2 Theoretical Background

Imagine being born and raised on the Hawaiian island Kaua'i, close to the shield volcano Wai'ale'ale. On this island, yearly rainfall reaches 15 meters and more (Kido, Ha, & Kinzie, 1993, p. 44). You were stuck in this small region on this remote island your entire life, without any information ever having reached you to indicate that this extreme amount of rainfall was extra ordinary. To you, heavy rain is the daily norm. Your day-to-day decision-making has been thus influenced by this routine and led you to form the belief that constant rain is entirely normal. Even small periods of "rain dropouts" will not change your belief that rain is the regular "status quo" of life. You develop some strategy to survive on the island making use of the rain, by building water mills, collecting rain water to drink and recover energy in warm baths. Your tribe members too develop survival strategies based on the stream of rain, however, while all of them do not question there being lots of annual rain, some have noted that the small periods of "rain dropouts" were influenced by godly external factors, which cannot be influenced and were entirely random. Others question this worldview, suggesting that they had observed some regularities in the occurrences of "rain dropouts", which, to their understanding, could be used to maximize the water mills effectiveness. Some tribe members even assure you that "rain dropouts" could not only be anticipated, but were influenced by tribal sacrifices.

While worldviews of each tribe member might differ, all of them are true experts when it comes to making use of rain. Despite this, all individual worldviews of the tribe are wrong, since they lack global information about the true nature of rainfall. However, chance of collective survival was enhanced by actions and believes based on some mental model surrounding local experience with rain. So even though worldviews were at best a true representation of reality locally, in other words a homeomorphic mental model, these mental models did produce

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good performance measured in days of survival. These mental models had even proven to be effective in a group. Individual expert knowledge led to collective strategies following some focal point being "dealing with heavy rainfalls". This focal point enabled the tribe to include heterogeneous decisions into a "direction" or path towards a common goal, even though each individual's decision is also influenced by other tribe members' decisions. It might also be that some individual decisions were bad decisions, based on a locally wrong mental model, but ultimately led to a good group outcome, vice versa.

These outcomes might lead to falsely confirming a certain mental model. A tribe member who believes in having found some pattern regarding "rain dropouts", might invest less working time on "water mills" shortly before he anticipates lack of rain, focusing more on bathing in warm rain water. This lack of work discipline might alter decision-making of those who belief that bathing enraged the gods, which, to their understanding, led to less rain. As they see more and more "pattern-belief members" bathing, the "sacrifice-belief group" begins to collect more rain water, working in nightshifts, as a sacrifice to soothe the gods. Assuming that a short "rain dropout" actually occurred, which was no surprise to the "chaos-belief-group", who regard short dropouts to happen randomly all the time, the sacrifice-, the pattern-, and the chaos-belief groups are all locally confirmed in their believe. However, group performance was still upholding well, since one group gathered strength by relaxing, others collected more resources for drier times, while the rest maintained their working routine. The collective group performance equilibrium was proven to be stable.

A change in environmental conditions, such as "rain dropouts" only impede performance when individual strategies are touched, meaning, as long as there is enough rainfall reliability, individual decisions will not change too much. With a growing duration of "rain dropouts", chances are that individual decisions will adapt to these changes, even influencing group performance, "perturbing" the collective group decision network. These perturbations can themselves lead to a change in individual decision making, when tribe members' decision output, such as production, depend on each other. Causally linked decisions might break or be formed anew, re-arranging the "rules" of the network. In any case, "change in rules" of this network, whether it stemmed from environmental changes, mental models, third-party decisions or group-dynamics has to be first identified by an individual decision maker, building a new mental model based on this novel knowledge, before a new strategy was applied based on this new knowledge to reach a certain goal.

From this small island economy "Gedankenexperiment" several important aspects can be derived that play a role in modern scientific approaches to decision-making.

As mentioned at the beginning of the story, all tribe members (agents) only had access to local information: represented metaphorically by the small island, which can be regarded as a market, where decision-making takes place. Even though each individual had full access to necessary market information, decision-making differed and was not optimal, as the delay of rainfall was interpreted differently. Feedback was interpreted myopically to confirm the own belief. Agents do not even act optimally when provided perfect information and knowledge of the system structure, due to the "misperception of feedback", which is part of day-to-day economic reality (Sterman, 1989). The tribe had three different theories regarding the "data" stemming from rainfall observations: the first group believed in being able to anticipate rainfall-dropouts by observing "patterns", the second group thought it to be possible to control "rain-dropouts" and the third group saw "rain-dropouts" as an entirely random environmental condition, which cannot be controlled at all. The discrepancy between the tribe's data and their theories lead to "errors", which will influence outcomes of decision-making. From an empirical perspective, defining "error" is a complex task, which has a long history of development, and marks a corner stone in economic statistics (Louçã, 2007). Error can occur by an improper choice of some model, lacking precision in measurement or can even stem from cultural chaos (Louçã, 2007). The nature of an error may also vary. They can be seen as being part of nature, being an unobservable disturbance or as unpredictable random behavior. Some mathematical descriptions define error as residual and observable, some see them as corrigible, and some not. Disturbances can get "their own life" and are more than nonconformity of some anticipated value and in any event, an unobserved "disturbance vector" and an observed "residual vector" should be distinguished (Louçã, 2007, p. 151).

In other words, even a small and simple economy can develop complex and unpredictable self-organizing behavior. Durlauf (1998) defines "economic complexity" as a system where choices depend directly on the decisions of others. Such systems are evolving, and cannot by be fully understood or described by "steady states", when there is limited information about the intentions and goals of third party agents (Durlauf, 1998). Such "steady states" are unchanging regularities or "atoms" of a system. The author further explains that "complex systems" inhibit nonlinear attributes because of the interdependence in decisions of its acting agents, and that a very important aspect of complex systems is its past history of events or its order of information by which its future outcomes are dependent on. This complex history can possibly result in "path dependence"

(Durlauf, 1998). “Path dependence” roughly describes “ugly habits” of a system, which are persistent and can lead to recessions.

To understand a complex system’s behavior by applying models, several problems have to be coped with, being that simply looking at unchanging consistencies does not suffice, high volatility of predictions may arise from nonlinear dynamics, and “bad system behavior” can only be explained with large amounts of data. The human brain does not perform well at storing such large amounts of data, and are better suited in pattern recognition by visual inputs (Simoes & Hidalgo, 2011), as the human brain is in constant search of known patterns, acting as an “association machine” (Chlupsa, 2017). For this reason, clear visual representations are used in models, coping with “economic complexity”, such as the “Atlas Of Economic Complexity” (Hausmann et al., 2014). When no visual clues are provided to understand economic complexity, decision-makers might be overwhelmed by complexity, and even expert knowledge might not suffice. It was shown for example that antitrust analysis has become too complex for judges to evaluate accurately, when expertise knowledge is missing, and while basic economic training helps in simple cases, this training failed to show significant positive influence in complex cases, leading to the conclusion that there exist antitrust cases, which are in fact too complex for generalist judges (Baye & Wright, 2011).

Expert knowledge seems to be a necessity to successfully cope with problems concerning economic complexity. However, real world problems commonly are not well defined, can hardly be distinguished from their irrelevant environmental conditions and modelling such fuzzy problems in a way that makes them solvable often proves to be the true challenge (Davidson & Sternberg, 2003). This also relates to problems stemming from economic complexity, as the individual goals and interpretations of others are unknown and constantly changing, while this information or lack thereof is ultimately able to influence the outcome of one’s decision. Just like economic complexity, individual agents or decision-makers can also be described as constantly evolving systems, called “cognitive systems”, which are constantly modeling their environment, focusing on “local aspects” representing barriers to the effective solution of a problem (Holland, Holyoak, Nisbett, Thagard, & Smoliar, 2008).

It is then not a far-reaching assumption to define an economy in psychological terms. A market can be understood as a network of subjective instances serving as an input for strategies and volition in decision-making (Arthur, 1995). Agents or cognitive systems make choices based on their currently valid beliefs, which are subjective and often unknown to others. These beliefs are constantly tested by the system, which itself is built from all agents’ subjective beliefs (Arthur, 1995).

So, while the small island economy from the Gedankenexperiment does fulfill all mentioned attributes of "economic complexity", which economic systems are considered as "complex" in reality? The complexity of an economic system also represents national production capabilities as non-tradable inputs (Hausmann & Hidalgo, 2010; Hidalgo & Hausmann, 2009), which influence the country's productivity, where an increase of complexity in a country's production structure is positively related to its capabilities (Zhu & Li, 2017). According to Felipe et al. (2012) Japan, Germany, the U.S.A, France and other wealthy countries are considered countries with high complexity, while countries with relative low income per capita such as Cambodia, Papua New Guinea and Nigeria are considered to hold low complexity (Zhu & Li, 2017).

While real life economies do not have to cope with changes in "rain frequencies" such as the small island economy, a country does have to cope with climate, technological, socio-economic and political change, also holding uncertain future scenarios; a "best-guess" what might happen, as performed by the three different belief-groups from the Gedankenexperiment, fails to be a good way to cope with such uncertainty, as in such decision-making domains, multiple possible paths lead to different future scenarios, whose occurrence probabilities are not associated and probability ranking cannot be applied (Maier et al., 2016). It is then better to create some strategy, which performs well during multiple scenarios.

However, the development of such a "stable" strategy isn't easily constructed in complex economies, as belief alters decision-making. Whether or not a cognitive system considers some event being a random outcome or manmade, has an impact on the agent's decision-making. When an event is considered random, agents stick with simple rules to optimize their strategy—when an event is thought of being manmade, agents try to figure out patterns to optimize (Schul, Mayo, Burnstein, & Yahalom, 2007). Agents might stick to their personal belief even though new information indicated that a deviation from their strategy might be beneficial, which is linked to several decision anomalies, such as the confirmation bias, inertia bias, or weighting bias. It can also be linked to "routine". The three belief-groups from our Gedankenexperiment stick to their own routine, further strengthening their belief, possibly feeding their confirmation bias. It is known that strong routine enhances the preference of information that favors the routine, and makes information that contradicts one's routine less favorable (Betsch, Haberstroh, Glöckner, Haar, & Fiedler, 2001).

Altogether, the simple story about an island tribe, and respectful homage to the famous "Lucas islands model" by Nobel Prize winning economist Robert Lucas, Jr. (Lucas, 1972), shed light on many important aspects regarding decision-making

and problem-solving. These aspects are to be explained in greater detail with their latest insights from scientific experiments in the following chapters.

2.1 Key Aspects for Real Economic Problem-Solving

Many models attempt to describe, how humans engage in problem-solving. By modelling problem-solving, multiple questions arise: which instances of reality are seen by humans as problems and how can problems be categorized? How do humans define the boundaries of some problem and how can such boundaries be modelled? How can humans naturally engage in searching for solutions and which scientific insights describe such problem-solving attempts? In order to implement problem-solving into domains of real, economic decision-making, several key aspects are to be explained in the following. Namely, two major categories describing problems in general, the definition and role of complexity regarding problem-solving, the definition and meaning of heuristics, and the definition and background of uncertainty.

2.1.1 Well-Defined Problems

In general, two types of categories describe problems that are to be solved: well- and ill-defined problems; this distinguishing generalization is effective, as all domains hold well- and ill-defined problems (Nye, Boyce, & Sottilare, 2016) and different cognitive areas are required for solving well- and ill-defined problems (Schraw, Dunkle, & Bendixen, 1995).

Problems that can be broken down to a series of sub-problems, and also provide enough information about their goals, solution-path and obstacles, are considered well-defined problems; these problems can usually be solved using recursive algorithms (Davidson & Sternberg, 2003).

The famous “Tower of Hanoi” problem is considered a “well-defined” problem (Davidson & Sternberg, 2003). It can either be solved perfectly using an iterative or recursive algorithm or by applying some strategy, consisting of several steps that will always solve the problem in the least number of steps.

Multiple classifications exist in order to distinguish between well- and ill-defined problems, as well- and ill-defined problems exist in a continuum (Le, Loll, & Pinkwart, 2013).

2.1.2 Ill-Defined Problems

Contrary to well-defined problems, recursive algorithms cannot be applied to solve such problems, as the problem cannot be modelled as some set of steps necessary to solve them; they lack information about some clear path to the solution or do not provide some statement about how the problem at hand can be solved (Davidson & Sternberg, 2003).

From the perspective of a rookie facing some problem, this problem might seem to be "ill-defined" due to lack of experience. However, in such a case the problem is merely "undefined" and not "ill-defined" (Nye et al., 2016; Strunz, 2019). A person who has never played the well-defined game of "Tower of Hanoi" before, will begin to develop some strategy and optimizing it further, until the most efficient strategy is found. At this point, "Tower of Hanoi" is regarded as a well-defined problem. This process is known as "learning", and for this reason, applying the domain "learning" to successfully distinguish between well- and ill-defined problems is useful.

When learning is applied to ill-defined problems, further categories are required. Ill-defined problems are regarded as "complex problems" and the attempt to solve them is regarded as "complex problem solving" (CPS) (Dörner & Funke, 2017).

As described before, most problems in real life are "fuzzy" problems or lack relevant information that make them fall in the category of complex problems. Any complex problem is always an "ill-structured problem" (Grünig & Kühn, 2013), which can be understood analogous to an ill-defined problem. Multiple domains are then necessary to consider when trying to define some theory of "problem-solving", since an agent most likely faces some unknown, ill-defined or complex problem in economic reality: first, information might be interpreted differently by each agent, leading to heterogeneous problem perceptions. Second, rookies might lack some definitive "recipe" of action required to solve a problem. Third, even when some action is considered to be suitable, it is not yet clear, which intrinsic processes led to the decision-making itself. Fourth, if this process was successfully analyzed, it is unclear how an agent considered the action as positive or negative, as in "bringing the agent closer to the goal". Last but not least, it is unclear how an agent would "find" a problem and "recognize" it as such; agents differ in their goal setting priorities and it is unclear why a certain path towards some goal is being chosen. As depicted in Figure 2.1 (Ohlsson, 2012, p. 122) all these five domains would have to be combined in order to picture "problem-solving" fully, described as "heuristic search". The cognitive

psychologists Newell and Simon stated that humans were able to solve unfamiliar problems by tentatively choosing different actions, mentally projecting their outcomes of the chosen action, followed by some evaluation, which is then used as a new input for their decision-making process, such that they are able to alter their approach to solve a problem; Newell and Simon referred to this as "heuristic search" (Ohlsson, 2012).

Complex-Problem-Solving builds upon the understanding that ill-defined (ill-structured) problems lead to a lack of information, unattainable from the outset on first sight, where uncertainty follows up. Complex problems do not require complex solutions, however, a "bias bias" might lead to the underestimation of the performance of simplicity, which outperforms under conditions of high uncertainty (Brighton & Gigerenzer, 2015).

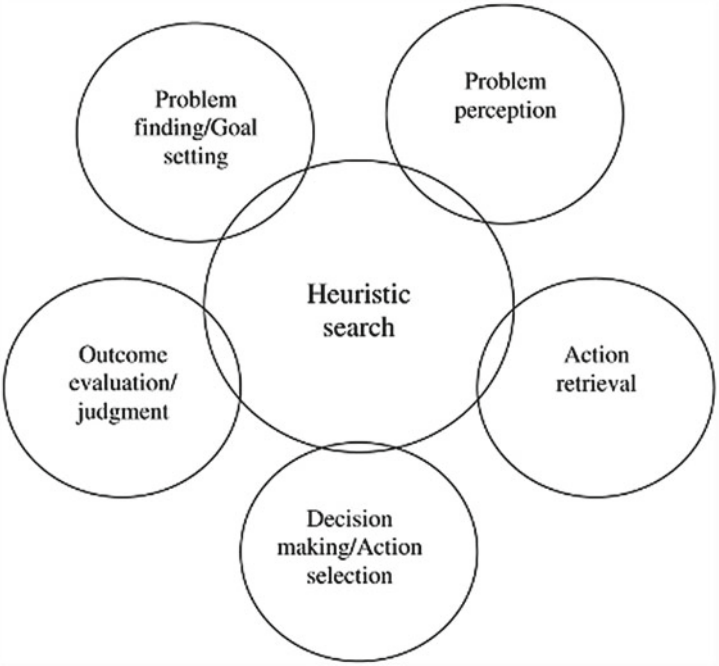

Figure 2.1 "The structure of a hypothetical theory of problem solving." *Source* Ohlsson, 2012, p. 122

2.1.3 Definitions of Complexity

"Complexity" in every-day language can describe problems that one regards as "difficult" to solve. In the economic domain task-difficulty and task-complexity are two different attributes: difficult problems are solved by incentivizing diverse problem-solving alternatives, while complexity is coped by institutions via selection criteria adjustment, different rates of variation and adjusting connectedness (Page, 2008). To make predictions about the future, economic models rely on assumptions about reality expressed by mathematical functions originating from theoretical physics, informatics or sociology.

