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Similar Chords, Different Tune? The Effects of Different Solution Formulations on the Identification of Collaborative Opportunities in Selective Revealing: A web-based Experiment

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Abstract

As selective revealing is being recognized as a new means to find collaboration partners, little attention has been paid on how selectively revealed solutions are best formulated in order to be positively perceived. Prior research has highlighted that technological gatekeepers, i.e. individuals with who handle the R&D communication network and hence potential recipients of revealed knowledge, rely on cognitive and perceptual abilities during the recognition and evaluation of novel technologies. To enrich existing knowledge about opportunity recognition in selective revealing, this study took a cognitive perspective and intended to explore the effects of different formulated revealed solutions on the identification of collaborative opportunities. By priorly manipulating the superficial and structural commonalities of two revealed solutions conducted in collaboration with industry experts, I designed a 2*2 within-subject experiment to validate whether such an induction of analogies increases the percipience of a selectively revealed opportunity. The data, which was attained during an online-experiment with university students from different fields of studies also included individual factors such as prior knowledge about markets and technologies, creative ability (proxied by divergent thinking test and creative self-efficacy) and other demographic characteristics. The gathered data was analyzed through a linear-mixed effect model to capture the repeated design of the experiment. The computation illustrated that relational commonalities between a market and a revealed solution considerably improved the perception about a revealed solution and the willingness to engage a collaboration. In addition, the results demonstrated that superficial similarities facilitate the retrieval of analogies from structural commonalities. For the individual factors, the provided evidence could not support the initial hypotheses that individual creativity and prior knowledge positively moderate the effects of superficial and structural similarities. Contrarily, the results revealed negative moderating effects of creativity and the field of study. Despite further research is necessary, this study delivered implications for both ends of the information flow in selective revealing by conjointly examining the effects of selectively revealed opportunities and personal traits, and enriched this field of study through comprehending the drivers of early action in open innovation and strategic renewal.

Keywords: Selective Revealing, Opportunity Recognition, Open Innovation, Analogical Reasoning, Gatekeepers

1. Introduction and problem statement

1.1. Background

Collaboration is an important aspect in business and usually gives the participating companies the prospect of increasing their competitive advantage (Ahuja (2000); Rothärmel (2012)). So, it is no wonder that firms constantly try to elaborate novel ways in finding new collaboration partners. Among researchers, selective revealing is reckoned to be a new approach in finding new collaboration partners of every description (Alexy et al. (2013)) and is interpreted as a firm's decision to voluntarily unveil parts of its intellectual property to the public (Harhoff et al. (2003); Henkel (2006); Henkel et al. (2014)). Within the last years, selective revealing gained public attention as organizations like Tesla or NASA climbed on the bandwagon and made some of their patents and technologies freely accessible to the public (Vance (2014)).

The approach of selective revealing is based on the formulation of firm-specific knowledge and its distribution to the public. In most instances though, the revealed knowledge is subsequently assessed by other companies and its gatekeepers, i.e. individuals within firms who screen the external environment for relevant knowledge to improve an organi-

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zation's innovative activity (Afuah and Afuah (2003); Allen (1977); Cohen and Levinthal (1990); Morrison (2008)). Freely revealed knowledge can thus be an important source of external knowledge for gatekeepers.

Due to the digital century, in hich innovation and knowledge becomes increasingly complex, more and more firms strive to obtain collaboration partners in order to stay innovative and gain external knowledge. As some studies have even illustrated (e.g. Haas and Ham (2015); Kaplan and Vakili (2015)), the achievement of disruption in innovation is increasingly achieved through the recombination of knowledge from different domains. Due to its wide reach and low coordination cost (Alexy et al. (2013)), selective revealing gives the focal firm the opportunity to reach potential collaboration partners from close and distant knowledge domains. However, researcher consent that the success of knowledge transfer significantly depends on the recipients' prior knowledge and expertise (Cohen and Levinthal (1990); Scheiner et al. (2015); Walsh (1995)).

By drawing upon cognitive theories' claim that the form of knowledge representation affects its processing and following use (Boland Jr et al. (2001); McClelland and Rumelhart (1985)), the revealing firm needs to find appropriate ways to illustrate the revealed knowledge so that it appeals to many different gatekeepers. Indeed, Alexy et al. (2013) stated that the formulation and presentation of the revealed knowledge by the focal firm can play a decisive role during the gatekeeper's evaluation of the revealed knowledge. The focal question is thus, whether different forms of knowledge representation affect the perceived benefits of selective revealing and impact the self-selection of technological gatekeepers.

