturally" rather than inducing such differences. A key advantage of this design is that it lies closer to a natural setting, in which differences among say, managers emerge naturally. An important disadvantage is that there might be confounding factors that could explain performance. To control for such factors, we performed a thorough study of factors that could affect performance or that could be related to working memory and we have these factors as controls.

In addition, we performed two complete replications studies with different participants and in different contexts. These results not only give us confidence in our findings, but also allow us to expand our results beyond the single environment (payoff function).

In a nutshell, we rely on a decision making task (four armed bandit) to observe the emergence of differences in behavior holding constant the time pressure (see a in figure 2 dotted as is equal for all participants), observe individuals' level of exploration (2 in figure 2 –in bold as we measure this) and their performance (3 in figure 2, also in bold as we measure it). We rely on another task (working memory task) to capture the working memory of an individual (see 1 in figure 2 –in bold as we measure this) that is associated with a broader attention focus (b in figure 2 dotted as we do not observe this).

Sample

Eighty-nine individuals (44 women and 45 men) completed a series of four-armed bandit tasks, as well as a battery of other psychological and decision-making tests. Participants were graduate students of management and the economics of innovation who had volunteered to participate in exchange for monetary compensation (mean USD75 or EUR62). Participants' mean age was 24 (SD = 2.289).

Exploration and exploitation behaviour: four-armed bandit task

All participants engaged in a four-armed bandit task. This type of task has also been frequently applied in organization studies, notably by Jim March and colleagues (e.g. Denrell and March 2001, March 2003, Posen and Levinthal 2012, Laureiro-Martinez 2014) to explain the antecedents and consequences of exploration/exploitation. In addition, this task has been used in neuroimaging studies of the neural bases of explorative vs. exploitative choice (Daw, O'Doherty et al. 2006, Boorman, Behrens et al. 2009, Kovach, Daw et al. 2012, Seymour, Daw et al. 2012, Laureiro-Martínez, Canessa et al. 2013).

The four-armed bandit belongs to the broader category of bandit problems, a group of dynamic decision-making tasks that are both well suited to controlled laboratory studies and also representative of a broad class of real-world problems (Steyvers, Lee et al. 2009). In terms of ecological validity, this task captures the key elements of a broad class of settings in which people must repeatedly choose among options with uncertain outcomes, during a period of learning (Meyer and Shi 1995). Participants had to choose multiple times between four computer-simulated slot machines, each offering unknown odds of winning (DeGroot 1970).

The slot machines' payoffs change continuously, simulating an environment full of change and uncertainty. Participants only learn the values of the different alternatives by actively sampling them. By no means does this task capture the elements of all strategic decision making tasks, but it does capture, in a parsimonious way, the key features of a class of decisions related to repeated choices between exploration and exploitation in uncertain environments.

In order to allow for sufficient trials to explore, and following what has been done in previous studies, participants completed four sessions, each consisting of 75 trials (i.e. decisions). Participants were instructed to maximize their total payoff and they were not aware of the underlying payoff structure (Daw, O'Doherty et al. (2006). The slot machines' payoffs were drawn from a distribution used in past laboratory studies on exploration/exploitation with human participants. We replicated the payoff instantiations used by Daw, O'Doherty et al. (2006).The payoff for choosing the i^{th} slot machine on trial t was between 1 and 100 points, drawn from a Gaussian distribution (standard deviation $\sigma_o = 4$) around a mean $\mu_{i,t}$ and rounded to the nearest integer. At each timestep, the means diffused in a decaying Gaussian random walk, with $\mu_{i,t}+1 = \lambda\mu_{i,t} + (1 - \lambda)\theta + \nu$ for each i. The decay parameter λ was 0.9836, the decay center θ was 50, and the diffusion noise ν was zero-mean Gaussian (standard deviation $\sigma d = 2.8$) (Daw, O'Doherty et al. 2006). The standard deviation of the noise and the decay parameter introduce uncertainty and make the payoff function resemble a turbulent environment.

Participants had a maximum of 1.5 seconds to choose a slot machine. On average, they took one-third of a second to make their choices.

Attention span: Working memory task

We measured our key construct, working memory, in a classical manner, using the "*n*-back" task (Kirchner 1958) one of the most widely used assessment tasks in cognitive neurosciences still widely used today (Conway, Kane et al. 2005, Gazzaley and Nobre 2012, Diamond 2013). In this task, the participant is presented with a sequence of stimuli (i.e., letters of the alphabet) and has to indicate, under time pressure, when the current stimulus matches the one that appeared n steps earlier in the sequence. This task measures the ability a participant has to hold information in mind (the current stimuli) and manipulating it (comparing it with the information presented in the past). The load factor *n* can be adjusted to make the task more or less demanding; we presented participants with load factors of two and three, which are neither easy nor too difficult. For example, in the case of *n*=2, when the participant sees the sequence "T E A D E Q **E** X S C E **C** T T M **T** P W" the correct answers would be to noticed when the third E, the second C, and fourth T as in each of these cases they were preceded by the same letter two positions before (correct answers are shown in bold). In the results tables, we show separate results for the load 2 and 3 (see 2back and 3back)

Control measures

We controlled for other functions that make part of the cognitive control capabilities, also called executive functions (Diamond 2013). Authors differ on the different capabilities they group under this family, but most cited models would agree on four functional components that involve a) sustained and focused attention control, b) planning and generativity, and c) reflective capacity and abstract thinking (Desimone and Duncan 1995, Miller and Cohen 2001, Sohlberg and Mateer 2001, Barkley, Murphy et al. 2007, Knudsen 2007). We used classical tasks that for each group of executive functions and followed the exact procedures used in previously published lab work (Laureiro 2014). Each task emphasizes a particular functional mechanism. To control for attention control, we used the "Flanker" task (see Flanker in the results tables); for planning and generativity, the "Tower of Hanoi" task (see TOH in the results tables), devised by Edouard Lucas in 1883, and still widely used today. To control for abstract thinking and cognitive reflection we used the "Progressive Raven" matrices and the "Cognitive Reflection test (see respectively Raven and CRT in the results tables) (Frederick 2005).

Analyses

The analyses are varied and entail a number of technical checks to foster the robustness of the findings. l. To comply with manuscript length, and taking into account a broad audience of management scholars as readers, we present a summary of the analyses here, and provide a more detailed presentation in the supplementary materials.

In a nutshell, our analyses followed two main steps. First, we aimed at understanding participant's exploration strategies by modelling them with an ε-greedy model and used a Kalman filter to estimate participants' key parameters. Second, we used optimization techniques to obtain, for each participant, a parameter that would capture their exploration propensity (i.e. epsilon parameter).

Model-based analysis: exploration strategies

To interpret participants' choices quantitatively, we used three exploration strategies that are commonly used to model choices in the bandit task (Daw, O'Doherty et al. 2006): win-stay-lose-shift ("WSLS"), ε-greedy, and softmax. From these three strategies, ε-greedy is most commonly used to analyze the behavior in similar tasks.

The key assumption behind ε-greedy, is that the participant accumulates beliefs about the value of the slots and chooses the one they believe is best most of the time, occasionally (with probability ε-) choosing another at random (Sutton and Barto 1998, Cohen, McClure et al. 2007). A higher ε- would indicate high exploration, as the participant chooses a slot at random more often. One of the disadvantages of ε-greedy is its arbitrariness: the slot chosen could be the worst, the second-worst, or the second best. We chose to report our analysis with the ε-greedy model as it is the most commonly used reinforcement learning model (Posen and Levinthal 2012, Mehlhorn, Newell et al. 2015). All analyses for the softmax and WSLS models were carried out identically to the ε-greedy model; for brevity, we report them in supplementary tables

A1–A4 rather than here.

Model-based analysis: Kalman filter

In order to maximize their payoff, at every trial participants have to choose the slot that provides the highest payoff. To do so, participants have to actively sample and learn the payoff offered by each slot. This learning process can be described by reinforcement-learning models (Howard-Jones, Demetriou et al. 2011). We used the Kalman filter model to analyze our participants' behavior quantitatively, replicating the model exactly as used by Daw, O'Doherty et al. (2006).

To model how participants, conduct their exploration, the Kalman filter estimates key parameters for each of the exploration strategies. For ε-greedy, the key parameter is ε-, which is the probability with which participants randomly choose a different slot. These central parameters are computed based on all choices made throughout the task by the participants.

Optimization

We performed a parameter estimation or fitting procedure based on optimization techniques. The aim was to identify a value of epsilon that would capture participants' actual choices. To do this, we first fitted the Kalman filter described above to our sample, using the choice rules of ε-greedy. Following the procedure used by Daw, O'Doherty et al. (2006), we obtained uniform values across all 89 participants for noise, lambda, standard deviation of noise, etc., plus individual values of ε- for each participant, reflecting their choice strategy.

We ran the optimizations in Matlab, trying several different input values such that the sequence generated resembled the participant as closely as possible. The goal was to maximize the probability that each slot chosen at time t was the one the participant actually chose. Mathematically, this meant minimizing the negative log-likelihood (NLL): the smaller the NLL, the better the fit. We run the optimizations using three different approaches: trying to find the exploration parameter to the entire group of 89 participants, trying to find the exploration parameter for each single individual, and trying to find the exploration parameters for clusters of participants who followed similar strategies.

In the first optimization approach, we tried out a large number (106) of input values to minimize the NLL for all 89 participants. Similar to Daw, O'Doherty et al. (2006), we found that several of the parameters attained extreme values, suggesting under-fitting of behavior.

In a second optimization approach, we carried out fully individualized fits, modeling each of the parameters separately for each subject. Similar to Daw, O'Doherty et al. (2006), we found that several of the parameters attained extreme values, suggesting over-fitting of behavior.

In a third approach, we repeated the same procedure, but instead of fitting ε-greedy to participants, we fitted each of the models to each of four clusters that were found through an analysis of similarities among the choices that each participant carried out. To find such clusters we used Hamming distance analysis that helped uncover four clusters that were significantly different among them and similar within them (see supplementary materials "Hamming distance and clustering procedure"). The fitting was done by calculating four different values for each of the six parameters (i.e. participants of each cluster shared the values on each of these six parameters) and 89 different values for ε- (i.e. every participant had their own exploration value).

For the sake of brevity, the different optimization and hamming distance procedures are reported in the supplementary materials (under headings "Hamming distance and clustering procedure", "Entire group optimization and performance", "Cluster-wise optimization and performance" and Table A5).

RESULTS

Descriptives

Table I presents the descriptive statistics and correlations for the variables of interest and controls. The correlations signs are as expected. Both load factors in the working memory task are positively correlated, but only the more demanding one is significantly correlated with the level of exploration, and performance.

< INSERT TABLE I ABOUT HERE >

Differences in exploration predict performance

To test whether a better level of exploration (i.e. lower exploration, in this setting) is associated with performance we ran an OLS regression with ε-as the independent variable and the total payoff in the bandit task as the dependent variable. Notice that we predict performance using the exploration parameters that were generated cluster-wise.

The regression shown in columns 1 and 2 of Table II shows that the proportion of performance explained is 44 percent. The regression results confirm our idea that low exploration improves performance. These results also indicate that performance is very sensitive to the models' key parameter, i.e. ε- ($p=0.0001$). For instance, holding all variables constant and increasing ε-by just 0.1 units would decrease performance by 1111.17 units (See Table II).

< INSERT TABLE II ABOUT HERE >

Working memory is an antecedent of exploration

To test whether better working memory is associated with a better level of exploration (i.e. lower exploration, in this setting); we ran an OLS regression with ε-as the dependent variable and working memory as the predictor. Table III columns 3 and 4 present the results. Importantly, we controlled for multiple factors at the demographic and cognitive levels, that could have affected performance. Since one participant did not complete the Flanker task, we report the next regressions with 88 participants.

The regression is statistically significant, and, as predicted, a higher working memory is associated with a lower ε-(β= -0.002 sig. 0.023).

An interpretation is that an increase in working memory of 10 points would decrease ε-by 0.02. The mean ε-among the participants was 0.05. Taking into account the value of β, if all the independent variables were standardized (β= -.282), we can see that working memory has the largest effect on ε-compared to the other independent variables.

< INSERT TABLE III ABOUT HERE >

Replication studies

We present two replication studies. One tested a different sample with a different incentive scheme, and the other focused on a different task context (i.e. different payoff function).

Replication study A

Readers may wonder whether our results—the emergent clusters with their different levels of exploration, and working memory as an antecedent of such levels—could be peculiar to our sample. To answer this objection, and in the spirit of past calls to replicate findings, we performed a replication study on a different sample, summarized briefly below due to length restrictions.

Sample

Forty-three students completed a series of four-armed bandit tasks, as well as the battery of psychological tests that measured their cognitive control capabilities. Participants were graduate students of a European engineering school with a mean age of 23.77 (SD = 1.89). As is common in engineering schools, the sample was male-dominated (12 women and 31 men). The students voluntarily performed the tasks as part of a class activity, and were incentivized by the chance to win a prize (USD300, USD200, and USD100 for the top three performers). (At the time of the study, USD1 = CHF1.)

Tasks, procedures, and methods

Participants performed identical tasks to the participants of the first study, and we also collected the same control measures. The only difference was that participants in the replication study performed the tasks outside the lab, in a location of their choice. To do so, all participants were directed to a URL that presented the tasks. They were requested to block out two uninterrupted hours, and to perform the tasks in a quiet place where they could focus and perform at their best. If we observed long interruptions during the time the participants performed the tasks, we dropped them from the sample. All hamming distance, clustering, and optimization procedures were followed as in the main study. Table IV presents descriptives and correlations of this sample (i.e. replication study A).

< INSERT TABLE IV ABOUT HERE >

Results

Given that we did not modify any essential aspect of our design or procedures, we expected to obtain the same results. In fact, we observed the emergence of different clusters, each with a different level of exploration. After running the optimization procedures, we again found that ε-, optimized cluster-wise, was a good predictor of performance (See Tables V and VI), and was in turn explained by working memory: The higher the working memory, the more appropriate the level of exploration. A 10-unit increase in two-back scores results in a 0.01 decrease in ε- (mean=0.04). Similar to the previous study, we found that none of the control-variable results were statistically significant, and working memory explained the largest variance in ε-.

< INSERT TABLES V and VI ABOUT HERE >

Replication study B

Conversely, readers might wonder whether our results are not sample-dependent, but only apply to the specific environment under which our participants made their decisions. In order to explore this, we modified the task environment by changing the payoff function to which participants were exposed, keeping other elements the same.

Sample

Thirty-nine students (31 men and 8 women) completed a series of four-armed bandit tasks, as well as a battery of psychological tests that measured their cognitive control capabilities. The setting, incentives and participant profile were the same as for replication study A. Participants' mean age was 25 (SD = 3.43).

Tasks, procedures, and methods

The procedure is identical to replication study A. In the results so far, participants had shown a tendency to over-explore. Even participants who obtained higher payoffs explored more than optimal, impairing their performance. To confirm that the level of exploration was not dependent on our particular choice of task environment, we set a new payoff function, in which to achieve the highest payoff would require participants to explore 22.6 percent of the time, compared to 8 percent in our previous task. All other elements and procedures were identical to replication study A.

