universität
wien

MASTERARBEIT / MASTER'S THESIS

Titel der Masterarbeit / Title of the Master's Thesis

„Differences in search behaviour: Maximizing cumulative versus exploring individually-highest payoffs on rugged landscapes "

verfasst von / submitted by

Olivia Stefanie Jazwinski, B.Sc.

angestrebter akademischer Grad / in partial fulfilment of the requirements for the degree of

Master of Science (MSc)

Wien, 2020 / Vienna 2020

Studienkennzahl lt. Studienblatt / degree programme code as it appears on the student record sheet:	UA 066 915
Studienrichtung lt. Studienblatt / degree programme as it appears on the student record sheet:	Masterstudium Betriebswirtschaft UG2002
Betreut von / Supervisor:	Univ.-Prof. Dipl.-Chem. Dr. Markus Georg Reitzig, MBR

List of Contents

List of Tables

List of Figures

1 Introduction

In order to develop, each organisation has the major task to innovate. Every organisation is in critical need of company performance and success, to strive for innovation and keep up with current market trends. But how do companies achieve these innovations? By searching for new information and recombining (Gilfillan 1935; Schumpeter 1939; Hunter and Usher 1955; Basalla 1988; Henderson and Clark 1990; Weitzman 1996; Hargadon and Sutton 1997) current resources, it is possible to reach an innovative product or idea. In order to better understand the process of getting to innovation and searching for new combinations, strategy literature has come up with numerous theories and ways to explain search behaviour in organisations, (sub-)groups and individuals. Individuals apply different search strategies that are led by search heuristics, such as using existing knowledge and being rationally bounded. To understand how organisations find innovation and search for it, it is essential, first to understand how individuals themselves search for information to be then able to develop ideas on search behaviour within groups and, eventually, organisations. While a decision made in a personal surrounding may not have implications on a person's environment, in organisations, each action has an impact on the people within it.

Researchers have come up with different methods to observe search behaviour in organisations and simulate those surroundings in experiential settings to gain insight into search behaviour. One way to observe search behaviour in an experiential environment is to construct a search space in which agents (inter-)act and search for different variables in an abstract way to strive for highest performance. The so-called fitness landscape is a means to understanding how individuals and groups move within a limited space that offers several possibilities of choice variables (Levinthal 1997). Fitness landscapes are widely used in strategy literature to portray and observe search behaviour since it helps to make assumptions about decision making in organisations but also for individuals. Kauffman (1993) has developed an algorithm to visualise the problems and difficulties agents may face when searching for innovation (Billinger et al. 2014). His NK-model creates a so-called fitness landscape which is a finite 3D space in which performance is measured in peaks of various height. This landscape can be varied by adapting the two parameters N and K, N being the number of search variables and K influencing the interdependencies between them. When K increases, so does the number of peaks and throughs in the landscape. Figure 1 illustrates two exemplary fitness landscapes.

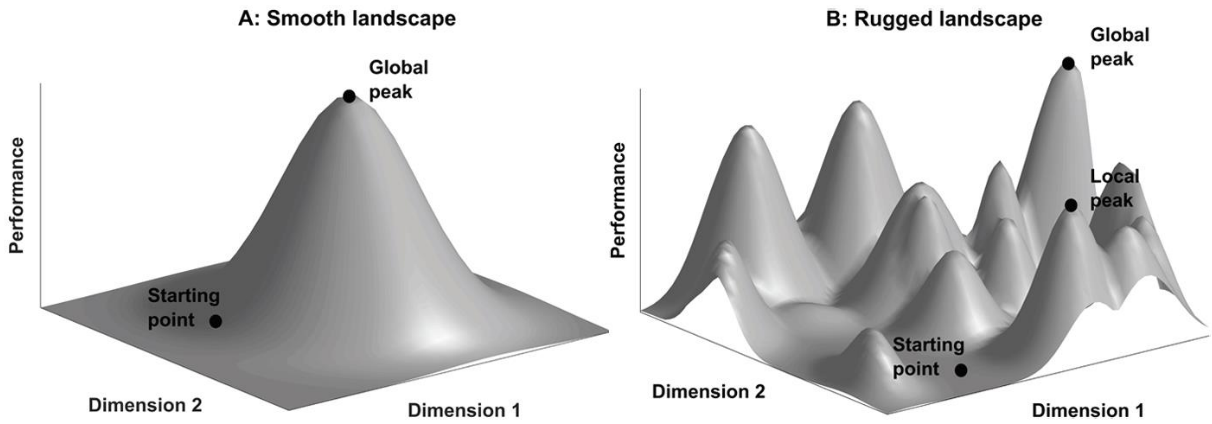


Figure 1 Stylised Performance Landscapes.
Reprinted from Effective Search in Rugged Performance Landscapes: A Review and Outlook, by Baumann et al., 2019.

Imagine the following: A landscape with N = 10 and K = 0 means that all ten variables are independent of each other. A landscape with N = 10 and K = 9 on the other hand results in a "rugged" landscape with lots of local peaks and one global maximum. This model means to portray decision making in real-life organisations where each decision variable chosen is – in a different way – dependent on other variables. In highly interdependent settings, we often get to a solution that might seem like the best option. However, we are never aware of the landscape and have no idea about whether there might be an even better solution. Thus, it might not be trivial how to get to the best solution overall, and interdependencies drive the decision space's complexity (Simon 1962). Billinger et al. (2014) have programmed the so-called Alien Game to portray and observe individual search behaviour and improve understanding of how individuals reach, or try to reach, the global optimum within a search space. During this lab-experiment, individuals are asked to create the best combination of ten objects. There is no prior knowledge necessary and participants have no reference points within the game – only the payoffs of their selected combinations. They observe that individuals use adaptive search behaviour, narrowing down to local search when success is experienced and opening to more distant search when failure occurs. This behaviour was observed for individuals that were shown individual payoffs after each round. One central question that comes up is whether this search behaviour is still pursued when the initial aim of the game is changed for participants to illustrate decision processes in organisations. We want to examine if there is a difference in search behaviour when aims are formulated to understand how, in management, goals should be postulated to increase performance. In the following, we will develop an experiment using the Alien Games' backend and frontend mechanics, observing whether there will be a difference in search behaviour for participants that do not only focus on finding the one best solution but focus on the cumulated payoff. How does this affect individual performance and search strategies?

2 Literature Review

In the following chapters, we will present an overview of literature on search behaviour and search strategies, as well as heuristics and boundaries. Further, a short introduction on goal setting and goal formulation will be outlined.

2.1 An introduction to search behaviour

A central aspect for organisations is the (re)combination of alternatives to be able to enter new scopes of action to increase performance. Individuals and groups in an organisation are searching for new options to create innovation by combining known decision variables (Levinthal 1997; Rivkin 2000). In management literature, this process is observed when wanting to gain insight on how individuals, groups and organisations search for innovation and evaluate which factors influence the way the actors "move" within their search space. In the innovation process, recombination is an essential factor (Gilfillan 1935; Schumpeter 1939; Hunter and Usher 1955; Basalla 1988; Henderson and Clark 1990; Weitzman 1996; Hargadon and Sutton 1997) in which old and new factors are recombined. This implies a constant search for new combinations of current and new information and features (Fleming and Sorenson 2001). Gavetti et al. (2017) name the process of recombination shaping and searching in which the payoff structure is created or changed through shaping. This process has enormous implications on the fitness landscape, which results in a continually evolving landscape, meaning that interdependencies adapt repeatedly.

New Product Development (NPD) is one example where interdependencies and search behaviour can be observed. Its task is to develop the next new product, which might be critical for a company's success since it can assure competitive advantage. The difficulty here is to allocate resources in a way that new information can be assigned and recombined to find a new product, which might be conflicting in an organisation where resources are limited. Further, corporate strategy, better said, long-term and short-term goals, may be conflicting when it comes to the allocation of resources in this process (Tushman and Oreilly 1996). While in the short-term, minimal improvements can already have a considerable impact, in the long-term, more drastic changes will potentially be more successful.

Search behaviour displays the individual's and group's approach to finding new combinations and moving around through the landscape. The essence of a company is to solve problems through search. To better understand organisations, Baumann (2015) defines them as Complex Adaptive Systems (CAS), which consist of several components that are interdependent and influenced by different dynamics within this construction. This construct then acts within its environment. The key message of CAS is that even though we can observe individual components, it is not possible to derive collective behaviour from it due to the interdependencies. This definition helps us understand the motivation behind fitness landscapes in which these interdependencies are displayed. The more interdependencies, the more "rugged" the landscape is. The agents must search for the best solution to reach the highest payoff.

The argument of interdependencies is supported in strategy literature, and the difficulties that arise within them are well known (Baumann 2015). Simon (1962) has already discovered that the search for the optimal choice set is not trivial, and interdependencies drive a system's complexity. However, this complexity might be beneficial in a market since it is more difficult to be imitated and give an organisation a competitive advantage (Porter 1996). One way of displaying interdependencies in search behaviour for optimal solutions is the NK model (Kauffman 1993; Kauffman 1996). The model helps understand how different decisions (N) and their interdependencies (K) change a search space, respective the possibilities of reaching the global optimum (Baumann 2015). A landscape that has been modelled with a high K is called "rugged" since it has many local peaks agents can reach. Within the landscape now agents search for solutions by either "jumping" around or adaptively changing small parameters (Baumann 2015).

2.2 Search strategies

There are different strategies to search on a landscape successfully. One way of searching for information in an organisation is the process of adaptation (Levinthal 1991) in which significant attributes are changed. The starting position of an organisation, e.g. the organisation's form at the founding, has a considerable influence on its search position within an environment (Stinchcombe 1965). This leads to diverse forms of companies since it not only influences the starting point within a search space but also the possibilities of finding optima in this space. Differently said, imagine organisation A that is located at the bottom of a global optimum while organisation B is far away, located next to a local optimum. By searching in this space, it is likely that – since all options and information are never available – both organisations might reach the peak of its nearest optimum which is the global one for organisation A, but only the local optimum for organisation B (Levinthal 1997).

However, not all landscapes in which organisations operate have the same level of interdependencies, and it is difficult for subjects to observe the level of interdependencies (= the degree of K). While for some organisations, the degree of interaction between various features is high and thus, the landscape is rugged, other organisational forms might experience smoother landscapes and hence, less local peaks (Levinthal 1997). Therefore, it is crucial to understand how interdependencies might change to be able to evaluate how to search for the best solution and which search strategy is the best. We will further have to decompose organisations and assess not only group decision behaviour and search strategies but also how individuals behave and search for innovation.

Generally, in real-life situations, the use of prior knowledge is essential to gain better understanding of the context in which the decision needs to be made. Especially in environments that are dynamic and not completely known, two search strategies are observed: Exploration and Exploitation. While the former refers to search for novel directions that deviate in substantial ways from current ones, the latter improves existing practices and uses existing knowledge to reach an optimal solution (Levinthal et al. 1993). The challenge is to balance both components to reach an optimal output. As mentioned above, one will also find a dynamic between long-term and short-term organisational goals. Exploration can be useful in long-term strategies and help develop new, ground-breaking ideas while exploitation helps in the short-term, and usually, firms tend to be biased towards the latter (Levinthal et al. 1993). This might result from the boundaries of a strategic plan. A plan can be isolated from long-term goals, and itself seem useful in its isolated consideration. In this context, it appears that the environment is simpler, which leads companies to choose exploitation rather than exploration. In fitness model terms, this can be expressed as searching smooth landscapes (Caldart and Ricart 2007). In rugged landscapes, however, meaning in more complex and interactive search spaces, exploration might the better strategy to go for.

Further, the agent's abilities have an impact on the search behaviour that is most effective. Consider a complex environment and an agent that is bounded in his understanding of evaluating alternatives. Should he exploit or explore? According to Caldart and Ricart (2007), a shift from exploitation to exploration might be the best solution.

When exploring, agents tend to take risks, variate and experiment (March 1991) and this can be associated with a search behaviour that is called distant search, more distant in time since it may take more effort. The so-called local search can be compared to exploitation within a search field, meaning that firms refine and implement alternatives within a local and stable environment (March 1991) for options and decisions to be made closer in time. Latter approach might generate more stable performance while exploration has possibilities to both, result in huge success or failure. Due to the insecurities both strategies have in their ways, a balance is key for company success (March 1991) and has been labelled ambidexterity (Tushman and Oreilly 1996; Birkinshaw and Gibson 2004). A different way of balancing search behaviour is called the Punctuated Equilibrium (Gersick 1991), which makes use of balancing exploration and exploitation in cyclic ways, not parallel. Here, agents cycle through periods in which they explore or exploit (Gupta et al. 2006).

Gittins (1989) and Sutton (1998) have carried out an exemplary study to observe exploration and exploitation in an N-armed bandit model in which agents need to choose between different alternatives that have an unknown payoff. To reach the maximum payoff, the agents estimate payoff probabilities based on available resources. They either choose an alternative or use available resources to continue searching. This study observes the effect of exploring and exploiting. While an agent that extensively uses resources will reach the average expected value of all arms alternatively, an agent who does not explore at all may settle too early on an alternative. One way to be able to balance exploration and exploitation is the ability of absorptive capacity, meaning, to understand knowledge available outside (Tortoriello 2015). This absorptive capacity is more easily acquired through a routine task, meaning, through exploitation, while organisations will need to put effort into gaining outside knowledge for unknown, explorative topics (Cohen and Levinthal 1990).

A common strategy to search for the best solutions within organisations is imitation. There is low risk for imitators, and it helps to close the gap between the agent and the imitating counterpart. An even better solution is to integrate an aspect of learning and adapting. However, imitation is a widely used strategy which may not only lead to success but also involves risks, especially when the intention is to close the gap between a company and its market leader. Without learning but purely imitating, mistakes the imitating organisation makes will be blindly copied and may lead to severe damages (Posen and Martignoni 2018). An experiment carried out by Ethiraj et al. (2008) examines the trade-off between innovation and imitation in which firms can engage in incremental innovation attempts. Within the setup, firms search for innovation. Once a stable position on respective local peaks is reached, the low-performing firms can imitate high-performing actors. This results in long jumps since the low-performing firms must move away from their local peaks and move to new positions within the search space. In general, imitation is a widely used strategy in which actors will mimic other successful agents. This imitation process will be reenacted as long as imitator and target become more similar, leading to diminished performance heterogeneity which can be called the expropriative effect of imitation (Posen and Martignoni 2018). But what happens if there is no other player that can be mimicked, e.g. the case for individuals' players or best-performers? In such a case, learning from their own experiences and using the current position as a reference point for new search attempts is crucial.

Summing up strategies, literature suggests optimising search behaviour: First, balancing exploration and exploitation is critical to be able to reach local and also global peaks (Rivkin and Siggelkow 2003). By exploring, a comprehensive view can be created, which then helps to exploit these new alternative options. This approach can be supported by paralleling search and an increased number of search trials (Baumann et al. 2019).

One problem of individuals that can be identified is the level of accuracy of the agent. A highly accurate agent may become trapped at the starting position since he tries to evaluate the location perfectly and may stick to a local peak while a less accurate agent may be able to move more freely on the map and may not be influenced in the same way by the starting position (Knudsen and Levinthal 2007). The feedback both agents receive is crucial for further steps taken since search behaviour is path-dependent (Billinger et al. 2011). As the search process can be described as a (re)combination of several decision variables, the more interdependencies between those variables exist, the more complex the choice of a specific combination and its evaluation becomes (Billinger et al. 2014). Further, the number of search trials and the resources that are available for this process are usually constrained and smaller than the number of total possible outcomes (Rivkin 2000).

Next to local and distant search, Podolny (2018) has identified so-called discerning search. Similar to local search, the agent starts at a randomly chosen position in a landscape. Instead of identifying and calculating each of the N attributes individually and eventually selecting the strategy that yields the highest payoff which then leads to ending the search process, a discerning searcher first compares all payoffs for each of the N attributes and identifies the one with the lowest value. Both search strategies are limited to the knowledge an agent possesses and the starting position as described above.

Moving through this landscape, recombining variables to reach the best outcome possible can be either done through simple trial-and-error or using strategies and giving the next steps thought. In the following, we will focus on two main search strategies which form the base for all further search strategies that partly have been mentioned above: Local and Distant Search; linked to exploitation and exploration (March 1991; Gavetti and Levinthal 2000; Siggelkow and Rivkin 2006).

2.2.1 Local Search

Local search can be thought of a search process that involves only a few changes in search behaviour and can be identified as the most common type of search in search literature (Ganco and Hoetker 2009) as well as the simplest search heuristic (Almirall and Casadesus-Masanell 2010). In particular, only one single attribute is changed, resulting in a single step within the immediate neighbourhood within the search space and implies that individuals do not have full knowledge about their search space and the attributes they are recombining (Almirall and Casadesus-Masanell 2010; Gavetti and Levinthal 2000). A search strategy following this approach is called hill-climbing adaptive behaviour in which agents search locally, evaluating each change. If the change results in a higher payoff, the new combination is adopted. Otherwise, the choice will be revised, and a different option or none at all is chosen (Ganco and Agarwal 2009; Ganco and Hoetker 2009; Baumann et al. 2019). As the agent does only move very slowly through the search space, this strategy is referred to as the most myopic and straightforward type of search behaviour that can be implemented within the NK model (Ganco and Hoetker 2009; Almirall and Casadesus-Masanell 2010; Podolny 2018).

The situation in which the agent is located at the beginning of the search process is essential for success or failure and the probability of finding the global optimum. The current position reflects past searches for alternatives as search behaviour is path-dependent (Afuah and Tucci 2012). An agent that searches locally uses prior and existing knowledge to search for new alternatives (Katila and Ahuja 2002). By resorting on this knowledge, the agent is acting intelligently, while cognitively limited otherwise due to bounded rationality (Afuah and Tucci 2012). Even though the accumulation of expertise and knowledge helps subjects learn, firms tend to search in areas in which they have expertise (Helfat 1994).

Decomposing and refining alternatives to reach a new position within the landscape by only changing one dimension rather than looking for entirely new options can be considered a form of exploitative adaptation (Uotila 2017). Exploitative search behaviour is success-induced, meaning that subjects enhance local search behaviour when a higher payoff is reached than before. Instead of exploring and making more distant moves, subjects tend to exploit within their current position (Billinger et al. 2014). Through this behaviour, firms learn and gather more knowledge (Ganco and Agarwal 2009). The exploitation process may imply that a peak is within reach. However, depending on the complexity of the landscape, this peak may not be global but rather a local peak which poses a particular challenge to local search as a subject may not be able to identify superior alternatives that may be more distant (Knudsen and Levinthal 2007).