1.2. Research question

Optimal information flows play an essential role in R&D and the innovation process (Allen (1977); Macdonald and Williams (1993); Tushman and Katz (1980); Whelan et al. (2010)). In this context, such information flows may be affected by both the firm that conveys and the firm that absorbs the revealed solution. In the later section, both ends of the dichotomies of an information flow are under review, followed by the deduction of a research gap and a research question.

1.2.1. Research question from the revealing perspective

The effects of selective revealing have received considerable attention in the last years (e.g. Alexy et al. (2013); Harhoff et al. (2003); Henkel (2006)). Revealing stands for the voluntary spillover of internal resources to the external environment. Instead of monetary advantages, it offers the focal firm other benefits (Alexy et al. (2013); Dahlander and Gann (2010); Harhoff et al. (2003)) such as finding new collaboration partners. It is generally accepted that openness positively affects a firm's ability to profit from innovation (Alexy et al. (2013); Dahlander and Gann (2010); Harhoff et al. (2003); Henkel (2006); Von Hippel and Von Krogh (2006)).

To benefit from openness in innovation, different researchers tried to investigate the conditions under which it is more probable to pursue the practice of selective revealing. Alexy et al. (2013), von Hippel (1988) and Harhoff et al. (2003) have stressed that revealing enhances the generation of uniform industry standards – especially in early technology life-cycles (Teece (1986)) – which allows the focal firm to enlarge its markets. The revealing of intellectual property might even be beneficial if a standard already exists; but only if the revealed knowledge increases the compatibility to the existing standard (Alexy and Dahlander (2014)). Reputational-related benefits are also among the factors that explain higher activity in revealing (Harhoff et al. (2003)) and have been empirically confirmed by investigating in the behavior of software developers in open source environments (Henkel (2006)). Further explanations why firms freely reveal are expected support from incumbents (Harhoff et al. (2003)), the modularity of a firm's knowledge (Alexy et al. (2013)), firm policies (Henkel (2006)) and complementary assets (Henkel (2006)). Notwithstanding its benefits, revealing may also sometimes come along with disadvantages, especially when it gives the competitors an opportunity of free-riding on the revealed knowledge (Harhoff et al. (2003)). Firms often fear that revealing triggers imitation among incumbent firms, leading to a loss of its competitive advantage.

Nonetheless, selective revealing is recognized as a strategic tool that shapes strategic collaboration. Alexy et al. (2013) proposed a process model in which the authors determined the antecedents of a voluntary spillover. The authors argued, that amongst others, high partner uncertainty, high coordination cost and high unwillingness to collaborate facilitate the company's decision to reveal its intellectual property. Thus, selective revealing may be seen as an instrument which helps firms to find new partnerships; especially when external preconditions don't allow for traditional collaboration modes (Alexy et al. (2013)).

Apart from the different contingencies, a collaboration based on selective revealing can arise according to Alexy et al. (2013) from two different modes of revealing: solution revealing and problem revealing. As the term already suggests, problem revealing is about sharing a problem with externals and enables the firm to obtain a solution to this problem. In contrast, solution revealing implies that firms voluntarily (and sometimes also strategically) unveil their solution to a problem (e.g. specific solutions) to the public.

The last section showed that selective revealing offers many important implications for innovation and strategy. Yet, none of the studies on selective revealing questioned the role of the formulation and structure of the revealed solutions. Even researchers such as Alexy et al. (2013) or Baer et al. (2013) acknowledge, that the savoir-faire about the formulation and illustration of selectively revealed knowledge is important in order to maximize its benefits. Considering that the recipients of such revealed solutions, i.e. gatekeepers, usually conduct a mere 'rapid analysis' (Scheiner et al. (2015)), the first impression from a revealed solution is very important. The revealing firm hence needs to mitigate a potential communication noise by properly illustrating a solution which increases the perceived quality of that solution.

Up to now, most of the studies which aimed at reducing communication barriers in technology transfer focused on the receiving instead of the revealing instances. Many researcher for example argued that social tactics (c.f. Foster et al. (2011); Storper and Venables (2004)), information and communication technology (c.f. Roberts (2000)) or multiple gatekeepers (c.f. Gassmann and Gaso (2004)) could enhance the information flows in R&D and the innovation process.

Instead, this research pursues the argument that the revealing firm could use formulation techniques in order reduce noise and complexity, and help the recipient of the revealed solution to better identify novel and valuable solutions. An important role in technology transfer processes is given to the structure of the transferred knowledge (Gentner et al. (1993b)). Thereby, scientists argue that structural alignment, i.e. the ability to perceive similarities between existing know-how and novel information, facilitates information processing (c.f. Gentner (1983); Gentner et al. (1993b); Reeves and Weisberg (1994)). While research in the sector of entrepreneurial opportunity recognition confirmed this finding (c.f. Grégoire and Shepherd (2012); Gregoire et al. (2010)), it remains unclear, if the same effect will occur in selective revealing. In this respect, the effect of different formulated revealed solutions on the identification and evaluation of collaborative opportunities deserves further investigation. Consequently, the first research question is posited in the following way:

> Research Question 1.a: Do different formulations of selectively revealed solutions influence the recognition of collaborative opportunities by technological gatekeepers?