In previous studies, the payoff instantiation had always been identical to the one used by Daw, O'Doherty et al. (2006). In order to test whether participants with better working memory would still be able to explore appropriately in an environment of higher turbulence (i.e. explore more than before), we modified the decay rate of the payoff function. As stated before, the payoff for choosing the ith slot machine on trial t was between 1 and 100 points, drawn from a Gaussian distribution with a mean that at each time step diffused in a decaying Gaussian random walk. We maintained the function and all parameters ($\mu i,t+1 = \lambda\mu i,t + (1 - \lambda)\theta + \nu$) except for the decay parameter λ, which we reduced from 0.9836 to 0.93. This change meant that the slot machines' payoff decayed more quickly, resulting in a faster-changing environment. To achieve the highest payoff this environment demands an exploration level three times that of the previous task, but over-exploration beyond this level will lead to declining payoffs. We hypothesize that if working memory leads to a more appropriate level of exploration, in this new task environment, participants with higher working memory will still have still lower levels of ε-. Table VII presents descriptives and correlations of this sample (i.e. replication study A).

< INSERT TABLE VII ABOUT HERE >

Results

The new environment, though faster changing, was not enough to compensate for over-exploration. Even under these conditions, participants with higher working memory explored in more appropriate ways. Participants in the best-performing cluster had, on average, an ε-of 0.02, while participants in the worst-performing cluster had an average ε-of 0.07 (sig. 0.01). We found working memory to be the strongest predictor of ε-(β = -372, p=0.06) (see tables VIII and IX).

The three regression results from all three samples point towards very similar findings, in terms of both statistical significances and effect sizes. We find statistically significant results for working memory in all three samples, despite small sample sizes. Moreover, in each case, working memory explains the largest chunk of variance in the exploration parameter. Finally, our task environment demands a low level of exploration, and our results show that those with better working memory tend to have a lower level of exploration.

< INSERT TABLES VIII AND IX ABOUT HERE >

DISCUSSION

This paper set out to study the emergence of heterogeneous in exploratory decisions by decision-makers facing the same context, and in particular, what micro-process governs the emergence and performance of such strategies. In 1958 March and Simon put forward a decision-making model that incorporated the cognitive limits of organizational members and identified working memory as a key antecedent of performance heterogeneity. Thirty-three years later, in 1991, March proposed exploration and exploitation as a central dilemma for organizations. In this paper, we theoretically and empirically tie these two foundational works with the objective to propose an antecedent that explains the heterogeneity in exploratory decisions.

To theorize and operationalize how working memory and the span of attention are related to heterogeneity and performance, we build on March and Simon (1958)'s model and proposed that even holding constant time pressure (see (a) in figure 2), working memory (see (1) in figure 2) is associated with higher attention focus (see (b) in figure 2), a better selection of alternatives, thus a more appropriate level of exploration (see (2) in figure 2) and higher performance (see (3) in figure 2).

This paper contributes to the newly proposed discussion about heterogeneity in 'managerial cognitive capabilities' (Helfat and Peteraf 2015) and by building on advances in mathematical psychology (Gans, Knox et al. 2007, Knox, Otto et al. 2011, Knox, Otto et al. 2011, Lee, Zhang et al. 2011, Payzan-LeNestour and Bossaerts 2011), we found—in three different samples, and two different task environments—that individuals with different levels of working memory develop strategies that are associated with different exploration rates. In turn, higher performance is related to the ability of choosing the appropriate exploration rate.

Based on these findings we propose working memory as a specifically important cognitive ability that acts as a managers' note-pad, helping to focus the attention on particular stimuli and to draw connections between them. Hence, people with high working memory have a higher likelihood to choose the appropriate exploration level, given the environment they are in. In turn, this leads them to achieve superior decision making performance.

Our findings are also a contribution to the conceptual model developed by Helfat and Peteraf (2015), in which perception and attentional processes allow certain individuals to sense opportunities before others do. Whereas various abilities could help direct perception and attention more effectively, working memory is the key to overcoming failures of memory and learning, as it lies at the core of both perception and attention (Baddeley 1992, Bechara, Damasio et al. 1998, Baddeley 2003). Working memory temporarily stores information and supports thinking by providing an interface through prior experience, stored as long term memory, which is activated and possibly recombined with contextual clues. The larger the available working memory, the better the set of inputs captured by their attention focus, and the better informed the input they can rely on to make their decisions.

Our findings provide evidence consistent with the idea that perception and attention do interact to enable individuals to sense and recognize opportunities (Ocasio 1997, Joseph and Ocasio 2012). Because of their higher working memory, a sub-sample of our participants was indeed capable of navigating the highly complex task environment they faced in Studies 1 and 2 to sense the appropriate extent of explorative choices. They developed one specific strategic pattern, characterized by lower exploration levels, and consequently perform better than the others.

These results are important for several reasons. First, studying heterogeneity in choice patterns (using laboratory data) helps us understand how people search, sample, and learn in uncertain environments. In the evolutionary economics tradition, the emergence and persistence of heterogeneity is an important driver of innovation and change (Gavetti, Levinthal et al. 2007), yet we know very little about how it affects performance. Second, our results are important for the ongoing efforts to develop micro-foundations of strategy, as they propose a cognitive capability (i.e. working memory) as a driver of appropriate levels of exploration and performance.

Last, our results also show that the level at which analysis is conducted in the study of performance heterogeneity is paramount. We find that individual-level choices about the type of exploration strategy do not in fact influence the model's ability to explain performance heterogeneity. However, when the models are optimized to take cluster-level differences in strategies into account, their explanatory power increases consistently and uniformly. Therefore, the evidence points to a primary role of strategic patterns in the explanation of performance, rather than a direct explanatory power of individual characteristics. Individual cognitive capabilities matter as antecedents of the emergence of strategic patterns, which in turn influence performance.

Strategy scholars have discussed myopia as an important consequence from the inability to keep the bigger picture in mind (Levinthal and March 1993). Mental representations impact the amount of exploration, and the resulting performance (Martignoni, Menon et al. 2015). In the data we examined, working memory appears as a good predictor of the ability to keep the big picture in mind, and thus develop a good mental representation by sensing changes in the environment and hence choose an appropriate exploration rate.

With respect to the managerial cognition literature, this paper contributes by proposing working memory as a micro-foundation that explains differences in individual decision-making and strategic patterns, which are likely to be a source of variation at more aggregate levels (Felin and Foss 2005, Gavetti, Levinthal et al. 2007, Hodgkinson and Healey 2008, Helfat and Peteraf 2015). More generally, Nelson (1991) made the case for devoting more attention to understanding the "economic significance of discretionary firm differences" . The differences in strategic patterns emerging from individual choice are discretionary because firms have the possibility to develop and maintain different strategies while remaining viable within the same economic environment (Nelson 1991). Nelson's line of reasoning is very much consistent with the ongoing discussion of appropriate and robust micro-foundations for strategy research (see, particularly (Helfat and Peteraf 2015)), since bottom-up processes of learning and decision-making are a likely source of differences at more aggregate levels. In this paper, we built upon Helfat and Peteraf (2015)'s conceptual model by looking for the individual-level origins of differences in (sensing) strategies, because "to some extent these differences are the result of different strategies that are used to guide decision making at various levels in firms" (Nelson 1991 p. 62).

This paper has potentially relevant managerial implications. If working memory is associated with better exploration and performance, managers could endeavor either to train this capability, or to shield it from distractions so that it performs at its best. The holy grail of cognitive training is a capability that, following training, not only improves the task for which it was trained, but can also be transferred to other task environments. Recent studies support the idea that improving working memory in one task environment also improves it in others (Houben, Wiers et al. 2011). For managers, protecting attention by minimizing cognitive load is a challenging but rewarding task. We currently have some empirical evidence at the organizational level on the harm caused by a rising activity load (Castellaneta and Zollo 2014). Cognitive load theory states that intrinsic and extraneous load overloads working memory (Schnotz and Kürschner 2007). Being aware of distractions and the pitfalls of multitasking can help managers protect their attention, make best use of their working memory and make the most of their sensing capability.

Future research

Although we present two replication studies, we can only posit that our results are valid for environments involving significant change. It may be that, in stable environments, working memory is not needed, or is needed less, as there are fewer changes that must be kept in mind to define a strategy. Our results could be extended to other settings unlike our own, in which participants receive less frequent feedback—just as managers often have to rely on much smaller samples to identify patterns and relationships (March, Sproull et al. 1991). In our case, the payoff instantiation for each of the alternatives was fixed before the task, so all participants faced the same odds. In addition, in our study, feedback was given immediately after the decision in the form of a payoff. Future studies could explore the effect of different types of feedback, and analyze whether strategies vary depending on whether the feedback is immediate or delayed.

It might also be useful to consider environments where the cost of exploring alternatives varies. In our study, we assumed identical costs, but this assumption could be released by taking into account different cost matrices in the Hamming distance method. Finally, we only consider decisions taken over the entire duration of the task as a strategy. The justification is based on the objective participants were aiming for: maximize their total payoff over 300 trials. Future studies could test what strategies arise when participants either play for fewer trials, or are only told to maximize their payoff during certain trials.

Alternatively, researchers could explore settings involving more alternatives than our four-armed bandit task. This latter is a complex, yet overall well-structured problem, where decision options (but not their outcomes) are transparent to the participant. Ill structured problems might require different cognitive abilities.

Also, and with reference to the Helfat and Peteraf's (2015) conceptual model, this paper focuses mainly on individual level heterogeneity in cognitive abilities related to the sensing phase of new opportunities. Future research should devote more attention to the micro-level differences underpinning seizing and reconfiguring capabilities, in so doing also shifting the attention from purely cognitive abilities such as working memory, toward social cognitive skills related to empathy, communication and, even more generally, leadership. Similarly, our setting allows to collect precise data about abilities related to 'cold' rationality, but is not suited to discuss how emotions might enable or hinder 'better' decisions. Hodgkinson and Healey (2008) have argued in favor of a model of organizational decision making that combines elements of both hot and cold rationality. In our operationalization of exploration, namely forward-looking moves across the four-armed bandit space, this is not easy to observe. Future work could incorporate more complex operationalizations of exploration that could reveal the emotional underpinnings of the decision to explore in an uncertain environment.

To conclude, we would like to argue that the approach suggested many years ago by March and Simon still provides a vital framework to develop studies about learning and decision making in organizations. Their framework is vital because it allows both to generate testable predictions, but also because it is flexible enough to integrate, build upon and extend recent insights from the cognitive sciences. The management field is often accused to be incapable of producing theories that advance our ability to predict and explain managerially relevant human behavior. Lack of cumulative and replicable results are often put on the table to stress how little managerial theories contribute to practice and policy discussions. We suggest that having a closer look at the work inspired by March and Simon may provide a different perspective.

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FIGURES AND TABLES

Figure 1: March and Simon 1958 model

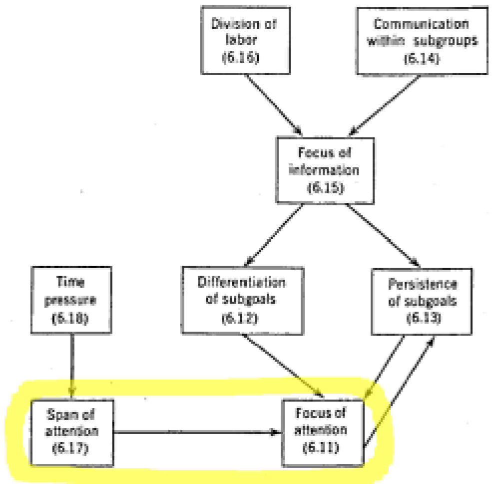

Figure 2: Working memory as an antecedent of exploration and performance

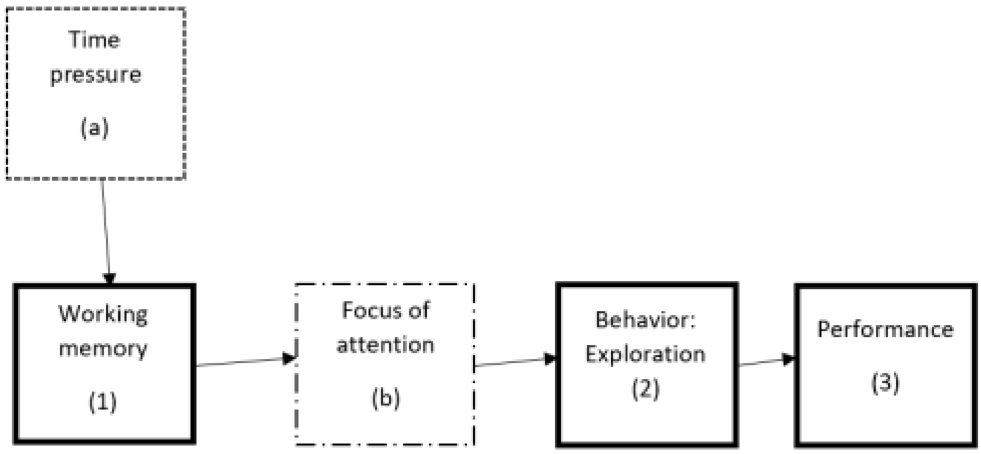

Table I: Descriptives and correlations for primary sample

	Mean	Std Dev	N	Age	Gender	Raven	TOH	Flanker	CRT	2 Back	3 Back	Epsilon	Performance
Controls													
Age	24.26	2.3	89	1									
Gender	0.49	0.5	89	0.046	1								
Raven	8.55	2.05	89	-0.063	0.1	1							
TOH	16.53	9.49	89	-0.091	0.108	-0.101	1						
Flanker	46.44	3.05	88	0.129	0.034	0.056	-0.105	1					
CRT	6.58	2.49	89	-0.1	-0.152	0.479**	-0.275**	0.145	1				
Dependent variables													
2 Back	28.93	5.31	89	-0.099	-0.188	0.096	-0.018	0.026	0.168	1			
3 Back	28.72	5.15	89	-0.153	-0.189	0.157	-0.041	-0.053	0.262*	0.463**	1		
Independent variables													
Epsilon	0.05	0.04	89	-0.044	0.17	-0.105	0.051	0.045	-0.188	-0.145	-0.327**	1	
Performance	18072.9	675.12	89	0.019	-0.167	0.116	-0.055	0.092	.276**	0.141	.226*	-.672**	1

*p < 0.05. **p <0 .01. ***p < 0.001.

Table II: OLS regression using epsilon obtained cluster wise, to understand payoff in the bandit task

Dependent variable: Total Payoff in the bandit task			
	B	*SE B*	*Beta*
Constant	18620.93	84.17	
ε-	-11111.7	1319.1	-0.67***
R^2		0.449	
Adjusted R^2		0.443	
F Statistic		70.96***	

*p < 0.05. **p <0 .01. ***p < 0.001.

Table III: OLS regression using working memory, to predict epsilon obtained cluster wise in primary sample

Sample (N=88)							
Model 1 (Only controls)				**Model 2**			
	B	*SE B*	*Beta*		*B*	*SE B*	*Beta*
(Constant)	-0.014	0.093		(Constant)	0.075	0.098	
Age	-0.002	0.002	-0.089	Age	-0.002	0.002	-0.118
Gender	0.013	0.009	0.164	Gender	0.01	0.009	0.121
Raven	-0.001	0.002	-0.056	Raven	-0.001	0.002	-0.036
TOH	0.000	0.000	-0.005	TOH	0	0	-0.001
Flanker	0.003	0.002	0.165	Flanker	0.002	0.002	0.131
CRT	-0.003	0.002	-0.196	CRT	-0.002	0.002	-0.134
				2 Back	0	0.001	0.018
				3 Back	-0.002	0.001	-0.282*
R^2		0.092				0.158	
Adjusted R^2		0.025				0.073	
F Statistic		1.372 (p=0.24)				1.855*(p=0.08)	

*p < 0.05. **p <0 .01. ***p < 0.001.