One reason why subjects still involve in local search even though it might not be the ideal search strategy is bounded rationality. Subjects are never fully aware of all possible options and thus have difficulties in evaluating the next potential steps that might lead to higher payoffs and results (Simon 1978). A pure local search strategy is only successful in simple landscapes in which no local but only one global optimum exists. As soon as an agent experiences increased results, it is sure that he is located near the optimum, and each further steps will probably lead him towards the peak (Billinger et al. 2014). The more success is experienced, the more exploitative behaviour will be performed, and search will be narrowed down to the neighbourhood of the status-quo (Billinger et al. 2014). This behaviour is supported by empirical evidence, stating that firms' search behaviour tends toward local search (Rosenkopf and Nerkar 2001).

Searching on a landscape of unknown complexity, agents do neither know their position on this landscape, nor which step to take next. This uncertainty may lead to agents not jumping around randomly to different spots but rather adopting sequential search (Baumann et al. 2019) in which agents use existing knowledge to identify better solutions (Nelson and Winter 1982; Simon 1955). Assuming bounded rational decision-makers, so-called local and sequential search generates new solutions rather than "long-jumps" and distant search. Actors tend to discover their immediate neighbourhood, changing only one dimension at a time, evaluating new solutions (Baumann et al. 2019).

Experiments on search behaviour, however, observe, that agents do not only engage in pure local search, but different search behaviours can be found in various settings. Vuculescu (2017) notes that actors, with the increasing availability of information, make so-called model-based moves, which are a type of cognitive search.

2.2.2 Distant Search

As soon as a subject breaks out of local search, the term distant search can be applied. This search behaviour is observed whenever subjects vary more than one decision element at a time, implying that they can look beyond their immediate neighbourhood. This strategy accelerates search and may help the agent become more powerful so that they may be able to traverse local optima and move forward to a different peak (Ganco and Hoetker 2009; Uotila 2017). This behaviour is typically observed whenever failure occurs (Billinger et al. 2014). As no higher payoff can be made at the current location, the agents tend to break off local search and "jump" to a new position. However, the agent has no information on the performance of this new position and whether or not he locates himself near a high- or low-performing peak (Baumann et al. 2019). The shift in search strategy is, therefore, riskier than sticking to the peak that is already being exploited. As individuals weigh losses higher than gains (Kahneman and Tversky 1979), breaking off is not likely to be pursued. However, when stuck on a local optimum, a more distant search is the only way out to find a new position that may lead to higher payoffs. However, this poses a challenge to the sequential search process (Baumann et al. 2019). In reality, organisations further face restrictions through rules, routines and knowledge bases that need to be overcome to be able to explore rather than exploit (March 1991; Miner et al. 2001; Katila and Ahuja 2002). Performing so-called "long-jumps" is a result of a failure-induced radical reorientation (Billinger et al. 2014). An alternative search strategy might be to broaden the search sequentially rather than "jumping around" on the search space (Baumann et al. 2019).

An adapted model is Vuculescu's (2017) approach, distinguishing not only between local and distant search but focusing on a so-called model-based distant search, in which agents do not only perform pure local or distant search. Instead, agents are assumed to use cognition and, while moving through the landscape, try to identify and exploit patterns. This search behaviour differs from the findings Billinger et al. (2014) as it states that it is not directly influenced by feedback.

2.3 Search heuristics & boundaries

While moving around the landscape and looking for innovation and new combinations of alternatives, individuals subconsciously use search heuristics and encounter boundaries they are not fully aware of. Particularly in management literature, actors are assumed to be rational, meaning they have information of all decision variables and, based on this, make the best decision (March and Simon 1958). In literature focusing on search behaviour however, it is common to categorise actors as boundedly rational. Such agents do not have information about all options, are not aware of the interdependencies between decision variables and will be influenced by their decision within a search space, meaning the reference point given. Consequently, they will never be able to find the global maximum, only if they are positioned next to it (just as organisation A above). This implies that bounded rational actors are not capable of distant search but do only search locally (Afuah and Tucci 2012). Cognition might help individuals to evaluate alternatives based on their understanding of the world (Lippman and Mccall 1976). Several aspects, such as an agent's starting position in a landscape, path-dependency and an agent's search accuracy further have a significant impact on the performance. The theory of bounded rationality implies that agents will only be able to perform local search on search spaces and can only identify positive or negative gradients around their current position and thus will only be able to find the global peak when located next to it (Afuah and Tucci 2012). One solution to this is the adaptation of sequential search (Baumann et al. 2019).

As individuals use prior and existing knowledge to move around a landscape, different concepts of using this knowledge and implementing it in a search strategy have emerged. One of them is the cognition-based logic, based on an agent's perception. Here, an agent has a belief about linkages between the choices of action and its impact on outcomes. This belief is forward-looking and derives from an actor's mental model of the world (Holland et al. 1987). A second concept is an experiential-based logic which builds on experiential wisdom. Prior choices and their accumulation of reinforcement impact an actor's further decisions (Levitt and March 1988). Opposed to cognitive-based logic, this approach is based on backward-looking wisdom (Gavetti and Levinthal 2000).

A further question in strategy literature is how actors consider alternative strategies. Mental representations are one way. Individuals use a model of reality held in mind to generate predictions about reality (Craik 1967; Holland et al. 1987). Using these representations, an agent does not need to carry out an alternative but can evaluate consequences. This element is crucial to be able to search for different solutions and balance exploration and exploitation and can help, especially individual players on an isolated map where no imitation is possible to reach the global maximum. The Alien Game (Billinger et al. 2014) uses this information and creates a world in which no prior knowledge is necessary to isolate cognition as an influencing factor. Agents can figure out the best solution by trial-and-error and thus, their personal experience within this new context (Gavetti and Levinthal 2000).

2.4 The role of goal setting

Goal setting is a widely discussed topic in management and decision-making literature (Cyert and March 1963; Simon 1964; Boyle and Shapira 2012; Sitkin et al. 2011) and can be described as a regulator of human action and a representation of a final stage which a person wants to reach (Erez and Kanfer 1983). A goal characterises what each individual, team or organization wants to accomplish (Locke et al. 1981) and can also be described as aspiration levels (Gary et al. 2017). According to Locke et al. (1981), goal setting has a positive impact on performance in the majority of studies reporting on work motivation. In addition to that, goal setting literature observes a linear relationship between the goal difficulty and performance (Locke and Latham 2012a). Formulating and setting goals, however, poses a challenge to management. No goals at all, very vague formulations and abstract goals might lead to lower performance outputs than particularly difficult and hard to reach goals (Locke and Latham 2012a). Stretching goals is, thus, a conventional means used in order to boost performance (Collins and Porras 1996; Kerr and Landauer 2004; Locke and Latham 2012b; Thompson et al. 1997). Furthermore, performance is moderated by the individual's abilities and performance feedback. When feedback is available, goals regulate performance more successfully compared to a state in which no feedback is accessible, as feedback offers a reference point that helps individuals decide if more effort is needed or a new strategy should be adopted in order to reach the goal (Locke and Latham 2012a). This feedback then may impact search distances and a decision maker's actions within a decision space.

3 Fitness Landscapes & the NK model

A fitness landscape helps understand how individuals and groups move within a limited space that offers several possibilities of choice variables (Levinthal 1997). Initially, this idea was developed in the context of biology literature by Wright (1932, 1931), in which each point represents an organism's genetic structure and the according fitness level (Levinthal and Warglien 1999; Levinthal 1997). Levinthal (1997) used this representation as a basis to map organisational change. Each adaptation on an organisational level leads to a modification of their existing form to enhance their fitness. Such an adjustment may refer to a business strategy or an internal policy. On an individual level, the same principle can be applied: An individual strives to increase his payoff function which is conditional on his action as well as on the steps of other members of his group and organisation (Levinthal and Warglien 1999). Kauffman (1993) has constructed a model, which helps describe the abstract theory of fitness levels by characterising fitness landscapes with two structural variables: N and K. This model creates a fitness landscape in which performance is measured in peaks of various height. The landscape can be seen as a metaphor for a search space in which agents act. A point on the landscape is represented by a possible choice combination with the height representing the performance of each combination. A peak can be described as a point for which performance cannot be improved by changing only one choice. The higher the interdependencies among choices are, the higher the level of ruggedness of the landscape and the more peaks appear. In a real-life context, we might look at managers who need to solve complex problems. Changing one attribute might have significant implications in a different area (Baumann et al. 2019). The problems itself are only complex because of the interdependencies among them.

The structure of the landscape can be differently rugged or smooth depending on the interdependencies between the variable K, e.g. an organisation's strategy that has an impact on the organisation's performance. The higher the effect, the more rugged the fitness landscape is. This has implications on changes within a business's strategy, which might lead to a significant change of the fitness landscape. Generally, whenever organisational fitness is highly interactive, meaning, one feature of an organisation depends on a variety of other features, the landscape is rather rugged while otherwise smooth (Levinthal 1997). In the latter landscape, no action interferes with another actor's action, meaning that there is always and only one optimal behaviour that is independent of others' behaviour (Levinthal and Warglien 1999). This simple model can help us explore the interrelationship between different attributes taking several aspects into account. The starting position of an organisation in a landscape has a persistent effect on its future. Whether an organisation can adapt to environmental changes is highly conditioned by the degree of interaction within their organisation (Levinthal 1997).

In literature, designing landscapes, meaning the tuning of fitness landscapes, helps to understand how different organisational designs influence behaviour. With reduced interdependencies, it is usually expected to be able to predict behaviour and get a robust design while designs with many interdependences tend to lead to greater exploration, which might lead to coordination difficulties. Landscape design does not impact behaviour but influences feedback performance which then directs individual actions (Billinger et al. 2014). Building on Simon (1955) and March and Simon (1958), individual behaviour is adaptive and driven by adaptive search processes. Thus, design concerns should allow to let actors adapt (Levinthal and Warglien 1999).

3.1 The NK model

The NK model was defined by Kauffman (1993) and characterises organisations as consisting of N attributes where each can take on two possible values (binary). These attributes can be interdependent, which is specified by the variable K. If K = 0, the contribution of one attribute in the organisation is independent of all other attributes (e.g. strategy, personal systems…). Such a landscape is smooth, meaning that changing one single attribute will not influence the fitness contribution of all other attributes. If K = N-1, all attributes depend on the value of all other attributes of the organisation, meaning that everything is interdependent. K thus determines the intensity of interaction. A higher K is displayed in a more rugged landscape with more peaks. For K = 1, we can observe one single peak while for K greater 1, multiple peaks are available (Levinthal 1997).

One main limitation of the NK model is the search behaviour that is usually observed. In most experiments based on the NK model, only experiential search can be seen. Further, only single-level interdependence can be represented. This causes a problem whenever innovation problems have interdependencies between levels and are hierarchical (Yu et al. 2009). The challenge posed in an NK model relatively differs from the empirical phenomenon (Winter et al. 2007) as, for instance, the random ruggedness of the NK landscape (Mckelvey et al. 2013) limits evolving the model in a sense that supports the implementation of more cognitively plausible assumptions regarding search (Vuculescu 2017).

3.2 Search behaviour in Fitness Landscapes built with NK model

The search process within a fitness landscape can be described as a recombination of several variables. Agents recombine a variety of variables that may be unknown in their sum. Their search behaviour is mostly indirectly affected by the complexity of the landscape, i.e. the degree of K rather than that of N, and directly affected by the feedback received during the search process (Billinger et al. 2014). When K increases faster than N, searching within a landscape becomes harder since adaptation becomes more difficult over time. Agents cannot learn about N and determine which new variables to recombine. Instead, the complexity increases and causal effects – or seemingly causal effects – cannot be detected (Kauffman 1993).

Whether agents are successful in their search and find specific peaks, the global peak in the best case, is highly dependent on the size of the search space, as Fleming and Sorenson (2001) stated. As discussed above, the search strategy adopted within different landscapes then further has an impact on how successful the agent is and a balance between local exploitation of already discovered solutions and non-local exploration for new solutions is significant (Mason and Watts 2012). The possibility to recombine in a way that leads to successfully reaching a global peak further depends on the starting position of an agent. Due to bounded rationality, judgments about more distant positions are only difficult to make, which may lead to being trapped in a so-called competency trap (Levinthal and Warglien 1999; Levitt and March 1988).

On landscapes that are characterised by low interdependencies (low K), local search is more favourable, meaning that incremental improvements will lead to finding the global peak while this strategy will not lead to success in highly dependent landscapes (high K). In this case, incremental adaptation is not the right solution (Fleming and Sorenson 2001).

In each game, the agent is embedded in a landscape that is exogenously affected and influenced. An agent's search behaviour then is influenced by these exogenously embedded circumstances and his endogenously given search strategies. Exogenous factors are the problem that needs to be searched as well as agents' search capabilities. Through trial and error, the agent locally searches within the landscape by altering one component at a time (Ganco 2017).

4 Observing search behaviour in games – using the Alien Game

The Alien Game by Billinger et al. (2014) is based on the NK fitness landscape and observes individual human search behaviour on a landscape in which agents are faced with solving a complex combinatorial task. In organisations, this is the daily business of management – solving complex tasks that emerge from the combination of interdependent decision variables (Billinger et al. 2014). Exploration and exploitation of these is crucial for moving forward, and the more interdependencies arise between the variables, the more difficult the task can be classified (Page 1996; Simon 1962). Exploring such complex environments becomes even more challenging when the resources for exploration are scarce (Billinger et al. 2014). In the Alien Game, individuals start with a random choice combination giving agents a reference point. Now, players either move forward by picking one new alternative at a time or by discarding the current choice option and choosing new alternatives. If the new choice set yields higher performance, it is likely that the next search processes will then exploit rather than explore the search space (Baumann and Siggelkow 2013).

In total, 61 agents are asked to sell art to aliens without knowing their art preferences. This makes sure that agents cannot rely on personal behaviour and heuristics but search in a space in which experience will not help, hindering mental representations. The object that is asked to be sold to the aliens is a combination of several attributes that need to be combined in a way that matches the aliens' unknown preferences. Through an experiential search on the search space, individuals discover different payoffs but only have limited search trials which are far fewer than the number of all possible combinations. Displayed is only the absolute payoff. Billinger et al. (2014) carried out the experiment on three different landscapes with varying task complexity: A simple landscape with no interactions between the variables (K = 0), a rugged landscape with intermediate complexity (K = 5) and a maximally rugged landscape (K = 9). While holding the number of choice variables constant (parameter N), the landscape's degree of ruggedness was regulated, i.e. the key independent variable *Complexity* (parameter K) was varied.

In Billinger et al. (2014), agents were asked to choose a combination of N = 10 alternatives. These geometric choices could be toggled on or off as a binary choice. In total, participants were able to choose between 2^{10} (1,024) combinations that yield a payoff that is configured through the NK model in the background. Each session had 25 rounds and started with an introduction to the task and agents being given an initial combination that was randomly chosen and a respective payoff which was always the lowest-performing. As only absolute and not relative payoffs were displayed, agents could not rank the information given and, hence, did not know that the payoff was the lowest that could be reached. In the next 24 trials, participants had the task to reach the highest payoff possible by toggling on and off as many alternatives as wished. After each round, agents could see the payoffs respective to each round. After the experiment, participants were rewarded with a monetary incentive, US$7.50 for participation and the three best students were rewarded with a special price (Billinger et al. 2014).

The goal of the experiment is to figure out how alternative organisations would move on search spaces with different complexities, with local peaks posing a challenge to the process of local search. This process might be challenging to rationally bounded actors that might fail in overcoming these local optima and will not be able to find the global maximum peak (Knudsen and Levinthal 2007).

4.1 Main empirical findings of The Alien Game

One main finding of The Alien Game is the fact that search behaviour gradually adapts to performance feedback. The more complex the landscape becomes, the more feedback agents receive influencing them, which has further impact on search behaviour. The more rounds agents play, the better, on average, their performance becomes.

Furthermore, the complexity of the landscape and the performance difference are highly significant. In a smooth landscape, more than 57% of participants found the global optimum while only 1.6% reached the global optimum in the intermediate landscape and nobody was able to find it in the complex landscape (Billinger et al. 2014). Further, the search strategy does significantly differ between the three complexities. In the landscape with K = 0, local search was most prominent while in the landscape with K = 5, human participants did not follow a local search strategy which would have been the better option. This might indicate that agents decided for an inefficient search strategy. In the landscape with K = 9, human participants performed better than local search strategy, suggesting that human search behaviour is more varied than local search and a combination, meaning a balance between exploration and exploitation, is the best strategy to choose here.

The difference between local and distant search was measured by measuring the number of changes an agent made from one round to another and is called the search distance. The measure is discrete and ranges from 1 (change of one attribute) and 10 (change of all attributes), allowing for a precise analysis of search behaviour. In their experiment, Billinger et al. (2014) use the Hamming Distance (Hamming 1950) to measure the search distance. It measures the number of changed attributes from one round to another by comparing two strings and identifying how many attributes have changed. This search distance measure is widely used in strategy literature (Frenken 2006; Vuculescu 2017; Ghemawat and Levinthal 2008; Khraisha 2019; Vuculescu 2017). The analysis of search distance shows that it is highest in the intermediate landscape, meaning that exploration was a predominant search strategy. Agents tend to start with a distant search in the beginning and shift towards local search within later rounds when success-induced feedback leads to this strategy (Billinger et al. 2014).

As feedback influences search behaviour, feedback itself is influenced by task complexity and different fitness landscapes will lead to different search strategies. Simple landscapes allow for local search, changing one attribute only, and indeed, this strategy is quite predominant since no local optima exist, and the fear of being trapped on a local optimum is obsolete. Very distant search, however, is quite rare and instead, agents occupy an intermediate instance of distant search, changing between three and eight attributes. Very distant search, changing nine or ten attributes, allows for more risk and failure but can also lead to higher outputs (Billinger et al. 2014).

Even though local search might be the best solution in simple landscapes, human agents tend to outbreak and engage in exploration even here while in highly complex landscapes this approach might lead to better results since local search endangers being trapped on local peaks. In intermediate complexity tasks, a mix between those two extremes might be the only optimal solution (Billinger et al. 2014). An explanation for such a search behaviour can be given by Prospect Theory (Kahneman and Tversky 1979): As exploration is riskier than exploitation, the reference points given drive risk attitude.

4.2 Implications of The Alien Game

A major success of the Alien Game is that it fosters theoretical results in search behaviour literature. The Alien Game confirms that performance increases with the number of search trials, and task complexity and the associated feedback lower performance since the identification of improvements becomes more difficult. Interestingly, human participants do only outperform a local strategy in high complexity tasks. In simple tasks, they break off the pure local search – which is the best strategy – and tend to explore the landscape rather than exploit (Billinger et al. 2014).