1.2.2. Research question from the receiving perspective

By getting to the other end of the dichotomy, the upcoming section takes a closer look at the role of the receiving instance in optimal information flows. As previously mentioned, this study assumes that technological gatekeepers represent the most important recipients of selectively revealed solutions. In the scientific community, the role of a technological gatekeeper has obtained much attention in the last decades (Ettlie and Elsenbach (2007)). Researchers thus generally agree that outside information is best assimilated when it is processed by only a small number of uniquely skilled technological gatekeepers (Allen (1970); Allen (1977); Klobas and McGill (1995); Tushman and Katz (1980); Tushman and Scanlan (1981); Whelan et al. (2010)).

Allen, who coined the concept of technological gatekeepers in the late 60's, defined them as "individuals who occupy key positions in the communication network of the laboratory." (Allen and Cohen (1969): 13). Gatekeepers act as translators (Scheiner et al. (2015); Whelan et al. (2010)), trying to overcome communication barriers and preventing irrelevant information from being further transferred into the company (Hauschildt and Gemünden (1999)). As a result of the increasing importance of external information for a firm's innovative capacity (Chesbrough (2006)), it is commonly suggested, that gatekeeper play a key role in identifying, acquiring, integrating and exploiting new technologies in the R&D processes of a company in order to stay competitive (Allen and Cohen (1969); Ettlie and Elsenbach (2007); Scheiner et al. (2015); Whelan et al. (2010)). Thus, the presented evidence strengthens the assumption that gatekeepers can be regarded as important recipients of selectively revealed solutions.

Considering the importance of technological gatekeepers in companies, studies have suggested that not everybody can fill this post. Technological gatekeepers usually exhibit particular characteristics. Macdonald and Williams (1993) and Allen (1977) for example have shown, that gatekeepers tend to be extroverted, technologically proficient and socially capable. Furthermore, they usually hold high hierarchical positions in firms (Scheiner et al. (2015)). Because of the necessity to build and cultivate a social network, it takes however a considerable amount of time become a gatekeeper (Nochur and Allen (1992)).

During the acquisition of external information technological gatekeepers are confronted with a vast amount of information. Within this mass of stimuli, they should detect relevant technologies and disregard irrelevant ones. The consensus of researchers is that the identification of valuable external information depends on a gatekeepers' cognitive and perceptual abilities and intuition (Scheiner et al. (2015)). In particularly, schemata, i.e. generic relics in the long-term memory from past situations or experiences, guide the recognition and understanding of new information (Matlin (2008); Walsh (1995)). Schemata and their categorizations facilitate the decision-making process and enable gatekeepers to evaluate the consequences of new technologies in a very fast manner (Scheiner et al. (2015); Winkielman et al. (2006)).

Albeit the myriad of studies which investigated in the cognitive and perceptual abilities of gatekeepers, most of them have failed to recognize importance of individual creativity. Plucker et al. (2004) defined creativity as 'the interaction among aptitude, process, and environment by which an individual ... produces a perceptible product that is both novel and useful ...'. Creativity could be of ample significance for gatekeepers, because it enables an individual to see interconnections among different elements and to combine them to something new.

In addition, this research will take a stance on the role of prior knowledge. Even though many studies successfully investigated the effects of prior knowledge (e.g. Grégoire and Shepherd (2012)), only few have recognized, that successful problem solvers are not necessarily coming from the same knowledge field as the problem itself (Jeppesen and Lakhani (2010)). Indeed Kaplan and Vakili (2015) have found that breakthrough innovations require distant and diverse knowledge recombination. Alas, the role of prior knowledge is still ambiguous in the study fields of selective revealing and technological gatekeeping, and deserves further examination. The second part of the research question can be accordingly stated in the following way:

> Research Question 1.b: Do creativity and prior knowledge of technological gatekeepers impact the identification of collaborative opportunities in selective revealing?"