Table IV: Descriptives and correlations for replication sample A

	Mean	Std Dev	N	Age	Gender	Raven	TOH	Flanker	CRT	2 Back	3 Back	Epsilon	Performance
Controls													
Age	23.77	1.89	43	1									
Gender	0.23	0.43	43	-0.108	1								
Raven	9.79	2.18	43	-.499**	0.002	1							
TOH	13.91	7.88	43	0.208	-0.05	-0.176	1						
Flanker	47.4	0.9	43	0.027	-0.12	0.2	-0.135	1					
CRT	8.21	1.68	43	-.359*	-0.268	.480**	-0.273	0.242	1				
Dependent variables													
2 Back	29.47	6.39	43	0.027	0.186	0.067	-.404**	0.037	0.104	1			
3 Back	27.12	4.46	43	-0.036	0.073	0.142	-0.128	0	0.247	0.233^{T}	1		
Independent variables													
Epsilon	0.04	0.03	43	0.195	0.144	-0.239	0.247	-0.248	-0.244	-.348*	-0.25	1	
Performance	18005.7	428.96	43	-0.244	0.064	.425**	-0.146	-0.069	0.205	0.15	0.189	-.511**	1

*p < 0.05. **p <0 .01. ***p < 0.001.

Table V: OLS regression using epsilon obtained cluster wise, to understand payoff in the bandit task (replication sample-A)

Dependent variable: Total Payoff in the bandit task			
	B	*SE B*	*Beta*
Constant	18312.597	98.763	
ε-	-8456.686	2223.839	-0.51***
R^2		0.261	
Adjusted R^2		0.243	
F Statistic		373.30***	

*p < 0.05. **p <0 .01. ***p < 0.001.

Table VI: OLS regression using working memory, to predict epsilon obtained cluster wise in replication sample B

Replication Sample A (N=43)							
Model 1 (Only controls)				**Model 2**			
	B	*SE B*	*Beta*		*B*	*SE B*	*Beta*
(Constant)	0.252	0.216		(Constant)	0.317	0.206	
Age	0.002	0.003	0.119	Age	0.003	0.002	0.211
Gender	0.008	0.01	0.138	Gender	0.014	0.01	0.238
Raven	-0.001	0.002	-0.1	Raven	-0.001	0.002	-0.071
TOH	0.001	0.001	0.181	TOH	0	0.001	0.034
Flanker	-0.005	0.005	-0.184	Flanker	-0.006	0.004	-0.21
CRT	0	0.003	-0.023	CRT	0.001	0.003	0.069
2 Back				2 Back	-0.001	0.001	-0.335*
3 Back				3 Back	-0.001	0.001	-0.184
R^2		0.163		**R^2**		0.299	
Adjusted R^2		0.023		**Adjusted R^2**		0.134	
F Statistic		1.17*(p=0.35)		**F Statistic**		1.81*(p=0.10)	

*p < 0.05. **p <0 .01. ***p < 0.001.

Table VII: Descriptives and correlations for replication sample B

	Mean	Std Dev	N	Age	Gender	Raven	TOH	Flanker	CRT	2 Back	3 Back	Epsilon	Performance
Controls													
Age	19	3.43	39	1									
Gender	0.21	0.41	39	0.094	1								
Raven	10.33	2.06	39	0.306	0.01	1							
TOH	14.36	8.51	39	-0.195	-0.037	-0.147	1						
Flanker	43.08	12.87	39	0.093	0.092	0.119	-0.227	1					
CRT	7.92	1.78	39	-0.219	-0.158	0.251	-0.154	0.09	1				
Dependent variables													
2 Back	30.02	6.13	39	-0.117	-0.064	0.125	-0.113	-0.016	0.683**	1			
3 Back	26.98	5.6	39	-0.146	0.197	-0.074	-0.313	-0.07	0.354*	0.450**	1		
Independent variables													
Epsilon	0.04	0.03	39	0.007	-0.102	-0.082	.317*	-0.173	-0.16	-0.347*	-0.457**	1	
Performance	16052.15	234.01	39	-0.31	-0.087	0.03	-0.023	-0.006	.506**	.431**	.476**	-.391*	1

*p < 0.05. **p <0 .01. ***p < 0.001.

Table VIII: OLS regression using epsilon obtained cluster wise, to understand payoff in the bandit task (replication sample-2)

Dependent variable: Total Payoff in the bandit task			
	B	*SE B*	*Beta*
Constant	16190.408	63.868	
ε-	-3292.761	1273.223	-0.391**
R^2		0.153	
Adjusted R^2		0.13	
F Statistic		6.69**	

*p < 0.05. **p <0 .01. ***p < 0.001.

Table IX: OLS regression using working memory, to predict epsilon obtained cluster wise in replication sample 2

Replication Sample B (N=39)							
Model 1 (Only controls)				**Model 2**			
	B	*SE B*	*Beta*		*B*	*SE B*	*Beta*
(Constant)	0.042	0.051		(Constant)	0.119	0.049	
Age	0.001	0.002	0.065	Age	0	0.001	0.058
Gender	-0.007	0.011	-0.105	Gender	0.001	0.011	0.014
Raven	0	0.002	-0.022	Raven	-0.001	0.002	-0.112
TOH	0.001	0.001	0.285	TOH	0.003	0.003	0.159
Flanker	0	0	-0.093	Flanker	0	0	-0.188
CRT	-0.002	0.003	-0.105	CRT	0.005	0.004	0.289
2 Back				2 Back	-0.002	0.001	-0.34
3 Back				3 Back	-0.002	0.001	-0.372^{T}
R^2		0.136		**R^2**		0.333	
Adjusted R^2		-0.026		**Adjusted R^2**		0.155	
F Statistic		0.840(p=0.54)		**F Statistic**		1.872*(p=0.10)	

^{T} p< 0.10*p < 0.05. **p <0 .01. ***p < 0.001.

END NOTES

[i] A recent literature review by Cowan found that the number of items that can be held in working memory is lower than we used to think. The so-called "magic number" of seven has been reduced to around four. Depending on the task and the individual, it can range between one and five. See Cowan, N. (2010). "The magical mystery four how is working memory capacity limited, and why?" Current Directions in Psychological Science 19(1): 51-57.

[ii] It is out of the scope of this paper to discuss the complex and still not completely defined relation between the different functional components that comprise the executive functions/cognitive control capabilities. For a recent discussion, please see Diamond, A. (2013). "Executive functions." Annual Review of Psychology 64: 135-168. And for a model on the relation of working memory and other executive functions, see Baddeley, A. (2003). "Working memory: looking back and looking forward." Nat Rev Neurosci **4**(10): 829-839. In our methods, we include as control variables measures aimed at capturing other functional components (e.g. sustained attention, abstract thinking, planning and generativity, etc.).

SUPPLEMENTARY METHODS

In our study, we rely on Kalman filters and reinforcement learning exploration models (e-greedy, WSLS, softmax) to better understand heterogeneity in strategies of our participants in the bandit task. Given that Kalman filters are prone to over-fitting or under-fitting, we applied Kalman filters on three levels, on each individual, clusters and the entire group. Consistent with prior studies we find that the cluster-level is most suitable and all exploration values reported in the main body arise from Kalman filters applied at the cluster level. In the following section, we describe the three optimizations on our primary sample, additionally we report the findings of the two reinforcement learning models softmax and WSLS (on primary sample) which are not reported in the main text for the sake of brevity.

Kalman filter

Kalman filter models estimate the mental parameters participants are using to make their choices, on the assumption they are relying on one of the three exploration strategies described above. The underlying assumption is that the participant has beliefs about the expected payoffs of a slot at the outset. Having tried a slot and observed its payoff, they update their mental parameters (for example, their propensity to explore) based on the difference between the payoff they expected and the one they actually got.

Importantly, the Kalman filter has a variable that captures uncertainty (σ2). Playing a slot reduces the participant's uncertainty about its payoff; this parameter influences how much the expected payoff is modified. For slots that have not been chosen for a long time, uncertainty is high, and the expected payoff is modified considerably when they are chosen. The other parameter that influences expected payoff is noise: If a participant assumes that there is considerable noise, their expected payoff is not changed significantly when they see a new payoff. Finally, there is an element of forgetting: If a participant does not choose a slot, its expected payoff decays with a rate lambda λ towards a value described by parameter theta θ.

To model how participants conduct their exploration, the Kalman filter estimates key parameters for each of the exploration strategies. For ε-greedy, the key parameter is ε-, which is the probability with which participants randomly choose a different slot. For WSLS, it is the payoff threshold below which they start to explore other slots. These central parameters are computed based on all choices made throughout the task by the participants.

Entire group optimization and performance

We ran three optimizations in which we applied the above described Kalman filter on the sample. We first ran optimizations similar to Daw, O'Doherty et al. (2006), on the entire sample of participants. We found under fitting of data. Appendix Table A1 shows the results for ε-greedy, softmax and WSLS when fitted to the entire group. Table A2 shows the predictive power of this regression is very low: ε- was not statistically significant in explaining variation in performance. Additionally, the standard error of the ε- value was double the coefficient value. Similar results can be found in table A3 for softmax and WSLS models.

This result indicates that we cannot understand performance by optimizing the models to the group as a whole. This is interesting, and a key differentiating point between our analysis and prior works. Few past studies have aimed to identify the specific learning strategy that best fits to an entire study population; hence, analyses are commonly run at the level of the whole study population. This is the case in fields as diverse as behavioural strategy (Daw, O'Doherty et al. 2006, Steyvers, Lee et al. 2009, Posen and Levinthal 2012) and cognitive sciences (Daw, O'Doherty et al. 2006). However, our objective is different: to link strategies to variance in performance. Hence, it is not enough to fit the parameters of the chosen learning strategy to the entire group—unless we assume that heterogeneity in strategies is merely a transient phenomenon.

< INSERT TABLE A1 and A2 and A3 ABOUT HERE >

Cluster optimization and performance

To prevent overfitting or under fitting of data, we relied on cluster analysis to generate a suitable level of analysis. In the following sections, we describe our clustering strategy.

Hamming distance and clustering procedure

To maintain and highlight the differences between our participants, we looked for a way to compare the choice patterns they developed. We opted for sequence analysis using the hamming distance method (HAM). This method was initially developed to study DNA or protein patterns, and was subsequently applied in sociology, where Abbott and colleagues used similar techniques to study career patterns (Abbott and Hrycak 1990, Abbott 1995, Stovel, Savage et al. 1996). The core of HAM consists of two steps. First, an iterative minimization procedure is applied to a given set of patterns of equal length to find the distance between pairs of patterns. This generates a distance matrix for all the patterns. Secondly, a clustering procedure is applied to check whether the patterns fall into distinct types. If a typology exists, this can be further used as a dependent variable (Chan 1995) or an independent variable (Chan 1999, Han and Moen 1999).

We analyzed the pattern of each participant's choices with modified optimal matching (HAM) techniques (Kruskal and Sankoff 1983, Abbott 1995). Taking our lead from past studies (Daw, O'Doherty et al. 2006, Laureiro-Martínez, Brusoni et al. 2014), we discounted each participant's first four trials, to exclude pure exploration. Thus 89 choice patterns, each consisting of 296 choices, were available for analysis. A constant cost function was chosen to treat all five options (slots 1–4, plus no response) equally. The seqdist function in Traminer package in Cran R was used to return a matrix of minimum distances between individual patterns (Gabadinho, Ritschard et al. 2011, Team 2011) using the HAM (hamming distance) method.

To check whether choice patterns fell into distinct types, we applied clustering methods to group together those patterns with lower hamming distances. Mindful that different cluster algorithms can yield different solutions (Aldenderfer and Blashfield 1984), we tried out several distance measures and clustering methods. We generated the clusters on the Euclidian distance of the hamming distance matrix by running Ward's minimum variance procedure and employed the "Dunn index" (Lebart, Morineau et al. 1995) in package "NbClust" in Cran R (Charrad, Ghazzali et al. 2012) to select the optimal number of clusters.

We used t-tests, a dendogram, and the Dunn index to check the robustness of our clustering method. A dendogram indicating cluster formation is presented in Figure 1. Its vertical axis represents the distance or dissimilarity between clusters, while the horizontal axis represents the participants and their respective clusters. The length of the path between two participants represents the degree of similarity in their choice patterns. Figure 1 shows that one of the clusters is the most distant from the others. The majority of participants are in the largest cluster that separates from the rest in the first cut. The dendogram illustrates that the distances between participants within clusters are very small if we take four clusters into account (compared to the distances if we were to use fewer).

< INSERT FIGURE A1 ABOUT HERE >

We ran t-tests to compare the differences between the average distance between individuals within a cluster and the average distances between the clusters themselves. They revealed that within-cluster distances were much lower than average between-cluster distances: t (-2,19) =3.9, p-value = 0.09482. These results suggest that cluster members are similar to members of the same cluster, but different from the members of other clusters. As an additional robustness check, we calculated the Dunn index (Figure 2), which confirmed that the optimum number of clusters for our hamming-distance matrix was four.

< INSERT FIGURE A2 ABOUT HERE >

Based on the above analysis, we divided our pool of participants into four clusters (Clusters 1–4), comprising 47, 16, 20, and 6 participants respectively. We then analyzed the choice sequences used by participants in each cluster. In Figure 3, the colored legend at the bottom represents the choices made by each participant during each trial, varying between slots 1, 2, 3, and 4 (plus 0 for "no choice made"). Along the x-axis, the "pixels" represent the choices in trials 5–300, while the y-axis represents the 89 participants. This graph indicates when a particular slot was selected by most participants: for example, around trials 140–170, many participants chose slot 2 (orange). We can also see that certain individuals changed more often than others; however, it is difficult to spot differences in strategies, or the origin of differences in performance.

< INSERT FIGURE A3 ABOUT HERE >

Next, we plotted the entire pattern of choices for our four clusters. The images in Figure 4 show the entire pattern (trials 5–300) on the x-axis cluster-wise, with the y-axis representing the participants in that cluster. For example, the image for Cluster 4 shows the patterns of choices for each of the 300 trials (horizontally) for each of the six participants in that cluster (vertically). (The color scheme of the slots is the same as in Figure 3.) These four graphs clearly show that different clusters capture different patterns of sequential choices. Specifically, we can see two very different patterns emerging in Clusters 1 and 4. Cluster 1 has grouped participants who make very similar choices to each other, and also seem to explore less often and in short bursts (blocks of the same color across participants, followed by short bursts of different colors). Cluster 4, on the other hand, groups participants who explore a lot without settling on any specific slot. Clusters 2 and 3 show different patterns, but it is harder to discern them visually.

We also find differences in the average response times in the bandit task. Cluster 1 participants were the fastest, followed by cluster 4, cluster 2 and finally cluster 3. The average response times (in microseconds) for these clusters (1,2,3 and 4) were 287.9, 327.38, 338.88 and 308.80. A one-way ANOVA revealed statistical significant differences ($F(3, 85) = 2.481$, $p = 0.06$).