Whenever complexity of some entity such as a market, country, global economy or project is to be measured, the modeler first has to define the "system" boundaries, its instances and their relations, which together equal the "system" itself that is separated from its environment. Before even defining "complexity" itself, it has to be noted that the modeler might run into the "frame problem" defining a system. By defining entities (states) and their relations, it makes sense to choose from a set of things that are meaningful to describe the system. For example, defining the system "engine" results in a meaningful list of cogs, metal rods and other things that when being changed in their structure or behavior, will also change the engine itself. However, by defining a list of things that are changed, everything else is ignored and assumed to not change at all, regarded as the "commonsense law of inertia" (Kameramans & Schmits, 2004). While this assumption solves the "frame problem" for more common models, more sophisticated solutions have to be applied to actually solve the frame problem when cognitive agents are to be modeled, such as the "Thielscher's Fluent Calculus", which is used, for example, when robots are required to face "non-determinism and uncertainty" (Kameramans & Schmits, 2004, p. 45).

In other words, when the modeler is interested in defining some "system" that is scanning its environment for change, in order to adapt its behavior to novel circumstances, just like a cognitive agent, its "states" or "entities" and their relations are to be modelled as "fluent" states. Fluent states' truth-values depend on the current context. Functions running on such fluent states are therefore adaptive. When a system is defined, its complexity can be measured.

Complexity enjoys many definitions that vary amongst the scientific domain it is used in. "Complexity" was first mentioned in an 1948 article titled "Science and Complexity", where it was stated that physical science was mostly interested in two-variable problems, and that life science regards such simplicity as not significant (Efatmaneshnik & Ryan, 2016). Today, the term "complexity" had been used in so many different variations and contexts that its meaning

became unclear (Efatmaneshnik & Ryan, 2016). Efatmaneshnik and Ryan (2016) differentiate between objective and subjective complexity in their generic framework. They define objective complexity as the size of the minimum descriptions necessary to describe a system. Objective complexity is not dependent on any observer's perspective or viewpoint, but can be context and goal dependent. Subjective complexity on the other hand is dependent on the modeler's choice of reference model. As depicted in Figure 2.2 (Efatmaneshnik & Ryan, 2016, p. 4) objective complexity is defined by context and by the modeler's (observer's) definition of the system. So, while it is independent of the subjective viewpoint of some modeler, it still is dependent on the modeler's subjective definition of the observed "system".

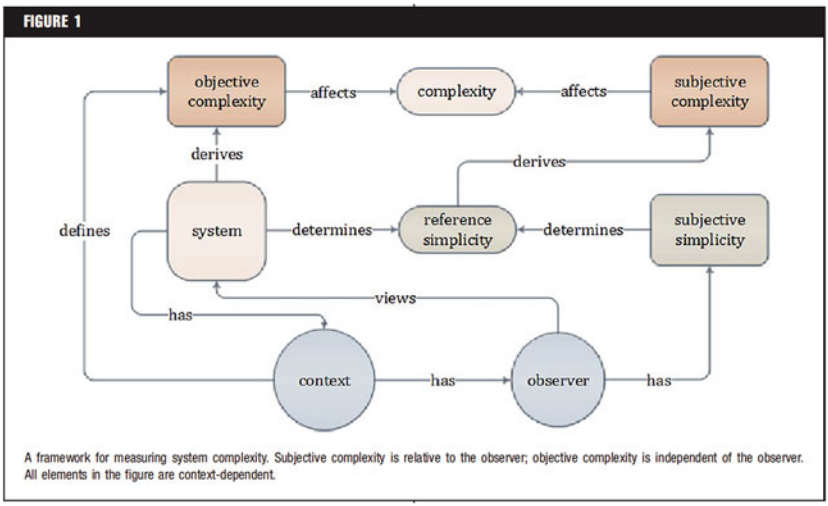

Figure 2.2 A generic framework for measuring complexity. *Source* Efatmaneshnik & Ryan, 2016, p. 4

The definition of the "system" and whatever the modeler subjectively regards as simple, both determine some "reference simplicity". Complexity is then the distance and size from this "reference simplicity". This generic framework by Efatmaneshnik and Ryan (2016) can be used for a variety of complexity measures, such as Statistical Complexity, Complexity in Engineered Systems, Complexity

Measures for Graphs, Complexity of Repeating Patterns and can be used for evolving, dynamic models, which include learning agents. Distinguishing between objective and subjective complexity enables the modeler to include multiple perspectives, whose reference simplicities naturally differ, leading to a "gap" between the agents' views. Every reference point comes with an objective complexity constant and various subjective complexity measures, which are dependent on the agent'.

As multiple cognitive agents will ultimately have different views on what defines (subjective) simplicity, they will inevitably have different viewpoints on the measure of complexity. This is where "complexity economics" sees reason to include these derivations into the conclusion of contracts. Complexity Economics states that multiple agents will disagree on the "reality" of a system after some written agreement or contract has been made. The agents then disagree on performance indicators, as indicated by figure 2.3 (Nota & Aiello, 2014, p. 88).

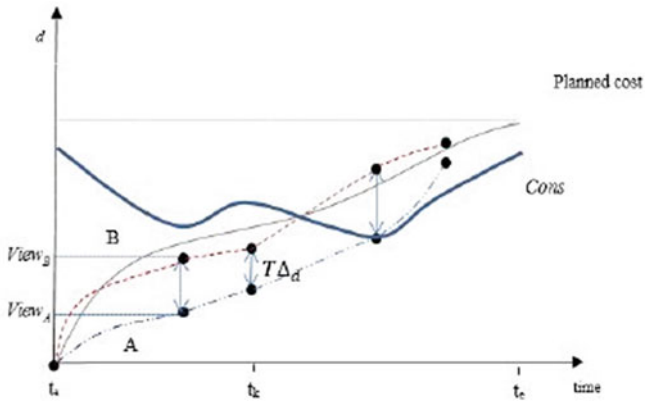

Figure 2.3 Deviation distance of two perspectives on the individually perceived reality of some project over time. *Source* Nota & Aiello, 2014, p. 88

This deviation of perspectives occurs when "system boundaries" are set by more than one modeler. For this reason "corporate decision-makers need to reflect the company as part of an open system" (Jeschke & Mahnke, 2016, p. 73), where system and its environment are defined by some meaningful boundary ("Sinngrenze"), which is open to a set of other meaningful entities coming from

heterogeneous perspectives, definitions and viewpoints, as long as some internal selection rules are applied, where such entities can be approved or denied (Luhmann, 2012, p. 178).

In the domain of corporate decisions, such selection rules should be defined neither too broadly nor too narrowly, such that critical information is included and managerial focus is preserved (Jeschke & Mahnke, 2016). As depictured in figure 2.4, such system boundaries can be modelled by two dimensions: the range of the considered system constituents and the time horizon of system analysis (Jeschke & Mahnke, 2016, p. 74).

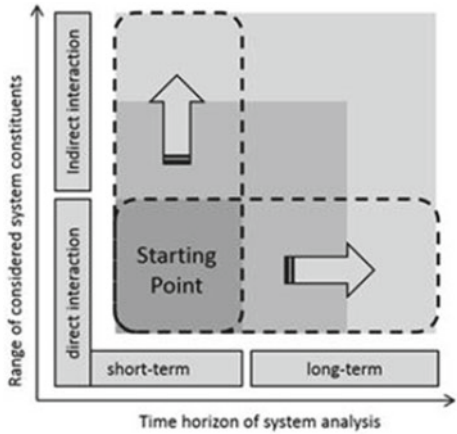

Figure 2.4 System boundaries defined by 2-dimensional selection rule. *Source* Jeschke & Mahnke, 2016, p. 74

Based upon such a selection rule, the complexity of a system can be categorized, e.g. by multiple non-correlative dimensions such as multiplicity, interdependency, diversity, dynamics (Jeschke & Mahnke, 2016) and imponderability (Jeschke, 2017). By analyzing the system's complexity with this 5-dimensional model, 32 distinguishable types of complexity describe different scenarios of decision-making complexity. For each type, different approaches for CPS or operations to reduce uncertainty are suggested by Jeschke (2017), such as clustering-analysis to reduce uncertainty from high multiplicity, cross-impact-analysis to cope with interdependency, specialization to counter high diversity, sound Business-Process-Management in order to stay above high dynamics, and risk-management to handle high imponderability.

In the end, the reduction of uncertainty by heuristic processes can be assigned to all mentioned tasks in this sub-chapter. Heuristics are defined as conscious or

unconscious processes that efficiently ignore information (Gigerenzer & Gaissmaier, 2011). To define some system or in order to being able to talk about a system, it has to be instantiated by a meaningful boundary or Sinngrenze, which is performed by ignoring information, i.e. relying on selection rules. In order to measure system complexity, after the system was defined, the measurement of complexity is not only affected by objective complexity but also by subjective complexity, which—again—includes ignoring information, stemming from subjective simplicity, e.g. relying on expert knowledge. To categorize complexity, models such as the "MIDDI"-model (Jeschke, 2017) can be applied to produce multiple types of decision-making scenarios, so that suitable problem-solving operations can be used to reduce uncertainty in a context-specific manner, relying on approved and proficient methods; ultimately ignoring alternative approaches, and therefore information, in order to be capable of acting efficiently and effectively.

The three tasks of defining a system, measuring the system's complexity and categorizing its complexity all frame reality by ignoring information to balance the amount of relevant information and associated costs to manipulate this information. Heuristic decision-making is not applied in all decision-making scenarios mentioned in this sub-chapter, but is applied when a suitable model is developed (e.g. defining some system), when a model is adapted to context (e.g. measuring system complexity) and when models are linked (e.g. categorizing complexity), to frame limitless information in order to make cost-efficient or cost-effective predictions. Therefore, to make capital favorable decisions, it is necessary for some agent to possess as much information as possible in order to frame it in a productive way. A game-theoretical analysis showed that it was favorable to possess information rather than to have access to it (Ravid, Roesler, & Szentes, 2019), as agents must be incentivized to gather costly information, overlook information when its price is in equilibrium and because cheap information does not necessarily approximate full information. Ravid, Roesler and Szentes (2019) strengthen the need for the design of information channels by which agents in a certain decision-making systems, such as a market, can learn, as knowing that certain information can be obtained is not the same as actually knowing this information (Ravid et al., 2019).

2.1.4 Ignoring Information

While there exists debate on whether the concept of heuristic search was falsified, can be falsified at all by the Popperian manner or if it even was an empirical hypothesis (Ohlsson, 2012), the concept of heuristic search is still brought into

context with "planning" in more current studies (Baier, Bacchus, & McIlraith, 2007). Baier, Bacchus and McIlraith use a simplified "relaxed planning graph" that ignores information on negative effects. In other words, they compute a simplified model to reduce complexity to build a new model that processes costs to achieve a certain goal (Baier et al., 2007, p. 614).

Analogous to modern approaches to model planning-paths using heuristic search, the original idea of heuristic search was to also consider humans as information processing entities, who simplify reality by ignoring information due to their biological limitation (Simon & Newell, 1971). Just like mentioned algorithms, many papers from the 70's considered humans to conduct "heuristic processing", defined as an efficient problem-solving method, suitable for difficult problems by ignoring certain solutions in the set of possible solutions. This restriction is based on certain evaluations of the problem structure (Payne, 1976).

The most famous example on research regarding "heuristics" comes manifold from Kahneman and Tversky, who described three major heuristics, being "availability", "representativeness" and "anchoring and adjustment" (Tversky & Kahneman, 1974), which were used in human decision-making under uncertainty; "under uncertainty" refers to any decision-making process with the absence of known probabilities regarding events of the state-space. Decisions can also be made "under risk", where subjective or objective probabilities are provided. This basic differentiation dates back to 1921 and is still used to categorize decision-making scenarios (Knight, 1957). When a decision is made "under certainty", the consequence of each possible action is known (Mousavi & Gigerenzer, 2014).

In other words, human decision making was and still is theorized to be influenced by belief on the likelihood of events, where subjective or objective probabilities are not provided. Linked to this set of heuristics, a list of "biases" was given by Kahneman and Tversky, which represent deviations from the normative rational theory, caused by error in memory retrieval or violations of basic laws of probability (Gilovich, Griffin, & Kahneman, 2002).

Kahneman's and Tversky's heuristics-and-biases program had been challenged and criticized by the famous psychologist Gerd Gigerenzer (Gigerenzer, 1996). Gigerenzer (2011) states that heuristics are neither rational nor irrational. While heuristics can outperform statistical decision-making in complex environments, as rational models perform badly during uncertainty, caused by complexity (Mousavi & Gigerenzer, 2014), their accuracy depend on environmental circumstances. People are able to learn to choose adaptively from a collection of heuristics; he further states that it was necessary to develop simple decision-making guidelines for complex environments and to connect the simple heuristics framework with other theoretical frameworks (Gigerenzer & Gaissmaier, 2011).

Decision-making under uncertainty does not necessarily benefit from logic and statistics according to Artinger, et al. (2015). Their research showed that decisions made in complex and uncertainty environments actually benefit from simple heuristics, as they are less sensitive to chaotic environmental disturbances, such as variance in data, thus generating less error (Artinger, Petersen, Gigerenzer, & Weibler, 2015). An intuitive example, where a much simpler heuristic decision-making rule outperformed a more complex model under uncertainty, is the "Simple hiatus rule vs. Pareto/NBD" model. Here, the complex model inhibits more information than the heuristic approach, but the heuristic approach resulted in better predictions (Samson & Gigerenzer, 2016).

From these insights it can be derived that heuristic decision-making still plays an important role in modern approaches to cope with complexity. It not only seems to be natural for humans to use heuristics when making decisions under uncertainty—such an approach can also outperform statistical and logical models in anticipating development, when being computed by machines. Anyhow, uncertainty is an important factor to consider when predicting complex behavior. A case study had shown that failure to include stochastic effects derived from uncertainty in models analyzing traffic led to prediction biases up to 200% (Calvert, Taale, Snelder, & Hoogendoorn, 2018). Still, decision-making using heuristics is not a one-fits-all tool, outperforming statistical and logical computations in all circumstances. It rather presents itself as a skill that can be learned to overcome bias and reduce uncertainty to make predictions that can outperform chance when being surrounded by complexity.

2.1.5 Uncertainty

Living beings, such as cognitive systems or decision-making agents, can be considered as complex systems, where predicting their behavior might be of extreme challenge under uncertain or novel decision situations (Hernán et al., 2015). In day to day life the neural system reacts to different levels of uncertainty in a complex way, and subjective utility theory fails to correctly model human behavior. According to the reduction of uncertainty hypothesis, the human brain might be biased towards data which reduces uncertainty (Onnis, Christiansen, Chater, & Gómez, 2002).

In a purely formal, mathematical context required for simulation, uncertainty enjoys crisp definitions and even its own "Uncertainty Theory", which has become a branch of mathematics (Liu, 2018). This thesis relies on the explanation of uncertainty being

"any departure from the unachievable ideal of complete determinism"

(Walker et al., 2003, p. 8). Risk and ambiguity are to be "limiting cases of a general system evaluating uncertainty", where decision makers differ in preference/aversion of risk and ambiguity (Hsu, Bhatt, Adolphs, Tranel, & Camerer, 2005).