1.3. Outline of the thesis

This master thesis is a response to Alexy et al. (2013) call for research on the formulation of selectively revealed solutions. It attempts to examine the effects of different formulations of selectively revealed solutions on the recognition of collaborative opportunities. Thereby, I hope to provide valuable insights for the research of open innovation and knowledge transfer processes in selective revealing. Similar to the work of Grégoire and Shepherd (2012) on entrepreneurial opportunity recognition, an empirical study was conducted to examine if high similarities between a revealed solution and its target market ceteris paribus creativity and prior knowledge could facilitate the recognition of opportunities which arise from selective revealing. In order to answer both research questions, the next section emphasizes the existing theories on cognition, analogical reasoning, prior knowledge and creativity in the context of opportunity recognition. From the presented theory, I will deduce a conceptual framework and a body of hypotheses for the later analysis. Subsequent to the presentation of the contemporary theories, the third section demonstrates how the online-experiment and the manipulation of the stimuli were executed to address the research question. Furthermore, this section provides an insight on the operationalization of the experiment and the data analysis. The results from the descriptive statistics and a generalized linear model (GLM), which capture the within-variance of the outcome, are examined in the fourth section of this thesis. Besides an examination of the effectiveness of the randomization, this section will focus on the effects of the superficial and structural similarities on the evaluation of a collaborative opportunity and the additive and interactive effects of prior knowledge and creativity. The results provide the basis for the acceptance or the rejection of the elaborated hypotheses from section two. In the last section, the implications for theory and praxis as well as the limitations will be discussed.

2. Current state of research and hypothesis

2.1. Drawing upon a theory of cognition

This proposal builds on the broad foundation of cognitive theories (Matlin (2008); Reed (2006); Walsh (1995)), and more specifically on theories about individual cognitive patterns in the technology evaluation and identification process (Grégoire and Shepherd (2012); Scheiner et al. (2015)). The past research has shown that cognitive science is a salient element when it comes to the understanding of human behavior. Cognition, which is often also referred to as 'information processing', describes how an individual acquires, stores, memorizes, remembers and utilizes information, and hence covers a wide range of mental processes (Matlin (2008); Pecher and Zwaan (2005a)).

As Figure 1 exemplifies , information processing in individual's mind is a multi-stage processes. According to Reed (2006), information processing commences with the sensory store, where outside stimuli are stored untapped for several seconds. A mental filter, which is triggered by attention and concentration and occurs unconsciously, subsequently recognizes only specific parts of the afore stored information. The filtered information then runs through a stage that is called pattern recognition. This mechanism helps individuals to identify the stimulus through matching the information with existing and similar patterns that are retrieved from existing memory and knowledge. As multiple patterns may occur for a piece of information, a final selection phase determines which information enters the short-term memory (STM) and are used for information processing.

The mechanism of pattern recognition is thus a crucial step for information processing. It helps to transform and organize the raw information provided through our senses by matching the outside information with existing patterns that are retrieved from the LTM (Matlin (2008); Reed (2006)). Among cognitive science researchers, there are three plausible theories how patterns are recognized from sensory stimuli: a) the template theory, i.e. the overlap of similarities between two patterns, b) the feature theory, i.e. the recognition of certain parts of a pattern, and c) the structure theory, i.e. the pooling of several parts of multiple patterns. Pattern recognition is understood as a top-down process. This means that information flows from the LTM to the sensory store and that past experiences affect current decisions (Walsh (1995)). Nevertheless, it may also be the case that information processing occurs in form of a bottom-up approach. In such a case, information is directed from the sensory store to the LTM. Bottom-up flows usually occur due to a lack of context or experience, which leads to the outcome that the information itself shapes response to a sensory stimulus (Walsh (1995)).

While the previous passage was concerned with how patterns are matched with external stimulus, the following paragraph goes one step further and attempts to clarify another crucial topic in cognitive science: how is knowledge organized and which impact does it have on the recognition on patterns. In this case, researchers mostly refer to semantic memory, which is of high importance for many brain functions such as interpretations, the retrieval of apprehended concepts or the acquisition of new information and concepts (Posner et al. (1988); Saumier and Chertkow (2002)). Only if the semantic memory is stored and organized effectively, it can be retrieved properly from the LTM (Reed (2006)). However, due to the brain's immense complexity, there are several models that try to explain how semantic memory is organized and recalled. Two of the most popular models are the network model and the feature model (Matlin (2008)). A