Further, the Alien Game emphasizes the importance of search distance as it indicates and gives further insights into how subjects try to find better-performing combinations on a performance landscape. This behaviour is significantly influenced by the feedback agents receive and thus linked to the complexity of a task (Billinger et al. 2014). When feedback does not correspond with expectations, human subjects might become impatient, supporting the results of the Alien Game, and explaining why human agents perform poorly in simple and intermediate complexity tasks. At the beginning of the search trials, performance improvements are frequent and thus trigger local search. Agents then broaden the search distance as a response to negative feedback which is more common in later trials, making it more challenging to identify performance-improvements (Billinger et al. 2014).

The search behaviour further is highly influenced by the starting position of an agent (reference point). Giving agents a reference point in the beginning or leaving them the possibility to choose their starting position will have a significant effect on the results of the feedback and, thus, the search behaviour.

4.3 Limitations of The Alien Game

However, the Alien Game also encounters several limitations. No prior knowledge could be used to solve the task (Gavetti and Levinthal 2000), which is a considerable limitation in terms of drawing on reality. Same can be said about the complete isolation in which players engage. Further, information about the search space can profoundly influence search behaviour. Repeating the experiment and, for instance, giving participants an idea about the complexity of relative instead of absolute payoff information, might lead to entirely different results. Future experiments might also want to choose different levels of complexity and decision variables (Page 1996). Since search behaviour significantly changed in later search trials, this parameter could be another independent variable to observe. Negative feedback is more prevalent with increasing task complexity and makes it more difficult to identify better alternatives, supporting theoretical findings of the relationship between performance feedback and search behaviour (Billinger et al. 2014).

Controlling for task complexity, the lab-experiment serves as a basis for further experimental settings, focusing on different aspects. In the following, an adaptation of the Alien Game will be introduced, focusing on the manipulation of the subjects' search aim to evaluate whether this might affect search distance as a proxy for search behaviour.

5 Research gap and Hypotheses

Based on the experiment outlined by Billinger et al. (2014), the following thesis will compare the findings of the Alien Game and use their hypotheses as a foundation. This thesis aims to explore whether there are differences in performance and search distance, as a proxy for former, when agents are faced with different goals within the experiment. The primary question that arises here and differs from the original experiment thus focuses on whether the search aim (measured as *Type*) has an impact on search distance. Human agents do not only have individual approaches on how to reach the highest payoff but also businesses pursue different strategies and enforce aims that have to be pursued by teams or individuals. The tasks given are formulated vaguely with no quantitative goal defined, in order to avoid a given reference point (Locke and Latham 2012a) which makes the task hard to accomplish (Locke et al. 1981). While one group is trying to find the ultimate best innovation or develops a new product that has to meet specific needs and fit into a product line, a different group might pursue the strategy of finding multiple right combinations or services, that, in their sum, achieve the best possible outcome for, e.g. the customer. The subjects did not have all information necessary in order to accomplish the tasks easily, neither did they receive relative performance feedback. Further, we will compare results with those of the original Alien Game and evaluate whether feedback received, the number of unsuccessful trials, the trial number, prior payoff, the highest payoff reached, and previous search distance influence the dependent variable search distance (Billinger et al. 2014).

The main question that is pursued in Billinger et al. (2014) tries to evaluate how feedback conditions, based on a landscape's complexity, influence search behaviour, i.e. search distance, while the experiment outlined here will focus on the search aim and its impact on search behaviour and whether or not there is one. Keeping the landscape complexity constant, it is assumed that different search aims will influence the way how individuals maximise their payoffs and, respectively, how they move on the landscape since the relationship between goals and performance is moderated by performance feedback (Locke and Latham 2012a). Following Billinger et al. (2014), it is assumed that the agents' performance will increase with the number of search trials. Subjects learn from their prior search and adapt behaviour to reach a maximum payoff that becomes their new reference point. This implies that the number of unsuccessful trials, a further feedback variable, might also influence the search distance. The more rounds an agent plays and the more or less unsuccessful rounds have been played, i.e. the more rounds pass by since a new reference point is found, the more feedback is received, which will impact the search distance, ultimately. Feedback has a significant influence and meaning in this setup, as has been proved by Billinger et al. (2014). In their original Alien Game, feedback from prior search trials influences the decision where to search, which leads to an adaptation in search behaviour according to the tasks' complexity. The feedback received is encoded as success or failure based on a reference point that is decoded into exploitative, more local search or exploratory, more distant search. It is thus central to observe whether the feedback received will not only have a significant influence on search behaviour in landscapes of different complexities. Instead, we will focus on whether feedback influences search behaviour when the initial aim of maximising payoff differs. While encoding feedback, human participants will always compare their current and prior results to each other, keeping in mind both, the previous combination chosen, and the preceding payoff received and connected to a particular combination. In the Alien Game, Billinger et al. (2014) observe that agents use an adaptive search strategy to move through the landscape and assume a path-dependent search behaviour by testing whether prior search distance influences search behaviour.

6 Methodology

The experiment outlined differs in the sense that the variable controlled is not the underlying complexity of the landscape (Billinger et al. 2014). Instead, this variable is kept constant, and the experiment is manipulated by defining and communicating two different search aims. Subjects assigned to type 1 are asked to discover the maximum single payoff, better said, playing the best round, while individuals in the second group want to discover the maximum aggregated payoff. Subjects belonging to type 2 not only see the payoff per round but are displayed a cumulated payoff which is missing for type 1 subjects. The variable *Search Distance* is used as a proxy to describe the subjects' performance. We want to evaluate what behavioural regularities influence what search distance is used.

6.1 Variables

By carrying out the experiment, we want to measure the subjects' performance and observe whether differences in the frontend and in the instructions have an impact on this variable. Performance is the single outcome variable of an NK model and is measured absolutely in this setup, with no relative information and thus no given reference points but their own. The ordinal variable *Total Payoff* will be measured as the cumulated payoff of all rounds. To compare both experiments, Billinger et al.'s (2014) variables were replicated in this setup as much as possible. Table 1 gives an overview of all variables used in both configurations and shows possible differences. The dependent variable that is observed is the *Search Distance*, used as a proxy for performance and thus payoff, calculated based on the Hamming Distance (Hamming 1950). This distance measure is frequently used in organisational search literature (Billinger et al. 2014; Vuculescu 2017; Ghemawat and Levinthal 2008; Khraisha 2019; Frenken 2006; Levinthal 1991; Rivkin and Siggelkow 2002; Rivkin 2000; Vuculescu 2017).

The Hamming Distance examines how many attributes have changed from one string to another. Based on this calculation, the *Search Distance* employed here compares the number of changes attributes with the search distance matching the highest-performing combination identified so far. In addition to Billinger et al. (2014), we computed two *Search Distance* variables with discrete values ranging from 0 to 10, called *Adjusted Search Distance*, and 1 to 10, called *Billinger Search Distance*, as we consider no change as pure exploitation, a strategic move for which the agents decide not to change any attributes. The key independent variable *Complexity* in the original Alien Game was replaced by focusing on the agents' search aim, equivalent to the *Type* they have been assigned to and distinguishes between two different performance feedback types. The agents' *Performance* is based on the input that corresponds with the highest payoff the subject has achieved so far, using the variable *Highest Payoff* as an auxiliary that can be translated into the reference point which influences human agents' behaviour. By calculating the previous highest payoff, it is possible to elaborate on whether *Feedback*, as a variable, has an impact on search behaviour. This variable is binary, taking the value 0 when the subject fails to improve in the previous round and 1 when he succeeds. In literature, feedback is considered to substantially influence search behaviour (Billinger et al. 2014). By encoding feedback into success or failure, different behavioural patterns can be observed, such as exploitative and explorative behaviour. As in the first round, no feedback can be derived from previous payoffs and experiences, there is no value calculated. The *Number of unsuccessful trials* helps us to associate how many rounds have passed since the subject's las performance-improvement. This binary variable is 0 if success is experienced and 1 if failure, i.e. no performance improvement, is experienced. Like *Feedback*, the first round has no values, and the variable starts in round 2.

Further auxiliary variables are calculated such as P*rior payoff*, measuring the payoff of the previous round as it is assumed that individuals use the payoff received in the last round to evaluate success and failure and compare it to their reference point, the *Highest Payoff* achieved so far (Billinger et al. 2014). Correspondingly, since the last input combination is displayed, the variable *Prior search distance* is calculated as the search distance from the previous round. Complementary to Billinger et al. (2014), here again, two variables, the *Adjusted Search Distance*, ranging from 0 to 10, and the *Billinger Search Distance*, ranging from 1 to 10, are calculated. The variable *Round number* is one basis of these calculations and helps us follow the agents' progress within the experiment, ranging from 1 to 30. Lastly, we dropped the variable *Task Position* used in the original setup since there is only one experiment outlined.

Coming back to search behaviour and search distances, Billinger et al. (2014) categorise this variable into so-called local search, whenever subjects only change one attribute, intermediate instances of distant search when 3 to 8 attributes are changed, and very distant search whenever subjects decide to change 9 or 10 attributes at once. As an extension, we will add two further categories: Pure exploitation is measured each time a subject does not change an attribute, and we call search behaviour for subjects that change two attributes low instances of distant search.

Table 1 Overview of variables

Variables used in The Alien Game (Billinger et al. 2014)	**Variables used here**	**Explanation**
Search Distance	Search Distance	Number of changed attributes compared with the highest-performing combination identified, thus, based on the performance variable. Ranging from 0 to 10 (Adjusted Search Distance), and 1 to 10 as in Billinger et al. (2014) (Billinger Search Distance)
Complexity	Search aim / type	Key independent variable *Type* instead of complexity Distinguishes between two different search aims and changes in the frontend for each type.
Performance	Performance	Input based on respective highest-performing combination identified by a subject in prior rounds
Feedback	Feedback	Failure to improve in the previous round = 0, success = 1
Highest Payoff	Highest Payoff	Highest payoff a subject has identified so far Interpreted as a subject's reference point
Number of unsuccessful trials	Number of unsuccessful trials	Number of rounds since the subject has achieved the last maximum payoff
Prior Payoff	Prior Payoff	Performance in the previous round
Prior Search Distance	Prior Search Distance	Search distance in the previous round Ranging from 0 to 10, instead of 1 to 10 as in Billinger et al. (2014)
Trial number	Round number	Number of completed rounds
Task position	-	Not applicable
-	Pure Exploitation	Search distance = 0
Local Search	Local Search	Search distance = 1
-	Low instances of distant search	Search distance = 2
Intermediate instances of distant search	Intermediate instances of distant search	Search distance = 3-8
Very distant search	Very distant search	Search distance = 9-10

Note. Adapted from "Search on Rugged Landscapes: An Experimental Study", by S. Billinger, N. Stieglitz and T. R. Schumacher, 2014, *Organization Science*, 25 (1), pp. 93–108.

6.2 Experimental Design

The lab-experiment is based on the design carried out by Billinger et al. (2014). In the backend, an NK fitness landscape was used. In the frontend, participants were confronted with a similar design as in the original Alien Game (Billinger et al. 2014). The goal is to examine performance and search behaviour in two different settings, which is why participants were assigned a type. Type 1 was asked to find the best performance out of all rounds while type 2 was asked to reach the highest cumulated payoff possible. The original Alien Game was adapted in the sense that we differentiate between two types that have different aims within the game, thus, creating an in-between setup and controlling for search aim rather than complexity, while the complexity of the task and the order and number of items within the game was held constant for both settings. Both types were given ten items in each round, and they did not know about payoffs and global or local optima or other key parameters. This thesis was written during the Covid-19 outbreak in 2020, which thus lead the experiment to be carried out remotely. Participants received the experiment via email, including an explanation and guidelines on how to start the experiment. The experimental lead was available at all time during the time the subjects carried out the experiment to answer any questions that may arise.

Participants were asked to play 30 instead of 25 rounds to ensure that learning behaviour can be observed. The setup starts with an introduction and explanation of the goal of the game, which was different and explicit for both types. As a reminder, the type's aim was displayed a second time after round 15. The payoff function changed neither during the game nor between games. After each round, subjects were able to see their previous inputs and combination as well as the respective payoff.

Type 1 was asked to play the best round, which implied that they were only able to see respective payoffs per round. In contrast, type 2 was asked to play the best overall game. They aimed to maximise their total, cumulated payoff and was thus able to see this cumulated payoff throughout the whole game in addition to the payoff per round.

In total, 40 subjects participated in this experiment. Further, subjects were drawn from a sample pool with similar educational background and age. This relatively small sample size and their resemblance might pose limitations to the validity of the results and should be taken care of in a repetition of this experiment. Further, no monetary incentive was given out as a result of performance, but instead, participation was based on reciprocity which might have an impact on the seriousness of participation and bias results. The results were extracted from the ztree output, merged into one file, and imported to STATA for further analysis.

7 Results

This section gives an overview of the results of the replicated Alien Game in comparison to the original (Billinger et al. 2014) with the search aim as the key independent variable.

7.1 Search behaviour and performance

What immediately stands out is that on first sight, search behaviour seems quite similar for both types of experiments. Figure 2 shows the average performance for the experimental tasks when controlling for task complexity, while Figure 3 shows the same performance measure based on the two different search aims. For both, the average performance increases with the number of search trials. We use the respective highest-performing combination identified in previous rounds to measure performance. The performance after each session between both types differs and is slightly higher for type 2 subjects. The average total payoff reached in the type 1 setting is 15.29 and 15.57 in the second group. However, there is no significant difference between both search aims with regard to total achieved payoff.

Further, it is interesting to observe where in the landscape subjects have ended their search trial. While only one out of 20 type 1 subjects has finished on the global optimum, type 2 subjects performed slightly better (3 subjects). No type 1 subjects ended their search on the second-best option while two subjects of the second group found their end at this option. Compared to Billinger et al. (2014), the subjects in this setup performed poorly.

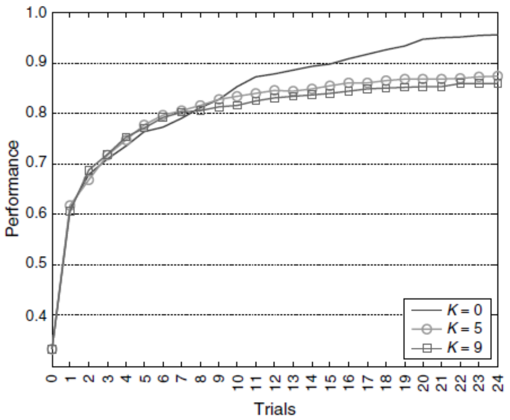


Figure 2 Average Performance in the Experimental Task. Reprinted from Search on Rugged Landscapes: An Experimental Study, by Billinger et al., 2019.

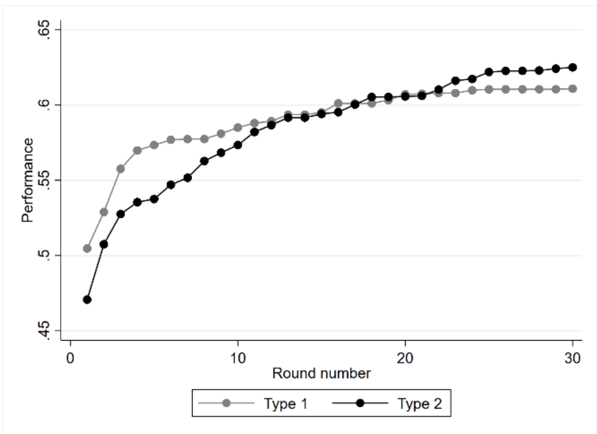
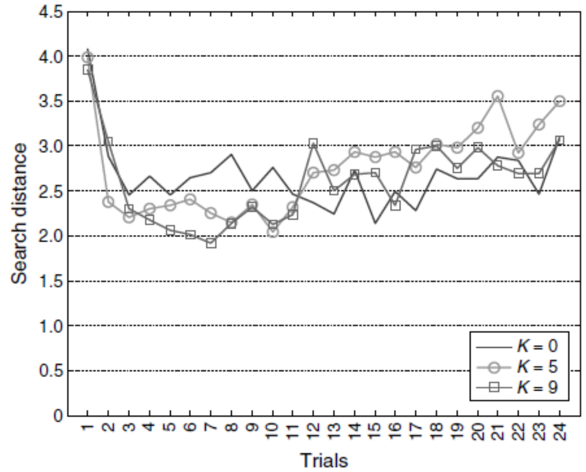


Figure 3 Average Performance in the Experimental Task with Search Aim as the key independent variable

The primary variable we focus on is the search distance, which describes how agents reached the respective payoffs and can thus be seen as a proxy for performance. Using this variable, we can observe how individuals move through the landscape and eventually extract patterns. The search distance is measured in two different ways: The first measure – *Billinger Search Distance* – ranges from 1 to 10 and only takes into account changes. The second measure – *Adjusted Search Distance* – ranges from 0 to 10 and takes into account changes (positive values) as well as no changes (search distance = 0) which occurs whenever a subject decides not to move on the landscape but “purely exploit”. We have mapped both search distances over time and compare it with the results from Billinger et al. (2014).



Note. The search distance is measured as the number of attributes changed in a trial relative to the best-performing combination of a decision maker.

Figure 4 Search Behaviour Over Time in The Alien Game. Reprinted from Search on Rugged Landscapes: An Experimental Study, by Billinger et al., 2019.

Figures 4, 5 and 6 show the search behaviour of subjects over time. In Figure 4 and 5 the same search distance, ranging from 1 to 10, is used to describe search behaviour. While for type 1 in Figure 5, a similar course can be observed, the search behaviour for type 2 seems to differ and decrease over time.

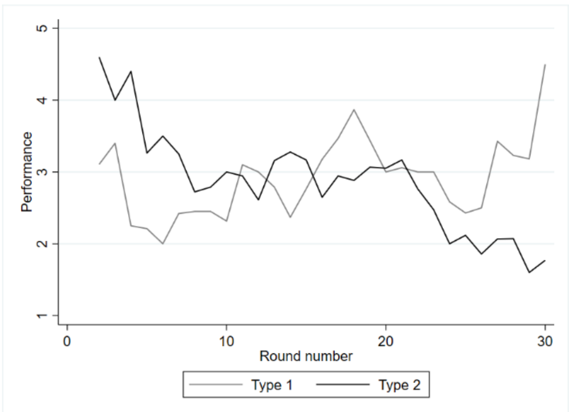


Figure 5 Search Behaviour Over Time using the Billinger Search Distance

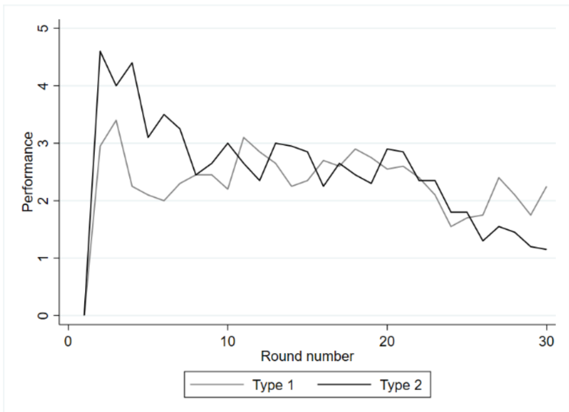


Figure 6 Search Behaviour Over Time using the Adjusted Search Distance

Comparing Figures 5 and 6, we observe that both, the starting and endpoints, for both types differ in Figure 6, but the course seems similar. For both, it is apparent that the average search distance is higher than it would be with a purely local strategy (search distance = 1) which is consistent with the results of Billinger et al. (2014). Table 2 gives an overview of the descriptive statistics of the two search measures used. For type 1, the average *Billinger Search Distance* is 2.86 (with a standard deviation of 2.02) while the *Adjusted Search Distance* is lower at 2.31 (with a standard deviation of 2.13). The search distances increase for type 2 subjects: The *Billinger Search Distance* reports an average search distance of 2.93 (with a standard deviation of 2.08) and the *Adjusted Search Distance* shows an average of 2.50 (with a standard deviation of 2.18). In general, not comparing between the types, the search distance reported by the *Billinger Search Distance* is higher with an average of 2.90 (*Adjusted Search Distance* average 2.41).