The overall meaning of uncertainty varies and depends on the scientific field and domain it is used in. However, uncertainty is part of organizational day-to-day reality (Schilke, Wiedenfels, Brettel, & Zucker, 2017). In enterprises for example, uncertainty in decision-making is being dealt by Information Systems, such as Expert Systems, Enterprise Resource Planning and Supply Chain Management (Irani, Sharif, Kamal, & Love, 2014). Project management is dominated by models, which assume or build upon determinism (Padalkar & Gopinath, 2016), while it is known that real-world problems mostly have access to incomplete or approximate information, limiting the uncertainty reducing capabilities of even an idealized algorithm (Traub, Wasilkowski, Wozniakowski, Bartholdi, & Ford, 1985). With the rise of technological progress, partly stemming from quantum physics more than 60 years ago, it was already considered to be "unscientific" to assume infinite accuracy in any measurement, and that inevitable errors must be included in any theory, as they are considered being part of the sense-making of an environment, making strict determinism in scientific prediction an impossibility (Brillouin, 1959). This perspective also translates to economic predictions, as uncertainty prevails even with lots of information provided (Walker et al., 2003). In meteorological science inevitable uncertainties in initial conditions and model equations led to a shift of predicting the most likely outcome to a distribution of probabilities, as well as to the understanding of the need to include and represent "doubt" in forecasts (Palmer, 2017). This new process of modelling predictions is also influenced by external third parties. Scientists need to withstand the pressure to predict in a more deterministic way than is justified by the given data, stemming from media attention (Palmer, 2017).

The urge to avoid or work around the understanding of unavoidable uncertainty might stem from "intolerance of uncertainty", which had been described as the "most fundamental, underlying variable of anxiety disorders" (Gosselin et al., 2008, p. 1428). "Uncertainty avoidance", being intensely researched as a cultural factor to be considered by the works of Hofstede since the 70s, failed to show significance in a more current experiment, when being applied outside of the IBM study (Schmitz & Weber, 2014). On the contrary, studies still build upon the hypothesis that cultures express different levels of "uncertainty avoidance" (Hofstede, 2001) and succeeded in finding correlations, e.g. participation

in decision-making (Jang, Shen, Allen, & Zhang, 2018). Nevertheless, when talking about problem-solving, "uncertainty" has to be considered: a model linking uncertainty and cognition has shown that despite complete certainty over some final stage of a decision-making process, happening in a vast cognitive space representing complexity, uncertainty will not stop growing (Hadfi & Ito, 2013). To cope with the inevitable persistence of uncertainty in algorithms and heuristic problem-solving, it was suggested to translate "complex problem solving" to "finding ways of reducing uncertainty" (Osman, 2017).

2.2 The Role of Information in Decision-Making

In order to understand "information" it might be meaningful to ask "How much information do I acquire, when I learn something new?". According to the "Kullback-Leibler divergence" the amount of information gained depends on what the agent had believed before (Baez & Pollard, 2016). If the agent assumed a fair coin-toss, or 50% chance of heads, it will gain one bit of information. When the agent expects a 25% chance to see heads, it will gain two bits of information when head actually appears.

This example helps defining "information". Just as "uncertainty" and "complexity", the term "information" is used in every-day language and in scientific contexts in many ways. The following chapters will show different perspectives and definitions of information, how information can lead to uncertainty and to what extend information influences 21st century decision-making.

2.2.1 Definitions of Information

Mentioned coin-toss example builds upon the Shannon and Weaver model, where the information content is expressed in "bits". The amount of information (I) is computed by $I = \log_2 n$, with n being the number of different output values. This model can be seen as translating the coin-tossing process into bits, a process which receives as input some belief about the future and translates it to some output, expressed in bits by the Shannon model. From this perspective, information reveals something about the input and its linked process. However, information is not the process itself, neither the input nor the output per se—the output expressed in bits merely is information *about* the input (belief) and the process (coin-toss and model) (Losee, 1998). However, the Shannon and Weaver model is limited to functional terms.

In physics information is commonly described as the entropy of a system. When nothing is known about a certain system, its entropy equals the logarithm of the number of possible states. Whether or not the observer of a system has to be included into the description of information and whether the observer can be seen in isolation is still debated in physics to this day (Brukner, 2018). While the problems and methods used in quantum physics might seem be too far-fetched and abstract for day-to-day economic decision-making, the intellectual basis for developing models used in problem-solving is identical in the two fields of study. "Bayesian-inference" is used in the thought experiment described by Brukner (2018), which is also common in game-theory and neuroscientific models about the human mind and brain. Knowledge or belief about a certain system and knowledge about the knowledge of others is part of game-theoretical analysis, as described in "The Dirty Faces and the Sage" (Fudenberg & Tirole, 1991, p. 547).

Using the "Hierarchical Model of Information Transmission" more abstract notions such as human perceptions, observation, belief, knowledge, as well as the influence of errors, misinformation and bad data can be considered (Losee, 1998). Based on this model, a discipline independent definition of information was provided by the author Losee (1998), who defined information as some output coming from some process, where the output tells something about both the input and process from which it originated (Losee, 1998).

This definition links the meaning of information to some process that might have an impact on the behavior of some agent being aware of the output of this process. An analogue definition describes information as "a stimulus which expands or amends the World View of the informed." (Madden, 2004, p. 9), the stimulus being the impact following the perception of some signal, altering the agent's "World View". The introducing Gedankenexperiment about the tribe holding different belief-groups is also based on the latter definition. Whatever information is, it leads to constant updates about some agent's world-view. When multiple agents are influencing each other's decision-making, game-theoretical models come into play.

In game-theory, information is considered "private information" when it is only obtainable by an individual agent, such as "a random thought or intrinsic motives". "Public information" refers to information, which is potentially obtainable by all agents, who are part of the "game" or decision-making frame. A typical assumption of game theory is that agents hold common knowledge about the given information structure of the game, and about the co-agents' rationality. It is further assumed that agents do so by conducting complicated mathematical calculations, i.e. applying Bayes theorem without error when updating their beliefs (McKelvey

& Page, 1990). McKelvey and Page (1990) show that this game-theoretical assumption on human behavior is approximated by experienced subjects with 85% efficiency and by inexperienced subjects with 69% efficiency. The concept of the "Bayesian-Brain" is often considered by psychologists, neuroscientists and cognitivists. The model assumes that the human brain is constantly predicting possible events and deviations from what is expected, by performing Bayesian inferences, and in doing so, the brain is limited by the requirement to minimize costs stemming from error (Hutchinson & Barrett, 2019, p. 280).

Hutchinson and Barrett (2019) hypothesize that mental events are not arising independently, but are always dependent on prior events. This hypothesis can be linked to the understanding of Durlauf (1998) that "history matters" for complex systems, such as cognitive agents. Opposing the more "simplistic model" of some cognitive agents receiving a "stimulus", translating it by perceptive senses into some "response", Hutchinson and Barrett (2019) offer a different model on both mind and brain, defining "information flow" from a novel psychological and neuroscientific view.

As shown in figure 2.5 both mind and brain are in a constant fluent state. Each state consists of a non-linear, complex system of neuronal activities (green arrows) and feedback (purple arrow), which are to be separated in mind and brain activities. In short, neurons activate memory from which certain "maps" of strategies are derived. Just like a scientific hypothesis, neurons try strategies in accordance to this map, choosing paths which deemed useful in the past and are then corrected by feedback. In a way, the brain simulates strategies by predicting the future based upon past experiences, hence "Bayesian Brain". When the distance between the chosen path and the correcting feedback is too great, this distance can be considered an "error" and the neuron can correct this error by altering its path, i.e. correcting a prediction-error. When the chosen path equals the feedback, the predicting neuron already is on its correct path (prediction) and the hypothesis was correct.

In a certain way, the brain constantly predicts the future and is constantly corrected by the environmental feedback and more importantly: the human brain is also corrected by *anticipated* prediction-error, and therefore not exclusively by environmental feedback. Each combined mind- and brain-state can be considered a "screenshot" of the agent's "World-View". A complex, non-linear network of trial- and error, constantly working on reducing uncertainty by choosing strategies that fits the current context.

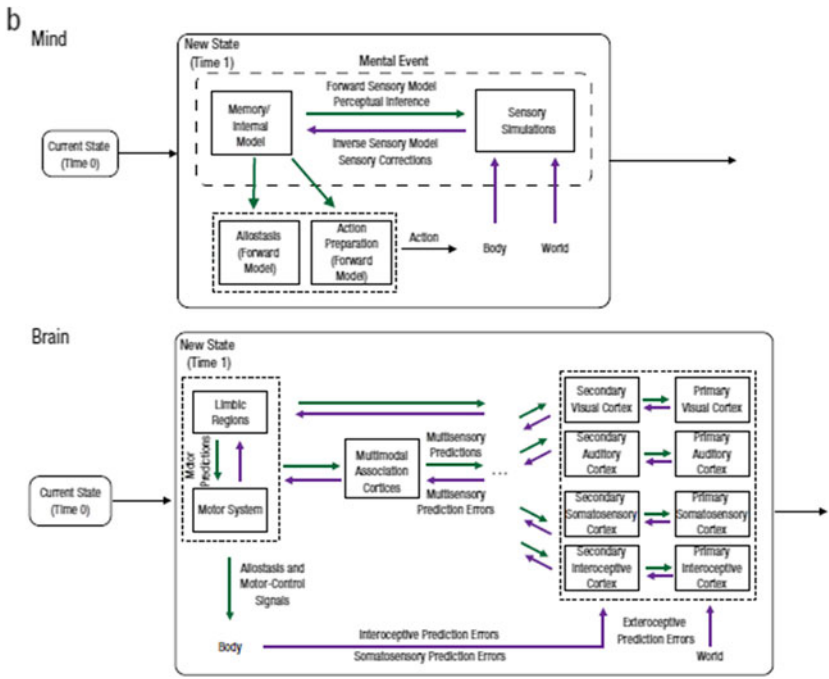

Figure 2.5 Model of the human brain functionality as a fluent state. *Source* Hutchinson & Barrett, 2019, p. 283

2.2.2 Derivation of a Definition for Information

These examples show that "information" can be described as a fluent process, which itself can be described by "packages", such as bits and providing an evaluation of the agent's "belief and reality distance". Physics, informatics and neurosciences can be combined in order to better understand information and its influence on human decision-making. In the end, a clear definition of information cannot be given; however, this thesis relies on the definitions of information by Losee (1998) and Madden (2004), integrating them into the novel predictive processing-framework by Hutchinson and Barrett (2019). Losee (1998) believes that information can be expressed by some value. While this value itself is not information, the value is informative about the input and process from which it

is derived. As an internal model or "World View" can be both altered by a stimulus and by the mere anticipation of a stimulus as shown by Hutchinson and Barrett (2019), information is not solely regarded as a stimulus as defined by Madden (2004). The predictive processing-framework (PPF) shows that each internal model is both input and process, so input and process cannot be clearly distinguished in PPF, as required by Losee (1998) to make sense of the information value. In accordance to PPF, a state is linked to a new state by a fluent transition process consisting of frequent updating of prediction and prediction-error distance, while this "linkage" also serves as the process. In PPF each state is both input and process or best described as fluent states.

Building upon the core statements of Losee (1998) that information can be expressed by some informative value, of Madden (2004) that information alters the internal model of some cognitive system and of Hutchinson and Berrett (2019) that cognitive agents both react to external stimuli and stimulated anticipation, the following is derived:

If each of these complex fluent states of some observer were grasped in isolation at time t_n and labelled by some integer, indicating its order of experience and an information theoretical function was applied to receive an informative value (e.g. based on $\log_2$), then—in theory—a string of these fluent states would be identical to the entire experiences and all possible prediction results of the observing agent at time t_n. Information can then be regarded as a redundant function operating on itself, embedding an uncertainty value on possible outcomes, with this value being dependent on the agent's experience (chain of information states) and its belief (prediction vs. prediction-error).

2.2.3 Information Perturbing Events in Behavioral Experiments

Fudenberg and Tirole (1991) close their work "Game Theory" with a remarkable insight. First, they explain that finite state space games are not outmatched by infinite-state-space models approximations, as the latter can have a very different set of equilibria. Second, uncertainty about another's information can lead to state spaces that are even unaccountably infinite. Therefore, in real life economic decision-making, where uncertainty is inevitable and can only be reduced to zero by accepting some "deception potential", a game-theoretical model will either have to cope with uncountable infinity or potentially unprecise and therefore unreliable approximations. Third, while in practical applications of game-theoretical

models finite state-spaces are used, their sensitivity to perturbations leading to entirely different outcomes

> *"is another reason to think seriously about the robustness of one's conclusions to the information structure of the game."*

(Fudenberg & Tirole, 1991).

In other words, human decision-making is hardly grasped and simulated by game-theoretical models, as "doubt", mathematically expressed by perturbing some integer, can lead to entirely different outcomes. Even "heuristic approaches" are not immune to such perturbing events. Uncertainty or "doubt" stemming from deception or by how information is presented are important influencers for experiments in the field of behavioral economics and psychology. In the following, three major perturbing events will be briefly described: deception, the "frame effect" and the "order effect".

In short, while deception is commonly used in psychological experiments, deception is far less, if at all, accepted in the domain of economics (Krawczyk, 2019). The "frame effect" describes how human decision-making is influenced by how different choice options are presented (Tversky & Kahneman, 1981), whereas the "order effect" analyzes belief updating (Trueblood & Busemeyer, 2011). Deception, "frame effects" and "order effects" can have an influence on the maintenance and refutation of some agent's belief, which is a critical process in sequential decision-making (Yoshida & Ishii, 2006). All three effects can be manipulated in order to experience different decision-making results or to "nudge" agents, e.g. using the "frame effect" to display information provided by a search engine's result page in such a way that the agent's choices can be improved (Benkert & Netzer, 2018) or using the "order effect" to make agents perform riskier decisions (Aimone, Ball, & King-Casa, 2016). According to most economists, "deception" leads to noisy data and is considered unethical (Houser & McCabe, 2013), while no few psychologists saw deception as a way to produce useful results (Christensen, 1988). More recent research has shown that experimental economists' aversion towards deception is justified (Ortmann & Hertwig, 2005), however, to this day no clear definition of deception exists nor agreement on when deception appears to be used in some experiment (Krawczyk, 2019).

2.2.4 Making Decisions in a VUCA World

As mentioned before, most real world problems are ill-defined. Human agents solve problems by ignoring information (heuristics), which works well to reduce complexity and to solve problems under uncertainty. In order to successfully apply heuristic decision-making or ignore information effectively, information has to be collected first. Information was characterized in this thesis i) as modelled by fluent states, ii) as being linked to an informative value building upon information theory, iii) as being observer-dependent, iv) as a redundant function to alter uncertainty. In the final chapters it was noted that models, experiments and therefore decision-making outcomes are sensitive to information perturbing events caused by deception, the "order" or "framing" of information and that behavioral experiments disregard deception, as it leads to noisy data. All of these circumstances surrounding real economic problems and the complex role of information lead to the conclusion that today's world inhibits characteristics, rendering reliable long-term predictions challenging. This conclusion is expressed by the term "VUCA-world".

"VUCA" stands for "volatility, uncertainty, complexity and ambiguity" (Dörner & Funke, 2017, pp. 2–3) and is commonly used in economic contexts, referring to the unpredictable nature of today's economic decision-making domain. Its four features are similar to the attributes of complex systems, complexity, connectivity, dynamics and goal conflicts (Dörner & Funke, 2017). The term VUCA has been used in a variety of contexts such as to describe modern battlefield- (Nindl et al., 2018), work- (Seow, Pan, & Koh, 2019) and decision-making-environments (Giones, Brem, & Berger, 2019). The VUCA acronym has been misused i.e. providing the impression that leadership was powerless to plan ahead and strategize (Bennett & Lemoine, 2014). On the contrary, the VUCA framework can help to strategize and plan ahead effectively, even when the decision-making environment is inhibiting features of a complex system.

As shown in figure 2.6 (Green, Page, De'ath, Pei, & Lam, 2019, p. 2), two simple questions can be derived by the VUCA framework and consequently asked to categorize a complex system: "How well can you predict the results of your actions?" and "How much do you know about the situation?".