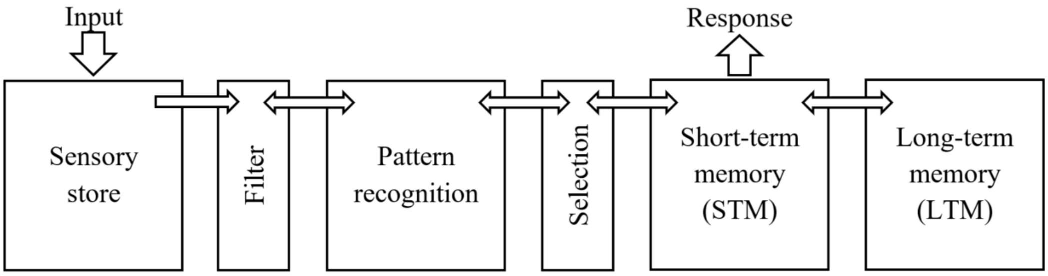

Figure 1: Stages of an Information-Processing Model, Source: Own rendering based on Reed (Reed (2006): 3)

network model consists of a set of elements (concepts, words, features) connected by means of links. Researchers like Barnden et al. (2002) argue that networks are composed in a hierarchical and a semantic way. In a semantic network, similar elements are linked with each other in the LTM and match patterns (Reed (2006)). Processing in this model usually occurs through spreading activation. This theory suggests that the activation of a word in the LTM propagates over the respective relationships with other stored words (Anderson (1983)). Contrary to the network model, the feature comparison model elaborated by Smith et al. (1974) postulates that every word or concept that is embedded in the LTM consists a one or several characteristic features, which in turn belongs to a superordinate category. Hence, with this model it is believed that pattern recognition and cognition happen through using features in order assert the resemblance of two concepts in order to create a response (McNamara and Miller (1989); Reed (2006)). However, the abovementioned models have the limitation of ignoring the importance of knowledge clusters (Reed (2006)). Scholars view the schema theory, which primarily assumes that the integration of knowledge takes place in larger clusters, as a remedy to this issue (Arbib (2002)). According to Rumelhart (1980) a schema contains information about a particular object or concept in an abstract, generalized form and may be understood as a representation of learned knowledge that facilitates information processing. This theory suggests that every schema consists of default knowledge, i.e. knowledge about the most important attribute of a schema, which allows people to make a decisions even though important information is missing (Anderson (1995); Naughton and Staub (2016)). Nonetheless, schemata are highly dynamic, and can be supplemented steadily by new knowledge that is derived from novel experiences (Reed (2006)).

In the managerial cognition research, scholars of strategic management and organization theory consent that managers who usually cope with very complex information worlds (Schwenk (1984)), unconsciously employ knowledge structures or schemata in order to support information processing and decision making (Walsh (1995)). Schemata are mental templates that rely on past experiences and memories (Matlin (2008); Walsh (1995)) and are reckoned as mental representations of an individual's perceived environment (Scheiner et al. (2015)). Yet, schemata are not only seen as mental concepts, but also as linkages between these components (Hayes-Roth (1977)). Accordingly, schemata must affect gatekeepers during identifying and evaluating new technologies by framing external information and giving guidance on how they are perceived.

As Section 1.2.2 has shown, gatekeepers are usually highly experienced. It can be assumed that their vast experience helped them to develop a myriad of schemata which facilitate the evaluation and identification of new technology. Indeed, researchers such as Matlin (2008) have shown that schemata are of v a very dynamic nature, are based on past events, and may change again within time (Walsh (1995)). In order that schemata can evolve, memories are selected, abstracted and integrated in the human mind (Matlin (2008)). However, due to its abstractedness and focus on past events, schemata can also mislead individuals in their decision making process (Matlin (2008)).

By recognizing the importance of schemata in human cognition and decision making, this study is extending cognitive research to open innovation and technological gatekeepers and is anchored on four main assumptions. First, this research assumes that cognitive processes are grounded. Grounded cognition is a theory of mental representation which assumes that there is an interaction between cognitive, perceptual and senso-motoric processes. Consequently, cognition coheres with the representation of thought processes and linguistic conceptualizations (Barsalou (2008); Borghi et al. (2013); Schilhab (2017); Wilson and Golonka (2013)). In contrast to the traditional cognitive theories, which assume that "cognition is computation on amodal symbols in a modular system" (Barsalou (2008): 617), grounded theories regard the brain as the central instance of cognition. This leads to the notion that independent thinking is not possible without multimodal embodiment (Pecher (2012); Pecher and Zwaan (2005b)). Recent work on embodied cognition suggests that even physical states (e.g. morality and dominance) affect human thinking and action (quote).

Secondly, this paper is built on the notion that, from a cognitive perspective, various forms of sensory stimuli may invoke different schemata, and hence affect an individual's cognition and decision making (Boland Jr et al. (2001); Thorndyke and Hayes-Roth (1979)). Cognitive research suggests that the assessment of an opportunity depends on how an external stimuli is linked with representations that exist in the memory of an individual (Macpherson (2017)) and that schemata are invoked by verbal and non-verbal stimuli (Paivio (1990)). Consequently, verbal and non-verbal stimuli not only serve as means of communicating our thoughts but also play an active role in shaping them (Burgoon et al. (2013); Lupyan and Clark (2015)). By extending the argument of Scheiner et al. (2015), technological gatekeepers should also be influenced in their decision-making by external semantic stimuli. Henceforward, this assumption corresponds to the first research question that differently formulated revealed solutions affect the evaluation and identification of technology.