Table 2 Summary Statistics of Search Distance Measures

Summary Statistics	Observations	Mean	Std. Dev.	Min	Max
Billinger Search Distance					
- *overall*	998	2.895792	2.046883	1	10
- *Type 1 subjects*	485	2.861856	2.017355	1	10
- *Type 2 subjects*	513	2.927875	2.075871	1	10
Adjusted Search Distance					
- *overall*	1,200	2.408333	2.158428	0	10
- *Type 1 subjects*	600	2.313333	2.13528	0	10
- *Type 2 subjects*	600	2.503333	2.178968	0	10

Note. Values presented are computed using StataCorp. 2019. Stata Statistical Software: Release 16. College Station, TX: StataCorp LLC.

The following tables 3, 4 and 5 give us an overview of the details of search behaviour showing the frequency distribution of search distances. Comparing the three frequencies, we observe three different search patterns: In the original Alien Game, human searchers tend to start with distant search in the first trial and narrow down in later trials (Billinger et al. 2014). By controlling for search aim rather than complexity, we observe different search patterns. Using the *Billinger Search Distance*, a cyclic search behaviour can be observed in which subjects tend to start with distant search changing three to four attributes at once, narrowing down, exploring again and moving back towards more local search in later trials (for more information see Figures 10-15, Appendix 3). When considering the *Adjusted Search*

Distance, the search pattern starts with intermediate instances of distant search, changing three attributes, which narrows down to local search toward the end. The average search distance in round two for the first search distance measure is at 3.87 and only slightly lower, 3.78, for latter.

Further, we can observe a temporal pattern in search behaviour that differs between the two types. For both search distance measures, search appears to become more local again in later search trials for type 2, while it becomes more distant for type 1. Overall, local search (changing one attribute) is the predominant search strategy not only in the original Alien Game (36.6%) but also in this setup when looking at both, the *Billinger Search Distance* (31.13%) and the *Adjusted Search Distance* (25.92%). The second most popular search strategy is to change only two attributes (Alien Game: 27.25%; Billinger Search Distance: 24.89%; Adjusted Search Distance: 20.67%), while "pure exploitation", changing 0 attributes which can only be measured using the *Adjusted Search Distance*, is on the third place of most common search strategies (16.84%).

The strategy of local search is especially pronounced for type 2 subjects while pure exploitation is more common for type 1 than for type 2 subjects. Intermediate instances of distant search are a common strategy for type 2 subjects, and very distant search is pronounced for type 1 subjects. It seems that type 1 subjects are engaging in a mix of more extreme search strategies, moving between exploitation and very distant search, even though latter is quite rare, while type 2 subjects level off in intermediate instances of distant search, changing between 3 and 8 attributes. Overall we can observe that search strategies are quite varied – in the original as well as in the replicated experiment.

Table 3 Frequency Distribution of Search Distances in the Alien Game

	Task complexity (*K*)							
	0		5		9		Average	
Search distance	Frequency (%)	Cumulative frequency (%)	Frequency (%)	Cumulative frequency (%)	Frequency (%)	Cumulative frequency (%)	Frequency (%)	Cumulative frequency (%)
1	40.94	40.94	35.04	35.04	33.85	33.85	36.61	36.61
2	25.56	66.50	26.30	61.34	29.90	63.75	27.25	63.86
3	8.47	74.97	10.22	71.56	11.26	75.01	9.98	73.85
4	6.46	81.43	10.74	82.30	11.40	86.41	9.53	83.38
5	7.06	88.49	7.19	89.49	5.26	91.67	6.50	89.88
6	4.46	92.95	5.33	94.82	3.80	95.47	4.53	94.41
7	2.23	95.18	2.37	97.19	2.34	97.81	2.31	96.73
8	1.04	96.22	1.26	98.45	0.66	98.47	0.99	97.71
9	2.30	98.52	0.81	99.26	0.80	99.27	1.30	99.02
10	1.49	100.00	0.74	100.00	0.73	100.00	0.99	100.00

Note. The search distance is measured as the number of attributes changed in a trial relative to the best-performing combination of a decision maker.

Note. Reprinted from Search on Rugged Landscapes: An Experimental Study, by Billinger et al., 2014.

Table 4 Frequency Distribution of Search Distance using the Billinger Search Distance

	Type					
	1		2		Average	
Search Distance	Frequency (%)	Cumulative frequency (%)	Frequency (%)	Cumulative frequency (%)	Frequency (%)	Cumulative frequency (%)
1	30,10	30,10	32,16	32,16	31,13	31,13
2	26,39	56,49	23,39	55,55	24,89	56,02
3	14,43	70,92	12,28	67,83	13,36	69,38
4	10,52	81,44	10,53	78,36	10,53	79,90
5	7,63	89,07	8,38	86,74	8,01	87,91
6	4,12	93,19	6,04	92,78	5,08	92,99
7	2,27	95,46	3,90	96,68	3,09	96,07
8	2,47	97,93	1,75	98,43	2,11	98,18
9	1,24	99,17	0,19	98,62	0,72	98,90
10	0,82	100,00	1,36	100,00	1,09	100,00

Note. Values presented are computed using StataCorp. 2019. Stata Statistical Software: Release 16. College Station, TX: StataCorp LLC.

Table 5 Frequency Distribution of Search Distance using the Adjusted Search Distance

	Type					
	1		2		Average	
Search Distance	Frequency (%)	Cumulative frequency (%)	Frequency (%)	Cumulative frequency (%)	Frequency (%)	Cumulative frequency (%)
0	19,17	19,17	14,50	14,50	16,84	16,84
1	24,33	43,50	27,50	42,00	25,92	42,75
2	21,33	64,83	20,00	62,00	20,67	63,42
3	11,67	76,50	10,50	72,50	11,09	74,50
4	8,50	85,00	9,00	81,50	8,75	83,25
5	6,17	91,17	7,17	88,67	6,67	89,92
6	3,33	94,50	5,17	93,84	4,25	94,17
7	1,83	96,33	3,33	97,17	2,58	96,75
8	2,00	98,33	1,50	98,67	1,75	98,50
9	1,00	99,33	0,17	98,84	0,59	99,09
10	0,67	100,00	1,17	100,00	0,92	100,00

Note. Values presented are computed using StataCorp. 2019. Stata Statistical Software: Release 16. College Station, TX: StataCorp LLC.

Descriptive statistics give us further insight on search behaviour. We can observe that average performance increases with the number of search trials. Subjects aiming to reach the highest cumulative payoff (type 2) perform comparatively better than subjects that want to play the best round (type 1). Further, similar to the findings of Billinger et al. (2014), performance increases with the number of search trials, but marginal gains decrease over time.

7.2 Regression Analysis

The search distance is treated as the dependent variable. We want to evaluate whether the search aim influences the search distance of subjects and if other variables, such as feedback, have an impact on search behaviour. The search distance is a discrete count variable that is computed in two different ways, ranging from 1 to 10, and from 0 to 10, based on the number of attributes changed (see tables 6 and 7). The average search distance is 2.90 when using the *Billinger Search Distance* and slightly lower (2.41) for the *Adjusted Search Distance*. Both are non-normally distributed.

Table 6 Variables and Descriptive Statistics in The Alien Game

Variable	Type	Min	Max	Mean	Std. dev.	Explanation
Feedback	Discrete	0	1	0.21	0.41	Failure to improve in the previous trial is coded with 0, success with 1
Highest payoff	Scale	0.31	1.00	0.79	0.15	Highest payoff that subject has identified so far
Complexity ($K = [0, 5, 9]$)	Discrete	0	9	—	—	Task complexity, where 0 = simple, 5 = intermediate, 9 = high complexity
Number of unsuccessful trials	Discrete	0	21	4.03	4.54	Number of trials since the subject has achieved the last maximum payoff
Prior payoff	Scale	0.31	1	0.67	0.14	Performance in the prior trial
Prior search distance	Discrete	1	10	2.64	2.02	Search distance in the prior trial
Search distance	Discrete	1	10	2.65	1.99	Number of changed attributes (Hamming distance)
Task position	Discrete	1	3	—	—	Sequence of search tasks (session with 24 trials)
Trial number	Discrete	1	24	—	—	Number of completed trials

Note. Reprinted from Search on Rugged Landscapes: An Experimental Study, by Billinger et al., 2014.

Table 7 Variables and Descriptive Statistics

Variable	Type	Min	Max	Mean	Std. Dev.	Explanation
Feedback	Discrete	0	1	0,12	0,33	Failure to improve in the previous trial is coded with 0, success with 1
Highest Payoff	Scale	0,32	0,71	0,59	0,05	Highest payoff that subject has identified so far
Type / Search Aim	Discrete	1	2	-	-	Search aim, where 1 is aiming for the best round, and 2 is aiming for highest total payoff
Number of unsuccessful trials	Discrete	0	29	7,20	6,78	Number of trials since the subject has achieved the last maximum payoff
Prior payoff	Scale	0,31	0,71	0,59	0,05	Performance in the prior trial
Prior Billinger Search Distance	Discrete	1	10	2,89	2,05	Search distance in the prior trial
Prior Adjusted Search Distance	Discrete	0	10	2,43	2,15	Search distance in the prior trial
Billinger Search Distance	Discrete	1	10	2,90	2,05	Number of changed attributes (Hamming distance)
Adjusted Search Distance	Discrete	0	10	2,41	2,16	Number of changed attributes (Hamming distance)
Trial Number	Discrete	1	30	-	-	Number of completed trials

Note. Values presented are computed using StataCorp. 2019. Stata Statistical Software: Release 16. College Station, TX: StataCorp LLC.

Therefore, and to compare our data with the original setup, we use a Poisson regression model with robust estimators to examine the determinants of search distance. Similar to Billinger et al. (2014), four models were computed using the Poisson regression. As the variance of the dependent variable is higher than the mean, a test for overdispersion was outlined, by running a negative binomial regression. The results were qualitatively similar, and because of model quality, the Poisson regression was chosen. Model 1 examines how the key independent variable *Search Aim* influences the search distance. The variable task sequence is omitted in this setup as only one task is performed, but we control for the number of rounds played. The second model focuses on the role of feedback and its possible impact on search distance. The feedback variable is computed using a reference point, which is the highest payoff that has been identified by a subject so far and is compared with the current payoff received. The subject either experiences positive (improvement) or negative (failure) feedback, and according to Billinger et al. (2014) will adapt search behaviour accordingly. Model number three and four add additional feedback variables to check whether further information during the search process influences the search distance in the two settings. The *number of unsuccessful trials* observes the number of rounds since a performance improvement. The variable *prior search distance* in model 4 is the search distance from the previous round and split into two variables, based on the search distance used as a basis.

Further information on the variables used in the models is available in Table 7. Table 6 serves as a reference and is transferred from the original Alien Game (Billinger et al. 2014) to compare how variables should be computed in this setup and give an overview of possible differences. Tables 8, 9 and 10 show the results of the Poisson regression. While Table 8 shows the results of the original Alien Game, Table 9 and 10 offer insight into the results of the replicated setup for both search distances used.

Table 8 Poisson Models with Search Distance as the Dependent Variable from The Alien Game

	Model 1	Model 2	Model 3	Model 4
Complexity ($K = 5$)	0.028	0.000	−0.033	0.002
	(0.032)	(0.032)	(0.032)	(0.032)
Complexity ($K = 9$)	−0.019	−0.053	−0.113***	−0.021
	(0.027)	(0.027)	(0.027)	(0.027)
Feedback		−0.391***	−0.379***	−0.376***
		(0.030)	(0.030)	(0.030)
Number of unsuccessful trials			0.064***	0.027***
			(0.003)	(0.003)
Prior search distance				0.161***
				(0.004)
Trial number	0.011***	0.001	−0.031***	−0.013***
	(0.002)	(0.002)	(0.002)	(0.002)
Task position 2	−0.046	−0.046	−0.066*	−0.029
	(0.027)	(0.027)	(0.027)	(0.027)
Task position 3	−0.038	−0.027	−0.018	−0.025
	(0.027)	(0.027)	(0.027)	(0.027)
Constant	0.826***	1.055***	1.215***	0.597***
	(0.033)	(0.039)	(0.040)	(0.043)
Deviance	4,662	4,479	4,007	2,781
Log likelihood	−7,407	−7,315	−7,079	−6,466
Pseudo-R^2	0.0112	0.0503	0.1503	0.4103
No. of observations	3,835	3,835	3,835	3,835

Note. Poisson regressions with robust estimators. Standard errors are reported in parentheses. Observations include all trials with a positive search distance after the first trial. Models 2–4 control for individual fixed effects. Pseudo-R^2 computed is based on the deviance (see Cameron and Windmeijer 1996).
$*p < 0.05$; $**p < 0.005$; $***p < 0.001$.

Note. Reprinted from Search on Rugged Landscapes: An Experimental Study, by Billinger et al., 2014.

Table 9 Poisson Models with Billinger Search Distance as the Dependent Variable

	Model 1	Model 2	Model 3	Model 4
Search Aim	0.028 (0.045)	0.035 (0.045)	0.089* (0.044)	0.021 (0.039)
Feedback		-0.118 (0.072)	0.036 (0.078)	-0.041 (0.076)
Number of unsuccessful trials			0.030*** (0.005)	0.017*** (0.004)
Prior search distance				0.148*** (0.009)
Round number	-0.008** (0.003)	-0.009** (0.003)	-0.021*** (0.003)	-0.007* (0.003)
Constant	1.144*** (0.076)	1.166*** (0.078)	1.034*** (0.079)	0.542*** (0.078)
Deviance	1,2280	1,275	1,223	781
Log likelihood	-2,015	-2,013	-1,987	-1,654
Pseudo-R²	0.0034	0.0045	0.0176	0.0985
No. of observations	998	998	998	916

Note. Poisson regressions with robust estimators. Standard errors are reported in parentheses. Observations include all trials with a positive search distance after the first trial. Models 2-4 control for individual fixed effects. According to the Goodness-of-Fit test, the Poisson model was rejected (excluding model 4) but still applied due to comparison reasons.
* $p < 0.05$; ** $p < 0.005$; *** $p < 0.001$
Values presented are computed using StataCorp. 2019. Stata Statistical Software: Release 16. College Station, TX: StataCorp LLC.

Table 10 Poisson Models with Adjusted Search Distance as the Dependent Variable

	Model 1	Model 2	Model 3	Model 4
Search Aim	-0.079 (0.051)	0.082 (0.049)	0.107* (0.049)	0.033 (0.046)
Feedback		-0.046 (0.073)	-0.002 (0.078)	0.009 (0.080)
Number of unsuccessful trials			0.009 (0.005)	0.003 (0.005)
Prior search distance				0.160*** (0.011)
Round number	-0.015*** (0.003)	-0.024*** (0.003)	-0.027*** (0.004)	-0.018*** (0.004)
Constant	0.980*** (0.087)	1.153*** (0.085)	1.105*** (0.087)	0.645*** (0.090)
Deviance	2,308	2,052	2,046	1,601
Log likelihood	-2,529	-2,401	-2,399	-2,176
Pseudo-R²	0.0101	0.0227	0.0238	0.1144
No. of observations	1,200	1,160	1,160	1,160

Note. Poisson regressions with robust estimators. Standard errors are reported in parentheses. Observations include all trials. Models 2-4 control for individual fixed effects. According to the Goodness-of-Fit test, the Poisson model was rejected but still applied due to comparison reasons.
* $p < 0.05$; ** $p < 0.005$; *** $p < 0.001$
Values presented are computed using StataCorp. 2019. Stata Statistical Software: Release 16. College Station, TX: StataCorp LLC.

Model 1 reveals that the search aim has no significant impact on the search distance while the number of rounds played does. Model 2 takes feedback into account and shows that the variable *Feedback* is not significant, while the *number of rounds played* still has a significant impact on the search distance. The third model includes the feedback measure *Number of unsuccessful trials*. Using the *Billinger Search Distance*, the Poisson model shows significance of this variable while this is not the case when using the *Adjusted Search Distance*. Model 4 adds another feedback measure, the *prior search distance*, showing significant results for both search distance measures. The *number of rounds played* has a significant influence on all four models for both search distance measures. It is to remark that the Poisson model does not seem like the appropriate model to choose according to tests. However, this model is used for the sake of comparison with the original Alien Game outlined by Billinger et al. (2014).

When comparing the results with the original, it is evident that while the variable *Feedback* has a significant impact in the original Alien Game, the replicated experiment does not show such an outcome. Instead, the additional feedback measures seem to have an effect on the search distance as well as the *number of rounds played*. Focusing on the *Billinger Search Distance*, the *number of unsuccessful trials*, and the *prior search distance* both have a positive impact on search behaviour which supports the results from Billinger et al. (2014). The more unsuccessful trials are experienced, the more the subjects broaden their search space and explore instead of exploit. Looking at the Poisson model using the *Adjusted Search Distance*, only the feedback variable *Prior search distance* has a significant, positive impact on the search distance. This result in model 4 is consistent with the findings of Billinger et al. (2014), showing strong evidence for path dependency, as the previous search distance has a positive impact on the search distance. The key independent variable *Search Aim* only shows significance in model 3 while in all other models, other variables influence search behaviour. Contradicting to the findings of Billinger et al. (2014), we observe that in the early search trials, distant search behaviour is predominant. Subjects explore the landscape, this is especially the case for type 2 subjects while type 1 subjects tend to more exploitative search behaviour. In later trials then, search narrows down. The highest search distances can be observed in the middle of the trials, again, especially for type 2 subjects. These agents start with explorative behaviour and narrow down search toward the end. This, again, contradicts the findings of Billinger et al. (2014), where subjects start with a somewhat local search, broadening search toward the end.