The contents of these two questions can be linked to "expert knowledge". In their famous work "Human Problem Solving", Simon & Newell (1971) found expert chess players to outperform novice chess players in recalling and reproducing the positions of chess pieces after 5 seconds viewing. Experts would remember and thus hold more knowledge about the chess game. Consequently, experts seem to outperform novices when it comes to the question "How much is

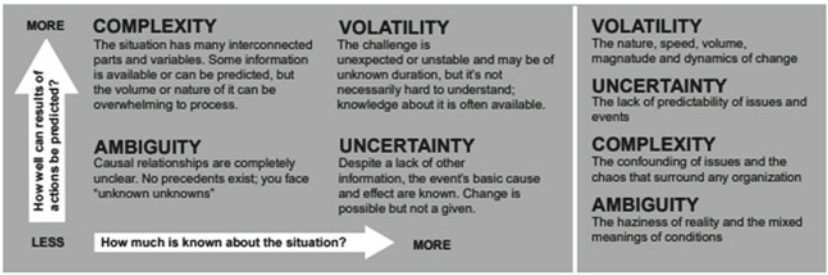

Figure 2.6 Dimensions of complex systems. *Source* Green, Page, De'ath, Pei, & Lam, 2019, p. 2

known about the situation?". Perceptual-Cognitive research has shown that expert surfers were more likely to predict waves as being too risky than amateur surfers (Furley & Dörr, 2016). Experts might then outperform novices in complex problem solving when answering "How well can results of actions be predicted?". The overall question is then, how expert knowledge can be defined and whether or not expert knowledge helps in problem solving in a VUCA world. This question is to be answered in detail in the next chapter.

2.3 Expert Knowledge and Problem-Solving

According to Zeleny (2005) information is only symbolic acting, whereas knowledge is true acting, which cannot be replaced by any amount of information. Information is seen by the author as a necessary ingredient, but insufficient recipe for effective volition (Zeleny, 2005). This is because codified knowledge became information, and information technology did not replace social interaction; it was necessary to transform information into effective action and not the other way around (Zeleny, 2005). The author further states that while there can be "too much information" there cannot be "too much knowledge". These statements suit mentioned problems arising from information-based models with high degrees of complexity, ultimately producing uncertainty, instead of reducing it. Just like the model by Hutchinson and Barrett (2019) distinguished between mind and brain or modelling and acting, there exists an analogue distinction between information

and knowledge. Knowledge relies on operative acts of measurable volition, rather than on words or letters (Zeleny, 2005).

Just as knowledge is not captured by information systems by these claims, there exists perspectives on expertise not being captured by knowledge management systems: expertise was mainly the result of tens of thousands of hours of acting (Trevelyan, 2014). According to Trevelyan (2014) expertise has to pass three tests in order to be considered as such: First, expertise has to lead to constant sub-par performance. Second, expertise has to lead to volition or concrete outcomes. And third, expertise has to be measurable.

Therefore, action or volition seems to be the key factor combining "knowledge" and "expertise". The resulting term of "Expert knowledge" is now to be defined in more detail, followed by a short description on expert knowledge being used as a resource, and how it is linked to learning.

2.3.1 Definition of Knowledge, Expertise and Expert Knowledge

Theoretical philosophy, building upon ancient Greek philosophy, defines "knowledge" as

"justified true belief, or true opinion combined with reason"

(Hilpinen, 1970, p. 109). This abstract approach in defining "knowledge" leads to logical discussions, whether the information I_1 of person A knowing some event p_1, which includes some uncertainty c that this knowledge was wrong, and the information I_2 of person A knowing that A himself knows that p_1, was the same information ($I_1 == I_2$) or not ($I_1 <> I_2$), I_2 also containing c. It also leads to "ad infinitum problems", such as whether "A knowing A knowing A knowing … knowing p", containing c, or paradox problems that there cannot exist knowledge since uncertainty c is always part of some information (Hilpinen, 1970).

An adequate definition of "knowledge" for the business environment was found to be more suitable, when being modelled less abstract than by attempts stemming from "epistemology". The meaning of "knowledge" is ought to be found in the domain of cognitive sciences (Bolisani & Bratianu, 2018). By defining some discrete system, such as "the static object of knowledge", the "frame problem" would again arise. There also exist studies claiming that knowledge did not find its boundaries from the works of one single agent, but was the result of an intellectual collective, such that knowledge is considered "cognitive contact", where

assumptions about reality arise from acts of intellectual confrontation with others (Zagzebski, 2017). To provide a more business oriented definition and to overcome problems arising from the frame problem, when trying to model knowledge with discrete states, so called "fluid flows" are used, leading to the definition of knowledge as "stocks and flows" (Bolisani & Bratianu, 2018, p. 19). This definition applies for both explicit and tacit knowledge and has to be combined with paradigms from physics regarding "entropic uncertainties" (Bolisani & Bratianu, 2018). This leads to the three "rational, emotional, and spiritual fields" defining knowledge (Bolisani & Bratianu, 2018, p. 24). The rational domain of knowledge is defined as being objective and explicit, outlined by language and logic. The emotional dimension of knowledge is subjective and context dependent, being a result of our body responses to the external environment. The spiritual field of knowledge regards ethics and values, which are essential in corporate decision making (Bolisani & Bratianu, 2018).

Decades ago, scientific research in human problem-solving found that expertise requires large amounts of knowledge; the expert has experienced many relevant patterns of some decision-frame and these patterns serve as a guide towards relevant parts of knowledge efficiently (Larkin, McDermott, Simon, & Simon, 1980): This knowledge storages contain varieties of patterns helping with the problem interpretation and problem-solving, while at the same time providing essential and relevant clues (Larkin et al., 1980). Intuition is described by Larkin et al. (1980) as largely being some ability to use "pattern-indexed schemata", distinguishing novices from experts in problem-solving. This broad definition of expertise links to the more recent understanding of "expert performance" reflecting high-level, circumstantial adaptation skills, resulting from long periods of experience and volition (Ericsson & Charness, 1994). Patterns leading to expertise are then automatically acquired in a confined area, where acting happens. Above-average performance is then the result of this iterative process. Defining and selecting "experts" solely based on their years of experience, e.g. for Delphi panels, is a debated selection process, and collective performance in forecasting does not necessarily depend on there being more experienced experts in some decision-making panel. In "Delphi decision-making groups" the total amount of expertise necessary remains uncertain (Baker, Lovell, & Harris, 2006).

Based upon the definitions of knowledge and expertise, expert knowledge is obtained by constant iterative acting in a certain confined domain, where the agent adapts to experienced patterns becoming more efficient in solving problems in the chosen domain, altering rational, emotional and spiritual mental models fluently, and doing so in constant exchange with other people.

Therefore, expert knowledge lives from acting. According to McBridge & Burgman (2012), expert knowledge is important for applied ecology and conservation, as it inhibits complex dynamics, where action is required to reduce uncertainty. When empirical data is lacking, expert knowledge is commonly seen as the optimal source of information; expert knowledge is simply what agents know from practice, training, and experience, and manifests itself in effective recognition of context-relevant information and efficient problem solving (McBride & Burgman, 2012).

2.3.2 Expert Knowledge as a Resource

Making predictions in complex and non-linear decision-environments can benefit from expert knowledge, but is no guarantee for precise forecasts. Age and work experience do not necessarily predict performance, and expert knowledge is context sensitive and has to be embedded in a suitable decision-making domain and framework (McBride & Burgman, 2012). Engineers for example debated many decades, whether or not system design was an intuitive art-form or a scientific process, which had to be systemized; nowadays, engineers rely on a mixed bag of instruments and a more holistic viewpoint when it comes to design, including complexity management, workflows and cognitive systems (Kreimeyer, Lauer, Lindemann, & Heyman, 2006). While iterations of act results in learning, thus building expertise, such iterations have to be minimized in order to reduce costs, as described by the commonly used "Pahl and Beitz Systematic Approach" framework (Kannengiesser & Gero, 2017). Applications of lean and agile software development are growing (Tripp, Saltz, & Turk, 2018) and show that there exists an interest of embedding expert knowledge in more lightweight and flexible frameworks. This is done to reduce costs and in order to be able to react to unpredictable change efficiently (Saini, Arif, & Kulonda, 2017). In other words, in a complex environment, expert knowledge is handled as a resource to save capital, and to better handle uncertainties. This concept is used in "sustainable management" and referred to as "salutogenesis" (Müller-Christ, 2014), which describes that capital can be used in order to stay capable of acting and reacting to unforeseeable events. So even though expert knowledge does not necessarily result in optimal results, it is still considered an important factor when facing dynamical decision-environments and can be effectively included in modern frameworks that save capital, leading to more sustainable problem-solving solutions.

2.3.3 The Role of Learning

According to Simon and Newell (1971), human decision-making consists of cognitive and environmental characteristics (Campitelli & Gobet, 2010). This is called the expertise approach, combining the understanding of expertise and decision-making. Campitelli & Gobet (2010) suggest that Simon's expertise approach should be included into decision-making research: experiments should test for level of expertise and apply different environmental circumstances. Experiments should contain participants with different level of expertise, in order to show whether or not experts and novices show different levels of bias, as predicted by Tversky and Kahneman (1981), and when and why such cognitive illusions disappear, as stated by Gigerenzer (1996). According to the "Simon and colleagues' approach", different environmental circumstances should be applied (Campitelli & Gobet, 2010), such that domain specific expertise can be compared to other domains, in order to test whether or not environmental circumstances have an impact on decision-making, whether this impact correlated to expertise, and if the type of heuristics applied by participants actually changed. Campitelli & Gobet (2010) also suggest that computational models that fit data of human behavior in a multitude of domains are more meaningful than models, which analyze human behavior in more specific cases.

Theories in behavioral economics are seeking generality, adding parameters incrementally, such that results or models can be easily compared to even more general models; even though adding behavioral assumptions to some models describing human behavior makes the model less tractable, behavioral models can outperform traditional ones in precision, when operating in domains of dynamics and strategic interaction (Camerer & Loewenstein, 2004). Behavioral economics relies on field experiments, computer simulation and brain scans, and Camerer & Loewenstein (2004) describe behavioral economists as methodological eclectics, who make use of psychological insights (Camerer & Loewenstein, 2004, p. 7), which distinguishes behavioral economics from experimental economics. "Behavioral Game Theory" generalizes the standard assumptions of game theory, using experimental evidence, and provides a model for "learning" in complex environments, even including neuroscientific evidence to support models about economic behavior (Camerer & Loewenstein, 2004).

The authors Reisch & Zhao (2017) describe behavioral economics as a theory, which does not rely on the view of the consumer acting as a rational Homo oeconomicus, but displaying "bounded rationality", as described by Kahneman (2003) and Simon (1955), where their deviations are predictable "errors". Behavioral

economics relies on the "information paradigm" in the sense that consumer behavior is incentivized by the information provided and by their learning progress in the form of preferences, biases and heuristic strategies; however, models building upon this understanding realized that even small incentives can have a big impact on decision-making (Reisch & Zhao, 2017). Key findings of behavioral economics include several biases and heuristics from prospect theory and mental account, and are used to design choice context; as consumers make decisions context-dependently, results by behavioral economic models can be used to nudge consumers (Reisch & Zhao, 2017).

The influence of expert knowledge, the "expertise approach" of decision-making research and behavioral economics find common ground in the domain of "learning". While "expertise" was defined as an "extreme adaption", "learning" too is linked to the concept of adaption, being defined as "ontogenetic adaption", being observed change in behavior of an agent, which stems from making use of regularities surrounding the agent (De Houwer, Barnes-Holmes, & Moors, 2013). To acquire a clear understanding about behavioral changes, it is recommended to rely on this functional definition of "learning", and to acquire information about when exactly learning occurs, so that insights of cognitive nature can also be derived (De Houwer et al., 2013). Experiments should then control *when* learning occurs to effectively measure behavioral changes, stepping away from inefficient models, which understand learning as a "mental mechanism" (De Houwer et al., 2013, p. 641). Experiments can be designed in such a way, as to include the "expertise approach", behavioral economics and "expert knowledge" by this understanding of "learning": the three concepts would meet common ground in software-based experiments, where controlled contextual changes increased the probability in behavioral changes, which can then be compared to novice and expert problem-solving performance, having either performed only a few or many iterations of the experiment before, including decades of insights on how biases and heuristics influence decision-making.

The next chapter will introduce the concept of learning, how it is related to measured behavioral changes, which are often influenced by biases and heuristics, and how individual agents can be understood as "disturbances".

2.4 Agents Acting as Disturbances

According to Erev and Roth (2014) mainstream behavioral economics attempts to find deviations from the rational model, offering descriptive models. The authors discuss human learning in order to find domains where people learn fast and

maximize their expected return, to better understand how the structure of an economic environment influences behavior (Erev & Roth, 2014). Important insights regard feedback and its influence on decisions. When feedback is limited to the chosen option—that is, when consequences of discarded options are not provided to the agent—the behavioral impact of negative outcomes last longer than the impact of good outcomes. This is because bad outcomes reduce the probability of the agent trying to reevaluate the option (Erev & Roth, 2014). This can lead to a certain "attitude" towards options through such exploration, where invalid negative prejudices are hardly overcome (Fazio, Eiser, & Shook, 2004).

Exploration can be described as a requirement to obtain information during complex problem solving, since in such problem solving scenarios, information is hidden from the agents on the outset. As most real economic problems are complex or can be considered as problems under uncertainty, this chapter or in fact this thesis as a whole, will mainly consider problems under uncertainty. There exists a mathematical expression of the continuum from risk to uncertainty, coming from the "bias variance theory", written as

$$"total\,error = (bias)^2 + variance + \varepsilon",$$

where "ε" equals noise. The meaning of this continuum is very intuitively explained by Gerd Gigerenzer in his introducing article "Taking Heuristics Seriously" to the whitepaper "The Behavioral Economics Guide 2016" (Samson & Gigerenzer, 2016).

As depicted in figure 2.7 the left person shows bias towards the bottom right, next to no variance and overall superior performance as opposed to the right person, who shows no bias, high variance and a lower score. This intuitive example shows that error can stem from either bias or variance. Fine-tuned complex models, according to Mousavi & Gigerenzer (2014), lead to high variance when being applied to different samples, while heuristics with fixed parameters have no variance, but bias. Still, problems under risk are different from problems under uncertainty, and while uncertainty is part of many day-to-day situations in real life, uncertainty has to be reduced to a form of risk, in order to make calculations dealing with uncertainty compatible to risk calculations. (Mousavi & Gigerenzer, 2014). Anyhow, this thesis wants to assemble more theoretical background mainly about problems under uncertainty, while not ignoring important aspects of problems under risk.

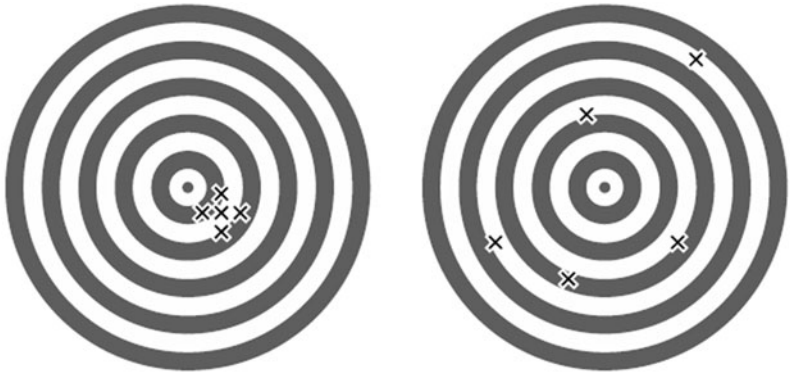

Figure 2: A visual depiction of the two errors in prediction, bias and variance. The bull's eye represents the unknown true value to be predicted. Each dart represents a predicted value, based on different random samples of information. Bias is the distance between the bull's eye and the mean dart location; variance is the variability of the individual darts around their mean.

Figure 2.7 Bias vs. Variance. *Source* Samson & Gigerenzer, 2016, p. VIII

The following sub-chapter will capture the importance of feedback, and its potential influence on following decisions during complex problem-solving under uncertainty, where the agent has to explore, and possibly adapt to contextual changes. Following subchapters will specify the role of non-routine tasks, routine strength in decision-making, derive non-routine problem solving, providing a short summary of these insights by referring to "complexity economics".