Thirdly, I follow the argument that the capability to process novel information is guided by schemata that were formed by past experiences (Rauss and Pourtois (2013); Walsh (1995)). This means that gatekeepers hold diverging perceptions of revealed opportunities which vary due to pre-existing mental representations, and their content and complexity (Gaglio and Katz (2001); Paivio (1990)). According to schemata theory an appropriate response and action to an external stimulus can only arise, if there's a match between the received information and a schema (Gaglio and Katz (2001)).

In turn, this master thesis is also based on the assumption that individual information processing is enhanced through personal creative ability. Plucker and Makel (2010) found that creativity is constituted by the interconnection of ideas (consequently schemata) and the environment. Creativity is hence understood as the individual ability to shift knowledge from one situation to another (Gick and Holyoak (1983); Hunter et al. (2008)). Thus, creative ability depends on the mental process and is a reached partly through the retrieval and shift of memory (Nijstad et al. (2010)). Creativity could turn out to be an important personal trait for technological gatekeepers and enhance the decision-making process in the evaluation and identification of novel opportunities.

With the four assumptions formulated, the following subsections will provide a deeper insight into the theories of analogical reasoning, prior knowledge and creativity with a specific reference to opportunity recognition.

2.2. Opportunity recognition from a cognitive perspective

This section builds on the aforementioned assumptions and the claim that technological opportunity recognition is supported by cognitive processes (Alvarez and Busenitz (2001); Baron (2006); Butler et al. (2010); Grégoire and Shepherd (2012); Gregoire et al. (2010)). Being considered of utmost importance in entrepreneurship (George et al. (2016)), opportunity recognition has received substantial attention among scholars. Before taking the matter into context of selective revealing, the major theories of opportunity recognition and its underlying cognitive mechanisms are reviewed. First, I will examine the term from an etymological and ontological perspective. Among the myriad of definitions for an opportunity, Baron (2004) concluded that an opportunity is characterized by three major criteria: its perceived desirability (i.e. legal and moral suitability), its newness and its potential to generate profits. However, opportunity recognition, i.e. the identification of a novel opportunity that features subjective and monetary advantages, is only the initial step in a continuing process (see Figure 2). In the context of this research, the study will solely focus on the discovery and recognition of an opportunity, which is distinct from the evaluation of an opportunity and further steps.

Research on the entrepreneurial opportunity is distinguished by the origins of an opportunity. In their extensive literature review on opportunity recognition, George et al. (2016) point to a dichotomy which becomes apparent through the usage of two similar terms: "opportunity discovery" and "opportunity recognition". Researchers deem opportunity discovery if a product or a demand in a market already exists and is merely identified. The term opportunity recognition, however, refers to the reorganization of such a product or market demands in order to explore new ways of that opportunity (George et al. (2016)). A third stream, opportunity creation, was identified by Sarasvathy et al. (2010). According to the authors, opportunity creation is the means of bringing an opportunity into existence through invention or the establishment of a new market.

Notwithstanding the importance of all three research streams, I advance the same view as Grégoire et al. (Gregoire et al. (2010): 415), who refused to focus on one nature of opportunity but rather proposed that opportunities are "courses of action that seek to derive benefits from these changes." Also in the context of this research, a determination of whether a technological gatekeeper discovers or recognizes an opportunity would miss the mark. Instead, I focus on the widely accepted assertion that cognition and personality traits affect opportunity recognition. As the further course of the theory section will show, cognition is only one of many influencing factors. The framework on opportunity recognition by Shane (Shane (2003): 11) confirms that the pursuit of an opportunity depends on a myriad of interrelated factors in which cognition is only a piece in the puzzle. According to the author, both individual attributes and external factors affect every single step of opportunity acquirement process (Shane and Eckhardt (2003)).

Despite that multidisciplinary framework, researchers consent that the recognition of an opportunity can be seen as a cognitive process in which people reason about finding interesting opportunities (Garcia-Cabrera and Garcia-Soto (2009)). Baron (2006) argued that pattern recognition provides the cognitive fundament for identifying opportunities. The researcher thereby argued that prior knowledge and experience helps an individual to find a pattern among unrelated events to recognize opportunities. Indeed, empirical findings have shown that schemata of experts are richer than those of novices and subsequently illustrated that the ability to recognize an opportunity rises with the sophistication of the held schemata (Baron (2006)).