Figures 7, 8 and 9 give an overview of the effects measured in the Poisson regression. It shows how the prior search distance and feedback influenced the chosen search distance in each round. In Billinger et al.'s (2014) figure (Figure 7) it is visible that failure in the previous round induces explorative search behaviour, enlarging the search distance, while success in the last round induces exploitation. This pattern can also be observed in the replicated experiment, showing that failure in the previous round leads to more explorative search in the current round. This is especially the case when the search distance in the last round was more distant, i.e. seven or more. In such a case, subjects tend to explore the landscape in the next round. However, when failure is experienced after more local search, i.e. a search distance below four, the following search step is lower than for subjects who experience success when using the *Billinger Search Distance* as a measure. Considering the *Adjusted Search Distance*, we observe a similar pattern for failure-induced exploration but see differences when subjects experience success. In such a case, the search distance in the current round is, on average, higher to the search distance after experiencing failure, which contradicts the findings of Billinger et al. (2014). For more distant search in the previous round, the pattern converges and shows similar results in all three figures.

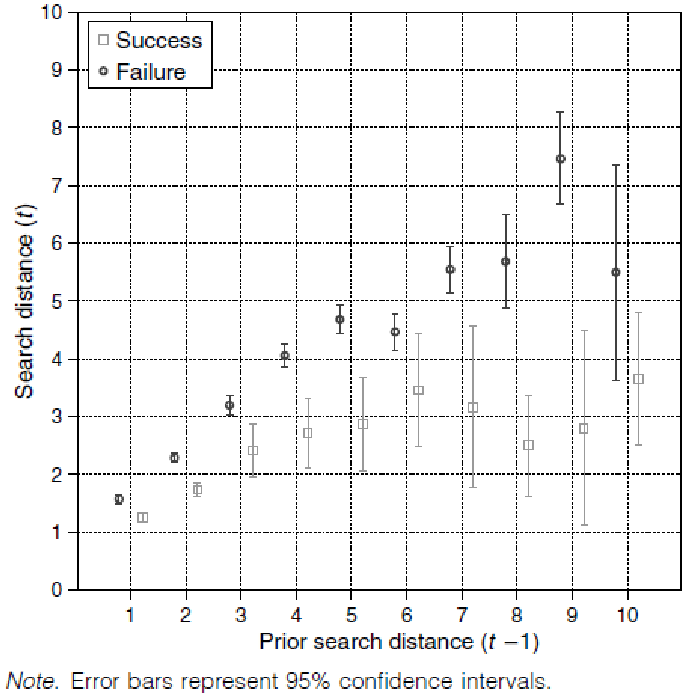


Figure 7 Summary of Main Effects in the Empirical Model of Adaptive Search in The Alien Game. Reprinted from Search on Rugged Landscapes: An Experimental Study, by Billinger et al., 2019.

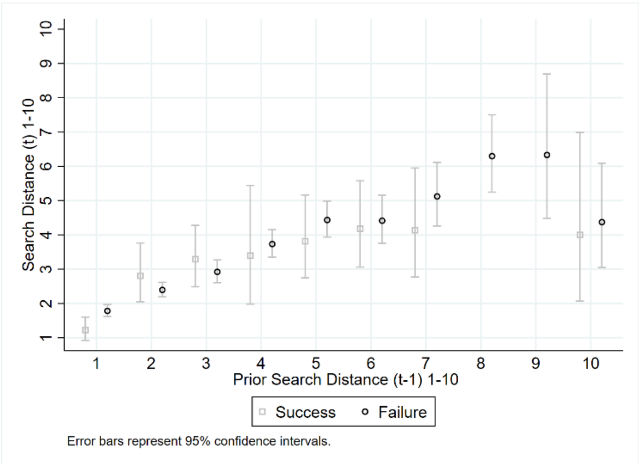


Figure 8 Summary of Main Effects in the Empirical Model of Adaptive Search using the Billinger Search Distance

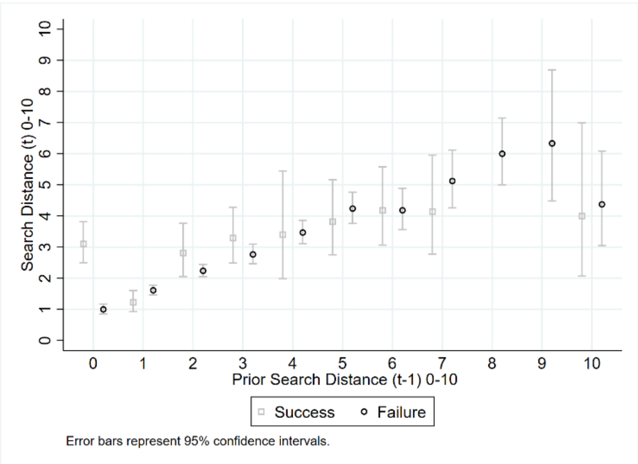


Figure 9 Summary of Main Effects in the Empirical Model of Adaptive Search using the Adjusted Search Distance

To go into more detail and further examine the feedback variables, additional regressions were run to evaluate a possible relationship between search aim and feedback (see tables 11 and 12). Table 11 gives an overview of the regression results reported in Billinger et al. (2014). Table 12 shows the results of the regression analysis using the feedback variables – *Feedback*, *Highest Payoff*, *Number of unsuccessful trials* – as the dependent variables to test whether the search aim and the round number influence feedback. As mentioned before, even though the search aim does not have a significant influence on the search behaviour, the search aim, however, is significant on all three feedback variables. The search aim positively influences feedback and thus, the rate of success, but reduces the highest payoff while simultaneously reducing the number of unsuccessful trials. The findings add to the fundamental relationship between performance feedback and search behaviour by showing how search aim systematically influences feedback conditions and enlarges the results of Billinger et al. (2014) by adding a new dimension.

Table 11 Task Complexity and Feedback Conditions in The Alien Game

	Feedback variables (dependent variables)		
Variables	*Feedback*	*Highest payoff*	*Number of unsuccessful trials*
Complexity (K)	−0.077*** (0.011)	−0.004*** (0.000)	0.029*** (0.0041)
Trial number	−0.160*** (0.007)	0.014*** (0.000)	0.152*** (0.0022)
Task position	0.122* (0.051)	−0.009*** (0.002)	−0.041* (0.0186)
Log likelihood/R^2/ pseudo R^2	3,626.63	0.439	0.4362
Number of observations	4,204	4,204	4,204

Notes. The analysis examines how task complexity influences feedback conditions. *Feedback* is a binary variable, and we used a logit regression. The continuous variable *highest payoff* was examined with an ordinary least-square (OLS) regression. The discrete variable *number of unsuccessful trials* was examined using a negative binomial regression.
*$p < 0.05$; **$p < 0.005$; ***$p < 0.001$.

Note. Reprinted from Search on Rugged Landscapes: An Experimental Study, by Billinger et al., 2014.

Table 12 Search Aim and Feedback Conditions

	Feedback variables (dependent variables)		
Variables	*Feedback*	*Highest Payoff*	*Number of unsuccessful trials*
Search Aim (Type)	0.570** (0.1889)	-0.006* (0.0027)	-0.440*** (0.0487)
Trial Number	-0.100*** (0.0126)	0.003*** (0.0002)	0.076*** (0.0032)
Log likelihood/R^2 / *pseudo R^2*	0.0923	0.2765	0.0764
Number of observations	1,160	1,200	1,160

Notes. The analysis examines how search aim influences feedback conditions. *Feedback* is a binary variable, and we used a logit regression. The continuous variable *highest payoff* was examined with an ordinary lead-square (OLS) regression. The discrete variable *number of unsuccessful trials* was examined using a negative binomial regression.
* $p < 0.05$; ** $p < 0.005$; *** $p < 0.001$
Values presented are computed using StataCorp. 2019. Stata Statistical Software: Release 16. College Station, TX: StataCorp LLC.

8 Discussion and Conclusions

The design of landscapes and its application in management literature help to understand how different organisational designs can influence behaviour. To understand how individual agents search on such a landscape and evaluate, which factors may influence the search behaviour, Billinger et al. (2014) created a lab experiment. By replicating the experimental design and changing the key independent variable, it is the aim to evaluate whether different measures may or may not influence the search behaviour of agents on a fitness landscape. In particular, the objective of this experiment is to examine how individuals search for performance improvements when controlling for different search aims and with this extend the original Alien Game (Billinger et al. 2014).

8.1 Critical assessment

The principal finding of the original Alien Game outlined by Billinger et al. (2014) is that search behaviour gradually adapts to performance feedback and task complexity does not have a direct effect on search behaviour. Instead, adaptive search behaviour is observed, i.e. failure-induced exploration and success-induced exploitation. By replicating the Alien Game and controlling for different search aims however, contradicting results were observed. When the search distance is high in the previous round, we observe failure-induced exploration and success-induced exploitation which is consistent with the results of Billinger et al. (2014). However, when prior search distance is narrower, we observe the opposite: success-induced exploration and failure-induced exploitation. The average search distance in the current round is higher when subjects experience success. Such a result may lead to overthinking the search pattern mentioned above. When subjects search more locally and experience success through this search behaviour, it seems that subjects want to mark the area of search and explore, how far away they can move from their reference value. Subjects that experience failure after a somewhat local search seem to exploit their neighbourhood more deeply to see whether or not there is another, more successful optimum in the neighbourhood. Going more into detail, we further observe difference in search behaviour over the two different types. Type 2 agents, trying to reach the highest cumulated payoff, engage, on average, in more explorative behaviour compared to type 1 agents and also their average payoff is higher, even though not significantly.

Further, more type 2 agents than type 1 agents were able to find the global optimum of the landscape. It seems that the search approach applied by type 2 subjects and lead by the search aim, lead to higher payoffs and thus, is more successful in the corresponding landscape. When comparing the search behaviour over time, we observe that the curve for type 1 agents is similar to the curve observed on the original alien game while the performance of type 2 agents over time differs. One possible reason for this deviation for type 2 agents might be, that the search aim chosen for type 1 agents and the initial task set up in the Alien Game was similar. To evaluate pure exploitation, i.e. a search distance of zero changes, we have created the *Adjusted Search Distance* measure which ranges from 0 to 10 while the here called *Billinger Search Distance* is similar to the search distance measure applied in the original Alien Game, ranging from 1 to 10. In the initial setup, we observe a search behaviour in which agents start with distant search and narrow down search in later trials. In the replicated setup, we can see a similar search pattern when using the *Adjusted Search Distance* measure for which individuals start with intermediate instances of distant search and narrow down in later trials. Examining the *Billinger Search Distance,* we can observe cyclic, a so-called Punctuated Equilibrium, search behaviour which is further elaborated by Gersick (1991). Here, agents adapt a balance between exploration and exploitation. Individuals start with distant search, narrow down search, explore again and narrow down finally in later trials. The predominant search strategies used are similar in both setups. The agents predominantly use local search, with a search distance of 1, and follow low instances of distant search, changing two elements at once, as a second choice. These two search strategies especially prevail for type 2 subjects. As type 1 subjects engage in cyclic search behaviour, also their predominant search strategies are diverse. These subjects most commonly choose between pure exploitation, low instances of distant search and very distant search, changing 9 or 10 attributes at once. Consistent with the findings of Billinger et al. (2014), path-dependent search behaviour is observed. Also, the number of rounds played has a significant impact on search distance. The more rounds played, the lower the search distance, supporting the findings that search narrows down towards the end.

As in Billinger et al. (2014), we tested the relationship between the search aim and the feedback variables constructed and observed a significant influence. Just as complexity impacts feedback in the original Alien Game, the search aim has a significant impact on feedback variables which supports the concept that the key independent variable moderates feedback variables which impact search behaviour.

8.2 Limitations

As replication of the Alien Game by Billinger et al. (2014), several limitations that have been mentioned in the original setup apply. The experiment was built to avoid any usage of prior knowledge, and agents were not given any information about the search space (Gavetti and Levinthal 2000). Further, agents did not interact with each other but were isolated. This setup is helpful to evaluate individual search behaviour and evaluate the influences of the key dependent variable. Including direct performance might lead to different results as it may change reference points (Knudsen 2008). Giving agents information about the search space might further lead to different results by adding additional reference points (Billinger et al. 2014).

Considering that this experiment is a replication and extension of the Alien Game, further limitations apply. Enlarging the number of subjects and diversifying the pool of which these are drawn might give more insight and more diverse findings for search behaviour and help segment results to understand search behaviour for specific groups. Carrying out the experiment in a controlled environment, such as a computer lab, and incentivising subjects will add to the seriousness of the experiment and the validity of results. Additionally, more variation in terms of dependent variables could be outlined by not only controlling for two different search aims but also for task complexity to compare it with the original Alien Game and evaluate how search aim influences search behaviour over complexity levels. Furthermore, the variable *Search Aim* offers potential in exploring diverse goal settings and formulations, manipulating it in terms of level of difficulty, precise formulation and acceptance levels to get a deeper understanding of the relationship between goal settings, feedback and performance.

References

Afuah, A.; Tucci, C. L. (2012): Crowdsourcing as a Solution to Distant Search. In *The Academy of Management Review* (37), pp. 355–375.

Almirall, E.; Casadesus-Masanell, R. (2010): Open versus Closed Innovation: A Model of Discovery and Divergence. In *The Academy of Management Review* (35), pp. 27–47.

Basalla, George (1988): The evolution of technology. Cambridge: Cambridge University Press (Cambridge history of science).

Baumann, Oliver (2015): Models of complex adaptive systems in strategy and organization research. In *Mind Soc* 14 (2), pp. 169–183. DOI: 10.1007/s11299-015-0168-x.

Baumann, Oliver; Schmidt, Jens; Stieglitz, Nils (2019): Effective Search in Rugged Performance Landscapes: A Review and Outlook. In *Journal of Management* 45 (1), pp. 285–318. DOI: 10.1177/0149206318808594.

Baumann, Oliver; Siggelkow, Nicolaj (2013): Dealing with Complexity: Integrated vs. Chunky Search Processes. In *Organization Science* 24 (1), pp. 116–132. DOI: 10.1287/orsc.1110.0729.

Billinger, Stephan; Stieglitz, Nils; Schumacher, Terry R. (2011): Rugged Landscapes Put to the Lab. Edited by University of Southern Denmark.

Billinger, Stephan; Stieglitz, Nils; Schumacher, Terry R. (2014): Search on Rugged Landscapes: An Experimental Study. In *Organization Science* 25 (1), pp. 93–108. DOI: 10.1287/orsc.2013.0829.

Birkinshaw, Julian; Gibson, Cristina (2004): Building ambidexterity into an organization: a company's ability to simultaneously execute today's strategy while developing tomorrow's arises from the context within which its employees operate. In *MIT Sloan Management Review* 45.

Boyle, E.; Shapira, Z. (2012): The Liability of Leading: Battling Aspiration and Survival Goals in the Jeopardy! Tournament of Champions. In *Organization Science* 23, p. 1113. DOI: 10.1287/orsc.1110.0690.

Caldart, Adrián Atilio; Ricart, Joan E. (2007): Corporate strategy: an agent-based approach. In *European Management Review* (4), pp. 107–120, checked on 4/27/2019.

Cohen, W. M.; Levinthal, Daniel A. (1990): Absorptive Capacity: A New Perspective on Learning and Innovation. In *Administrative Science Quarterly* (35), pp. 128–152.

Collins, J. C.; Porras, J. I. (1996): Built to last: Successful habits of visionary companies. In *Long Range Planning* 29, p. 262. DOI: 10.1016/S0024-6301(96)90211-3.

Craik, Kenneth J. W. (1967): The nature of explanation. Cambridge: Univ. Press. Available online at https://ubdata.univie.ac.at/AC00678443.

Cyert, Richard Michael; March, James G. (1963): A behavioral theory of the firm. Englewood Cliffs, NJ: Prentice-Hall (Prentice-Hall behavioral science in business series). Available online at https://ubdata.univie.ac.at/AC00170958.

Erez, M.; Kanfer, F. H. (1983): The Role of Goal Acceptance in Goal Setting and Task Performance. In *Academy of Management. The Academy of Management Review* (8), pp. 454–463.

Ethiraj, S. K.; Levinthal, Daniel A.; Roy, R. R. (2008): The Dual Role of Modularity: Innovation and Imitation. In *Management Science* (54), pp. 939–955.

Fleming, L.; Sorenson, O. (2001): Technology as a complex adaptive system: evidence from patent data. In *Research Policy* (30), pp. 1019–1039, checked on 4/27/2019.

Frenken, K. (2006): Innovation, Evolution and Complexity Theory: Edward Elgar Publishing, Incorporated. Available online at https://books.google.at/books?id=BZBg3GM4dpAC.

Ganco, Martin (2017): NK model as a representation of innovative search. In *Research Policy* 46 (10), pp. 1783–1800. DOI: 10.1016/j.respol.2017.08.009.

Ganco, Martin; Agarwal, R. (2009): Performance Differentials between Diversifying Entrants and Entrepreneurial Start-Ups: A Complexity Approach. In *The Academy of Management Review* (34), pp. 228–252.

Ganco, Martin; Hoetker, Glenn (2009): NK modeling methodology in the strategy literature: Bounded search on a rugged landscape. In David J. Ketchen, Donald D. Bergh (Eds.): Research methodology in strategy and management, vol. 5. Oxford, UK: Emerald Group Publishing Limited (Research Methodology in Strategy and Management, 5), pp. 237–268, checked on 4/27/2019.

Gary, Michael Shayne; Yang, Miles M.; Yetton, Philip W.; Sterman, John D. (2017): Stretch Goals and the Distribution of Organizational Performance. In *Organization Science* 28 (3), pp. 395–410. DOI: 10.1287/orsc.2017.1131.

Gavetti, G.; Levinthal, Daniel A. (2000): Looking Forward and Looking Backward: Cognitive and Experiential Search. In *Administrative Science Quarterly* (45), 113-137, checked on 4/27/2019.

Gavetti, Giovanni; Helfat, Constance E.; Marengo, Luigi (2017): Searching, Shaping, and the Quest for Superior Performance. In *Strategy Science* 2 (3), pp. 194–209. DOI: 10.1287/stsc.2017.0036.

Gersick, Connie J. G. (1991): Revolutionary Change Theories: A Multilevel Exploration of the Punctuated Equilibrium Paradigm. In *Academy of Management. The Academy of Management Review* 16. DOI: 10.2307/258605.

Ghemawat, P.; Levinthal, Daniel A. (2008): Choice Interactions and Business Strategy. In *Management Science* (54), pp. 1638–1651.

Gilfillan, S. Colum (1935): Inventing the ship : A study of the inventions made in her history between floating log and rotorship. A self-contained but companion volume to the author's "Sociology of invention". Chicago: Follett. Available online at https://ubdata.univie.ac.at/AC04645568.