2.4.1 The Role of Feedback in Complex Problems Under Uncertainty

According to Van der Kleij, Feskens, & Eggen, 2015 there does not exist a generally accepted model on how learning is created by feedback, but there does exist some evidence regarding the positive relationship of feedback on learning during computerized experiments. However, Van der Kleij et al. (2015) also mention that these conclusions are not sufficient enough for explaining detailed relationships of feedback and learning, defining feedback as follows: "Winne and Butler (1994) suggested

> *"feedback is information with which a learner can confirm, add to, overwrite, tune, or restructure information in memory, whether that information is domain knowledge, meta-cognitive knowledge, beliefs about self and tasks, or cognitive tactics and strategies" (p. 5740)."*

(Van der Kleij et al., 2015, pp. 2–3). The meta-analysis by Van der Kleij et al. (2015) considered 40 studies regarding the influence of item-based feedback on learning in a computer-based environment. "Item-based" feedback means that agents are granted immediate or delayed feedback on every item (Van der Kleij et al., 2015). Rich feedback led to more effective learning outcomes in "higher order learning" than "simple feedback", which is defined as feedback only providing information about the correctness of some response. Simple feedback is considered to be effective for „lower order learning outcomes" (p. 8). "Lower order learning" is restricted to recalling, recognizing and understanding concepts with no need to actually apply this knowledge. "Higher learning" requires the application of knowledge in novel domains, which is referred to as "transfer" (Van der Kleij et al., 2015, p. 5).

As people tend to think in short-sighted causal relations, commonly assume an effect to have a single cause and halt research for causes upon having found the first satisfying explanation, agents perceive only limited amounts of feedback to self-reinforce or self-correct strategies (Sterman, 2006). Time delays in feedback processes confound the agents' ability to learn, resulting in decision makers to perform corrections, even when enough corrective actions have already been taken "to restore equilibrium" (Sterman, 2006, p. 508).

According to Sterman (2006) "learning is a feedback process", as depictured in figure 2.8, where both dynamics in a complex system and all learning depend on feedback. When deviations from expected states are perceived, agents perform actions from which they think will close the gap. Therefore, strategies are influenced by misperceptions of feedback, unscientific reasoning and biases. In order to learn under conditions of high uncertainty, such as learning under crisis, this " expected states gap" is closed by pre-training, using virtual reality, learning by imitation, communication, information systems, past experiences and operating standards (Moynihan, 2008). It is assumed that knowledge gathered before facing a complex problem under uncertainty helps to better perform in its problem-solving. While Moynihan (2008) stresses that ad-hoc learning during a problem under uncertainty is possible, novel routines should be explored before a network of agents is required to use them.

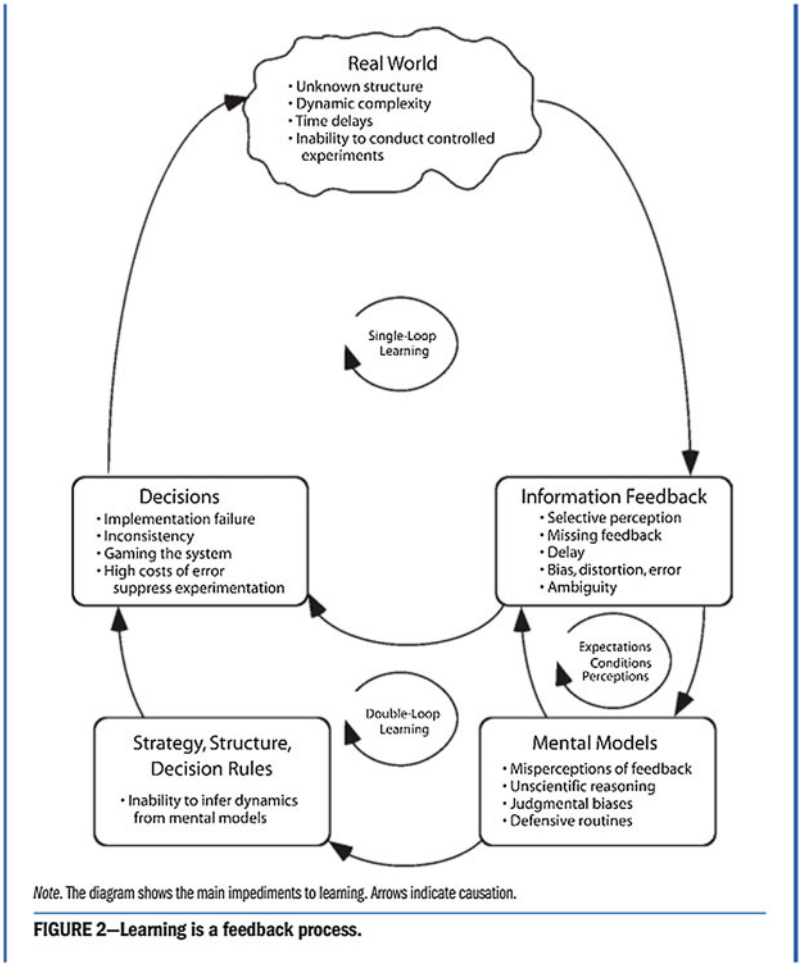

Figure 2.8 All learning is a feedback process. *Source* Sterman, 2006, p. 506

In conclusion, all learning results from feedback, while learning outcomes are influenced by the quality of feedback. Simple learning outcomes already benefit from feedback solely indicating correctness of some response, while transfer requires more sophisticated feedback, i.e.

> *"hints, additional information, extra study material, and an explanation of the correct answer."*

(Van der Kleij et al., 2015, p. 4). In situations of high uncertainty where such additional information cannot be provided, prior knowledge or exploration for new routines can be helpful. The latter real-world problem in crisis management is commonly referred to as "non-routine problem solving". The following subchapter will introduce this concept in greater detail.

2.4.2 Novel Problems, Real-World Problems, and Non-routine Tasks

According to thorough experimental results stemming from the "bean fest paradigm", where the relation of exploratory behavior and attitude formation was tested (Fazio et al., 2004), whether or not some novel decision alternative was considered good or bad—at least in a virtual world—is considered by agents in accordance to their weighting bias. Beans could be eaten or not, resulting in either positive or negative effects. Beans would differ in shape and pattern, and participants were able to defeat randomness by clustering the beans' appearances, as shown in figure 2.9.

The experiment attempted various conditions, such as providing feedback to all or only to the chosen bean, framing the experiment by granting points or subtracting life points. In the end, the game was always a performance-based experiment. When a novel alternative in form of some bean is faced by an agent in this experimental environment, where a problem under uncertainty with item-based feedback is simulated, and the agents can learn from feedback (with feedback only provided to the chosen option), agents' choice can partly be predicted by the common "negativity bias". Participants who learned the positive and negative decision alternatives (beans) equally well, tended towards a negative response, generally showing negativity bias towards novel beans (Fazio, Pietri, Rocklage, & Shook, 2015). Agents are influenced by the looks and resemblance of patterns to prior experiences (Fazio et al., 2015). Whether or not an agent had a larger tendency to classify a novel bean as a bad bean, than can be expected by the agent's learning pattern, defines the "valence weighting bias". It is regarded "as a fundamental personality characteristic", as

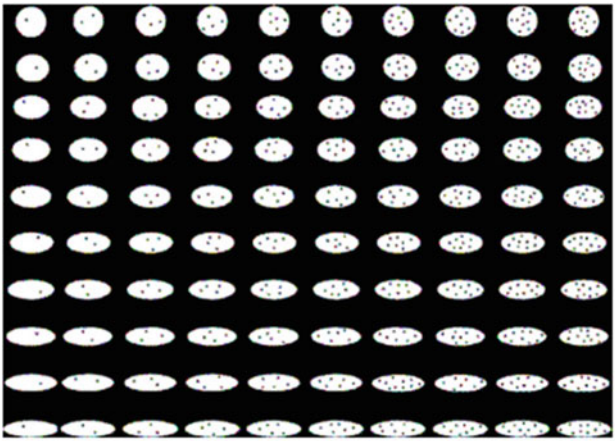

Figure 1 The population of bean stimuli forming the 10 × 10 matrix. *Reprinted from Deutsch and Fazio (2008).*

	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10
X1	+	+	+			−	−	−		
X2	+	+			−	−	−			
X3						−				
X4									+	+
X5		−						+	+	+
X6	−	−	−						+	
X7	−	−								
X8					+					
X9				+	+	+			−	−
X10			+	+	+			−	−	−

Figure 2 The bean matrix. X refers to shape, from circular (1) to oblong (10); Y refers to the number of speckles, from 1 to 10. The beans presented during the learning phase of the BeanFest procedure are noted with their corresponding positive (+) or negative (−) value. In any given study, the bean values are typically reversed for half the participants. This counterbalancing has not been found to influence outcomes.

Figure 2.9 "Bean-Fest" causal structure. *Source* Fazio et al., 2015, p. 107

> *"Individuals' valence weighting proclivities have proved relevant to sensitivity to interpersonal rejection, threat assessment, neophobia, decisions about risky alternatives, intentions to engage in novel risk behaviors, actual risk behavior, emotional reactivity to a failure experience, the expansion of friendship networks, and changes in depressive symptoms."*

(Fazio et al., 2015, p. 117). Unfortunately, the authors Fazio et al. (2015) found the valence weighting bias to not be self-reportable by questionnaires. Also, their finding are limited to experiments, where decision alternatives give visual clues, so that the Bayesian brain finds fruitful potential to learning. However, the Bean-Fest experiment enables to simulate a decision-making environment, where each problem is novel and different and further shows that individual differences are key at the very core of problem solving.

According to system theory, problems exist in real life—not only in science: reality reacts to problems by selection and problems are described as

> *"real and effective catalysts of social life"*

(Luhmann, 2012, p. 173). Chapter 2 defined many aspects of real economic problems so far. Most problems in reality are ill-defined, lack a clear instruction on how to solve them, happen under uncertainty, are solved by humans via heuristics, are complex, need to be solved by acquiring information or knowledge, are disturbed by error such as bias, will usually be solved by many interdependent decisions, require experience and learning to be solved and are embedded in an opaque network of cause-effect relations, whose feedback signals are not easily being interpreted correctly by humans.

Studies on learning from feedback in real world problems or economic problems in a complex environment are scarce. Keil et al. (2016) describe learning from performance feedback in complex environments, where outcomes are observed with time-delay and where a multitude of actions are combined to generate outcome in different research and development stages of 98 large US pharmaceutical companies during 1993 to 2013 (Keil, Kostopoulos, Syrigos, & Meissner, 2016). Here, the authors focus on a real world "order effect" of information. Negative feedback, such as performance below aspirations, in an early development stage, are interpreted differently, leading to different actions than negative feedback in later development stages. In addition, Keil et al. (2016) distance themselves from classical models of experiential learning regarding positive feedback. They argue that performance above expectations creates a buffer, whose size favors higher chances of organizational risk-taking. An increasing tolerance of

organizational risk-taking was described to favor search of novelties above aspirations, possibly leading to a shift of the company's core project management (Keil et al., 2016). Organizational recession can also have a positive impact, as it conserves unexplored potential, nourishing firms during times of "uncontrolled exogenous adversity" (Levinthal & March, 1981, p. 309).

Another core finding was that research should concentrate more on the relationship between cognitive biases and behavioral learning (Keil et al., 2016) and that interpretation of information of performance feedback plays an important role in experiential learning in complex processes. Performance feedback is interpreted differently and following action also depends on the "order effect" or stage of R&D process (W.-R. Chen & Miller, 2007), also in accordance to prospect theory (W. Chen, 2008).

From these examples it can be concluded that real-world problems and their related decision-making processes are indeed dependent on both interpretation and order of feedback information. For this very reason, the three information disturbing effects "frame effect", "order effect" and deception were mentioned earlier. Purposeful deception, such as lies, too commonly disturbs feedback information in real world problems and is referred to as "real world deception" (Fuller, Biros, & Delen, 2011).

Due to the high levels of uncertainty in complex environments, pre-training, exploration and routines are essential in coping with real world problems, especially when time pressure does not incentivize investing in reflection time, novel routines or finding new alternative paths. Such a complex decision-making environment with high time pressure is represented by challenges in hospital settings. To reduce costs, the concept of "shared decision-making" and consumer education was tested back in the year 2000 by use of software. Here, treatments were not only chosen by the physician in terms of clinical considerations, but the treatment choice was also influenced by consideration of the patient's values and preferences (Holmes-Rovner et al., 2000). However, as the study showed, the program faced many problems, which can be collectively explained by the effects of "information interpretation", personal bias, and problems stemming from initial hurdles of novel routines: physicians restricted treatments to patients who wanted additional information about the treatment. Physicians also decided not to participate in the randomized study due to personal enthusiasm for the program, and therefore tried to avoid inducing bias by participating. So, physicians did not implement the new shared decision-making process as a routine.

All three problems restricted the implementation of a new routine or in other words, made this task of implementing the non-routine, shared decision-making program a real-world problem and a tough challenge. Individual characteristics

facing novelties, the uncertainties stemming from unknown causal relations by misinterpretation of information or order effects and lack of resources to pre-test some novel strategy, render handling non-routine tasks difficult. Despite the difficulties when attempting non-routine tasks, they are considered as being part of important "21st Century Skills" in order to cope with a VUCA world, where circumstances vary frequently, and its features are linked to performance in complex problem solving (Neubert, Mainert, Kretzschmar, & Greiff, 2015).

In order to observe non-routine decision making and measure its related non-routine problem solving performance in an environment that does not incentivize reflection time, i.e. reflecting on a problem when time is cost-assigned, Strunz & Chlupsa (2019) developed a valid application-test scenario in form of a web-browser based online experiment. Its methods and findings are to be described in greater detail in section 2.4.4—in order to do so, problem solving and the role of routine are introduced in the following sub-chapter.

2.4.3 Problem Solving Search and Routine Strength

> *"In everyday speech the term problem solving refers to activities that are novel and effortful.",*

while not all tasks

> *"feel like problem solving. Some activities, like solving a Tower of Hanoi problem (…) feel like problem solving, whereas other more routine activities, such as using a familiar computer application (…) do not. (…) Newell (1980) argued that the dimension of difference between routine problem solving and real problem solving is the amount of search involved. (…) Newell claimed that we transit smoothly into problem-solving search and indeed that much of human cognition is a mixture of routine problem solving and problem solving that involves search. This claim is realized in his Soar model of cognition (Newell, 1990)"*

(Anderson, 1993).

When researching problem solving, the Tower of Hanoi task was one of the first experimental tools being used (Anderson, 1993), and still is applied in research today. Tower of Hanoi has also been used in the psychology of problem solving (Hinz, Kostov, Kneißl, Sürer, & Danek, 2009), in neuroscientific research (Ruiz-Díaz, Hernández-González, Guevara, Amezcua, & Ågmo, 2012), in order to test for executive function and planning (Donnarumma, Maisto, & Pezzulo, 2016), for working memory (Numminen, Lehto, & Ruoppila, 2001), and is being used

with children, adolescents, and adults from general and clinical samples (Robinson & Brewer, 2016). Tower of Hanoi (ToH) consists of simple rules, which are to be explained in greater detail in chapter 3. For now, as can be seen in figure 2.9, all that should be noted about the game is that it always consists of some "state", such as a starting configuration of 5 disks being put on the left most peg. The player than has to apply some "operator" to transform one state into a new state, by e.g. moving a disk onto another rod. In accordance to J.R. Anderson (1993) a "problem space" is then defined by both "state" and "operator". When all possible connections between states are modelled, by applying only valid operators, the entire state space represents the problem-space (Anderson, 1993). Whether humans hold a similar mental representation of this problem-space is still of interest to recent research and results show that the total time required to solve a ToH problem is proportional to its complexity; complexity is defined as the problem-space distance between the game's start and goal state, as well as the complexity of solution and its associated computational costs (Donnarumma et al., 2016). As Donnarumma et al. (2016) show, humans are having troubles to engage in counterintuitive moves, which are considered as being more complex, as they require the agent to "look-ahead" when playing ToH. The authors also link "subgoaling" to the possible mental representation of a problem-space, where the problem is divided into smaller portions, which have to be solved. The concept of "subgoals" is based upon scientific evidence that human behavior follows a hierarchical structure, where basic and simple actions are clustered into subtasks, which themselves can be combined for the achievement of high-order goals (Solway et al., 2014). According to Donnarumma et al. (2016), the subgoal concept can explain suboptimal decisions, during problems that require counterintuitive moves: humans have a tendency to simply draw a "direct path" from start to goal state by only being aware of the perceptual distance; the "subgoal" model forms an implicit metric from the problem space, and this implicit metric has a great impact on the decision-making outcome. Human problem solving or human search, is sensitive to its prior and often suboptimal mental, implicit representation. Implicit measures are considered as being useful for predicting behavior and analyzing change of mental problem representations (Blanton & Gawronski, 2019).