From a cognitive perspective, the retrieval of knowledge from our memory is crucial for information processing. As illustrated in Figure 3, individuals' make sense of new informa-

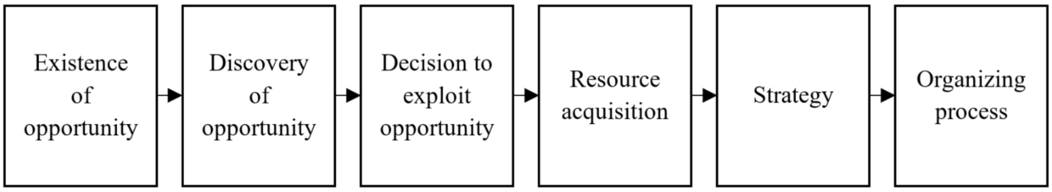

Figure 2: Directionality of the Opportunity Acquirement Process; Source: Own rendering based on Shane (Shane (2003): 12)

tion by comparing it with retrieved knowledge. Researchers mostly call this process analogical transfer or reasoning, i.e. the projection of knowledge from a domain to another (Gick and Holyoak (1983); Holyoak and Thagard (1995); Novick (1988); Ward and Kolomyts (2010)). Analogical reasoning is understood in multiple ways and can be the cognitive basis for learning, problem-solving, or as in this research, opportunity recognition. The vast amount of research on this topic bred many different theories such as Tversky (1977) contrast theory or Biederman (1987) Geon Model. This research draws on the 'structure-mapping theory of analogy' by Gentner (1983). The main notion of structure-mapping is that analogies are created through spanning knowledge from a domain (source) to another (target). Analogical thinking is a mental process which is domain-general and helps individuals to find relational commonalities between two objects or situations on a deeper level (Markman and Gentner (2001); Ward and Kolomyts (2010)). According to Gentner (1989), structure-mapping consists of several sub-processes that are: (a) retrieve knowledge, (b) finding an analogy between source and target, (c) evaluating the analogy and the fit between source and target, (d) making interferences about the target and (e) extracting the common principle .

The main assertion of the structure-mapping theory is that analogies are characterized by mapping the relational similarities or differences among objects (Gentner (1983)). In order to trigger analogies, knowledge needs to be mentally illustrated in such a specific way so that systematic comparisons can be conducted (Holyoak and Thagard (1995)). In this regard, the perception of semantic and sensory similarities between two objects or situations is the key determinant of analogical transfer (Gentner (1989)). Vallacher and Wegner (1987) and Whittlesea (1997) have shown that similarities in verbal stimuli induce and facilitate information processing and decision making.

But how are similarities assessed and what are the underlying cognitive processes so that analogies occur? Markman and Gentner (Markman and Gentner (1993b): 435) proposed that "similarity comparisons involve a process of structural alignment." Under structural alignment, scholars mean the cognitive process which facilitates the fabrication of comparisons and the comprehension of its implications (Gentner (1983); Gregoire et al. (2010); Holyoak and Thagard (1995); Markman and Gentner (1993a), Markman and Gentner (1993b), Markman and Gentner (2001)). Thus, when encountered with a new object or situations, people build on the observed similarities from old objects or situations in order to understand a new context. According to Gentner and Markman (1995) the cognitive process of structural alignment ensures that only the highest structurally consistent match between two objects will evolve as an analogy.

The structure-mapping theory of Gentner (1983) distinguishes between different kinds of similarities, depending on how many attributes (superficial elements) or relations (structural elements) two objects share. As Figure 4 illustrates , similarities can vary according to their shared attribute-relation combination.

A literal similarity for instance, comprises a large extent of both relational and attributional commonalities, while an anomaly comprises none. According to Gentner (1989), the different sub-processes of structure-mapping that have been mentioned previously are differently affected by different kinds of similarities.

According to Gentner and Markman (1995) a good analogical match is also characterized by its systematicity and structural consistency. Systematicity increases with the interconnectedness of an analogical map, i.e. the number of interdependent objects that are connected through mutual superordinate, or so called high-order, relations (Gentner (1983)). A structural consistent analogy prevails if there are parallel, mutual connections to at least another domain (Markman and Gentner (2000)). Given the latter requirements for a good analogy and its holistic perspective, thinking analogically is much more than just a mere finding and comparing of similarities.

With the insight that there are two categories of similarities and that these similarities have a different effect on the human mind, I advance this argument to the field of selective revealing and technological gatekeepers. Accordingly, this research assumes, similar to Grégoire and Shepherd (2012), that firstly collaborative opportunities which arise from selective revealing consist of unexploited matches between the supply of a new technology or process and a market demand, and that secondly technological gatekeepers utilize cognitive processes such as structural alignment in order to make sense of new opportunities. Based on these assumptions, both types of similarities between selectively revealed technologies and market demands should affect a gatekeeper's capability to recognize a collaborative opportunity.