Gittins, John C. (1989): Multi-armed bandit allocation indices. New York, NY [u.a.]: Wiley (Wiley series in probability and mathematical statistics : Applied probability and statistics). Available online at https://ubdata.univie.ac.at/AC00861122.

Gupta, Anil K.; Shalley, Christina E.; Smith, Ken G. (2006): The interplay between exploration and exploitation. In *AMJ* 49. DOI: 10.5465/AMJ.2006.22083026.

Hamming, R. W. (1950): Error Detecting and Error Correcting Codes. In *Bell System Technical Journal* 29, p. 160. DOI: 10.1002/j.1538-7305.1950.tb00463.x.

Hargadon, Andrew; Sutton, Robert (1997): Technology Brokering and Innovation in a Product Development Firm. In *Administrative Science Quarterly* 42. DOI: 10.2307/2393655.

Helfat, C. E. (1994): Evolutionary Trajectories in Petroleum Firm R&D. In *Management Science* (40), pp. 1720–1747.

Henderson, Rebecca; Clark, Kim (1990): Architectural Innovation: The Reconfiguration of Existing Product Technologies and the Failure of Established Firms. In *Administrative Science Quarterly* 35.

Holland, John H.; Holyoak, Keith J.; Nisbett, Richard E.; Thagard, Paul R.; Smoliar, Stephen W. (1987): Induction: Processes of Inference, Learning, and Discovery (2). In *IEEE Expert*.

Hunter, Louis C.; Usher, Abbott Payson (1955): A History of Mechanical Inventions. In *Military Affairs* 19. DOI: 10.2307/1983351.

Kahneman, Daniel; Tversky, Amos (1979): PROSPECT THEORY: AN ANALYSIS OF DECISION UNDER RISK. In *Econometrica (pre-1986)* 47. DOI: 10.2307/1914185.

Katila, Riitta; Ahuja, Gautam (2002): Something Old, Something New: A Longitudinal Study of Search Behavior and New Product Introduction. In *AMJ* 45 (6), pp. 1183–1194. DOI: 10.5465/3069433.

Kauffman, S. A. (1993): The origins of order: self organization and selection in evolution. New York, NY: Oxford University.

Kauffman, Stuart A. (1996): At Home in the Universe : The Search for the Laws of Self-Organization and Complexity. New York: Oxford University Press. Available online at http://search.ebscohost.com/login.aspx?direct=true&db=nlebk&AN=364446&site=ehost-live.

Kerr, S.; Landauer, S. (2004): Using stretch goals to promote organizational effectiveness and personal growth: General electric and Goldman Sachs. In *Academy of Management Perspectives* (18), pp. 134–138.

Khraisha, Tamer (2019): Complex economic problems and fitness landscapes: Assessment and methodological perspectives. In *Structural Change and Economic Dynamics*. DOI: 10.1016/j.strueco.2019.01.002.

Knudsen, T.; Levinthal, Daniel A. (2007): Two Faces of Search: Alternative Generation and Alternative Evaluation. In *Organization Science* (18), pp. 39–54.

Knudsen, Thorbjørn (2008): Reference groups and variable risk strategies. In *Journal of Economic Behavior and Organization* 66, p. 36. DOI: 10.1016/j.jebo.2007.02.004.

Levinthal, Daniel A. (1991): Organizational Adaptation and Environmental Selection-Interrelated Processes of Change. In *Organization Science* (2), pp. 140–145, checked on 5/2/2020.

Levinthal, Daniel A. (1997): Adaptation on Rugged Landscapes. In *Management Science* 43 (7), pp. 934–950. Available online at https://www.jstor.org/stable/2634336.

Levinthal, Daniel A.; March, James G.; Schendel, Dan (1993): The myopia of learning. In *Strat Mgmt J* 14, p. 112. DOI: 10.1002/smj.4250141009.

Levinthal, Daniel A.; Warglien, M. (1999): Landscape Design: Designing for Local Action in Complex Worlds. In *Organization Science* (10), pp. 342–357.

Levitt, Barbara; March, James (1988): Organizational Learning. In *Annual Review of Sociology* 14, p. 340.

Lippman, Steven A.; Mccall, John J. (1976): THE ECONOMICS OF JOB SEARCH: A SURVEY. In *Economic Inquiry* 14, p. 189. DOI: 10.1111/j.1465-7295.1976.tb00386.x.

Locke, E. A.; Latham, G. P. (2012a): Goal Setting Theory, 1990. In Edwin A. Locke, G. P. Latham (Eds.): New Developments in Goal Setting and Task Performance. With assistance of Edwin A. Locke, Gary P. Latham, pp. 3–15.

Locke, E. A.; Shaw, K. N.; Saari, L. M.; Latham, G. P. (1981): Goal Setting and Task Performance: 1969-1980. In *Psychological Bulletin* (90), pp. 125–152.

Locke, Edwin A.; Latham, G. P. (Eds.) (2012b): New Developments in Goal Setting and Task Performance. With assistance of Edwin A. Locke, Gary P. Latham.

March, J. G. (1991): Exploration and Exploitation in Organizational Learning. In *Organization Science* (2), pp. 71–87.

March, James G.; Simon, Herbert A. (1958): Organizations. New York [u.a.]: Wiley. Available online at https://ubdata.univie.ac.at/AC00457052.

Mason, Winter; Watts, Duncan J. (2012): Collaborative learning in networks. In *Proceedings of the National Academy of Sciences* 109. DOI: 10.1073/pnas.1110069108.

Mckelvey, Bill; Xu, Haoyue; Vidgen, Richard (2013): Re-thinking Kauffman's NK fitness landscape: From artifact & groupthink to weak-tie effects. In *Human Systems Management* 32, pp. 17–42. DOI: 10.3233/HSM-130782.

Miner, A. S.; Bassoff, P.; Moorman, C. (2001): Organizational Improvisation and Learning: A Field Study. In *Administrative Science Quarterly* (46), pp. 304–337.

Nelson, Richard R.; Winter, Sidney G. (1982): An evolutionary theory of economic change. Cambridge, Mass. [u.a.]: Belknap Press of Harvard Univ. Press. Available online at https://ubdata.univie.ac.at/AC00074485.

Page, Scott (1996): Two measures of difficulty. In *Econ Theory* 8, p. 346. DOI: 10.1007/BF01211821.

Podolny, Joel M. (2018): An Exploration of Discerning Search. In *Strategy Science* 3 (1), pp. 295–305. DOI: 10.1287/stsc.2017.0051.

Porter, M. E. (1996): What is Strategy? In *Harvard Business Review* (74), pp. 61–78.

Posen, Hart E.; Martignoni, Dirk (2018): Revisiting the imitation assumption: Why imitation may increase, rather than decrease, performance heterogeneity. In *Strat Mgmt J* 39 (5), pp. 1350–1369. DOI: 10.1002/smj.2751.

Rivkin, Jan W. (2000): Imitation of Complex Strategies. In *Management Science* (46), pp. 824–844.

Rivkin, Jan W.; Siggelkow, Nicolaj (2002): Organizational sticking points on NK Landscapes. In *Complexity* 7 (5), pp. 31–43. DOI: 10.1002/cplx.10037.

Rivkin, Jan W.; Siggelkow, Nicolaj (2003): Balancing Search and Stability: Interdependencies among Elements Organizational Design. In *Management Science* 49 (3), pp. 290–311, checked on 4/27/2019.

Rosenkopf, L.; Nerkar, A. (2001): Beyond Local Search: Boundary-Spanning, Exploration, and Impact in the Optical Disk Industry. In *Strat. Mgmt. J.* (22), pp. 287–306.

Schumpeter, Joseph A. (1939): Business cycles : a theoretical, historical, and statistical analysis of the capitalist process : 1. London [u.a.]: McGraw-Hill. Available online at https://ubdata.univie.ac.at/AC01183637.

Siggelkow, Nicolaj; Rivkin, Jan W. (2006): When Exploration Backfires: Unintended Consequences of Multilevel Organizational Search. In *The Academy of Management Journal* (49), pp. 779–795.

Simon, H. (1964): On the concept of organizational goal. In *Administrative Science Quarterly* 9, p. 22. DOI: 10.2307/2391519.

Simon, Herbert A. (1955): A Behavioral Model of Rational Choice. In *The Quarterly Journal of Economics* 69, p. 118. DOI: 10.2307/1884852.

Simon, Herbert A. (1962): The Architecture of Complexity. In *Proceedings of the American Philosophical Society* (106), pp. 467–482. Available online at https://www.jstor.org/stable/985254?seq=1&cid=pdf-reference#references_tab_contents, checked on 5/2/2020.

Simon, Herbert A. (1978): Rationality as Process and as Product of Thought. In *American Economic Review* 68, p. 16. DOI: 10.2307/1816653.

Sitkin, Sim B.; See, Kelly E.; Miller, C. Chet; Lawless, Michael W.; Carton, Andrew M. (2011): The paradox of stretch goals: organizations in pursuit of the seemingly impossible.(Report). In *Academy of Management. The Academy of Management Review* 36. DOI: 10.5465/AMR.2011.61031811.

Stinchcombe, Arthur L. (1965): Social structure and organizations. Indianapolis, IN: Bobbs-Merrill.

Sutton, Richard S. (1998): Reinforcement learning : an introduction. With assistance of Andrew G. Barto. Cambridge, Mass.: MIT Press (Adaptive computation and machine learning). Available online at http://search.ebscohost.com/login.aspx?direct=true&scope=site&db=nlebk&AN=1094.

Thompson, K. R.; Hochwarter, W. A.; Mathys, N. J. (1997): Stretch targets: What makes them effective? In *Academy of Management Executive* 11, p. 60.

Tortoriello, Marco (2015): The social underpinnings of absorptive capacity: The moderating effects of structural holes on innovation generation based on external knowledge. In *Strat. Mgmt. J.* 36 (4), pp. 586–597. DOI: 10.1002/smj.2228.

Tushman, Ml; Oreilly, Ca (1996): Ambidextrous organizations: Managing evolutionary and revolutionary change. In *Calif. Manage. Rev.* 38, &.

Uotila, Juha (2017): Exploration, exploitation, and variability: Competition for primacy revisited. In *Strategic Organization* 15 (4), pp. 461–480. DOI: 10.1177/1476127017705103.

Vuculescu, Oana (2017): Searching far away from the lamp-post: An agent-based model. In *Strategic Organization* 15 (2), pp. 242–263. DOI: 10.1177/1476127016669869.

Weitzman, Martin L. (1996): Hybridizing growth theory. (economic growth). In *American Economic Review* 86.

Winter, S. G.; Cattani, G.; Dorsch, A. (2007): The Value of Moderate Obsession: Insights from a New Model of Organizational Search. In *Organization Science* (18), pp. 403–419.

Wright, S. (1931): Evolution in Mendelian Populations. In *Genetics* 16.

Wright, S. (1932): The roles of mutation, inbreeding, crossbreeding and selection in evolution. In *Proc. XI International Congress of Genetics* (1), pp. 356–366.

Yu, Tl; de Goldberg; Sastry, K.; Lima, Cf; Pelikan, M. (2009): Dependency Structure Matrix, Genetic Algorithms, and Effective Recombination. In *Evol. Comput.* 17, U3.

9 Appendix

Appendix 1: Abstract English

This thesis elaborates on the relationship between search aims and individual search behaviour by replicating the Alien Game carried out by Billinger et al. (2014), a lab experiment on human decision making, based on the canonical NK model, and manipulating search aims rather than complexity. This thesis aims to explore whether there are differences in individual performance and search behaviour when agents are faced with different goals within the experiment. Building on the Alien Game, we examine whether search behaviour is influenced by search aims and determine whether a similar effect between feedback conditions and search behaviour can be observed. The analysis of findings shows inconsistencies with the original Alien Game, and partly conflicting results compared to one of its principal outcome of success-induced exploitation and failure-induced exploration. Our results show that this search behaviour is conditional on previous search distance. However, our results support the second principal finding of Billinger et al. (2014) that the key dependent variable does not have a direct effect on search distance. Instead, it has an impact on feedback variables which then influences search behaviour.

Appendix 2: Abstract German

In dieser Arbeit wird die Beziehung zwischen Suchzielen und individuellem Suchverhalten anhand der Nachbildung des *Alien Games* von Billinger et al. (2014), einem Laborexperiment zur menschlichen Entscheidungsfindung das auf dem kanonischen NK-Modell basiert, und der Manipulation von Suchzielen anstelle von Komplexität untersucht. Die Arbeit zielt darauf ab herauszufinden, ob es Unterschiede in der individuellen Leistung und im Suchverhalten gibt, wenn die Agenten innerhalb des Experimentes mit unterschiedlichen Zielen konfrontiert werden. Aufbauend auf dem *Alien Game* wird geprüft, ob das Suchverhalten durch Suchziele beeinflusst wird und ob ein ähnlicher Effekt zwischen Feedbackbedingungen und Suchverhalten beobachtet werden kann. Die Analyse der Ergebnisse zeigt Inkonsistenzen mit dem ursprünglichen *Alien Game* und teilweise widersprüchliche Ergebnisse im Vergleich zu einem seiner Hauptergebnisse, der erfolgsinduzierten Ausbeutung und der scheiterungsinduzierten Exploration. Unsere Ergebnisse zeigen, dass dieses Suchverhalten von der bisherigen Suchdistanz abhängig ist. Unsere Ergebnisse unterstützen jedoch die zweite Haupterkenntnis von Billinger et al. (2014), dass die Hauptvariable keinen direkten Einfluss auf die Suchdistanz hat. Stattdessen wirkt sie sich auf Feedbackbedingungen aus, die dann das Suchverhalten beeinflussen.

Appendix 3: Average Search Distance Over Time

The following figures further elaborate on the average search distance over time and offer more detailed insights. Figure 1 and Figure 2 compare the overall average search distance over time. Figure 1 displays the average search distance over time using the Billinger Search Distance. We can observe the cyclic search behaviour mentioned above, while in Figure 2, displaying the average search distance over time using the Adjusted Search Distance, shows that search starts somewhat distant and narrows down over time which is consistent with the findings of Billinger et al. (2014).

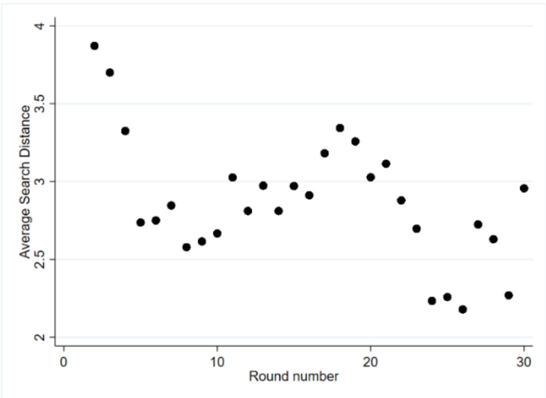


Figure 10 Average Search Distance Over Time using the Billinger Search Distance

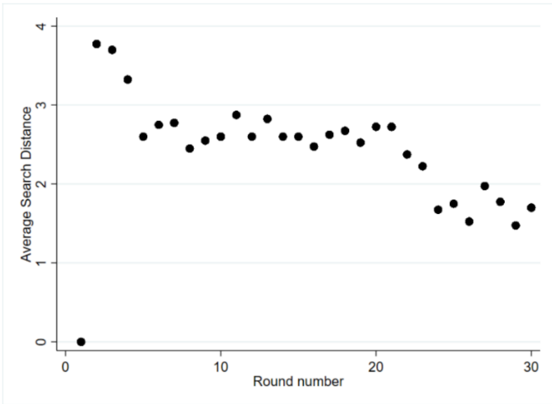


Figure 11 Average Search Distance Over Time using the Adjusted Search Distance

Going into more detail, we can further observe differences between the two types and search distance measures. The *Billinger Search Distance* shows no clear pattern but a rather dispersed search pattern, while the *Adjusted Search Distance* displays are more explicit search behaviour. We can observe that subjects cycled between local and distant search, ending their search behaviour on local search, which is consistent with the findings mentioned above.

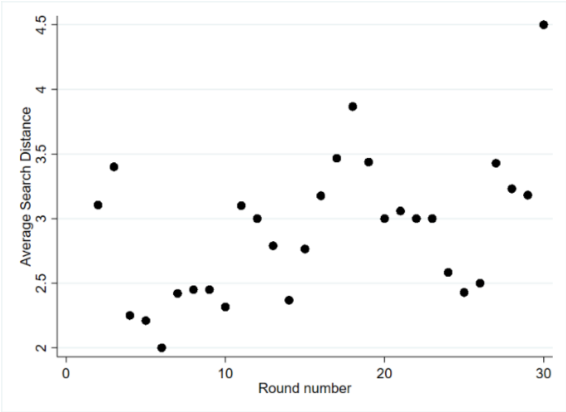


Figure 12 Average Search Distance Over Time for Type 1 using the Billinger Search Distance

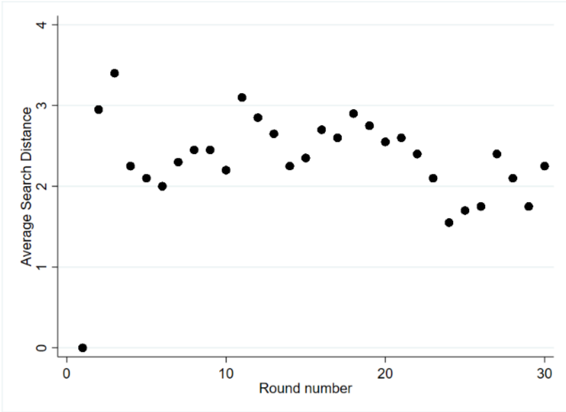


Figure 13 Average Search Distance Over Time for Type 1 using the Adjusted Search Distance

It is interesting to observe that search behaviour over time for type 2 is similar for both search distance measures, starting with a somewhat distant search and narrowing down over time.