Human problem solving is also sensitive to routines. Routine is defined as a

> *"behavioral option that comes to mind as a solution",*

which is not considered being some strategy but a

> *"behavioral option that is most strongly associated with a specific decision situation"*

(Betsch et al., 2001, p. 24). According to Betsch et al. (2001), prior-belief effects stemming from high routine participants resulted in agents being reluctant to overcome routine, despite novel feedback suggesting a change of routine as being a lucrative option. Participants who experienced high success rates acting upon a certain strategy, and who then showed high routine, were adapting at slower rates. However, instant adaption with strong routine induced participants were found, when novel feedback could be understood or correctly interpreted by prior knowledge. In their second experiment Betsch et al. (2001) had shown that strong routine participants were falling for the confirmation bias, when tasks were framed as being similar, but were able to discard old strategies, when a task was being explicitly described as being novel. All in all, routine strength significantly influences decision-making, yielding confirmation biases in information acquisitions, and being sensitive towards how tasks are framed. Still, confirmatory tendencies can be overcome when a task is being described as being novel. Adaption in recurring decision-making is being slowed by strongly induced routine and high values in routine strength correlates with the underestimation or negligence of feedback, which encourages overcoming routine, i.e. change in routine strategy (Betsch et al., 2001).

Extrinsic incentives, such as financial rewards are generally assumed to influence human decision-making performance. McDaniel & Rutström (2001) compared two different theories regarding extrinsic reward, intrinsic reward and performance using a Tower of Hanoi experiment. While extrinsic reward can come in form of bonus pay, intrinsic reward was researched by observing monkeys solving mechanical puzzles repeatedly. The animals did so without extrinsic reward, such as food. Therefore, it was understood that there exist actions, which are motivated intrinsically and are performed for their "own sake", independent of extrinsic incentives (Eisenberger & Cameron, 1996, p. 1154).

The first theory analyzed by McDaniel & Rutström (2001) is the psychological theory of "detrimental reward" effects. It was interpreted by the authors in two different ways: First, whether an increase in extrinsic reward lowered perception of attractiveness of the to-be-solved problem, leading to a reduction in intrinsic reward, followed by a decrease in effort, which led to worse performance overall. Second, whether an increase of extrinsic reward induced a distraction effect, leading to a reduction of productivity. The second theory and third hypothesis were named "costly rationality" theory, and stated that an increase in extrinsic reward led to an increase in effort and performance. Extrinsic reward was implemented as error-costs, which differed in the low- and high-cost treatment. Therefore, an increase in error-costs or an increase in penalty was interpreted as a decrease in external reward. In short, participants reported longer time-use when the penalty

was increased. The authors interpreted the increase in time-use as high effort, and the increased penalty as a decrease in extrinsic reward, thus rejecting their first hypothesis (McDaniel & Rutström, 2001). McDaniel & Rutström also found the penalty effect to have an insignificant effect on performance; they observed lots of individual variation in performance, potentially dominating any treatment effect, which they found to be in-line with research—however, whether individual variation was the true cause for treatment insignificance is described as being unclear (McDaniel & Rutström, 2001). The executive function, defined as

> *"a combination of working memory and inhibition inhibitory processes"*

(Zook, Davalos, DeLosh, & Davis, 2004, p. 286), had been found to predict heterogeneous performance in Tower of Hanoi experiments.

Betsch et al. (2001) used a "microworld simulation" to research the influence of routine strength. In order to measure complex problem solving, which includes non-routine problem solving, software-based methods either include mentioned microworlds or "minimal complex systems". Different influencers on non-routine problem performance and their measurement procedures, as well as current scientific debate on their usefulness and how non-routine problem solving (NPS) can be measured, using a software-based "minimal complex system", are explained in the following sub-chapters.

2.4.4 NPS: Adaptation, Beliefs, Response Times and Emotion

In order to research human decision-making in dynamic and complex domains complex, computer-simulated scenarios where proposed, which are to shed light on details of agents performing complex problem solving (CPS) under uncertainty (Funke, 2014). Realistic, computer-simulated problems, including multiple changing and interdependent variables, also referred to as microworlds (Funke, 2014), require a certain order of actions to be performed, in order to efficiently and effectively solve them (Güss, Fadil, & Strohschneider, 2012). Due to the complexity of such problems, the decision-making agent cannot possibly retrieve all causal relations, and therefore has to optimize its strategies through heuristics—here, cultural differences were found. Difference in problem-solving were explained by differences stemming from strategic expertise, which themselves are based on heterogeneous cultural learning environments (Funke, 2014). Significant differences in NPS performance by country origin, being India, US-America

and Germany, were confirmed, but whether this difference was related to learning environment characteristics remained unclear (Strunz, 2019).

While recent research on cultural influences in CPS were less clear (Güss, 2011), and the influences of cultural uncertainty avoidance were conflicting at times (Güss et al., 2012), strategy making remains a strong predictor in performance under CPS. This leads to the understanding that complex and knowledge-rich problems not only require the use of heuristic decision rules, but further strengthens the importance of general and domain specific knowledge (Funke, 2014). Experts are found to spend more time exploring, showing higher adaptability and flexibility in their strategy making, which predicted performance (Güss, Devore Edelstein, Badibanga, & Bartow, 2017).

Minimal complex systems are less complex and their causal structure can be obtained by strategies helping with precise causal analyses. For example, the "Vary One Thing At a Time" (VOTAT) strategy can be applied to the minimal complex system "MicroDYN", with its causal structure being displayed in figure 2.10, to successfully obtain full information on structure and behavior of the problem (Funke, 2014, p. 2). There seem to be two schools of thought, when deciding whether or not performance in complex problem solving can be equally measured with less complex simulations or "minimal complex systems". How to clearly define and perform "Complex Problem Solving" (CPS) experiments still is heavily debated (Greiff, Stadler, Sonnleitner, Wolff, & Martin, 2015; Funke, Fischer, & Holt, 2017; Greiff, Stadler, Sonnleitner, Wolff, & Martin, 2017). Agreement on the question how to measure CPS performance exists in that participants have to overcome barriers that arise from opacity of relevant information and uncertainty about true causal relations governing the problem's functionality (Strunz & Chlupsa, 2019).

Two other important influencers on performance under CPS are environmental changes and learning of counterintuitive concepts. Both influencers have been mentioned before. Environmental conditions predict learning and maximization (Erev & Roth, 2014) can lead to confirmation bias and failure to adapt a strategy due to routine strengths (Betsch et al., 2001). According to evidence from CPS simulations, and as found in Strunz & Chlupsa (2019), environmental changes only change participants' behavior when those changes actually meddle with an agent's strategy performance (Cañas, Quesada, Antolí, & Fajardo, 2003).

As explained before, performing counterintuitive actions is troublesome for humans to do (Donnarumma et al., 2016). Even when environmental conditions have an impact on an agent's strategy, overcoming its routine strategy might require counter-intuitive concepts or the realization that one is self-deceiving

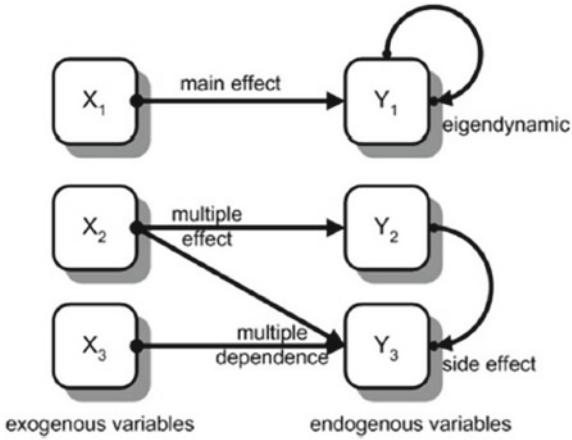

FIGURE 1 | A typical MicroDYN item as an example for a more simple system with different kinds of effects. For the selected sets of endogenous and exogenous variables any cover story is possible (from Greiff et al., 2012, p. 192).

Figure 2.10 Causal structure of Minimal Complex System „MicroDYN“. *Source* Greiff et al. 2012, p. 192

himself with a mental model, which is by definition always an incorrect representation of reality (Sterman, 2002). Learning and knowledge are described as being essential in order to cope with a change in routine, as described in a study coping with supply chain management (Scholten, Sharkey Scott, & Fynes, 2019). Scholten, Sharkey Scott & Fynes (2019) describe various types of learning and knowledge processes that are to be implemented in order to adapt operating routines towards uncertainties stemming from supply chain disruptions. One aspect found to be of significant importance is to reflect on positive outcomes, in order to use the full potential of knowledge creation (Scholten et al., 2019). As described before, positive performance feedback can result in taking more risks (Keil et al., 2016), meaning that an oversimplification of some above average performance or a misinterpretation of its causal relation leading to the good performance, can result in too risky and costly actions by the decision-makers, who have not spent enough time reflecting on the feedback. However, as described in the former sub-chapter, implicit motives and bias that cannot be self-reported, such as valence weighting bias, deeply influence decision-making. Mathematics (Sidenvall, Jäder, & Sumpter,

2015) and education science (Chong, Shahrill, Putri, & Zulkardi, 2018) are also more and more concerned with non-routine tasks and problems, with both fields coming to the conclusion that non-routine problem solving requires real world knowledge and is being influenced by individual beliefs: Whether a solution to a problem is simply imitated or constructed creatively depends on whether a student felt "secure" enough to do so, and less complex and wrong solutions were favored to the correct and more complex solution, when "it felt too complicated" (Sidenvall et al., 2015, p. 123). This not only applies to the behavior of students. Implicit motives influencing economic decision-making have been confirmed by neuronal evidence, however, this insight is still confronted with resistance in the field of business administration (Chlupsa, 2014).

Beliefs and implicit processes can lead to bias in decision-situations, where the decision-maker is lacking information to make a decision based on former knowledge (Fazio et al., 2015). Following an inner "status-quo" or "inertia" bias, the decision-maker might prefer consistency over positive feedback (Alós-Ferrer, Hügelschäfer, & Li, 2016). In other words, the decision-maker might fail to overcome routine, despite feedback, while others overcome their bias and proceed with non-routine decisions, to effectively react to novel circumstances (Chlupsa & Strunz, 2019; Strunz, 2019; Strunz & Chlupsa, 2019).

Thinking time as a resource, approximately measured as response time, can be helpful to overcome these biases. Response time is defined as the server-side time span between problem activation and client response (Rubinstein, 2007). Research looking at response times in an economic decision-making context, stems from brain studies and neuroeconomics, where brain activity is monitored e.g. via resonance imaging (fMRI). Research regarding response time is also commonly used in psychology (Rubinstein, 2007). While there exists criticism that most neuroeconomic studies resulted in "unimpressive economics" (Harrison, 2008, p. 41), some neuroscientific insights have guided behavioral economic research to this day. Cognitive processes coping with complexity, e.g., answering survey questions of different lengths, are linked to response times (Yan & Tourangeau, 2008), which are a well-researched indicator for overcoming decision biases (Alós-Ferrer, Garagnani, & Hügelschäfer, 2016). Response times have predictive power when decision-makers are facing strategic uncertainty (Kiss, Rodriguez-Lara, & Rosa-Garcia, 2018), e.g. decision-makers show longer response times when multiple options are seen as equally attractive (Krajbich, Oud, & Fehr, 2014). In order to deduce meaningful information from response times, an agent's action has to be identified either as a cognitive action, as an instinctive action, or as a reasonless action. A reasonless action can be the results of

some mental decision-making process with low or no logical reasoning (Rubinstein, 2007). Section 4.1.12 "Logic and Expected States" refers to this three-fold distinction later on.

Performance in CPS stems from thinking time, but also from the agents' ability to effectively "identify rules" governing a problem, gaining "rule knowledge" by understanding the problem's internal causal relations (true rule knowledge) and "applying knowledge" by controlling the problem and achieving goals (Wüstenberg, Greiff, & Funke, 2012).

Engaging in non-routine problem solving (NPS) is influenced by a multitude of factors. Very complex decision-making domains will favor heuristic search, while less complex domains will make it possible for the agent to engage in maximization (by algorithmic operators such as VOTAT), obtaining the true causal relations (true rule knowledge about structure and behavior of the domain). Both problem solutions can lead to positive feedback, from which routine can grow, and both solutions benefit from knowledge and learning. When environmental change leads to the routine becoming less favorable, individual valence weighting bias, power of routine, time pressure, beliefs and intrinsic metrics can either hinder or favor a change in strategy. In this case reflection time evidently is a good predictor in overcoming these mental hurdles. Less than 10% of mixed-country participants, about 10% of US-American participants, about 5% of Indian and slightly more than 20% of German participants (Strunz, 2019; Strunz & Chlupsa, 2019) were able to overcome mental hurdles in the NPS experiment "Flag Run", engaging in a change of strategy, built upon a mental model "closer" to the true rules governing the complex problem or in other words: obtaining true rules. Rules do not change throughout the "Flag Run" experiment. However, the starting levels of the experiment "Flag Run" were constructed in such a way that agents would be nudged into building a routine, based upon a wrong mental model of the causal relations. Agents were nudged into thinking that they were able to control the direction of some playing piece, where in fact the direction of the playing piece was always set by default towards "left". As can be seen in figure 2.11, the distance from the playing piece to the goal field is "two steps", when counting from going left, jumping edges, or when counting right, going to the goal field using the more intuitive and visible path. Therefore, the left- and right-hand distance to the goal field are identical. The problem space of "Flag Run" is simple and the true causal relations are even simpler than in most "Minimal Complex Systems". However, not a single agent has proven from its behavior to having understood the true causal relations. The reason for this can only be speculated upon, however, Strunz & Chlupsa (2019) suspect that the implicit mental model of causally relating "direction buttons" and "controlling directions" is very strongly embedded, leading to a

very high strength in routine. As the experiment was short, not enough time was given for most agents to find out all "hidden rules" governing the decision-making system's structure and behavior. Strunz & Chlupsa (2019) also tested for a possible correlation between overcoming routine and self-reported levels in "Joyous Exploration", which is part of the multi-dimensional emotion "Curiosity". However, no relation between any of the 5 curiosity dimensions (Kashdan et al., 2018) and NPS performance was found. Participants who gained true rule knowledge did not report higher scores in "Joyous Exploration" and in fact, no correlation to any of the remaining 4 curiosity-dimension were found. The study did confirm that reflection time—that is thinking time measured as response time—did pay off.