In our task, the best sequence would be the one where the participant achieved the highest possible cumulative payoff by choosing the slot machine offering the largest payoff in each individual trial. Since our objective was to understand the differences in the emerging strategies' performance, we compared this best sequence with each of the 89 participants' sequences. This gave us a variable that captured individual distances from the best sequence. We ran a one-way ANOVA on these hamming distances from the best sequence for each of the clusters, which revealed statistically significant distances between them ($F(3, 85) = 11.146$, $p = 1E-06$). Post-hoc tests revealed that differences in the distance were statistically significant between all combinations of clusters. On average, Cluster 1 participants got closest to the best sequence, Clusters 2 and 3 were equally distant, and Cluster 4 was the furthest away. Hence we can conclude that the clusters captured choice patterns that are significantly different; in other words, we confirm the emergence of distinct groups following different strategies.

< INSERT FIGURE A4 ABOUT HERE >

Cluster-wise optimization and performance

The hamming distance procedure revealed significantly different clusters of participants, each following a different strategy. To understand whether such differences could be used to understand performance, we first fitted each of the three models to all four clusters. Table A4 and A5 below lists the values for the best-fitting parameters for each of the models, cluster-wise. As can be seen, the four clusters differ in their ε-values. It is very interesting to note how

Clusters 2 and 3 are not statistically significantly different in their ε-values, but they do differ in their threshold values. In contrast, at the extremes, Cluster 4 has the highest average value of ε-, and Cluster 1 the lowest. These values capture beliefs that guide exploration, and these differences in individuals can be observed through clustering and optimization. It is interesting to observe a general tendency among participants to exceed the optimal exploration level. In table A6 we also report OLS regressions similar to those in table 2 in the main text, instead of epsilon we rely on beta in the softmax and threshold in the WSLS model to predict performance.

< INSERT TABLE A4, A5 and A6 ABOUT HERE >

Individual optimization and performance

In a third optimization approach, we carried out fully individualized fits, modelling each of the parameters separately for each subject. Similar to Daw, O'Doherty et al. (2006), we found that several of the parameters attained extreme values, suggesting over-fitting of behaviour.. We fit parameters from each of the choice models to each participant individually. Many individuals obtained values, which were extreme. For example, consider ε-greedy choice model. When the optimization is carried out at a cluster or a group level, other individuals in the group restrict the degrees of freedom for a variable of an individual, instead when a similar optimization is carried out over a single individual, the 7 variables in the ε-greedy model have much more degrees of freedom. This leads to extreme values. For example, in the ε-greedy choice model some individuals had values for decay centers that were negative. An individual had initial mean value of -762; this is not meaningful as the participants were told that the task has a payoff from 0 to 100. Thus optimization at the group level of 89 participants leads to underfitting. Instead, individual level optimization leads to overfitting. In table A7 we report OLS regressions to predict performance using values obtained from individual optimization for all three models.

< INSERT TABLE A7 ABOUT HERE >

SUPPLEMENTARY FIGURES AND TABLES

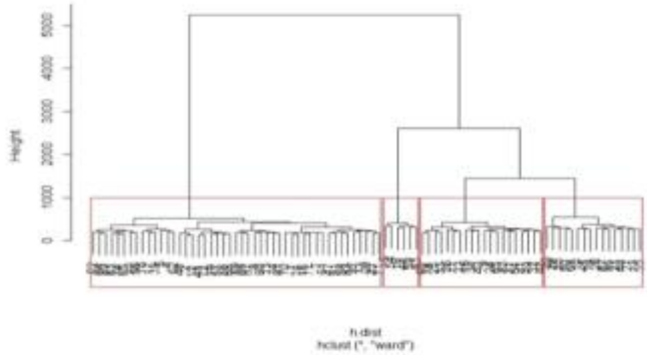

Figure A1. Dendogram indicating cluster formation

Notes to figure 1: Participants are represented in the horizontal axis. On its vertical axis the dendogram illustrates the distances between participants. As one can see, the distances between participants within clusters are very small if we take four clusters into account (compared to the distances if we were to use fewer clusters).

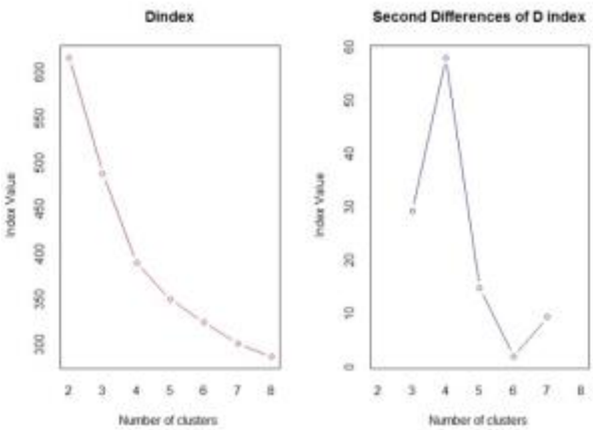

Figure A2. Dunn index: finding the ideal number of clusters

Notes to figure 2: The Dunn Index (d index) identifies sets of clusters that are compact, with a small variance between members of the cluster, and well separated, where the means of different clusters are sufficiently far apart. The second derivative of the D index indicates the ideal number of clusters is four.

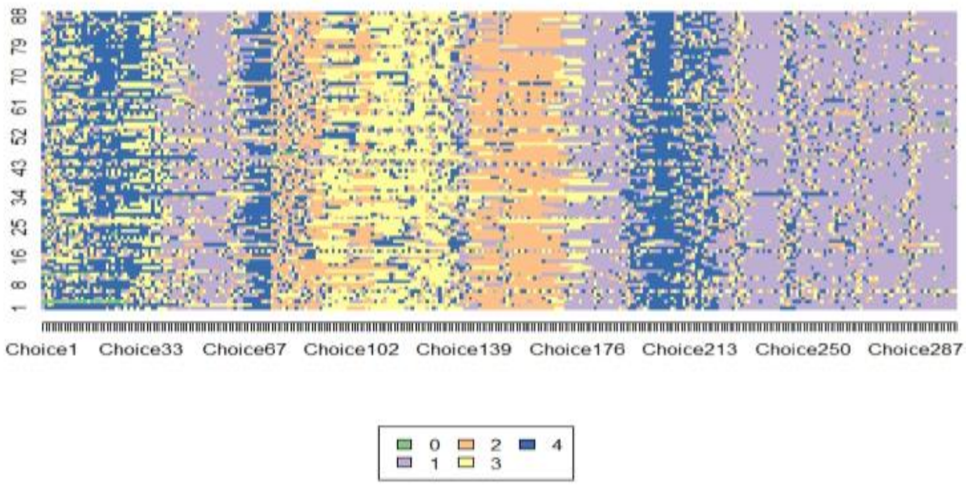

Figure A3. Sequence of choices of all 89 participants

Notes to figure 3: In the figure, each "pixel" represents the choices made by each participant. The sequence is depicted horizontally, starting on from trial 5 and ending on trial 300. The colors represent the slot chosen at each trial (for example, the first participant chose slot 1 –in lilac- in the last trial). The y-axis represents the 89 participants, so for example, the higher line is the sequence of choices for the 89th participant

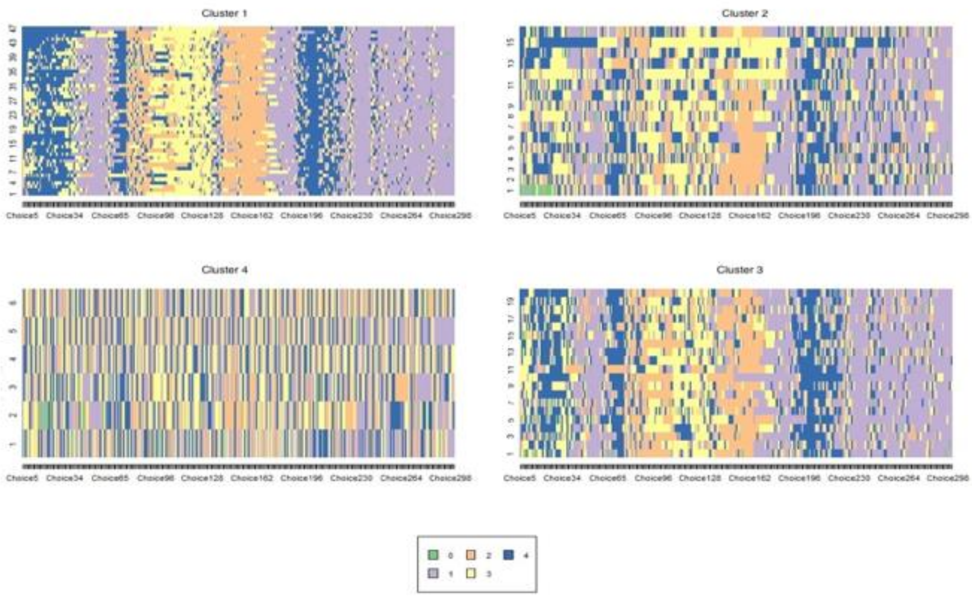

Figure A4. Sequence of choices of participants cluster wise

Notes to figure 4: The four figures represent the choice patterns by the participants in the four clusters. As in figure 3, also here the "pixels" represent the choices made by each participant. On each figure, the y-axis represents the number of participants in the cluster, so for example, for cluster 4, the y axis depicts six participants.

Tables

As described in the main manuscript, all optimization and analysis procedures, which were carried out with choice models ε-greedy, were carried out with choice model WSLS and softmax as well. This appendix report the analyses performed with WSLS and softmax (as well as E-greedy, this latter is also reported in the main paper). The table A1 lists best fitting parameters of the three models fitted to all participants.

Table A1: Optimization of models to all 89 participants.

Parameter	E-greedy	WSLS	Softmax
Epsilon/Threshold/Beta	.062 ± .05	56.1 ± 1.17	0.169 ± .06
SD Payoff	0.0838		3.531
SD Noise	3.8679		4.603
Decay Rate	0.8667		0.604
Decay Center	52.1452		48.099
Initial Mean	77.6371		17.992
Initial SD	11.6134		0.000
Memory		6	
Initial Threshold		55.46	
NLL	2.3459e+04	4.0306e+04	2.39E+04

Table A2. OLS regression using parameters of the above models to understand payoff in the bandit task

	E-greedy		
Dependent Variable	Total payoff in the bandit task		
	B	*SE B*	*Beta*
Constant	18040.26	114.25	
E-	522.6	1421.5	0.04
Threshold			
R^2	0.002		
Adjusted R^2	-0.010		
F Statistic	0.135		

*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

Table A3. OLS regression using parameters of the above models from table A1 to understand payoff in the bandit task

	Softmax			**WSLS**		
Dependent Variable	Total payoff in the bandit task					
	B	*SE B*	*Beta*	*B*	*SE B*	*Beta*
Constant	18119.01	211.96		18860.14	3469.10	
Beta	-272.98	1180.35	-0.03			
Threshold				-14.03	61.82	-0.02
R^2	0.001			0.001		
Adjusted R^2	-0.011			-0.011		
F Statistic	0.053			0.052		

*p <0.05. **p < 0.01. ***p < 0.001.

Note: Using the value of beta and threshold from table A1, as it is the only parameter that was varied within all individuals, a regression to understand overall performance in the bandit task was carried out. Similar to the results with E-greedy, softmax and WSLS does a poor job at explaining performance.

Table A4. Optimization of E-greedy model done cluster-wise

Variable	**E-greedy**			
Cluster:	1	2	3	4
Number of cluster members	47	16	20	6
SD Payoff	0.05	20	0.02	0.01
SD Noise	3.85	6.32	3.24	43.73
Decay Rate	0.90	3.35	0.82	0.60
Decay Center	52.71	0.37	51.82	100
Initial Mean	76.87	41.69	81.55	47.84
Initial SD	4.14	36.25	10.32	2.45
Memory		3.09		
Initial threshold				
Average ε-	0.03 ± 0.01	0.06 ± 0.04	0.06 ± 0.01	0.15 ± 0.04
Threshold				

Table A5. Lists the best fitting parameters of the softmax model and WSLS for each cluster. The values below were obtained by running the optimization on on each cluster instead of the whole group of participants. This table is similar to table 2 from the main paper.

Variable	**Softmax**				**WSLS**			
Cluster:	1	2	3	4	1	2	3	4
Number of cluster members	47	16	20	6	47	16	20	6
SD Payoff	0.00	2.03	0.00	0.52				
SD Noise	8.2	8.56	11.90	7.29				
Decay Rate	0.88	0.37	0.78	0.79				
Decay Center	51.45	42.26	49.62	125.0				
Initial Mean	74.21	45.82	78.35	61.09				
Initial SD	10.26	1.21	4.76	9.0				
Memory					4	6	5	4
Initial threshold					52.27	57.49	53.06	65.12
Beta	0.20 ± 0.04	0.09 ± 0.03	0.14 ± 0.02	0.02 ± 0.01				
Threshold					53.31 ± 1.10	57.97. ± 1.35	54.40 ± 1.17	68.96 ± 2.89

Table A6 represents three regressions similar to table 2 in the results section. Model 1 is similar to table 3, where in order to understand performance regression was carried out with only the key parameter Beta and threshold.

Softmax				Threshold			
Dependent variable: Total Payoff in the bandit task							
	B	*SE B*	*Beta*		*B*	*SE B*	*Beta*
Constant	16812.14	117.28		Constant	25177.1	562.27	
E-	7953.49	683.24	0.78***	Threshold	-128.11	10.11	-0.80***
R^2	0.609			R^2	0.649		
Adjusted R^2	0.605			AdjustedR^2	0.645		
F Statistic	135.507***			F Statistic	160.56***		

*p <0.05. **p < 0.01. ***p < 0.001.

Table A7. Regression for parameters optimized at the individual level

E-greedy				Softmax				Threshold			
Dependent variable: Total Payoff in the bandit task											
	B	*SE B*	*Beta*		*B*	*SE B*	*Beta*		*B*	*SE B*	*Beta*
Constant	17711.82	169.39		Constant	18287.08	226.51		Constant	21009.17	1074.52	
E-	-11832.04	1360.58	-0.62***	Beta	-4.42	16.61	-0.03	Threshold	-73.21	20.93	-0.36***
SD Payoff	-11.96	16.72	-0.14	SD Payoff	-3.92	11.46	-0.04	Initial Threshold	23.55	7.46	0.32**
SD Noise	17.60	9.19	0.36	SD Noise	1.35	5.83	0.03*	Memory	-74.59	43.53	-0.17
Decay Rate	732.72	188.67	0.31***	Decay Rate	554.84	254.23	0.24***				
Decay Center	0.33	0.67	0,12	Decay Center	-11.14	2.18	-0.48				
Initial Mean	1.82	0.57	0.25**	Initial Mean	0.07	0.15	0.05				
Initial SD	0.18	3.34	0.02	Initial SD	2.52	2.41	0.10				
R^2	0.64			**R^2**	0.30			**R^2**	0.23		
Adjusted R^2	0.61			**Adjusted R^2**	0.24			**Adjusted R^2**	0.2		
F Statistic	20.71***			**F Statistic**	5.02***			**F Statistic**	8.22***		

PAPER 4

When the going gets tough, should the tough get going?

The role of individual persistence in search behaviour

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The role of individual persistence in search behaviour

ABSTRACT

In this paper, we explore how adaptive search is influenced by one's tendency to persist. We manipulate the environment using key organization level-variables – namely, the number of decision elements (scope) and the duration of the search (slack) – to link individual-level processes to organization-level factors. Adopting a between-subjects experimental design, we expose participants to search landscapes with a varying likelihood of failure. We find that search behaviour differs depending on the environment, and that persistence emerges as an important antecedent of exploitative behaviour. We also contribute to the literature on performance feedback, which has yet to take account of how individual dispositions moderate the relationship between performance feedback and search behaviour. We find that an individual's tendency to persist moderates the relationship between performance feedback and distant search. Interestingly, while search scope does not have a direct influence on search behaviour, increasing search duration promotes more exploratory behaviours. Our findings contribute to a better understanding of individual search and its relationship with organizational factors.