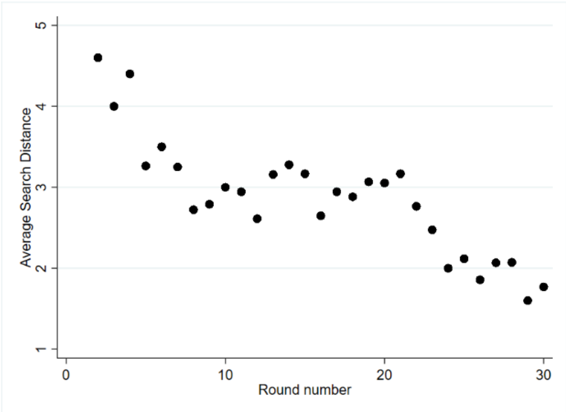


Figure 14 Average Search Distance Over Time for Type 2 using the Billinger Search Distance

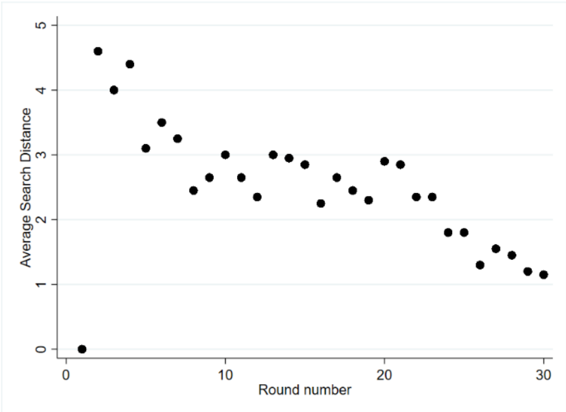


Figure 15 Average Search Distance Over Time for Type 2 using the Adjusted Search Distance

Appendix 4: STATA Code

```
cd "C:\Users\OliviaJazwinski\Dropbox (Privat)\Uni Wien\Analysis\STATA"
import excel "C:\Users\OliviaJazwinski\Dropbox (Privat)\Uni
Wien\Analysis\STATA\alien_game_data_20200405_v1-01.xlsx", sheet("Sheet1") firstrow allstring
clear

//Create new payoff variable, converting string to numeric variable
gen payoff_num = real(Payoff)
gen round_num = real(Round)
gen type_num = real(Type)

//sort list and create new variable, showing cumulative payoffs per round/subject/type & creating total
payoff variable
bysort type_num Subject (round_num) : gen payoff_cum = sum(payoff_num)
gen payoff_total=payoff_cum if round_num==30

//Order list
order type_num Subject round_num Input payoff_num payoff_cum payoff_total

//Clean up list, dropping unnecessary variables
drop Round Payoff Type

//Create variable showing previous input items
sort type_num Subject round_num
gen input_prev=Input[_n-1]
replace input_prev="0000000000" if round_num==1 //default starting position with 0000000000 to
get search distance for first input in round 1

//Hamming Distance
gen hammingsd = 0
 quietly forval k = 1/10 {
replace hammingsd = hammingsd + (substr(Input, `k', 1) != substr(input_prev, `k', 1))
}

//variables according to Billinger et al. 2014
*Highest Payoff - so far, per subject and round
ssc inst rangestat
rangestat (max) payoff_num, interval(round_num . 0) by(type_num Subject)
rename payoff_num_max highest_payoff_rolling

*Performance - Input based on max payoff achieved by subject so far
gen Performance = Input if highest_payoff_rolling==payoff_num
replace Performance = Performance[_n-1] if missing(Performance)
*defined first value for first highest_payoff_rolling, dann aufgefüllt mit werten aus vorangegangener
zelle

*Feedback - 0 = failure, 1 = success -> based on improvement from one round to next round ->
subtract value of payoff from reference point
gen prev_highest_payoff_rolling=highest_payoff_rolling[_n-1]
*Auxiliary variable prev_highest_payoff_rolling to calculate Feedback
gen Feedback = 0
*0 by default
replace Feedback = 1 if payoff_num > prev_highest_payoff_rolling
```

```
replace prev_highest_payoff_rolling=. if round_num==1
replace Feedback =. if round_num==1
*no value for first round, because no improvement possible

*#unsuccessful trials -> counts number of trials since an improvement in performance
gen unsuccessful_trials = 0 if Feedback == 1
replace unsuccessful_trials = 1 if Feedback == 0 & round_num==2
*Starting value set from round two if subject had no improvement to the previous round
replace unsuccessful_trials = unsuccessful_trials[_n-1] + 1 if missing(unsuccessful_trials) &
round_num != 1
*Starting value for a new subject, because in the first round there is no feedback, i.e. no improvement,
so no unsuccessful trials possible

*prior payoff - performance in prior trial
gen prev_payoff = payoff_num[_n-1]
replace prev_payoff = . if round_num == 1

*trial number = round_num

*ind_sd_performance - individual search distance based on performance variable, so far --> central
variable, only called SD in the following
*ind_sd_performance - ranges from 0 - 10
gen prev_Performance = Performance[_n-1]
replace prev_Performance=Performance if round_num==1

gen ind_sd_performance = 0
 quietly forval k = 1/10 {
replace ind_sd_performance = ind_sd_performance + (substr(Input, `k', 1) !=
substr(prev_Performance, `k', 1))
}

*create search distance variable ranging from 1 to 10 (only positive values) to compare with billinger
sort type_num Subject round_num
gen ind_sd_performance_billinger = ind_sd_performance
replace ind_sd_performance_billinger = . if ind_sd_performance ==0

*prior search distance - ind_sd_performance one round before
gen prev_ind_sd_performance = ind_sd_performance[_n-1]
replace prev_ind_sd_performance = . if round_num == 1
replace prev_ind_sd_performance = 0 if round_num == 2
*round 1 = ., da keine prior sd vorhanden
*round 2 = 0, da sd in round 1 immer gleich 0
*previous search distance variable ranging from 1-10 (only positive values) to compare with billinger
gen prev_ind_sd_performance_bil = prev_ind_sd_performance
replace prev_ind_sd_performance_bil = . if prev_ind_sd_performance ==0

*complexity – replaced by type_num

//label variable
label var ind_sd_performance "Adjusted Search Distance"
label var ind_sd_performance_billinger "Billinger Search Distance"
label var type_num "Search Aim"
label var round_num "Round Number"
label var Feedback "Feedback"
label var unsuccessful_trials "Number of unsuccessful trials"
label var prev_ind_sd_performance "Prior Adjusted Search Distance"
```

```
label var prev_ind_sd_performance_bil "Prior Billinger Search Distance"

//definition search behaviour based on newly created key variable ind_sd_performance
*measuring search distance according to Billinger et al. 2014
*Local Search = Hamming Distance = 1
*Intermediate instances of distant search = hamming Distance = 3-8
*Very distant search = Hamming distance = 9-10
*additional search distance catergories (new because missing in billinger)
*Pure Exploitation = Hamming Distance = 0
*Low instances of distant search = Hamming distance = 2

gen pure_exploitation = ind_sd_performance == 0
label var pure_exploitation "Pure Exploitation"
gen local_search = ind_sd_performance == 1
label var local_search "Local Search"
gen low_instance_distant_search = ind_sd_performance == 2
label var low_instance_distant_search "Low instances of distant search"
gen intermediate_search = ind_sd_performance > 2 & hammingsd < 9
label var intermediate_search "Intermediate instances of distant search"
gen vdistant_search = ind_sd_performance > 8 & hammingsd < 11
label var vdistant_search "Very Distant search"

//group search distances
generate ind_sd_performance_groups = ind_sd_performance
recode  ind_sd_performance_groups (0=0) (1=1) (2=2) (3/8=3) (9/10=4)
label define ind_sd_performance_groups1 0 "Pure Exploitation" 1 "Local Search" 2 "Low instances of
distant search" 3 "Intermediate instances of distant search" 4 "Very Distant search"
label values ind_sd_performance_groups ind_sd_performance_groups1
table ind_sd_performance_groups

//frequency search behavior & cumulative frequency
tabulate pure_exploitation
tabulate local_search
tabulate low_instance_distant_search
tabulate intermediate_search
tabulate vdistant_search

//Figure 3: Average Performance in the Experimental Tasks (compare billinger)
*development Performance based on highest payoff rolling over time (rounds) type 1 vs. type 2
gen highest_payoff_rolling_type1 = highest_payoff_rolling if type_num==1
gen highest_payoff_rolling_type2 = highest_payoff_rolling if type_num==2
by round_num, sort: egen avg_highest_payoff_rolling = mean(highest_payoff_rolling)
by round_num, sort: egen avg_highest_payoff_rolling_type1 = mean(highest_payoff_rolling_type1)
by round_num, sort: egen avg_highest_payoff_rolling_type2 = mean(highest_payoff_rolling_type2)
twoway connected avg_highest_payoff_rolling_type1 avg_highest_payoff_rolling_type2 round_num,
xtitle("Round number") ytitle("Performance") graphregion(fcolor(white)) legend(label(1 "Type 1")
label(2 "Type 2")) lcolor(gray black) mcolor (gray black)

//Figure 5: Search Behavior Over Time with Billinger Search Distance
gen ind_sd_performance_bil_type1 = ind_sd_performance_billinger if type_num==1
gen ind_sd_performance_bil_type2 = ind_sd_performance_billinger if type_num==2
by round_num, sort: egen avg_ind_sd_performance_billinger = mean(ind_sd_performance_billinger)
by round_num, sort: egen avg_ind_sd_performance_bil_type1 =
mean(ind_sd_performance_bil_type1)
by round_num, sort: egen avg_ind_sd_performance_bil_type2 =
mean(ind_sd_performance_bil_type2)
```

```
twoway line avg_ind_sd_performance_bil_type1 avg_ind_sd_performance_bil_type2 round_num,
xtitle("Round number") ytitle("Performance") graphregion(fcolor(white)) graphregion(fcolor(white))
legend(label(1 "Type 1") label(2 "Type 2")) lcolor(gray black)

//Figure 6: Search Behavior Over Time with Adjusted Search Distance
gen ind_sd_performance_type1 = ind_sd_performance if type_num==1
gen ind_sd_performance_type2 = ind_sd_performance if type_num==2
by round_num, sort: egen avg_ind_sd_performance = mean(ind_sd_performance)
by round_num, sort: egen avg_ind_sd_performance_type1 = mean(ind_sd_performance_type1)
by round_num, sort: egen avg_ind_sd_performance_type2 = mean(ind_sd_performance_type2)
twoway line avg_ind_sd_performance_type1 avg_ind_sd_performance_type2 round_num,
xtitle("Round number") ytitle("Performance") graphregion(fcolor(white)) graphregion(fcolor(white))
graphregion(fcolor(white)) legend(label(1 "Type 1") label(2 "Type 2")) lcolor(gray black)

//Table 4: Frequency Distribution of Seach behavior with Billinger Search Distance
tab ind_sd_performance_billinger type_num, column nofreq

//Table 5: Frequency Distribution of Seach behavior with Adjusted Search Distance
tab ind_sd_performance type_num, column nofreq

//Table 7: Variables and Descriptive Statistics
sum Feedback highest_payoff_rolling type_num unsuccessful_trials prev_highest_payoff_rolling
prev_ind_sd_performance_bil prev_ind_sd_performance ind_sd_performance_billinger
ind_sd_performance round_num

//DV: Variance > Mean
sum ind_sd_performance ind_sd_performance_billinger, detail

//Table 9: Poisson Models with Search Distance as DV with Billinger Search Distance
*Model 1: how IV influences SD; control for possible influences of number of prior search trials
eststo clear
eststo: poisson ind_sd_performance_billinger type_num round_num, vce(robust)
estat gof
*Model 2: role of feedback for search behaviour; including feedback, control: Highest payoff, prior
payoff, feedback
eststo: poisson ind_sd_performance_billinger type_num Feedback round_num, vce(robust)
estat gof
*Model 3: adds number of unsuccessful trials
eststo: poisson ind_sd_performance_billinger type_num Feedback unsuccessful_trials round_num,
vce(robust)
estat gof
*Model 4: adds prior search distance
eststo: poisson ind_sd_performance_billinger type_num Feedback unsuccessful_trials
prev_ind_sd_performance_bil round_num, vce(robust)
estat gof
esttab * using "C:\Users\OliviaJazwinski\Dropbox (Privat)\Uni Wien\Analysis\STATA\Graphs &
Tables\Table4a_poisson_billinger.rtf", replace label nodepvars se pr2 scalars(ll)

//Table 10: Poisson Models with Search Distance as DV with Adjusted Search Distance
*Model 1: how IV influences SD; control for possible influences of number of prior search trials
eststo clear
eststo: poisson ind_sd_performance type_num round_num, vce(robust)
estat gof
*Model 2: role of feedback for search behaviour; including feedback, control: Highest payoff, prior
payoff, feedback
eststo: eststo: poisson ind_sd_performance type_num Feedback round_num, vce(robust)
```

```
estat gof
*Model 3: adds number of unsuccessful trials
eststo: eststo: poisson ind_sd_performance type_num Feedback unsuccessful_trials round_num,
vce(robust)
estat gof
*Model 4: adds prior search distance
eststo: poisson ind_sd_performance type_num Feedback unsuccessful_trials
prev_ind_sd_performance round_num, vce(robust)
estat gof
esttab * using "C:\Users\OliviaJazwinski\Dropbox (Privat)\Uni Wien\Analysis\STATA\Graphs &
Tables\Table4b_poisson_adjusted.rtf", replace label nodepvars se pr2 scalars(ll)

//Figure 8: Summary of Main Effect in the Empirical Model of Adaptive Search with Billinger SD
ssc install ciplot
gen ind_sd_success_bil = ind_sd_performance_billinger if Feedback==1
gen ind_sd_failure_bil = ind_sd_performance_billinger if Feedback==0
*shows ci for means -> -4 to 12 for prev sd 10 for normal distribution -> solution: use poisson
distribution
bysort prev_ind_sd_performance_bil: ci means ind_sd_success_bil
*ci plot
ciplot ind_sd_success_bil ind_sd_failure_bil, by(prev_ind_sd_performance_bil) inclusive poisson
msymbol(sh oh) mlcolor("194 194 194" black) rcap(lcolor("194 194 194")) xlabel(, grid)
ylabel(1(1)10, grid) ytitle ("Search Distance (t) 1-10") xtitle(" Prior Search Distance (t-1) 1-10")
legend(label(2 "Success") label(3 "Failure")) note("Error bars represent 95% confidence intervals.")
graphregion(fcolor(white))

//Figure 9: Summary of Main Effect in the Empirical Model of Adaptive Search with Adjusted SD
gen ind_sd_success = ind_sd_performance if Feedback==1
gen ind_sd_failure = ind_sd_performance if Feedback==0
*shows ci for means -> -4 to 12 for prev sd 10 for normal distribution -> solution: use poisson
distribution
bysort prev_ind_sd_performance: ci means ind_sd_success
*ci plot
ciplot ind_sd_success ind_sd_failure, by(prev_ind_sd_performance) inclusive poisson msymbol(sh
oh) mlcolor("194 194 194" black) rcap(lcolor("194 194 194")) xlabel(, grid)  ylabel(0(1)10, grid) ytitle
("Search Distance (t) 0-10") xtitle(" Prior Search Distance (t-1) 0-10") legend(label(2 "Success")
label(3 "Failure")) note("Error bars represent 95% confidence intervals.") graphregion(fcolor(white))

//label variables
label var highest_payoff_rolling "Highest Payoff"

//Table 12: Search Aim (Type) and Feedback Conditions
eststo clear
eststo: logit Feedback type_num round_num
eststo: regress highest_payoff_rolling type_num round_num
eststo: nbreg unsuccessful_trials type_num round_num
esttab * using "C:\Users\OliviaJazwinski\Dropbox (Privat)\Uni Wien\Analysis\STATA\Graphs &
Tables\Table5_Complexity_Feedback.rtf", replace label nonumbers se pr2 scalars(ll)

//7.1 Results - descriptive statistics
*performance at conclusion between search aims
ranksum payoff_total, by(type_num)
sort type_num
by type_num: sum payoff_total
regress type_num payoff_total
*where did subjects end their search?
```

```
gen global_optimum = 0
replace global_optimum = 1 if payoff_num>=.7072557
gen secondbest_optimum = 0
replace secondbest_optimum = 1 if payoff_num>.7008642 & payoff_num <.7008644

sort global_optimum
by global_optimum: tab Subject if type_num==1 //1 subject
by global_optimum: tab Subject if type_num==2 //3 subjects

sort secondbest_optimum
by secondbest_optimum: tab Subject if type_num==1 //0 subjects
by secondbest_optimum: tab Subject if type_num==2 //2 subjects

*comparing average sd
sort type_num
by type_num: sum ind_sd_performance ind_sd_performance_billinger
sum ind_sd_performance ind_sd_performance_billinger
*sd for round 2
sum ind_sd_performance_billinger if round_num == 2
sum ind_sd_performance if round_num == 2
*search behavior over time
sort round_num
by round_num: sum ind_sd_performance ind_sd_performance_billinger
twoway scatter avg_ind_sd_performance round_num, xtitle("Round number") ytitle("Average Search
Distance") graphregion(fcolor(white)) mcolor ( black)
twoway scatter avg_ind_sd_performance_billinger round_num, xtitle("Round number")
ytitle("Average Search Distance") graphregion(fcolor(white)) mcolor (black)
*temporal patterns of search behavior that differs for types
twoway scatter avg_ind_sd_performance_type1 round_num, xtitle("Round number") ytitle("Average
Search Distance") graphregion(fcolor(white)) mcolor (black)

twoway scatter avg_ind_sd_performance_type2 round_num, xtitle("Round number") ytitle("Average
Search Distance") graphregion(fcolor(white)) mcolor (black)

twoway scatter avg_ind_sd_performance_bil_type1 round_num, xtitle("Round number")
ytitle("Average Search Distance") graphregion(fcolor(white)) mcolor (black)

twoway scatter avg_ind_sd_performance_bil_type2 round_num, xtitle("Round number")
ytitle("Average Search Distance") graphregion(fcolor(white)) mcolor (black)

*frequency percentage and cumulative probabilities of search distance
*Performance over time
twoway line avg_highest_payoff_rolling round_num, xtitle("Round number") ytitle("Highest Payoff")
graphregion(fcolor(white)) lcolor(black)
*performance by search distance overall-> highest mean payoff for sd = 0, 1, 2
sort ind_sd_performance
by ind_sd_performance: sum payoff_num
*performance by search distance by type
sort ind_sd_performance_type1
by ind_sd_performance_type1: sum payoff_num
sort ind_sd_performance_type2
by ind_sd_performance_type2: sum payoff_num

//7.2 Regression Results
*average search distance
sort type_num
```