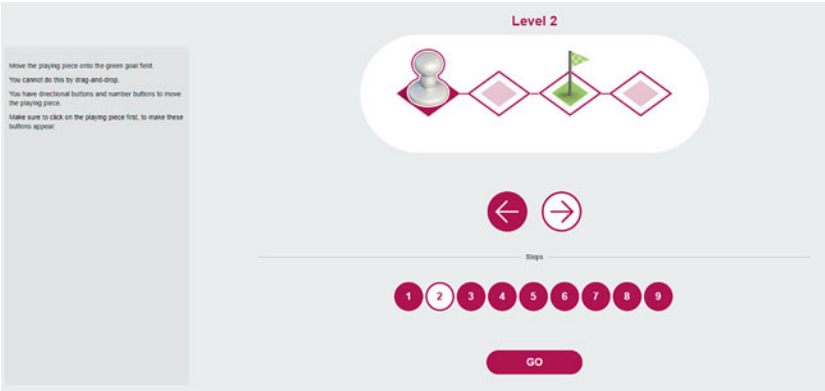

Figure 2.11 Client-side view of "Flag Run" experiment. *Source* Strunz & Chlupsa, 2019, p. 116

Participants consisted of Amazon Mechanical Turk freelancers (MTurks), who benefit financially from solving any task as fast as possible. Studies have shown that the main motivation of any MTurk was "compensation" (Lovett, Bajaba, Lovett, & Simmering, 2018), so that MTurks are suitable participants for experiments, where thinking time was associated with costs and is not incentivized (Strunz & Chlupsa, 2019). Noise from cultural differences in uncertainty avoidance, influenced by the cultural learning environment (Funke, 2014), all MTurks were expected, and differences in NPS performance by country-origin were indeed found (Strunz, 2019).

In all "Flag Run" experiments, agents who started investing in reflection time where more likely to find true rule knowledge (Chlupsa & Strunz, 2019; Strunz, 2019; Strunz & Chlupsa, 2019). This was true for all country origins. Agents who obtained true rule knowledge solved the overall experiment with less operators or "actions" and in a shorter timeframe, therefore being more efficient, even though having invested more time. Agents who obtained true rule knowledge showed less meaningless or random operators. Strunz & Chlupsa (2019) assume that these agents outperformed in learning from uncertainty or learning from unexpected feedback:

> *"While many researches and economists press the importance of skills that enhance adaption to changing conditions, it has to be understood that overcoming routine and its linked set of behavioral biases is not easily performed, and can probably only be done by a small fraction of leaders and employees, when there is not much time to reflect on the problem at hand"*

(p. 122).

While "Flag Run" is less complex in its causal structure than any Microworld experiment, and its causal structure is even simpler than most Minimal Complex Systems, "Flag Run" still is very knowledge-rich. Its hidden rules, making it a CPS task, have to be explored by overcoming a mental model, stemming from strong a-priori routine, to simulate real economic problems, where decisions have to be made quickly and in a non-routine manner, to adapt to the ever-changing VUCA world. Agents had to use heuristics as in ignoring information learnt before and also had to adapt a strategy similar to an algorithmic procedure. "Flag Run" has learnt from the advantages of both worlds: the simplicity of Minimal Complex Systems and the necessity of knowledge-rich structures of Microworlds. As a NPS task, "Flag Run" builds upon the understanding of "All models are wrong" (Sterman, 2002), and that experiments building upon this simple rule will probably further confirm the realization "Complexity from Simplicity", once beautifully shown by John Horton Conway's "Game of Life". Nature's true complexity is simulated in "Flag Run", as even simple structures can result in complex problems either due to our resistance in recognizing "being in error", human overconfidence or due to the circumstance of life that with unavoidable uncertainty comes immanent potential of self-deception. Being overconfident was shown to be influenced by testosterone (Dalton & Ghosal, 2018), which can result in socially beneficial values such as reduction of anxiety or providing information. Being overconfident can also have negative consequences when

it is mostly the result of self-deception, not carrying any psychological benefits—the social benefit from overconfidence mainly depends on the environment and private information (Schwardmann & Van der Weele, 2017).

This brings the current sub-chapter to the final conclusion that uncertainty can only be fully reduced by self-deception. An agent can either invest in some decision frame by communication, which is associated with costs, to reduce uncertainty with some risk-averse strategy. The agent can mentally nullify uncertainty by self-deception, risking potential follow-up costs, or in other words accepting "deception potential" by building upon some mental "truth". As this thesis remains upon the understanding that uncertainty cannot be fully "eradicated" and that "all models are wrong", deception potential is understood as being immanent. A full recap of section 2.4 will follow in section 2.4.5

2.4.5 The Human Class: An Unbounded Set of Strategies

In order to neither fall for the "bias bias" (Brighton & Gigerenzer, 2015), nor for unrealistic assumptions of agents always maximizing, the "middle ground" should not be ignored, as agents seem to be able to maximize under certain circumstances (Erev & Roth, 2014), while still forming biased attitudes (Fazio et al., 2004, 2015; Rocklage & Fazio, 2014) towards problems by exploration, reducing uncertainty. Problems under uncertainty and risk are to be separated, whereas risk and uncertainty can be linked in a continuum (Samson & Gigerenzer, 2016), controlling both ends by learning from feedback (Van der Kleij et al., 2015). Feedback is easily misinterpreted, and all learning is a feedback process (Sterman, 2006). In complex environments learning from feedback is also influenced by framing or interpreting information, the order of information coming from feedback (Keil et al., 2016) and real world deception (Fuller et al., 2011). Individual characteristics, fear of uncertainty or lack of resources (Chong et al., 2018; Holmes-Rovner et al., 2000) render adaption to new conditions a challenge, due to routine strength (Betsch et al., 2001) and cognitive dissonance facing counter-intuitive problems (Donnarumma et al., 2016). In order to measure CPS which is linked to NPS (Neubert et al., 2015) it is important to realize that strategy change will only occur when change actually interferes with an agent's strategy (Cañas, Quesada, Antolí, & Fajardo, 2003). Experiments should measure the critical success factor for NPS, being experiential learning (Scholten et al., 2019), by looking at *when* behavioral changes occurs (De Houwer et al., 2013). Thus, the experimenter can observe each performed action of all agents live, as shown in figure 2.12.

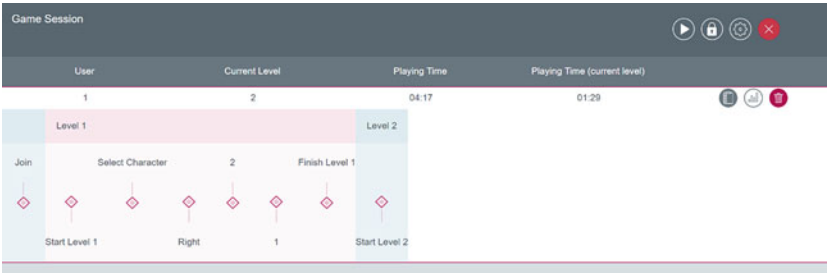

Figure 2.12 Paticipant's actions can be watched live via Curiosity IO backend. *Source* own source

Reflection time was found to be an effective predictor for overcoming "wrong" mental models (Strunz & Chlupsa, 2019), while this thesis remains upon the understanding that all mental models are wrong (Sterman, 2002), and that uncertainty can only be nullified by self-deception, which comes along with advantages and disadvantages (Schwardmann & Van der Weele, 2017). Therefore, deception potential is regarded as being immanent. For this reason, complexity can grow from very simple problem spaces, with "Flag Run" combining all advantages from both Microworlds and Minimal Complex Systems, when trying to measure whether or not some agent is able to find hidden information, and is able to adapt its strategy based upon novel knowledge under circumstances, where time is considered a resource.

Combining all mentioned insights agents are seen analogue to disturbances, which are able to inhibit special features leading to outcomes that are more than just a nonconformity to some anticipated value. Agents are regarded as an "unbounded set of strategies", producing perturbing deviations. As any model is wrong, no theory nor decision-making agent can ultimately nullify uncertainty (creating the bound of some set), and when it does, it can only do so by self-deception (defining some set with a bound), meaning that some theory predicting human behavior will always be wrong, given the right circumstances (redefining the set's boundary). Defining some model as being either "descriptive", "normative" or "prescriptive" seems to avoid this problem at first hand, but whether this differentiation led to sustainable "normative" models, more efficient "descriptive" re-evaluations or more precise "prescriptions" is to be discussed in section 2.5. In mathematics, problems which arise from set theory, which are much alike the problems in trying to establish various "types" of decision-making categories for models (normative, descriptive, prescriptive etc.), are elegantly solved by

introducing an "unbounded set", better expressed as "class": Getting rid of the more primitive "set theoretical" understanding, by basing mathematics on "category theory". In this understanding, a "human class" is always placed "at the first position of any model", and is then followed by whatever reality is framed by this very agent, with its interpretation of risk and/or uncertainty produced by some expert system. Framing reality is highly individualistic, dependent on beliefs, stemming from intrinsic motives and the attempt to combine models can always lead to unexpected disturbances, which are the result of the network of interdependent beliefs. The financial market, as mentioned before, was interpreted by W. Brian Arthur (1995) as such a network of interdependent beliefs. All of the above is expressed in "Complexity Economics". Complexity economics does not assume an economy necessarily to be in equilibrium. Agents change their actions and strategies according to the outcome, which they collectively create. This will constantly favor change, to which they adapt their strategy anew. In a complex economy, agents' strategies and beliefs are frequently tested, with the entire system being best described as a redundant, ever-changing function—analogue to the described definition of "information". Therefore, complexity economics defines an economy not as something physically existing, but rather as a network of contingent states, being embedded in indeterminacy, where outcome is based upon interdependent sense-making, with the entire system necessarily being open to change (Arthur, 1999).

Section 2.5 will focus on how agents' decision making is altered in a network where they can assume feedback being either random, machine- or human-made, can communicate with or deceive others, perform in problem-solving when communication is impossible. Putting the cart before the horse, section 2.5 will begin with a more precise definition of "model" and its linked categories from decision-making theory.

2.5 A Network of Interdependent Beliefs

Models in decision-making theory can be distinguished by three categories or types: normative, descriptive, and prescriptive. "The three-way distinction emerged clearly in the 1980s (Freeling, 1984; Baron, 1985; Bell et al., 1988)—all of whom wrote independently of each other), although various parts of it were implicit in the writing of Herbert Simon and many philosophers (such as J. S. Mill)." (Baron, 2012).

Descriptive models are interested in why agents decide as they do, while normative models try to describe how agents ideally behave, and prescriptive models

are concerned in prescribing enhancing feature for a certain decision-making process (Mandel, Navarrete, Dieckmann, & Nelson, 2019).

According to Baron (2012), normative models do not have to be or even must not be justified by observations, as long as enough data was acquired by observation to clearly frame the normative model; less obvious normative models i.e. simple correspondence are justified due by philosophical or mathematical argument.

Baron (2012) describes descriptive models as psychological theories, often explaining in cognitive ways how agents behave. These models include heuristics, strategies, and formal mathematical models. When observations depart from normative models, useful descriptive models can explain these departures, referring to such deviations in behavior as "bias" when such departure is systematic.

Prescriptive models are defined by Baron (2012) as engineering models, originally thought of including mathematical tools to analyze decisions or being educational interventions, such as teaching agents various heuristics to exclude certain decision-making strategies that can lead to bias during certain circumstances. Prescriptive models include the idea of nudging people for them to perform normatively better choices.

It is argued that this three-fold distinction is necessary, and none of the three model types should be combined, so that judgements and decisions can be improved or at least preserved in their quality (Baron, 2012); in order to do so, it has to be understood what makes judgements "good". Baron (2012) suggests the introduction of such distinguishing categories regarding quality, so that data can be collected on the "goodness" of certain judgements, monitored, and tested for improvement potential (Baron, 2012).

By the concept of "Judgment and decision making", models are to be defined in order to improve judgements and decisions, have to be re-evaluated by the three-fold criteria of a model, define what "good" judgements are and what circumstances alter them in a more positive or negative way. In this chapter, judgements in an interdependent network of beliefs are to be considered.

Section 2.5.1 introduces the theoretical approach to multiplayer decision-making and section 2.5.2 will focus on multiplayer experiments in behavioral economics.

2.5.1 From Game Theory to Behavioral Game Theory

Game theory has not only become a fundamental economic tool for theoretical, but also empirical science (Fudenberg & Levine, 2016). Game Theory is looking

at multiplayer decision-making scenarios, referred to as "games", and is not only some abstract economical model. According to Fudenberg & Tirole (1991), game theory was for example applied in theoretical biology, considering animals as being agents, who follow a set of pure strategies.

The most important aspect of game theory is that individual decisions and "games" are distinguished. While isolated agents are only concerned about uncertainties stemming from their surrounding environment, interdependent decisions by multiple agents being part of a common decision-making domain also have to consider uncertainties coming from their co-agents' behavior, whose behavior can potentially influence the actions of all agents (Fudenberg & Tirole, 1991). Another key difference between individual decisions and games are "zero probabilities" or decision potential, which are irrelevant for decisions but are an intrinsic cornerstone for games (Fudenberg & Tirole, 1991). In order to make predictions about how a game will play out or change its path, "Nash-Equilibria" are used. Nash equilibria describe a certain path or recipe on how a game will unfold, and if all agents figured out this Nash equilibrium to be reached, no agent had any reason not to behave as described by the prescribed recipe. According to this logic, only a Nash equilibrium can be predicted by agents, and can be assumed to be predicted by co-agents. Any prediction that comes to the conclusion that an equilibrium other than a Nash equilibrium is reached, the agent or another co-agent has to perform a "mistake" or "error" (Fudenberg & Tirole, 1991).

Fudenberg & Tirole (1991) follow up by stating that "errors", such as "mistakes", may likely occur, and in order to predict them requires the game theorists to know more about the outcome of the game than its participants. The authors state that "Nash equilibria" cannot be considered "good predictions" in all situations, as not all information is contained in the game theoretical model, such as individual experiences of the participants, which can be influenced by culture.

The authors state that in order to define a complete theory, "error" can be regarded as a human-made mistake "with small probability". Error can also find its origin in "Payoff Uncertainty". The latter renders both modeller and player being unable to be fully certain about any "payoff" value, as suggested by "Fudenberg, Kreps and Levine" (Fudenberg & Tirole, 1991, p. 467). Allowing small payoff uncertainty can have large effects. According to Fudenberg, Kreps and Levine no economically interesting situation is lacking payoff uncertainty, and thought-experiments excluding payoff uncertainty may not be reasonable. This is referred to as the "uncertainty problem". How the cause for "error" is defined by a certain model to be the most likely cause, defines the best model for this specific set of data, however, even small causes have the power to shift an equilibrium (Fudenberg & Tirole, 1991).

With the introduction of constant uncertainty, common knowledge is defined, which not only includes payoff uncertainty, but also the initial uncertainty of each agent about the game's structure (Fudenberg & Tirole, 1991). This formal definition of knowledge leads to "technical and philosophical problems" (Fudenberg & Tirole, 1991, p. 547), some of which were already noted with reference to the "frame problem". However, small changes (perturbations) in a game's information structure (common knowledge in an informal sense) has the power to change an agent's knowledge and therefore alters common knowledge, rendering an exact description of common knowledge to be fuzzy (Fudenberg & Tirole, 1991). A fuzzy common knowledge solution is the "almost common knowledge" concept by Monderer and Samet (1989), which "requires that all players be "pretty sure" that their opponents are "pretty sure" about payoffs (...)" (Fudenberg & Tirole, 1991, p. 564).

The authors show how Nash equilibria are changed entirely by perturbations in their information structure and that the sensitivity

> *"of even the Nash-equilibrium set to low-probability infinite-state perturbations is another reason to think seriously about the robustness of one's conclusions to the information structure of the game."*

(Fudenberg & Tirole, 1991, p. 570).

In more modern approaches of game theory, payoff uncertainty is usually always part of testing models for stability. To enhance game theory, several behavioral models where formed to establish "Behavioral Game Theory", such as the cognitive hierarchy (CH) model, used to predict initial conditions in a repeated game, the quantal response equilibrium (QRE), where agents may perform small mistakes, maintaining correct belief about co-agents' intentions, the Experience-Weighted Attraction Learning (EWA), which predict a decision path as a function operating on initial conditions, and various learning models, which include the understanding of the learning progress of co-agents, strategic teaching and reputation-building, leading to games outside of equilibrium (Camerer & Ho, 2015).

The term "behavioral" is being described by economical, psychological and decision sciences roughly as "being about mental processes" (Gavetti, 2012, p. 267). Modern behavioral economics still study "noise" in coordination games, where agents deviate from their routine because of mistakes, wrong perceptions, inertia or trial-and-error (Mäs & Nax, 2016). Mäs & Nax (2016) constructed a complex experiment, where agents played coordination games with multiple network partners, in games consisting of 20 subjects playing coordination games 150 times: The subjects were neither informed about the game's causal structure nor

about their co-agents' types; agents were informed about their own payoff, the last round's choice of their co-agents, but not about the payoff of their opponents. The experiment found 96% of decisions to be myopic best responses, and being highly sensitive to their costs.