INTRODUCTION

Search plays a central role in organization theory (Cyert and March 1963). Areas such as new product development, organization design, business strategy, planning and innovation contests are all affected by search behaviour (Atuahene-Gima and Li 2004; Levinthal 1997; Rivkin and Siggelkow 2003; Vuculescu 2016). It is rare that the environment alone dictates how it should be searched; therefore, success depends on who does the searching (Cohen and Levinthal 1990) and how they react to environmental variables. Gavetti (2012) has pointed out that a critical source of superior search performance lies in a strategic leader's ability to overcome the behavioural bounds of cognitively distant opportunities. Yet, the antecedents and patterns of search behaviour in individual decision-makers are poorly understood (Gruber et al. 2013; Li et al. 2013; Salter et al. 2015). Understanding how individuals search is important, as this impacts the assumptions theorists make about decision rules, and ultimately how innovation occurs (Billinger et al. 2014; Dahlander et al. 2014; Hey 1982).

In line with a growing call to better understand the micro-foundations of individual search (Csaszar and Levinthal 2015) and the antecedents of heterogeneous search strategies (Laureiro-Martinez 2014; Laureiro-Martínez et al. 2015; March and Simon 1958), we investigate how heterogeneity in terms of individual search abilities affects organizational outcomes. Individuals discover solutions through an adaptive search, applying re/combinations within a space of alternatives (Simon 1962). In the process, they create new knowledge – but they also increase the risk of failure, due to the greater complexity of the environment (Baumann 2010; Frenken et al. 1999).

Given the high frequency of failure during search in complex tasks, we focus on the individual ability that is known to predict behaviour in the face of failure and adversity – namely, *task persistence*. Task persistence is defined as the "ability to sustain goal directed action despite obstacles or failure" (Gusnard et al. 2003). The motivation to understand the role of task persistence comes from two different streams of literature. Firstly, based on their own decision-making model, March and Simon (1958) suggest that the tendency to persist influences attention and ultimately performance. This proposal was confirmed by modelling work at the firm level, where the tendency to persist was found to be an important determinant of search behaviour (Baumann 2010; Winter et al. 2007). Secondly, in entrepreneurship – a setting where complexity and failure are salient – individual persistence is considered a quintessential trait of successful entrepreneurs (Gartner et al. 1991). Previous research has associated the entrepreneur's propensity to persist with organization performance, e.g. start-up survival and venture growth (Baum and Locke 2004).

Despite the importance of task persistence in settings where search is essential, to the best of our knowledge no empirical work has examined whether and how search is actually influenced by an individual's tendency to persist. In an effort to apply findings on human decision-makers to theoretical models and search phenomena in organizations, we therefore ask: *How does an individual's tendency to persist influence search behaviour?*

In order to tackle our main research question, we build on a pioneering complex search experimental study by Billinger and colleagues (2014). They found that search is less myopic than theory suggests. Instead, individuals perform adaptive search with respect to performance feedback. Negative performance feedback increases an individual's propensity to explore new alternatives, while positive feedback prompts them to make only incremental improvements. Initially, we aim to understand how the results of adaptive search generalize to other populations. As Bettis et al. (2016) emphasized, this is the crucial first step in building a cumulative body of knowledge, and can help us not only establish whether an effect exists, but also gauge its magnitude.

Next, we explore the role of failure. When individuals need to solve complex problems, varying environmental factors lead them to search in spaces with numerous local optima. While this does generate new knowledge, it also increases the frequency of failure (Frenken et al. 1999; Page 1996). Individuals within organizations are exposed to search tasks of varying *scope* (size of the search space) and *slack* (search duration). Greater scope or slack will increase the complexity of search and exacerbate the risk of failure. As search scope increases, boundedly rational actors must hold more information. This, in turn, impairs exploration, as actors focus on particular aspects of a search space (Li et al. 2013). Increasing search slack by allowing more time eases resource constraints, and thus enables an actor to explore more (Billinger et al. 2014). Both search scope and search slack impact the cognition of searching individuals, and thus their search behaviour (Li et al. 2013). Understanding how two key variables that are known to impact search behaviour interact with variables at the individual level is essential to relate individual-level findings to the organizational level.

To tackle the gaps described above, we adopt a three-step empirical strategy that builds on the approach of Billinger et al. (2014) by adding the elements of task persistence, search scope and search slack (see Table 1) (Bettis et al. 2016). In the first step, we exactly replicate the study by Billinger et al. (2014) on a new population. We then modify search scope and search slack.

Throughout, we include multiple measures of task persistence to develop a more granular picture of how humans search.

Our results confirm that search behaviour is indeed adaptive, and that individual task persistence is an important antecedent and moderator in understanding human search strategies. Search scope does not influence behaviour directly, but rather influences the reaction to performance feedback. Easing resource constraints makes search more exploratory and improves performance in both the short and long run (Greve 2007). These findings help develop ideas about search in the behavioural theories of the firm (Cyert and March 1963; Gavetti and Levinthal 2000) and help provide a clearer picture of human search behaviour.

THEORY

In the sections that follow, we first build on what we know about human behaviour in complex search tasks. Next, we develop an argument about how task persistence can impact search behaviour. Finally, we examine the role of two key organizational factors – search scope and search slack – in explaining heterogeneity in search choices.

Performance feedback and search behaviour

The process of discovering a solution can be conceptualized as an adaptive search through a process of re/combination within a space of alternatives (Simon 1962). The approach based on the NK model has emerged as the primary modelling lens to study complex combinatorial search tasks, whether in individual strategy-making or new product development (Claussen et al. 2014;

Gavetti and Levinthal 2000). The NK model includes three main components: N represents the number of decisions in the landscape that can be activated or not; K denotes the number of interdependencies between these decisions and finally there is the agent who searches the landscape (Ganco and Hoetker 2009). The "landscape" analogy allows us to form a natural representation of search behaviours. Beginning at a given point in the landscape, agents try to reach the highest point within it through a search process that includes trying and evaluating new configurations (Ganco and Hoetker 2009). In a recent study, Billinger et al. (2014) conducted an experimental search task based on the NK model. Their primary finding aligns with the literature on organization learning: the search for new alternatives is sensitive to performance feedback (Greve 2003). Success leads to more local search (exploitation), whereas failure gradually promotes more distant (exploratory) search. Interestingly, complexity does not influence search behaviour directly, but rather affects performance feedback, which in turn affects the extent of exploration (Billinger et al. 2014). This study represents an important step towards confirming the behavioural plausibility of NK models. However, by replicating it, expanding its boundary conditions and examining the antecedents/moderator of the relationship between performance feedback and search behaviour, we can advance the assumptions that theorists use to model search.

Heterogeneity in search: task persistence

Individuals who tackle complex search tasks often fail (Baumann 2010). In the context of search, failure can be conceptualised as the absence of any improvement in performance. Previous research has shown that failure can enhance success (Sitkin 1992). Even though failure is both prevalent and significant in search, we still do not know how and why individuals behave differently under conditions of failure.

The main individual ability that determines an individual's response to failure is *task persistence*. Task persistence is defined as the ability to sustain goal-directed action despite obstacles or failures (Gusnard et al. 2003). The notion of task persistence has been an important variable in theorists' understanding of heterogeneity in search behaviours (Baumann 2010; Vuculescu 2016; Winter et al. 2007). Early work by Schwenk (1984) suggested that if managers are not persistent (i.e. they stop gathering new information once they have found a satisfactory alternative), they may remain ignorant of better alternatives. Levitt and March (1988) argued that if actors lack task persistence, they may overinvest in a suboptimal outcome and end up stuck in a competency trap.

So what determines the level of task persistence in search? One factor is the individual's own tendency to persist, and the other is the nature of the search environment. Individuals' tendency to persist has been studied and measured from both a trait-like and a behavioural perspective. For example, individual persistence has been proposed as the archetypical quality of an entrepreneur (Gartner et al. 1991), increasing the likelihood of start-up survival (Baum and Locke 2004), venture growth (Baum and Locke 2004), leadership success (Brockner and Guare 1983) and higher income (Duckworth et al. 2007). However, recent work suggests that persistence can have a dark side – i.e., excessive persistence leads to significant costs, escalation of commitment and failure (DeTienne et al. 2008).

What remains to be understood is whether and how task persistence plays a role in search behaviour. Modelling work by Winter et al. (2007) suggests that a moderate level of non-local task persistence is beneficial in a complex task, since high task persistence leads to getting stuck on local optima, while low persistence leads to abandoning exploitation too early and not taking advantage of the new knowledge. The task environment also plays a role in moderating the role of task persistence on search behaviour. It has been shown that persistent individuals only expend more effort than non-persistent individuals when they fail, and not when they succeed (Lucas et al. 2015). Thus, if a persistent individual were to encounter more failures, they would expend more effort, such that we would see an interaction between performance feedback and their level of task persistence.

Boundary conditions: search scope

Search scope can be defined as the size of the search landscape that is explored. In organizations, individuals are exposed to search tasks of varying sizes. Variation in problem size is known to play a role in search selection – i.e., where decision-makers look for new information (Li et al. 2013). Increasing search scope increases the likelihood of encountering failure, as the number of local peaks increases (Frenken et al. 1999). Search selection can impact both local and distant search, which in turn impacts the outcomes of search (Daft and Weick 1984). In the context of the NK model, search scope can be increased by simply increasing the number of decision elements (N), which expands the problem space. The more extensive the search terrain, the greater the likelihood of finding new information (Katila and Ahuja 2002). This, in turn, increases the amount of information that must be held by boundedly rational actors. Beyond a certain problem size, decision-makers are forced to decompose problems that may not be decomposable (Frenken et al. 1999). Thus, individuals focus only on certain areas of a search space, which can negatively impact exploration (Li et al. 2013). Search scope can also be considered a dimension of complexity. Previous research suggests complexity manifests in search behaviour indirectly, through performance feedback (Billinger et al. 2014). Rather than responding to information overload, individuals react instead to attainment discrepancies (the disparity between goals and actual performance) and modify their search behaviour accordingly (Gary et al. 2017). Based on these recent findings, we expect the relationship between performance feedback and exploration to be robust to changes in search scope.

Boundary conditions: search slack

Search slack is defined in our study as "the time/trials available for carrying out search". Search is typically assumed to be resource-constrained (Rivkin 2000). While possible configurations will typically outnumber trials, the number of trials available is not constant. For example, while engineer A might have a year to explore new configurations for a product, engineer B might only have enough budget to consider five variants. Neither can exhaust all the possible combinations in the search landscape, but A's extra slack can change their behaviour such that their first five variants are already more exploratory than B's total of five produced under resource restrictions. Slack can include increases in financial, temporal or human resources, but we focus on the temporal aspect, for two reasons. Firstly, temporal resource differences have been known to drive heterogeneity in human behaviour. Secondly, given the emergence of new forms of innovation based on deliberately rationing temporal resources – e.g. design thinking etc. – we want to understand whether more slack at the individual level does indeed promote exploration (Andrews and Farris 1972).

Some of the earliest theoretical work posited search slack as an important determinant of exploration (Cyert and March 1963). Unlike adaptive search, slack search is unrelated to immediate pressures and guided mainly by the interests of the individuals engaged in the search (Greve 2007). Two streams of research provide evidence that search slack plays a role in search behaviour. The first is derived from empirical work carried out in organizations (Nohria and Gulati 1996). In this domain, search slack allows individuals to respond to environmental events by giving them time to experiment and reflect on their choices. Search slack can enable experimentation with more distant alternatives than would have been possible without search slack (Nohria and Gulati 1996). What remains unclear is whether the performance benefits of slack can already be seen in the short run.

The second stream of work is based on individual experimental work in psychology. It suggests that reducing search slack by means such as increasing time pressure can increase task completion, but at the cost of fewer explorative, distant outcomes (Baer and Oldham 2006). In this context, the complete absence of time pressure has been shown to reduce motivation (Andrews and Farris 1972). Moreover, it has been shown that search slack can promote more exploratory behaviours (Greve 2007).

We expect search slack to change an individual's behaviour in a search task, such that they are less sensitive to performance feedback than individuals who have no search slack. Individuals who are less sensitive to performance feedback can search more distantly, increasing their chances of finding a better search outcome.

METHODS

To understand the antecedents, robustness, mechanisms and generalizability of adaptive search, we rely on an experimental study. According to Bettis et al. (2016), if the aim is to build and advance on a prior study of search behaviour, it is important to alter data, measures and models in stages. This incremental alteration to an existing research design is termed *quasi-replication*. Following the taxonomy of Bettis et al. (2016), in the first step we replicated the experimental study by Billinger and colleagues (2014) on a different population. We then made two extensions to their boundary conditions, to understand differences brought about by changes in scope and slack. Additionally, we wanted to go beyond the design by Billinger and colleagues (2014) to understand what drives the relationship between performance feedback and search behaviour. Hence, we included additional measures of task persistence and other controls during all treatments of our study (See Table 1)

Our experiment consists of four parts. Part 1 is the search task (the "alien" task), during which participants were exposed to the study treatment. This was followed by control questions related to the search task. Part 2 measures task persistence through the "anagram" task, while Part 3 measures it through various scale questionnaires that capture related variables. Finally, Part 4 measures demographic and control variables.

INSERT TABLE 1 ABOUT HERE

Part 1: Search task

Search task framing

To expose participants to a complex search task, we rely on the "alien" task designed by Billinger et al. (2014). In this task, participants are asked to design a product for extra-terrestrial visitors. The rationale behind making the customer an alien is that no prior knowledge or existing mental maps play a role in search behaviour. The participants are shown N shapes on a computer screen, which they have to combine. Each new combination results in a corresponding payoff, and the participant must search through various combinations to find the highest payoff. As in the setup by Billinger et al. (2014), participants were not given information on optimum performance, the type of landscape or the performance of other participants. We also replicated the feature that participants were shown the lowest performing combination in the first trial (although they were not told it was the lowest performer).

Experimental design

Our experiment consisted of four treatments carried out on the "alien" task (See Table 2)

Two hundred and fifty-nine subjects[5] were randomly allocated to one of the treatments. All experiments were carried out in a behavioural laboratory in cubicles with strict protocols. This enabled us to ensure that there was indeed no communication, and participants could only focus on the experiment in front of them.

Our sample of 259 participants was recruited from a large pool of participants (N=20,000). They had an average age of 23.71 years (SD = 3.05) and comprised 118 men and 141 women. They were paid a showup fee of 10 CHF, and were told they could earn up to 30 CHF depending on their performance in the "alien" and "anagram" tasks.

INSERT TABLE 2 ABOUT HERE

[5] 21 participants were dropped from the study either due to software crashes (n=6) or failing of attention checks (n=15) during the study.