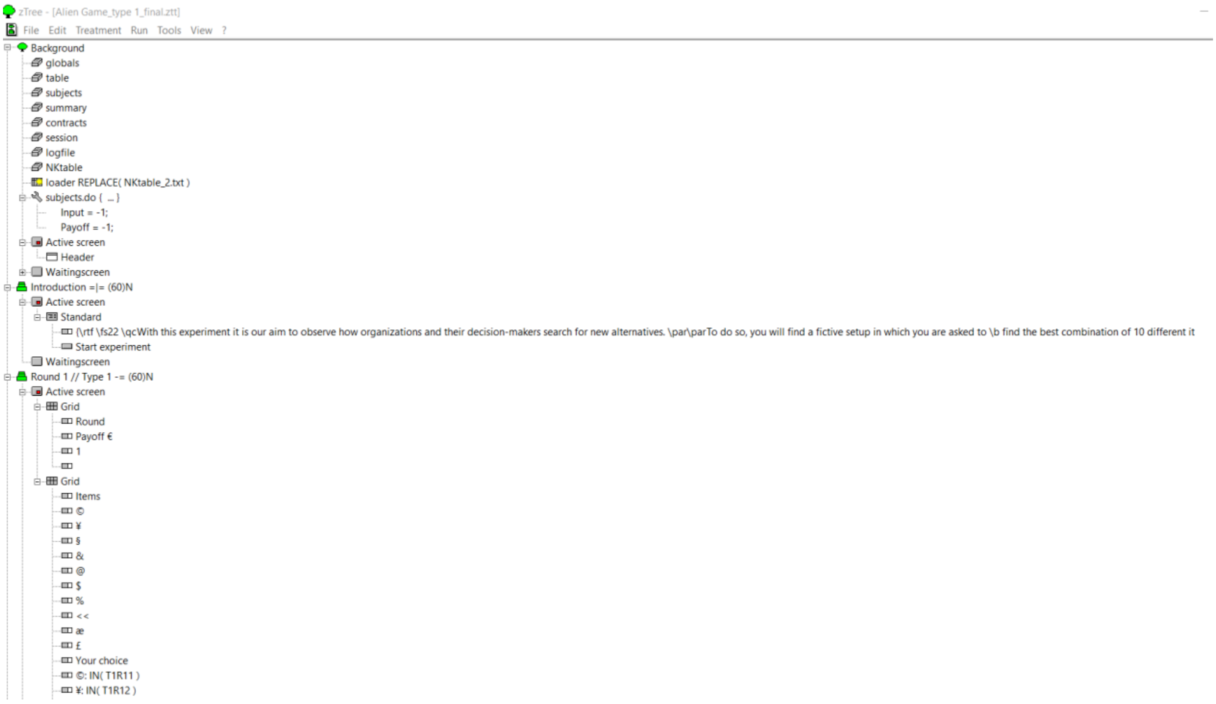
by type_num: sum ind_sd_performance_billinger ind_sd_performance
sum ind_sd_performance ind_sd_performance_billinger

//Table: Comparing descriptive statistics - billinger & adjusted sd
sum ind_sd_performance_billinger ind_sd_performance
sort type_num
by type_num: sum ind_sd_performance_billinger ind_sd_performance

///APPENDIX: Additional tests run

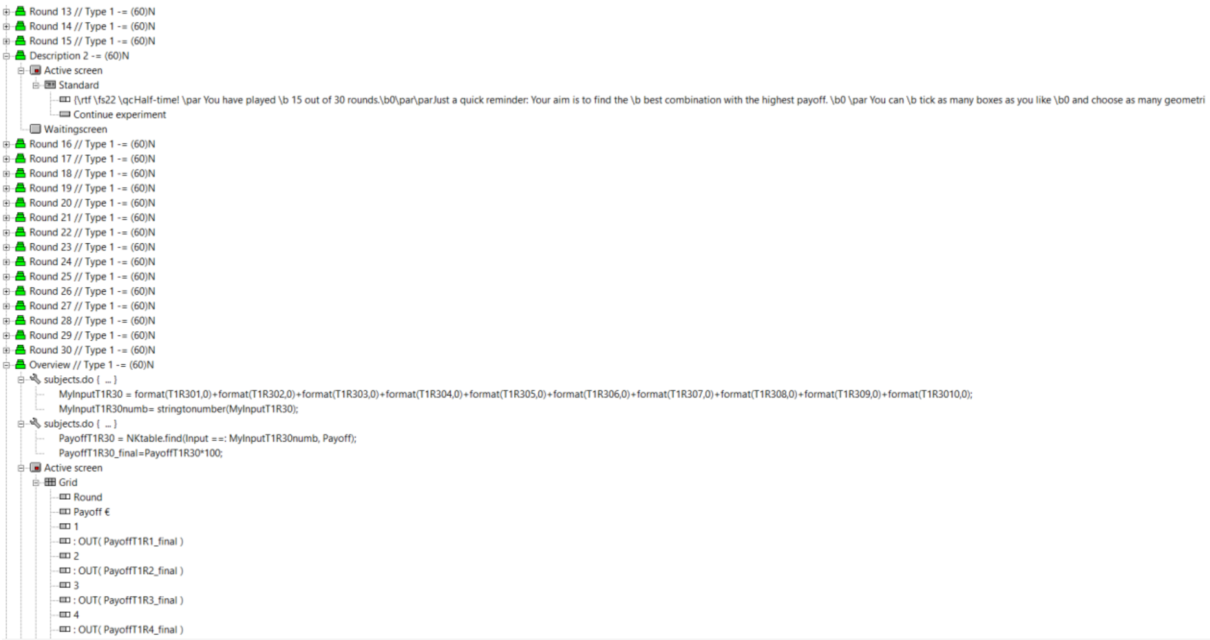
*distribution search distance 1: sktest -> not normal distribution
sktest ind_sd_performance ind_sd_performance_billinger
*distribution search distance 2: Shapiro Wilk p-value smaller 0,5, reject hypothesis of normal distribution, -> non-parametric-> not normal
swilk ind_sd_performance ind_sd_performance_billinger
*distribution search distance 3: Histogram ->non-normal
hist ind_sd_performance, discrete normal
hist ind_sd_performance_billinger, discrete normal
*distribution search distance 4: Wicoxon Rank Sum -> non-parametric test -> same distribution according to p-value
ranksum ind_sd_performance, by(type_num)
ranksum ind_sd_performance_billinger, by(type_num)
*distribution search distance 5: Q-Q-Plot
qnorm ind_sd_performance
qnorm ind_sd_performance_billinger
*heteroskedasticity check
regress type_num ind_sd_performance
estat hettest, rhs iid
estat imtest, white
regress type_num ind_sd_performance_billinger
estat hettest, rhs iid
estat imtest, white

Appendix 5: ztree Code



```
zTree - [Alien Game_type 1_final.ztt]
File  Edit  Treatment  Run  Tools  View  ?
Background
    globals
    table
    subjects
    summary
    contracts
    session
    logfile
    NKtable
    loader REPLACE( NKtable_2.txt )
    subjects.do { ... }
        Input = -1;
        Payoff = -1;
    Active screen
        Header
    Waitingscreen
Introduction =|= (60)N
    Active screen
        Standard
            {\rtf \fs22 \qcWith this experiment it is our aim to observe how organizations and their decision-makers search for new alternatives. \par\parTo do so, you will find a fictive setup in which you are asked to \b find the best combination of 10 different it
            Start experiment
    Waitingscreen
Round 1 // Type 1 -= (60)N
    Active screen
        Grid
            Round
            Payoff €
            1
            
        Grid
            Items
            ©
            ¥
            §
            &
            @
            $
            %
            < <
            æ
            £
            Your choice
            ©: IN( T1R11 )
            ¥: IN( T1R12 )
```

Figure 16 ztree backend for Type 1 – Introduction and first round



```
Round 13 // Type 1 -= (60)N
Round 14 // Type 1 -= (60)N
Round 15 // Type 1 -= (60)N
Description 2 -= (60)N
    Active screen
        Standard
            {\rtf \fs22 \qcHalf-time! \par You have played \b 15 out of 30 rounds.\b0\par\parJust a quick reminder: Your aim is to find the \b best combination with the highest payoff. \b0 \par You can \b tick as many boxes as you like \b0 and choose as many geometri
            Continue experiment
    Waitingscreen
Round 16 // Type 1 -= (60)N
Round 17 // Type 1 -= (60)N
Round 18 // Type 1 -= (60)N
Round 19 // Type 1 -= (60)N
Round 20 // Type 1 -= (60)N
Round 21 // Type 1 -= (60)N
Round 22 // Type 1 -= (60)N
Round 23 // Type 1 -= (60)N
Round 24 // Type 1 -= (60)N
Round 25 // Type 1 -= (60)N
Round 26 // Type 1 -= (60)N
Round 27 // Type 1 -= (60)N
Round 28 // Type 1 -= (60)N
Round 29 // Type 1 -= (60)N
Round 30 // Type 1 -= (60)N
Overview // Type 1 -= (60)N
    subjects.do { ... }
        MyInputT1R30 = format(T1R301,0)+format(T1R302,0)+format(T1R303,0)+format(T1R304,0)+format(T1R305,0)+format(T1R306,0)+format(T1R307,0)+format(T1R308,0)+format(T1R309,0)+format(T1R3010,0);
        MyInputT1R30numb= stringtonumber(MyInputT1R30);
    subjects.do { ... }
        PayoffT1R30 = NKtable.find(Input ==: MyInputT1R30numb, Payoff);
        PayoffT1R30_final=PayoffT1R30*100;
    Active screen
        Grid
            Round
            Payoff €
            1
            : OUT( PayoffT1R1_final )
            2
            : OUT( PayoffT1R2_final )
            3
            : OUT( PayoffT1R3_final )
            4
            : OUT( PayoffT1R4_final )
```

Figure 17 ztree backend for Type 1 - Reminder and final payoff calculation

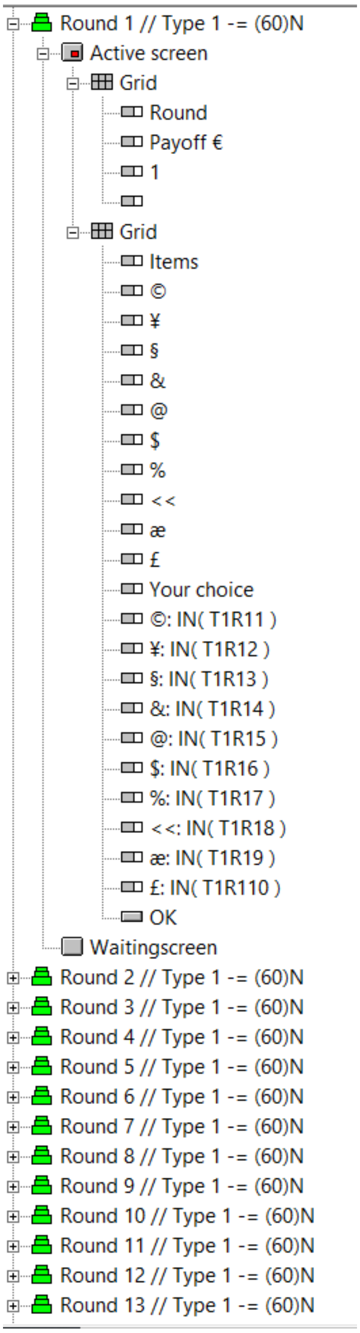


Figure 18 ztree backend for Type 1 - Round 1 setup

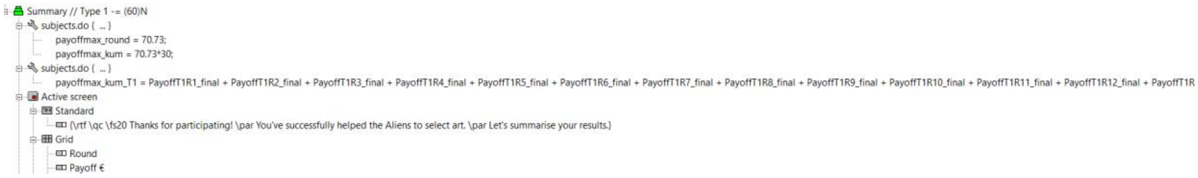


Figure 19 ztree backend for Type 1 – Summary

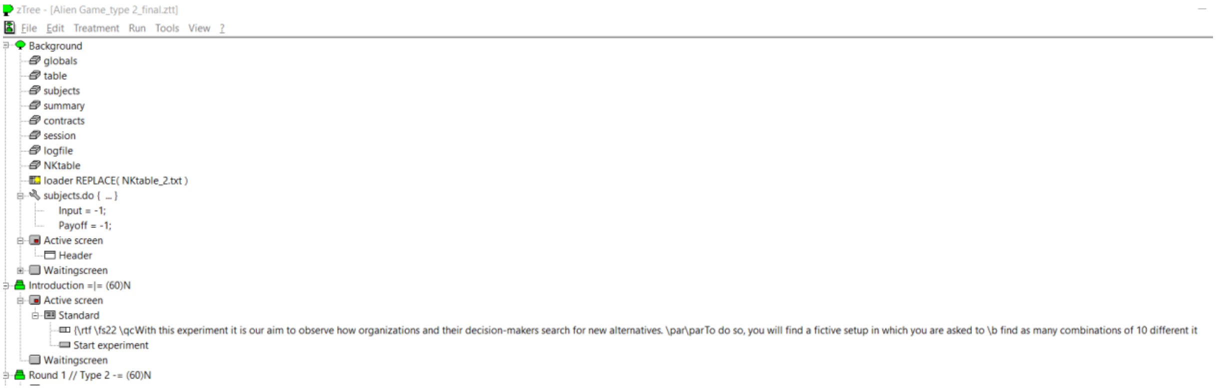


Figure 20 ztree backend for Type 2 – Introduction and first round

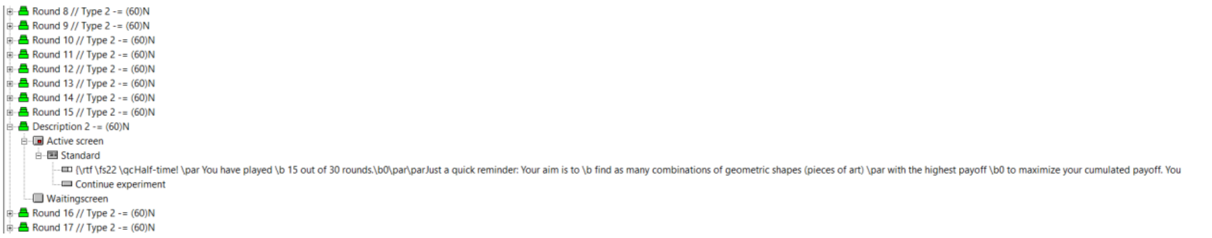


Figure 21 ztree backend for Type 2 - Reminder

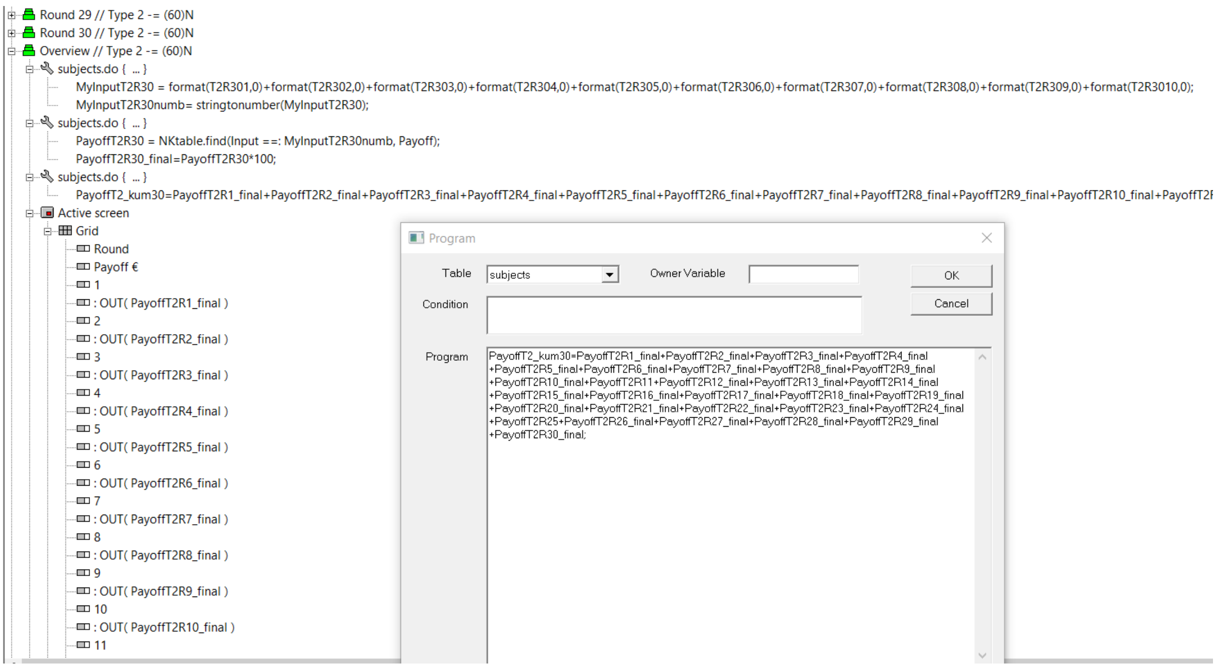


Figure 22 ztree backend for Type 2 - Final Payoff calculation

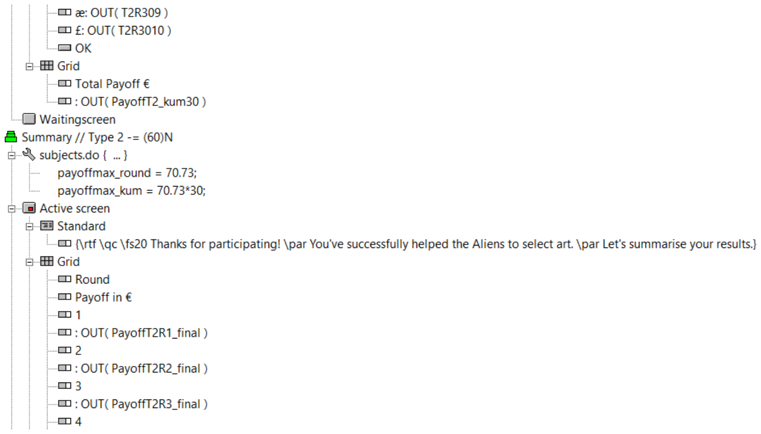


Figure 23 ztree backend for Type 2 – Summary

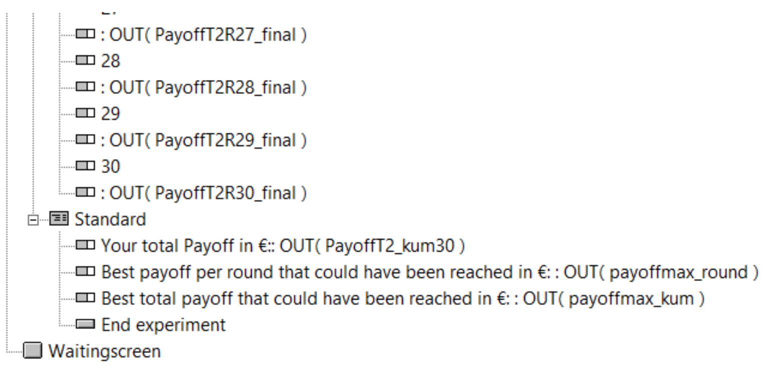


Figure 24 ztree backend for Type 2 – Final results