Costs and feedback create boundaries which have to be overcome in order to maximize by learning. A study by Bayer & Chan (2007) researched the famous "Dirty-Faces" game by a laboratory experiment, where iterative thinking ("He knows, that I know, that He knows…") is required in order follow common rationality. They authors arrived at the conclusion that a threshold exists between participants performing more than one and two or more meta-levels of iteration, due to the individuals being limited in their ability to apply such meta-cognitive thinking or because the agents considered higher order meta-level thinking to be useless, as their co-agents were expected to be unable to perform higher order meta-level thinking themselves (Bayer & Chan, 2007).

The cognitive hierarchy (CH) model attempts to anticipate human behavior in one-shot games, building upon the number of meta-thinking levels a participant performs (Camerer, Ho, & Chong, 2001). Agents who perform zero steps of thinking are considered behaving random, irrational or not strategically. With performing one level of iterated thinking, participants are considered to behave strategic. The CH model requires some estimate on how meta-level thinking is distributed amongst the participants. For this purpose, the efficient Poisson distribution is used, and participants' heterogeneity is modelled into a thinking-steps model, which calculates the initial probability of individual choice. The model was fitted to data from three studies with a 2558 subject-games (Camerer & Ho, 2001). The thinking-steps model outperformed the quantal response equilibrium model, which assumed only one type per participant. The strength of the thinking-steps model was considered to be its modelling of a multitude of types per participant, i.e. agent heterogeneity. The behavioral game theory model was compared to the classic Nash equilibrium predictions, where the thinking-model predictions were closer to data than Nash equilibrium predictions. The equilibrium predictions by Nash equilibrium were mostly distributed amongst the limits, being either "0" or "1". This is shown in figure 2.13 (Camerer & Ho, 2001).

Still, game theoretical assumptions about common knowledge and rationality have not been shown to be followed by participants in interactive games in real life experiments, and common knowledge and rationality were disregarded as being a model for social interaction (Colman, 2003). Drew Fudenberg and David K. Levine (2016) suggested to enhance game theory with learning theory by simulation, using belief-based learning models, maintaining simplicity, by embedding complex learning theory into game theory and establishing breadth by combining static game theory and dynamic learning theory (Fudenberg & Levine, 2016).

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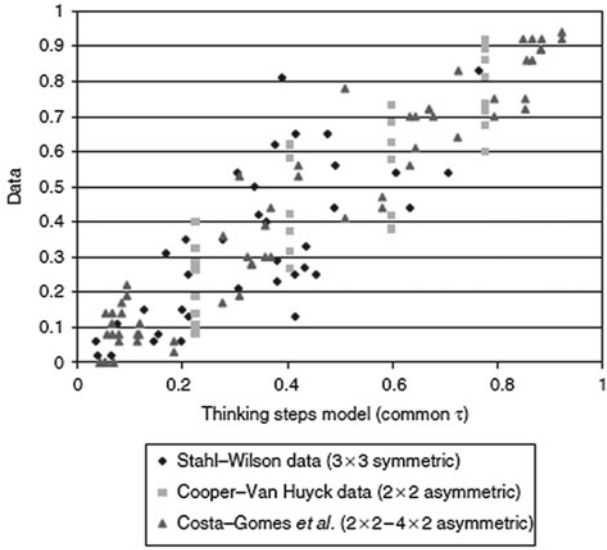

Figure 8.2 Fit of thinking-steps model to three games ($R^2 = 0.84$)

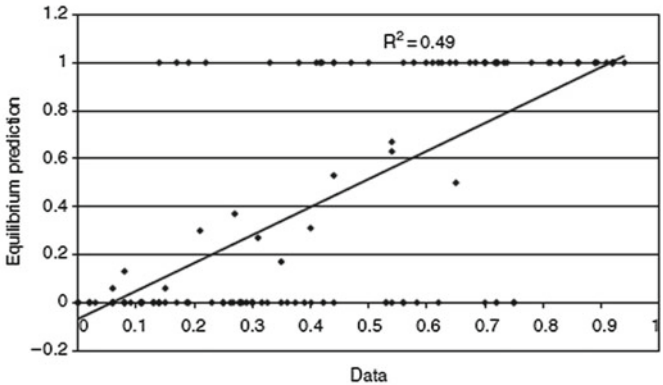

Figure 8.3 Nash equilibrium predictions versus data in three games

Figure 2.13 Behavioral game theory vs. game theory, experimental results. *Source* C. Camerer & Ho, 2001, p. 128

Today, there also exist claims that game theorists wrongly assume the uncertainty problem to be solved by agents accumulating information, even going as far as stating that the game-theoretical object of rationality cannot be described with persisting uncertainty, rendering game theory to be "irrelevant and useless", while the true challenge was to explain the existence of heterogeneous transactions and social interactions by accepting ever-remaining uncertainty (Syll, 2018). In another very critical article, the economist Berhard Guerrien (2018) quotes Andrew Schotter, a former Morgenstern student, to show that game theory has more fruitful potential in the domain of "cooperative", instead of "non-cooperative" game theory. According to this quote by Schotter, von Neumann and Morgenstern were originally trying to break problems stemming from the infinite chain of meta-thinking by introducing strategically interdependent situations that are independent of their expectation of their co-agent (Guerrien, 2018). Guerrien (2018) further states that game theoretical constraints concerning which information is available to participants, were unrealistic and never verified by experiments.

In total, game theory marks an important backbone for behavioral economics, from which many fruitful concepts, realizations and ideas were born. Learning, as a feedback process, benefits from knowledge. As stated before, knowledge cannot be formalized by any instant, game theory included, because such a process would render it instantly as information instead. A formalization of knowledge results in paradoxes, ad infinitum problems and logical debates, similar to the problems of old-fashioned "set theory" or as explained by the "frame problem". Therefore, game theory is constrained in its possibilities as is any other way to model reality: it offers normative models for efficient computations, can be used as a platform for useful explanations in form of descriptive models or used as a "language" to build decision-making enhancing predictive models. Game theory has also shown the importance of sensitivity to perturbations in any normative model that builds upon the concept of an information structure. To the understanding of the author, game theory does not claim having solved the uncertainty problem, at least not exceptionally. Fudenberg and Tirole (1991), one of the golden standards of game theory, summing up the entirety of game theoretical insights until 1989 in one book, have claimed various times that models assuming perfect information or zero uncertainty are not even meaningful—even as a Gedankenexperiment.

The next sub-chapter will concentrate on a few examples of group behavior phenomena observed under experimental conditions and described by game theoretical normative models.

2.5.2 Group Behavior

As stated before, this thesis is interested in group behavior changes, when being confronted with different types of information. Specifically, this thesis' experiment simulates group decision making under uncertainty, where communication between agents is *not* possible. In order to describe scientific research in such a domain, several phenomena of group decision making where communication *is* possible are also listed, in order to exclude such behavioral instances further on.

Decision problems including more than one decision maker are studied in the domain of group decision making (GDM) (G. Li, Kou, & Peng, 2018). Studies on GDM are usually considering how much communication is allowed and how the final outcome is created by group decision making (Tindale & Winget, 2019). Several insights from GDM are listed by Tindale & Winget (2019): groups holding members of high expertise on the task at hand can improve overall group performance; individual motivation for the whole group to perform "accurate decisions" has a positive impact on group performance; groups can perform well without communication; communication will decrease group performance in situations where members are "less than wise"; shared group bias on the decision environment will "exacerbate" these biases (p. 28). When communication between agents is possible, imitation and herding behavior are popular examples of group behavior.

Imitation and innovation have been described as the "dual engines of cultural learning" (Legare & Nielsen, 2015). It is known that humans imitate each other during social interactions, which positively influences action comprehension such as improving language comprehension (Adank, Hagoort, & Bekkering, 2010). Even emotions can be "imitated" in form of emotional contagion, which can improve perceptions of task performance (Barsade, 2002). "Imitate-the-best" and "imitate-the-majority" has been found to speed up individual learning under uncertainty (Garcia-Retamero, Takezawa, & Gigerenzer, 2009).

In a software based experiment it was found that groups were able to find novel solutions to problems that would have been missed by individuals, since interpersonal imitation shifts the group towards the urge to find more promising solutions; however, the size of the group can have significant and nonlinear impact on the groups behavior and performance using imitation (Wisdom & Goldstone, 2011).

Next to imitation, the herding effect is especially relevant for analysis in crowd psychology, where irrationality can arise from group behavior, accumulating deception potential, leading to such phenomena like "exploding market bubbles", which is also referred to as "information cascades" (Samson & Gigerenzer,

2016, p. 109). Herding describes individual agents to imitate group behavior as a whole, rather than following own strategies (Hwang & Salmon, 2004). It has been shown by game theoretical analysis that time and frequency of public information can impact the collective learning process, and that public information can help a herd to overcome a wrong belief and inefficient paths (Bohren, 2014). Neuroscientific models suggest that social alignment is mediated by a system that monitors misalignment and rewards actions leading back to alignment (Shamay-Tsoory, Saporta, Marton-Alper, & Gvirts, 2019). For this purpose, information is required. In international markets, herding was found to depend on the level of information transparency (Choi & Skiba, 2015).

When communication between agents is not possible, due to costs, security, technical problems or language barriers, coordination and cooperation without communication in some problem-space can be performed by "focal" real life decision influencers or prominent solutions, referred to as "focal points" or "Schelling points" (Zuckerman, Kraus, & Rosenschein, 2011). They are defined as "a point of convergence of expectations or beliefs without communication" (Teng, 2018, p. 250). Such Schelling points were proposed as equilibrium refinements of the Nash equilibrium, where the ideal game theoretical strategy has to both consider actions of cooperation and coordination of potential conflict (Teng, 2018). Experiments found groups to outperform individuals in coordination games with focal points, when individual interests of the group were compatible and cognitive input was helpful for controlling the coordination problem (Sitzia & Zheng, 2019); groups report worse levels of coordination when interests are not aligned. In coordination games, groups are also more sensitive to salience (Sitzia & Zheng, 2019).

Group planning behavior differs from individual planning behavior in decision environments governed by either objective risk or subjective risk, the latter being referred to as "ambiguity" (Carbone, Georgalos, & Infante, 2019). In their study, Carbone, Georgalos & Infante (2019) focused on sequential group decision making behavior reacting to novel information. In the objective risk treatment, participants were informed about the statistical chances of their income, i.e. agents were informed about the amount of balls being hidden in urns, such that agents could manifest a realistic mental model of the experiment's creation of risk. During the subjective risk treatment, no such information was provided to the participants. While individuals and groups were found to "substantially" deviate from the optimal, theoretical strategy, facing a stochastic and dynamic problem, individuals outperformed groups under objective risk, whereas groups outperformed individuals under subjective risk (Carbone et al., 2019). Furthermore, both group and individual were found to make myopic decisions under objective and

subjective risk (Carbone et al., 2019). When tested for planning, groups were closer to rationality under ambiguity, creating more welfare (Carbone et al., 2019). The study comes to the conclusion that there exists a non-neutral attitude towards ambiguity (Carbone et al., 2019), which affects trust decisions. A negative attitude towards ambiguity correlated with a more negative attitude towards trusting options, while agents who considered themselves as trustworthy, were more likely to trust other agents (C. Li, Turmunkh, & Wakker, 2019). Therefore, subjective belief about others can have a crucial influence in group decision making. It is suggested to not model subjective belief simply as subjective probability (Andersen, Fountain, Harrison, & Rutström, 2014), as risk attitudes of individual agents have to be carefully considered first (Andersen et al., 2014). How to model subjective belief is described as an open question, and agents may not only hold a traditional type of aversion towards risk, but also towards uncertainty, when decisions are made in a domain being governed by subjective instead of objective uncertainties (Andersen et al., 2014).

A good example on individual behavior towards uncertainty comes from random group matching procedures. Multiplayer experiments which match participants randomly, can result in the participants feeling to be treated unfairly, when their partners behave suboptimal towards them. This was in fact experienced during pre-tests of the thesis' experiment. Ballinger, Hudson, Karkoviata, & Wilcox (2011) claim that "working memory capacity" (WMC) mediates the ability of participants to react to such situations with more or less sovereignty, with WMC working as a mental buffer (Ballinger et al., 2011). WMC also supposedly predicts performance on how agents can adapt their "depth of reasoning" throughout experiments with growing structural complexity (Ballinger et al., 2011; Strunz, 2019).

Improved performance by groups compared to individual decision-making is commonly achieved by interpersonal communication (Charness, Cooper, & Grossman, 2015). When subjects work together via computer interfaces, communication costs can counterintuitively enhance group performance; while higher costs in communication reduces message quantity, they enhance message quality in groups, so that groups facing communication costs outperform individuals significantly (Charness et al., 2015). However, in cases when communication likely introduces error, more communication is not always better than less. In such cases, assigning costs to communication enhances performance (Charness et al., 2015).

Group decision making under uncertainty profits from communication, as shared information will increase decision quality, when information is sufficiently processed by the group; when shared information is insufficiently processed,

groups tend to be overconfident in their decision making (Sniezek, 1992). Social factors such as face-to-face discussions and the goal to reach consensus are described to influence group confidence (Sniezek, 1992).

Experimental research about the influence of expertise and information in GDM under uncertainty in an environment, where no communication is possible, is scarce. Such a domain could be thought of multiple agents working with a personal computer, making decisions by investing in a certain market, where each agent does not know its co-agents. Still, all of the agents' decisions are interdependent and all agents will collectively see the same market results. Uncertainties might arise from different sources, such as uncertainty about the number of co-agents, causal relationship of group invest and market results or whether own action is of effective relevance. Uncertainties can stem from doubt, e.g. by asking the question whether there was an optimal group strategy, if such a strategy could actually be achieved and if maximization was possible with limited information about the causal relations. In general, two kinds of uncertainties in group decision making are considered: environmental and social uncertainty (Messick, Allison, & Samuelson, 1988).

It has been shown that communication highly reduces environmental and social uncertainties "by enhancing group coordination and performance" (Messick et al., 1988, p. 678). Furthermore, it was experimentally shown that agents are risk-averse regarding environmental uncertainty, are less influenced by social uncertainty, while individual risk aversion was not influenced by communication at all (Messick et al., 1988).

Individual experience, such as proficiency, also mediates how external information is interpreted and which measures are ultimately taken, as shown by disaster risk reduction decision-making: risk expressed by numbers or by verbal clues differed in their impact, while its impact also depended on whether or not an agent was a scientist or not, as scientists had more experience with risk expressed via numerical probabilities (Doyle, McClure, Paton, & Johnston, 2014). However, verbal clues were consistently found to be regarded as more ambiguous than numerical terms (Doyle et al., 2014). In addition, probabilities were found to be commonly misinterpreted by the participants (Doyle et al., 2014).

In summary, GDM under uncertainty without the ability to communicate with other agents will be influenced by individual expertise regarding performance, due to routine strength and their interpretation of information. The lack of communication does not necessarily lead to worse group performance, which depends on the collective status of "wise" decision making, the decision-domain's resistance to error-perturbation, and individual motivation to let the group make accurate decisions. Biases stemming from communication such as social influences, herd

behavior, imitation, collective bias and overconfidence can be excluded. Prominent solutions or Schelling points can be expected, when all agents have had similar "single-player" experience and expertise. Ideally, working memory capacity is measured in such an experiment in order to understand individual stress resistance to "unfair" group constellations. The individual types of risk-aversion should not be influenced by the lack of communication. In the example of GDM under uncertainty, risk is seen as the individual attempt to try a strategy which deviates from a strategy that has been shown to be effective in the past. As participants in GDM have shown to be less risk averse towards social uncertainty, and are more risk averse to environmental uncertainty, information that is interpreted by an agent as there being good reason to belief that other agents are influencing the game, will more likely lead to deviation from the former "effective" strategy than with information that is interpreted by an agent as there being good reason to belief that random or uncontrollable instances are influencing the game.