Treatment 1: N10 (no search slack)

In treatment 1 we replicated the "alien" task exactly as it was conducted in the paper by Billinger et al. (2014). Participants were exposed to ten (N=10) geometric shapes, and the complexity of the landscape was varied (K=0,5,9) such that they saw these items in different sequences to prevent order effects. Participants could switch on or off as many of the 10 features as they wished – none, some or all. This resulted in a search space of 1024 combinations (2^10). Participants had 23 trials to explore each landscape (the first trial was a demonstration given by the software). Participants were told at the outset that they would be paid based only on the payoff they achieved in the 25th and final trial. This meant that participants searched for 23 trials before returning to their best-performing trial in round 24. Each participant could see all their previously explored combinations and the resulting payoff of each one. The payoff for each underlying combination was generated from the standard NK algorithm and normalized[6]. For each game the resulting NK payoff was multiplied by a game-dependent factor in order to prevent learning across games. Each time a new landscape was introduced, participants were told they were encountering a new alien, so as to prevent learning effects. Before the task began, participants were asked two questions about how they thought they would perform in the search task. After the task, they were asked questions related to the strategy they deployed and their

[6] To check the representativeness and similarity of landscapes we checked the number of local peaks in our landscapes compared to Billinger et al. (2014). In N=10, K=5, our landscape consisted of 39 local peaks in contrast to 32 local peaks in the study by Billinger et al., and in N=10, K=9, our landscape consisted of 94 local peaks in contrast to 95 in their study.

beliefs about the search space and highest payoff. We measure these variables because modelling work has indicated that imperfect evaluations of the search space and highest payoff can lead to differences in search behaviour (Knudsen and Levinthal 2007).

Treatment 2: N11 (No search slack)

In Treatment 2 we modified the search space. Participants were shown 11 geometric features rather than 10, thereby increasing the number of combinations to 2014 (2^11). They were exposed to three landscapes (K=0,5,10)[7] in random order. The number of local peaks increased such that N=11, K=5 consisted of 40 local peaks and N=11, K=10 consisted of 167 local peaks. All other features remained identical to Treatment 1.

Treatment 3: N10 (Search slack)

Treatment 3 differed from Treatment 1 in just one crucial respect. Instead of being given 24 trials, participants were informed that they could stop the task whenever they wanted. This was done to introduce search slack. Participants were exposed to only one landscape of moderate complexity (N=10, K=5). If participants were still playing the task after 30 minutes, they were automatically directed to the next task, but were not told of this time limit in advance.

[7] We choose N=11, K=10 in order to generate the most complex landscape.

Treatment 4: N11 (Search slack)

For this final treatment, one change was made to Treatment 3: participants were exposed to a larger landscape (N=11, K=5). As in Treatment 3, they were informed that they could stop the search whenever they wished[8].

Measures

The "alien" task provides us with seven trial-level measures. The two main ones are *performance* and *search distance*. *Performance* is measured as the highest payoff achieved by a participant up to and including that trial. *Search distance* is measured as the number of attributes changed compared to the highest payoff achieved so far. This variable provides a fine-grained measure of an individual's type of search, whether among local or more distant combinations. For example, if the best-performing combination an individual has identified thus far is [1,1,1,1,1,1,1,1,1,1,1], and in the next trial they try out [0,0,1,1,1,1,1,1,1,1,1], the search distance for this trial would be 2, as two attributes were changed relative to the best-performing combination (as opposed to the prior combination). The remaining variables from the "Alien" task and their descriptions are summarized in table 3.

INSERT TABLE 3 ABOUT HERE

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[8] Participants in treatments 1 and 2 spent 5.92 mins in the alien task compared to participants in treatment 3 and 4 who spent 15.85 mins on average.

Participants of all four treatments then proceeded to perform Parts 2, 3 and 4, which were identical across treatments.

Part 2: Persistence Task

Task persistence is defined as sustaining goal-directed actions towards completion of a task despite obstacles or difficulty (DiCerbo 2014). Previous research has found that to measure the behavioural component of persistence – i.e. coping with the distress of a frustrating or difficult task – behavioural tasks (e.g. the "anagram" or "mirror tracing" tasks) are a better analogue to the persistence required in search than perceptions of one's own tendency to persist (i.e. self-reported measures) (Quinn et al. 1996). Self-reported measures are subject to social desirability effects, which lead to false data about persistence (Ventura et al. 2013). Individuals interpret measures differently (e.g. "I work hard"), which leads to unreliability and lower validity (Ventura et al. 2013). Finally, such self-reported measures of persistence often require individuals to have explicit knowledge of their own dispositions, which is rarely the case (Ventura et al. 2013).

These drawbacks of self-reported measures have led behavioural researchers to rely on the "anagram" task as a measure of task persistence (Aspinwall and Richter 1999; Lucas et al. 2015; MacLeod et al. 2002; Quinn et al. 1996; Ventura et al. 2013). Participants were told that anagrams are strings of letters that can be reordered to make a word. They were told that they had 20 minutes to solve as many anagrams as they could. Participants could attempt 37 anagrams overall. Twenty-one were extremely difficult, with only one solution, while 16 were completely unsolvable[9]. To ensure similar difficulty, all participants were shown the anagrams in an identical sequence. Since 16 of the anagrams were unsolvable, participants should pass over them in order to perform well. Individuals high in task persistence are less likely to give up on such anagrams, and hence attempt fewer anagrams overall, despite the limited timeframe. Similar to previous work, the number of anagrams attempted serves as the measure for task persistence (Lucas et al. 2015).

Part 3: Self-reported scales

This section of the experiment included self-reported measures of personality (TCI), grit scale, self-efficacy scale and an intelligence test (Raven's matrices).

Personality

We asked participants to fill out the TCI-56 (Cloninger et al. 1994). The TCI is a bio-social model of personality that studies seven different dimensions (four temperament factors and three character ones). The questionnaire consists of eight questions for each of the seven dimensions. The four dimensions related to temperament are persistence (tendency to maintain behaviour in extinction conditions), reward dependence (tendency to respond markedly to signs of reward), novelty-seeking (exploratory activity in response to novel situation) and harm avoidance (inhibition of behaviour to signals of danger). We control for the four temperament factors because previous neuroscientific studies have suggested that these could influence exploration behaviour (Laureiro-Martínez et al. 2014). We do not focus on the character aspects

[9] The task was executed in identical fashion to the "anagram" task in the paper by Lucas et al. 2015. The authors of the paper also provided us with their 37 anagrams, which we used in the study. An example of an unsolvable anagram is GEIDLH, while a solvable example is HREAFTS ("FATHERS").

of the TCI as they focus mostly on leadership behaviours (cooperativeness, self-transcendence and self-directedness).

Grit

Participants completed the 12-item grit scale, which measures tendency towards perseverance and passion for long-term goals (Duckworth et al. 2007). The scale can be further divided into consistency of interest and persistence of effort[10].

Self-efficacy

A 12-item scale devised by Jerusalem et al. (1992) was used to measure self-efficacy. Self-efficacy is the belief in one's own ability to reach certain tasks and goals[11].

Part 4: Controls

Apart from standard demographic controls of age, gender, education, occupation and nationality, we also collected data on English proficiency, opportunity costs, enjoyment of the tasks and motivation to attend a study again[12]. To measure intelligence and abstract thinking, participants attempted 10 of Raven's progressive matrices (Raven 1998). A summary of all variables at the individual level can be found in table 4.

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[10] Including the grit scores in our analysis did not change the results, we do not report them for the sake of brevity.

[11] Controlling for self-efficacy did not change any results in the study. For the sake of brevity, it is not reported.

[12] We found that these controls do not impact the results we find in the study.

INSERT TABLE 4 ABOUT HERE

RESULTS

First, we describe the descriptive results of the "alien" task, followed by trial-level regression analysis to study replication, scope and search slack. We then focus on individual-level analysis to better understand the microfoundations of search behaviour.

Descriptive results: "alien" task

To understand how the performance of human participants varies depending upon the treatment, we compare the average performance of participants per trial (until trial 24) for the four treatments (see Figure 1)

Figure 1 validates prior results from the NK model literature – i.e. that performance increases over time, but performance gains for each trial decrease (Billinger et al. 2014). Figure 1 also reveals that participants in Treatments 3 and 4 (no limit on number of trials) outperform those working within constraints (Treatments 1 and 2).

INSERT FIGURE 1 ABOUT HERE

To compare performance differences across conditions, we run ANOVA's and find performance differences to be significant between all four treatments ($p < 0.001$). We find that individuals in the lower scope condition achieve higher performance. Interestingly, those in the search slack condition perform better not only in the long run (as many trials as they chose to experiment) but also in the short run (24 trials) in comparison to those the non-search-slack condition (24 trials). In Figure 2 we see that performance gains for those in the search-slack condition decline drastically after 100 trials.

INSERT FIGURE 2 ABOUT HERE

In Figure 3, we compare the average search distance of participants per trial across treatments. As in the case of Billinger et al. (2014), our participants do not adopt a purely local search strategy. Interestingly, despite being exposed to the same landscape, participants in the long treatments exhibit different search behaviour compared to those in the short treatments – i.e. they are more exploratory. What is notable is that these differences are salient even if we compare only the first 24 trials (See Figure 3). In Figure 4, we compare the average search distance for participants in the search slack condition, and observe that exploration increases over time.

Table 5 confirms these findings: local search is highest when the search scope is 10 and participants are in no-search-slack condition, and lowest when search scope is 11 and participants are the search-slack treatment.

INSERT FIGURE 3 AND 4 ABOUT HERE

INSERT TABLE 5 ABOUT HERE

The descriptive analysis confirms several findings by Billinger et al. (2014). Firstly, that performance increases over time, while performance gains decrease. Second, human behaviour adapts to complexity, as shown by the differences in search distances[13]. The descriptive analysis cannot explain if search behaviour is indeed adaptive to performance feedback, and how varying scope and slack of search influences search behaviour. Hence, in order to understand the primary variable of interest (*search distance*), we conduct Poisson regressions with trial-level data from each participant.

[13] Separate analysis revealed that the local search was more predominant in non-rugged landscapes (K=0) and declined as the complexity of the landscape increased (K=5, 9, 10).

Replication

We start by comparing our results for Treatment 1 (replication) to the results found by Billinger et al. (2014). In order to do so, our dependent variable is *search distance*. Independent variables include the complexity of the task (K can be 0, 5, or 9) and the task order. The main independent variable of interest is a binary variable called *feedback*. If the difference between current payoff and highest found payoff is positive, then it is coded as a success (1) and if it is negative, a failure (0). The feedback obtained in the previous trial is used to predict the current search distance. Other independent variables include the number of unsuccessful trials (number of trials thus far with no performance improvements), prior search distance (the value of search distance in the previous trial) and time spent per trial. (See Table 3 for a summary of the variables).

Table 6 reports the comparison of the results of Billinger et al. 2014 and Treatment 1. It shows that search behaviour is indeed adaptive, and complexity does not impact search behaviour directly. Prior search distance and the number of unsuccessful trials both increase search distance. As trials increase, search distance increases. Individuals take more time while making distant searches compared to searches close to the status quo. We are able to successfully replicate the findings of Billinger et al. (2014), and the magnitude of effects are also very similar to those found in their study.

INSERT TABLE 6 ABOUT HERE

Search scope

We next seek to understand how changes in search scope impact search behaviour (See Table 7). In Model 1 we predict search distance of searchers in Treatments 1 and 2 (short condition) using the same independent variables as used in the above replication – i.e. *complexity, task order, feedback, number of unsuccessful trials, previous search distance* and *time per trial*. We also include a variable *scope*, which indicates whether participants were in Treatment 1 with N=10 or Treatment 2 with N=11. We find that search scope does not have a direct effect on search distance. Further analysis indicates that search scope impacts performance feedback, which in turn impacts search behaviour. Search scope (N) plays a similar role as complexity (K) in search behaviour. Even though the search space is twice as large, individuals rely heavily on reference points (which we capture in the feedback variable) to direct their search. These results are confirmed once again in model 2 (Table 7) where we predict the search distance of participants in Treatments 3 and 4, in which participants could search for as long as they wished. We find that search is still adaptive, i.e. negative feedback leads to a higher search distance. The main difference between models 1 and 2 is that the magnitude of the effect of performance feedback on search is reduced.

INSERT TABLE 7 ABOUT HERE

Search slack

In model 3 (Table 7) we want to understand whether introducing search slack changes search behaviour. To do so, we compare the first 24 trials across all treatments for landscapes with moderate complexity (K=5). We predict the search distance in these trials through *scope, feedback,* *number of unsuccessful trials, prior search distance, trial number* and *time per trial.* We additionally include a dummy variable indicating whether the trial belonged to condition with search slack or not. Our results indicate that individuals in the condition with search slack do indeed explore more. Being in the treatment with search slack increases average search distance by 2.01 compared with those in the non-search slack condition. In model 3, we compare only the first 24 trials of the individuals in Treatments 3 and 4 with all the trials of Treatments 1 and 2. By introducing search slack we could already see changes in the extent of exploration in the short term. A separate analysis reveals that individuals in these conditions are less sensitive to performance feedback, meaning that positive feedback does not reduce search distance as much as it would in the case when individuals are in the no-search-slack condition.

Antecedents of search behaviour: task persistence

Now we focus on the main research gap that we address, and turn to analyses at the individual level (rather than at the trial level). In order to explore the antecedents of search behaviour we split our data, depending on whether individuals were in the search-slack or non-search-slack condition. We then extract average values of search behaviour and feedback conditions from the "alien" task. From this point on, all analysis is at the individual level (as antecedents are at the individual level). A summary of all constructs used in the analysis is shown in Table 4.

Models 1–3 in Table 8 test the impact of search conditions and individual-level antecedents on the average search distance of a participants in the search-slack condition. Model 1 provides the OLS estimates using *average search distance* throughout the "alien" task (as dependent variable) and task-specific conditions, namely *number of trials, average time per trial, average number of unsuccessful trials* and the dummy variable of *search scope.* The individuals who executed a greater number of trials have a higher search distance (B = 0.005, $p < 0.05$). This result is consistent with prior work, which finds that as number of trials increases, finding performance-improving combinations becomes harder and negative feedback becomes more prominent, which individuals respond to by broadening their search (Billinger et al. 2014). In Model 2, we include individual-level controls and antecedents that can impact search behaviour. *Task persistence* and *average feedback* are negatively correlated to *search distance*. Individuals who receive greater positive feedback throughout the search task explore less than those who receive higher positive feedback on average (B= -2.86, p< 0.001). Additionally, individuals who are persistent also tend to explore less than those who have lower task persistence. To help interpret the effect size, the standardized coefficient for *task persistence* is -0.19, meaning that relative to *performance feedback* (standardized coefficient = -0.43) and *length of search* (standardized coefficient = 0.41) it has the third-strongest effect in explaining *search distance*. In Model 3, we include the interaction term by multiplying *task persistence* by *average feedback*. For high-task persistence individuals, the slope of the line between *average search distance* and *average performance feedback* is steeper than for those with low persistence (See Figure 5). This implies that the propensity for less distant search under negative feedback is more common in individuals with high task persistence.

Controls

Demographic controls and self-reported measures are not significant predictors of average search distance. The only control that is significant is the accuracy of belief of the search space. The higher the accuracy of beliefs of a search space, the lower the extent of exploration (B= -0.36, p <0.05)

INSERT FIGURE 5 ABOUT HERE

INSERT TABLE 8 ABOUT HERE

We next run analyses similar to those reported in Table 8: Models 1 and 2 for participants in the non-search slack condition. We do not find statistical significance for task persistence influencing search behaviour. We do find support for TCI Reward dependence ($B = -0.28$, $p < 0.01$) and intelligence impacting search distance negatively ($B = -0.10$, $p < 0.05$)

INSERT TABLE 9 ABOUT HERE

DISCUSSION

The goal of this paper is to understand the microfoundations of search behaviour under variation in search environment – namely, scope and slack. Given the growing calls in behavioural strategy to strengthen the psychological grounding of our models (Powell et al. 2011), we rely on task persistence, a well-studied psychological construct, and apply it to understand human search behaviour (Quinn et al. 1996). This paper makes three main contributions. First, it deepens our understanding of the influence of task persistence on search behaviour – in particular, on distant search under conditions of high complexity. Intuitively, task persistence is a direct antecedent of exploitative behaviour. Less intuitively, and perhaps more interestingly, task persistence also serves as a moderator in the relationship between performance feedback and exploitative behaviour. Second, this paper demonstrates the role of expanding search scope and search slack on human behaviour: whereas search scope only impacts search behaviour indirectly, search slack has a direct effect and increases exploratory behaviour. Third, this paper validates previous findings on adaptive human search behaviour (Billinger et al. 2014).

Persistence has been viewed as a trait by some, and as a behaviour by others (Eisenberger (1992). We take the latter view, and, like entrepreneurship scholars, regard it as a behavioural decision whose outcome can be good or bad depending on the environment (DeTienne et al. 2008; Gimeno et al. 1997; Holland and Shepherd 2013).

We find that the individual tendency to persist can indeed explain why some individuals abandon local search relatively early. Given the constraints of bounded rationality, an individual's persistence, along with performance feedback, serves as the filter that determines which part of the environment is attended to, and defines the allocation of cognitive resources that will, in turn, guide sense-making and decision-making (Laureiro-Martinez 2014; Ocasio 2011). These findings can also help us understand when escalation of commitment occurs, and why persisting with a course of action does not always result in success (Moon 2001). In our study, we find that persistence is salient only in the non-search-slack condition. This can be explained by the fact that likelihood of failure is much lower in the non-slack condition, and previous work has found that persistent individuals act the same as non-persistent individuals as long as they are succeeding.

In the search-slack condition, we also found that beliefs about the size of the search played a role in explaining exploratory behaviour. If an individual held accurate beliefs about the size of the search space, they tended to engage more in local search. This is an important finding, since an individual has to gauge the size of the landscape in most search tasks. This belief can feed into an actor's mental model and constrain adaptive search (Gavetti and Levinthal 2000). Interestingly, the accuracy of beliefs about global optima did not influence search behaviour. Future research can further examine which sources of inaccurate belief about the landscape are most important.

In the non-search-slack condition, we found that reward dependence (the tendency to markedly respond to signs of reward) correlated negatively with the tendency to engage in distant search. This finding supports conjectures in previous studies that temperament factors can indeed influence search behaviour (Laureiro-Martínez et al. 2014). Previous work has found that the expression of reward dependence is even more salient in social situations, through factors such as verbal signals of social approval (Cloninger et al. 1994). Future work can delve deeper into the relationship between reward dependence and search behaviour in contexts where social approval also plays an important role (e.g. teams). In the non-search-slack condition, an individual's intelligence also correlated negatively with the tendency to engage in distant search. This is consistent with previous research that has found intelligence to be correlated with exploitative behaviour when performing search under uncertainty ("bandit" tasks) (Steyvers et al. 2009).

Our study also has important implications for behaviour under different search conditions. As a baseline, we replicate results found recently by Billinger et al. (2014) to show that human search is indeed adaptive. These results could contribute to modelling work, which can incorporate adaptive search as one of the stylized strategies with which individuals search in landscapes, instead of confining strategy to local and myopic search. We also find that search scope (the size of the landscape) impacts search behaviour only indirectly. Individuals focus only on attainment discrepancies rather than devoting their attention to the size of the landscape.

A key empirical result in this study is the role of search slack (search duration) in search behaviour. Remarkably, individuals who are not constrained in terms of numbers of trials engage in significantly more exploratory search, even in the short term. As earlier conceptualized by March and Simon (1958) and in organization psychology, time pressure plays a significant role in determining the focus of attention (Andrews and Farris 1972). This finding has important implications for organizations looking to promote distant search. Organizations can relax time pressures in projects when they would like to promote new and exploratory innovations. This finding, though consistent with work by Greve (2007), is contradictory to current design thinking, scrum or agile techniques, where rapid prototyping under intense time pressure is the *de facto* operating principle. While these methods do result in implementation, the outcomes achieved could be incremental due to the localness of search. This could be a problem, since it has been long known that a fundamental shift is necessary to cope with hyper-competition (a period characterized by intense change and multiple competitors) (D'aveni 2010). Rather than focusing on sustaining existing advantages, managers should challenge themselves to disrupt them, or find new ones – which typically requires distant search.

LIMITATIONS AND FUTURE WORK

A recent call from the NK modelling community suggests that the NK model can serve as an excellent experimental platform to study complex search processes (Puranam et al. 2015). However, relying solely on an experimental setting, we encounter several limitations that limit the generalizability of our findings. Previous research in organizations has found that the determination to persist is affected by structural, political and psychological pressures to continue with past strategies (Lant et al. 1992). In our study, individuals were not exposed to any of these factors, nor were they given information about the other participants' performance, which can lead to social pressures. Additionally, there were no costs associated with the search process. Perception of sunk costs is an important driver of escalation of commitment (Moon 2001). Also, our tasks are relatively short-term, but the relationship between persistence and search behaviour can differ in longer-term search tasks, such that time invested becomes an important sunk cost. In terms of the landscape, similar to Billinger et al. (2014), we did not reveal any information on the global optima, the number of configurations or the complexity of the landscape.

Another important limitation of our study is the treatment of search scope. In one treatment participants are exposed to 10 decision variables (N) and in the other to 11 decision variables (N). This change may not be sufficient to see individuals focus on only some decision variables. A larger change – for example, N=50 – might result in narrowing of attention and hence more exploitative search. Similarly, in terms of introducing search slack, we only observe two extremes: a treatment with no search slack and a treatment with unlimited search slack. Future work can fill in these gaps, and explore the relationship between intermediate slack, increasing decision variables, the introduction of sunk costs and search behaviour.

This study marks an important step in understanding human behaviour and helps us make better theoretical assumptions as to how individuals in organizations search. Since assumptions about agents' search strategies are predominantly guided by the behavioural theory of the firm (Ethiraj and Levinthal 2004; Rivkin 2000; Rivkin and Siggelkow 2003), they can lead us to infer human decision rules that are far removed from reality. For example, Mason and Watts (2012) claim that current models of search behaviour fail to reflect heterogeneity among decision makers. This is crucial, as Herbert Simon has pointed out: "decision making is the heart of administration, …the vocabulary of administrative theory must be derived from the logic and psychology of human choice" (Simon, 1947 page xlvi), and "administrative theory must be concerned with the limits of rationality, and the manner in which organizations affect these limits for the person making a decision" (Simon, 1947, page 241). By introducing two commonly encountered organizational factors, scope and slack, we can sharpen our understanding of how these interact with the decision-maker, taking into account the systematic heterogeneity brought about by individual abilities.

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TABLES AND FIGURES

Figure 2: Average performance over 24 trials across four treatments

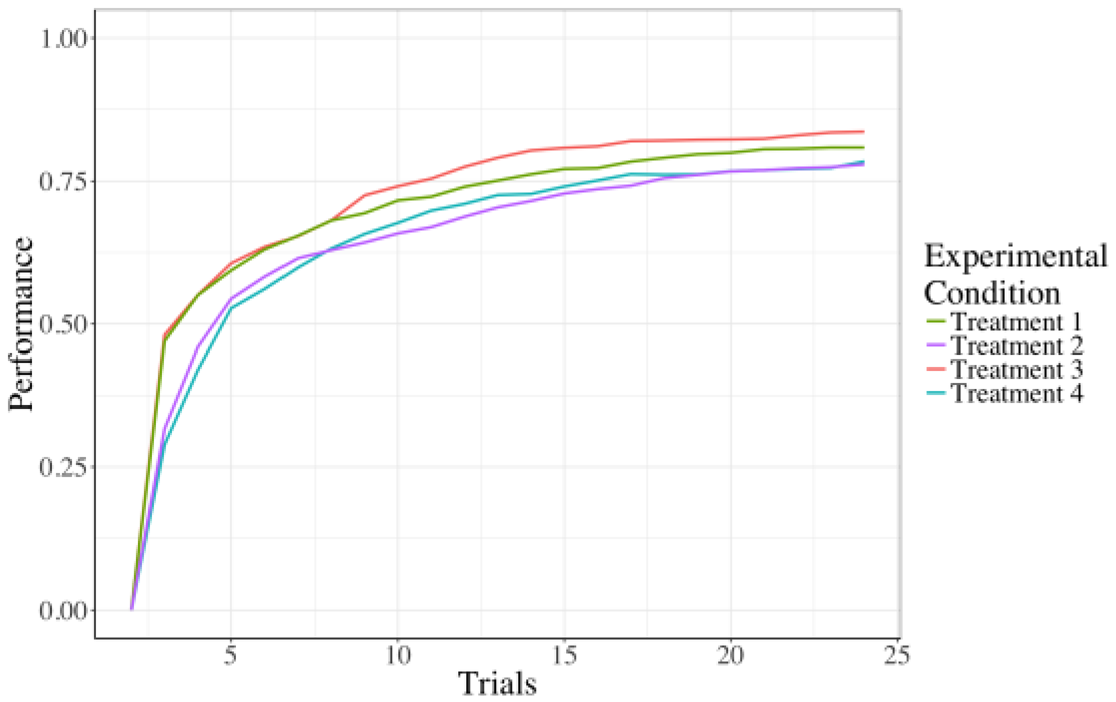

Figure 3: Average performance per trial in treatments 3 and 4

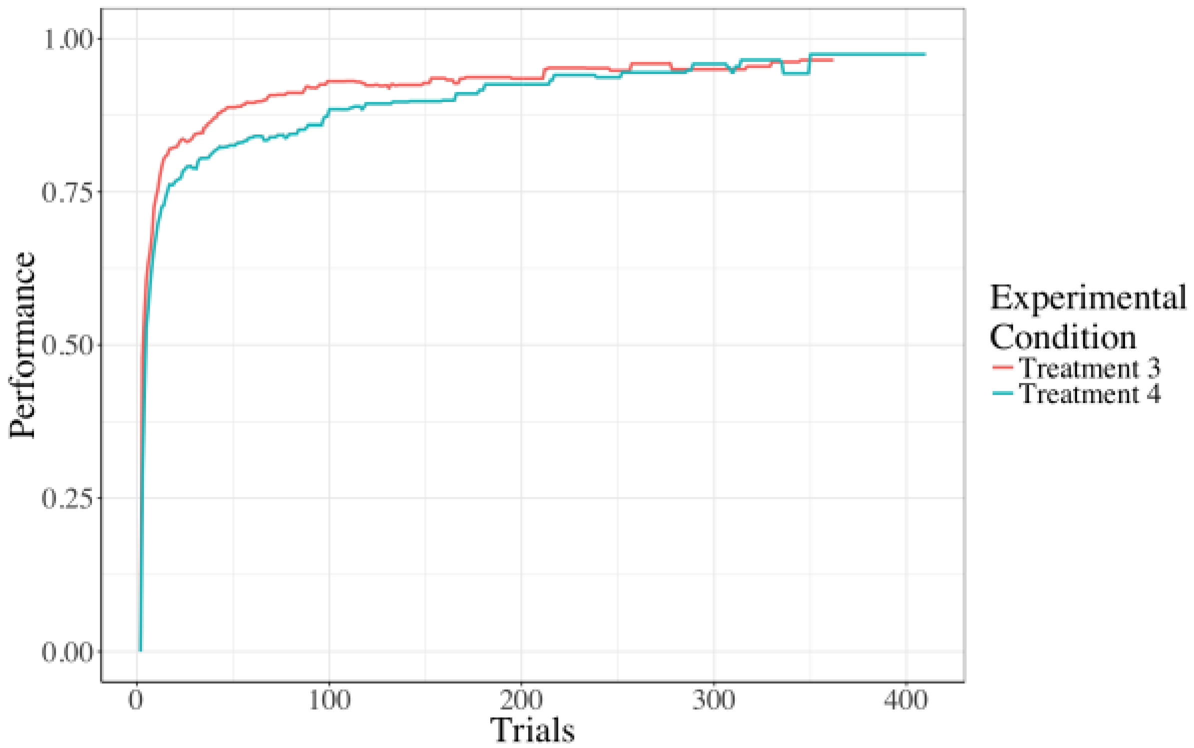

Figure 4: Average search distance over 24 trials across 4 treatments

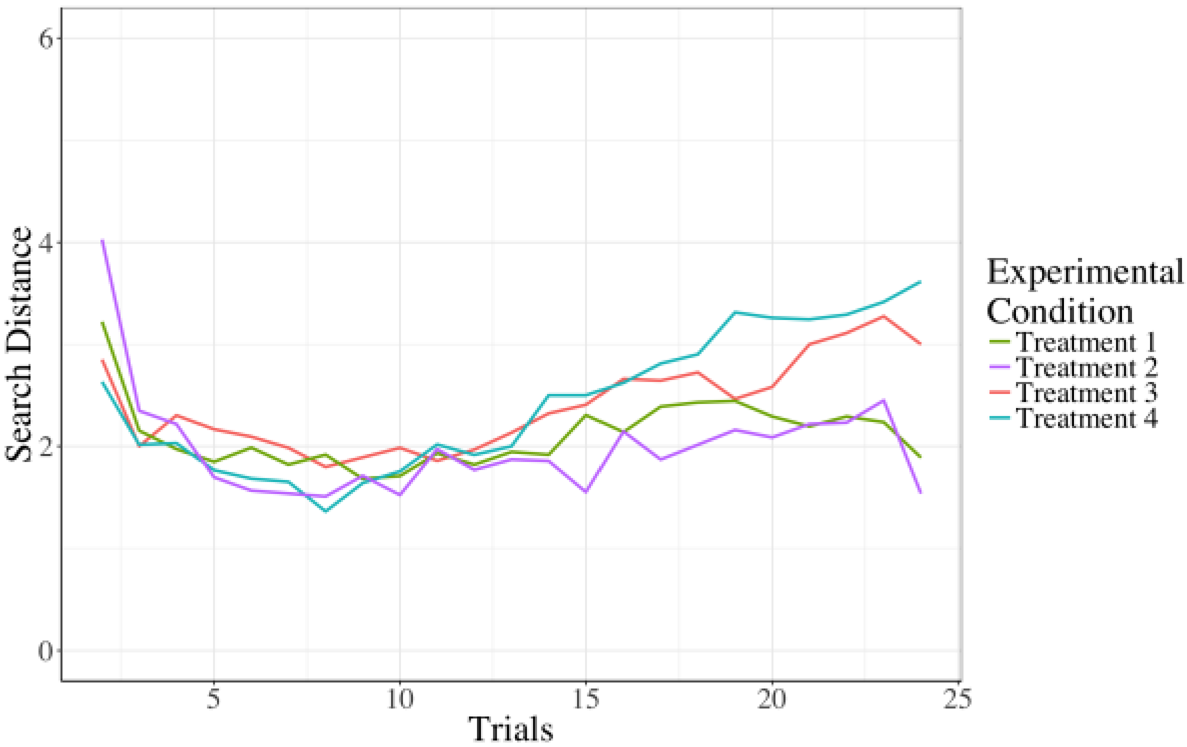

Figure 5: Average search distance per trial in treatment 3 and 4

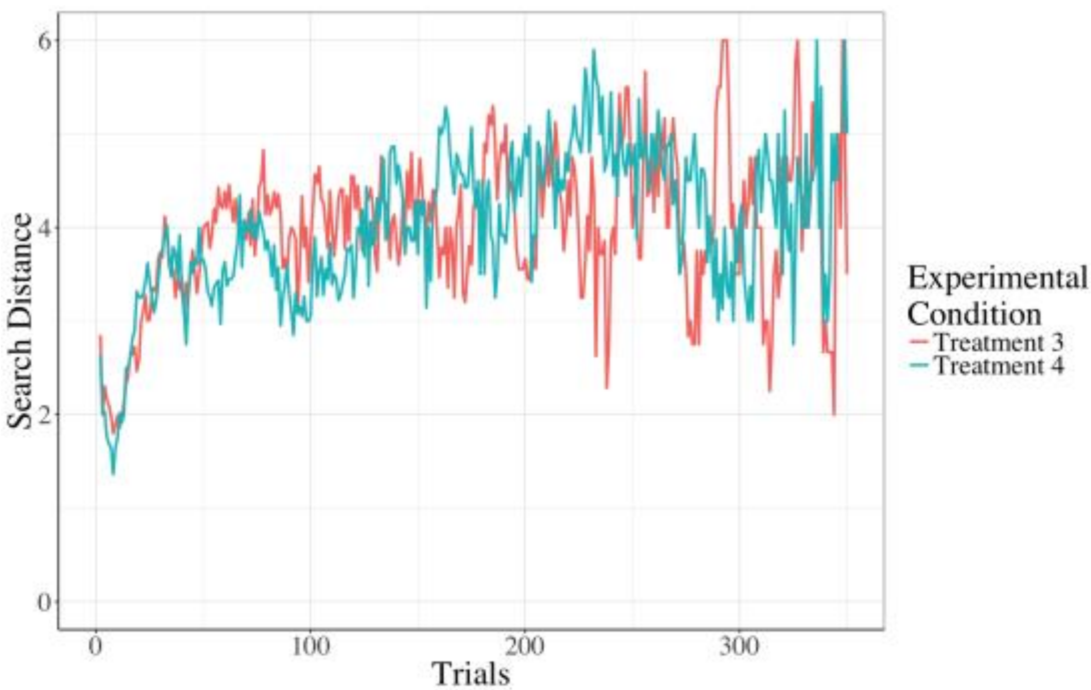

Figure 6: Interaction plot of individuals with high and low persistence

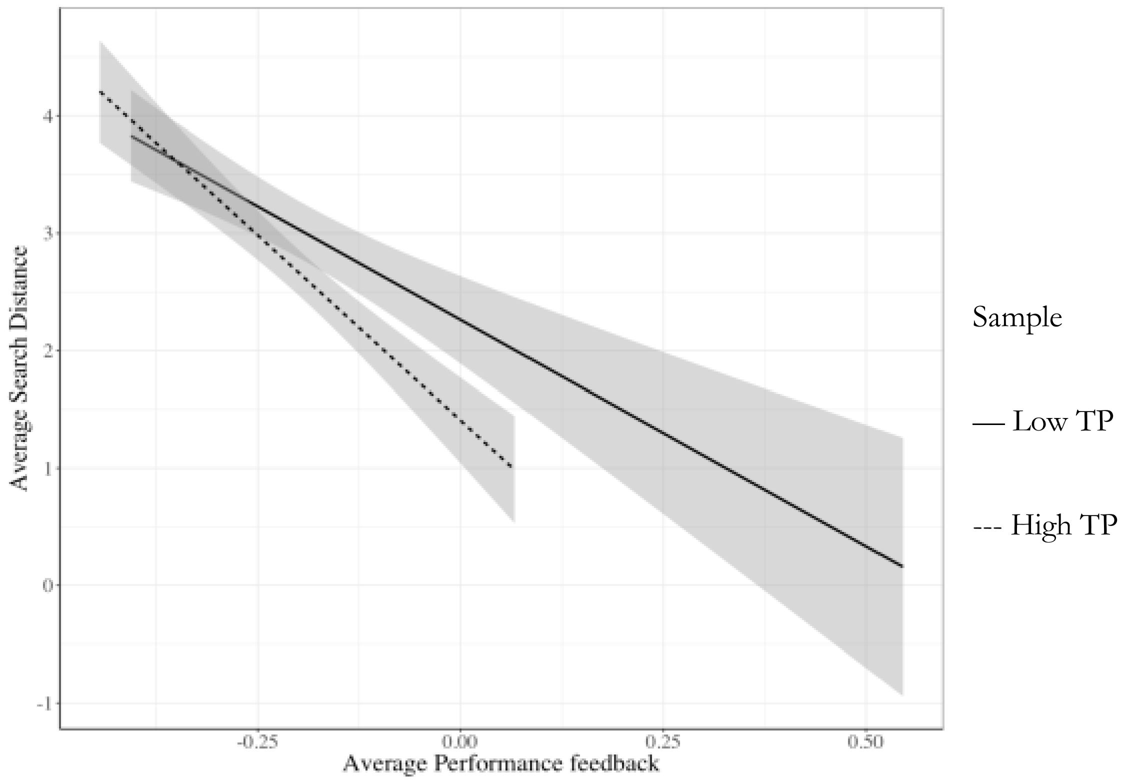

Table 1: Quasi-replication experimental design

	Same Research Design (Billinger et al. 2014)	Changing search scope	Changing search duration
Different Population with Different Sample + New measures (New persistence measures aid in better understanding the relationship between performance feedback and search behaviour)	Study 1 (To generalize to a new population)	Study 2 (To generalize to changing search landscape and assess robustness)	Study 3 (To generalize to changing search times and assess robustness)

Table 2: Summary of the four treatments in the experiment

		Duration	
		25 Trials	30 Mins
Scope	N=10 1024	Treatment 1 (K=0,5,9)	Treatment 3 (K=5)
	N=11 2048	Treatment 2 (K=0,5,9)	Treatment 4 (K=5)

Table 3: Constructs trial with Descriptives

Variable	Type	Search slack =0		Search Slack =1		Explanation
		Mean	Std. dev.	Mean	Std.dev	
Scope	Discrete					No. of attributes participants were exposed to either 10 (Treatment 1,3) or 11 (Treatment 2,4)
Search slack	Discrete					Treatment 1,2 had 25 trials, treatment 3,4 had unlimited* trials
Complexity (K=0,5,9,10)	Discrete					Complexity was 0,5,9 for treatment 1, it was 0, 5,10 for treatment 2 and 5 for treatment 3 & 4.
Feedback	Discrete	0.22	0.41	0.05	0.23	Failure to improve in the previous trial is coded with 0, and success with 1
Highest payoff	Scale	0.7	0.25	0.85	0.16	Highest payoff so far identified
Number of unsuccessful trials	Discrete	4.86	5.01	56.3	66.17	Number of trials since last maximum payoff
Prior search distance	Discrete	1.98	1.85	3.63	2.27	Search distance in the prior trial
Search distance	Discrete	1.96	1.86	3.61	2.28	Number of changed features
Task position	Discrete					Sequence of search tasks (in treatment 1 and 2)
Trial number	Discrete					Number of completed trials
Log (Time)	Scale	8647.48	10869.33	6191.11	11647.77	Time per trial

Table 4: Constructs person level with Descriptives

Variable	Type	Search slack =0		Search Slack =1	
		Mean	Std. dev.	Mean	Std.dev
No of trials	Discrete	23	0	92.67	100.79
Average failure duration	Scale	4.75	2.32	24.38	31.96
Average Time	Scale	8888.01	4355.18	8962.3	6583.97
TreatmentN11_K5	Discrete				
Average feedback magnitude	Scale	-0.13	0.05	-0.2	0.15
Task Persistence (TP)	Discrete	11.13	9.44	9.42	9.32
Age	Scale	23.71	3.12	24.28	2.99
Gender	Discrete	0.51	0.5	0.57	0.5
Tci Persistence	Discrete	3.39	0.71	3.37	0.7
Tci Reward Dependence	Discrete	3.48	0.78	3.46	0.78
Tci Novelty Seeking	Discrete	2.82	0.59	2.81	0.64
Tci Harm Avoidance	Discrete	2.92	0.75	2.96	0.82
Search space belief accuracy	Discrete	0.31	0.47	0.3	0.46
Payoff Belief accuracy	Discrete	-0.06	1.42	0.06	0.01
Intelligence	Discrete	7.27	1.55	7.24	1.61
Average search distance	Scale	1.96	0.87	2.84	1.15

Table 5: Frequency distribution of search distances across treatments

		Treatment							
		N=10 (NO SLACK)		N=10 (SLACK)		N=11 (NO SLACK)		N=11 (SLACK)	
		Frequency	Cumulative Freq.	Frequency	Cumulative Freq.	Frequency	Cumulative Freq.	Frequency	Cumulative Freq.
Search Distance	***1***	49.8	49.8	45.8	45.8	54.3	54.3	51.1	51.1
	2	22.7	72.5	22.7	68.5	24.1	78.4	17.4	68.5
	3	8.4	80.9	11.3	79.8	5.7	84.2	8.5	77.0
	4	6.8	87.7	5.7	85.5	4.3	88.5	5.3	82.3
	5	4.1	91.8	3.8	89.3	4.5	93.0	5.8	88.1
	6	3.5	95.2	3.6	92.9	2.3	95.3	4.2	92.3
	7	1.7	96.9	2.5	95.4	1.7	97.0	3.2	95.5
	8	1.0	98.0	2.5	97.8	0.9	97.8	2.3	97.8
	9	1.2	99.2	1.9	99.7	0.8	98.6	1.3	99.1
	10	0.8	100.0	0.3	100.0	0.3	99.0	0.4	99.5
	11					1.0	100.0	0.5	100.0

Table 6: Poisson models with search distance as dependent variable to test replication of results

	Billinger et al. (2014)	Treatment 1
Complexity (K = 5)	0.002 (0.032)	0.01 (0.03)
Complexity (K = 9)	−0.021 (0.027)	-0.04 (0.03)
Feedback	−0.376*** (0.030)	-0.26*** (0.04)
Number of unsuccessful trials	0.03*** (0.003)	0.03*** (0.004)
Prior search distance	0.16*** (0.004)	0.18*** (0.005)
Trial number	−0.01*** (0.002)	-0.01*** (0.003)
Task position 2	−0.03 (0.027)	0.02 (0.03)
Task position 3	−0.03 (0.027)	0.01 (0.03)
Log (time)		0.06*** (0.01)
Constant	0.597*** (0.043)	-0.18 (0.15)
Log likelihood	−6,466	-5,425.15
Pseudo-R2	0.4103	0.5279
No. of observations	3,835	3,617

Note: Standard errors in parenthesis. Observations include all trials with a positive search distance. Pseudo R2 computed based on deviance. *p < 0.05. **p <0 .01. ***p < 0.001.

Table 7: Poisson models with search distance as dependent variable to test extension of boundary conditions

	Model 1	Model 2	Model 3
	2	3	4
Complexity (K = 5)	0.005 (0.02)		
Complexity (K = 9)	-0.05 (0.03)		
Complexity (K = 10)	-0.02 (0.03)		
Scope (N=11)	-0.01 (0.02)	-0.01 (0.01)	-0.02 (0.02)
Duration (Long)			0.07^{***} (0.02)
Feedback	-0.24^{***} (0.03)	-0.60^{***} (0.03)	-0.27^{***} (0.03)
Number of unsuccessful trials	0.04^{***} (0.003)	0.001^{***} (0.0002)	0.03^{***} (0.003)
Prior search distance	0.18^{***} (0.004)	0.18^{***} (0.002)	0.17^{***} (0.004)
Trial number	-0.01^{***} (0.002)	0.00 (0.0001)	-0.005^{**} (0.002)
Task position 2	0.002 (0.02)		
Task position 3	0.01 (0.02)		
log(time)	0.06^{***} (0.01)	-0.01^{**} (0.01)	0.06^{***} (0.01)
Constant	-0.22^{*} (0.11)	0.66^{***} (0.06)	-0.04 (0.22)
Log Likelihood	-8,705.27	-20,997.50	-8,345.44
Pseudo-R2	0.5065	0.5822	0.6496

Note: Standard errors in parenthesis. Observations include all trials with a positive search distance. Pseudo R2 computed based on deviance. *p < 0.05. **p <0 .01. ***p < 0.001.

Table 8: OLS Regressions with average search distance as the dependent variable (Only individuals in the search slack condition)

	Model 1	Model 2	Model 3
No of trials	0.01^{***} (0.002)	0.005^{**} (0.002)	0.005^{**} (0.002)
Average failure duration	0.001 (0.01)	-0.0005 (0.01)	-0.002 (0.01)
Average Time	0.00 (0.00)	0.00^{*} (0.00)	0.00^{*} (0.00)
TreatmentN11_K5	-0.08 (0.16)	-0.04 (0.16)	-0.04 (0.16)
Average feedback magnitude		-3.39^{***} (0.77)	-2.68^{***} (0.82)
Task Persistence (TP)		-0.02^{***} (0.01)	-0.05^{***} (0.01)
Age		0.04 (0.03)	0.04 (0.03)
Gender		-0.12 (0.17)	-0.09 (0.17)
Tci Persistence		0.15 (0.12)	0.13 (0.12)
Tci Reward Dependence		0.17 (0.11)	0.17 (0.10)
Tci Novelty Seeking		0.05 (0.14)	0.04 (0.14)
Tci Harm Avoidance		0.01 (0.11)	-0.01 (0.11)
Search space belief accuracy		-0.32^{*} (0.18)	-0.36^{**} (0.18)
Payoff Belief accuracy		-0.001 (0.004)	-0.001 (0.004)
Intelligence		0.002 (0.05)	0.01 (0.05)
Feedback*TP			-0.13^{**} (0.06)
Constant	2.22^{***} (0.20)	0.08 (1.21)	0.30 (1.19)
Observations	132	132	132
R^2	0.38	0.53	0.55
Adjusted R^2	0.36	0.47	0.5
Residual Std. Error	0.92 (df = 127)	0.84 (df = 116)	0.82 (df = 115)
F Statistic	19.48^{***} (df = 4; 127)	8.82^{***} (df = 15; 116)	8.89^{***} (df = 16; 115)

*p < 0.05. **p <0 .01. ***p < 0.001.

Table 9: OLS Regressions with average search distance as the dependent variable (Only individuals in the non-search slack condition)

	Model 1	Model 2
Average failure duration	0.07^{**} (0.03)	0.02 (0.03)
Average Time	0.0001^{***} (0.00)	0.0001^{***} (0.00)
TreatmentN11_K5	-0.01 (0.15)	0.11 (0.15)
Average feedback magnitude		-6.25^{***} (1.46)
Task Persistence (TP)		-0.01 (0.01)
Age		0.01 (0.02)
Gender		0.003 (0.15)
Tci Persistence		-0.01 (0.11)
Tci Reward Dependence		-0.28^{***} (0.09)
Tci Novelty Seeking		0.07 (0.14)
Tci Harm Avoidance		0.01 (0.11)
Search space belief accuracy		-0.04 (0.15)
Payoff Belief accuracy		0.00 (0.00)
Intelligence		-0.10^{**} (0.05)
Constant	1.06^{***} (0.24)	1.90^{*} (1.07)
Observations	127	127
R^2	0.14	0.35
Adjusted R^2	0.12	0.27
Residual Std. Error	0.82 (df = 123)	0.74 (df = 112)
F Statistic	6.77^{***} (df = 3; 123)	4.30^{***} (df = 14; 112)

*p < 0.05. **p <0 .01. ***p < 0.001.