During the next section, I will further examine both categories of similarities, itemize their peculiarities in the context of the recognition of collaborative opportunities and elabo-

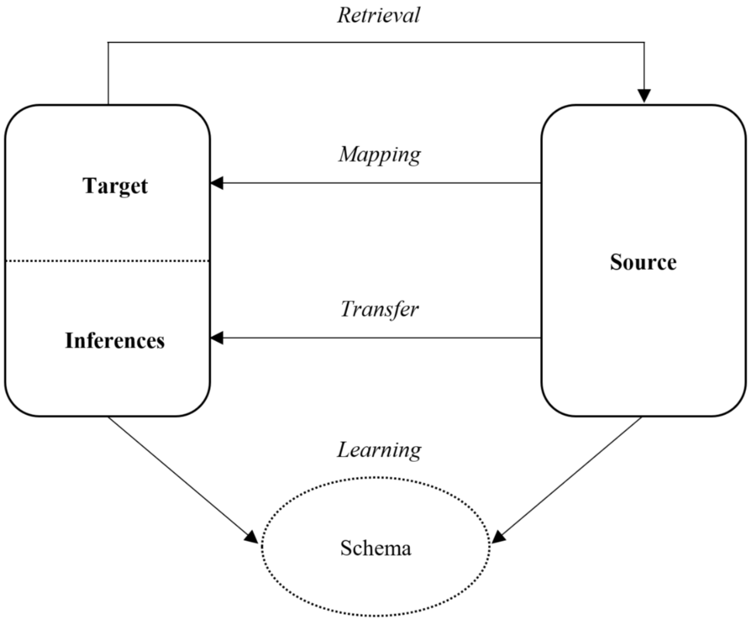

Figure 3: Major Components of Analogical Reasoning; Source: Own rendering based on Holyoak (Holyoak (2012): 236)

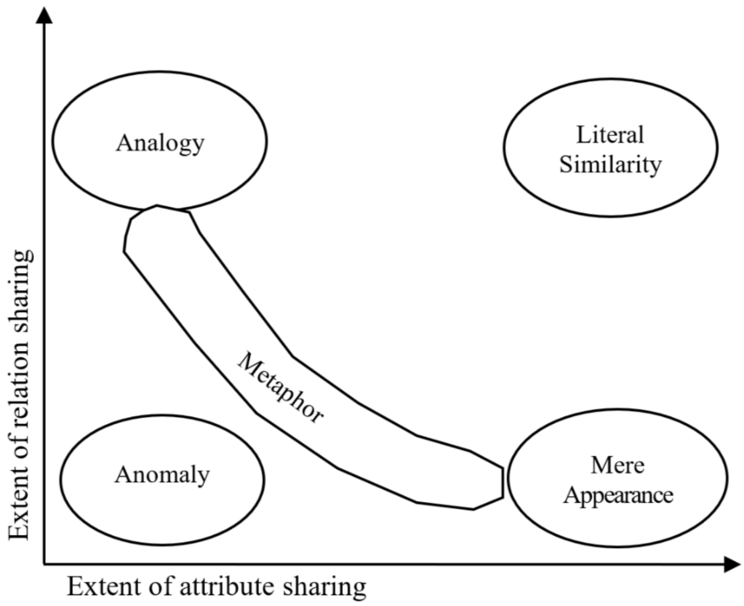

Figure 4: Kinds of Domain Comparisons; Source: Own rendering based on Gentner (Gentner (1989): 207)

rate hypothesis on the grounds of insights from cognitive science. Prior to this, Figure 5 gives an overview and an exemplification on the differences of both types of similarities. By comparing a planet system with an atom (which share both high superficial and structural similarities), this figure illustrates, how changes in the information about a revealed solution may impact the perception of structural and superficial similarities to a potential target market.

2.2.1. The effects of aligning superficial relationships

Two objects or situations are superficially similar if they have a resemblance in their external appearance, e.g. in their color, purpose or form (Gentner (1983)). An example for a superficial similarity can be exemplified in the comparison of a ball and a planet: both feature a circular form and can hence be seen superficially similar. In the context of this research and similarly to an entrepreneurial opportunity (Grégoire and Shepherd (2012)), a superficial similarity is at hand if the basic elements of a revealed solution (e.g. the material of the solution, the producer, the purpose and the context, as well as the used inputs and outputs) matches the basic elements of the market (the materials, inputs, outputs the people, etc.) in which the technological gatekeeper is active. As it is apparent from Figure 5, a planet and an elec-

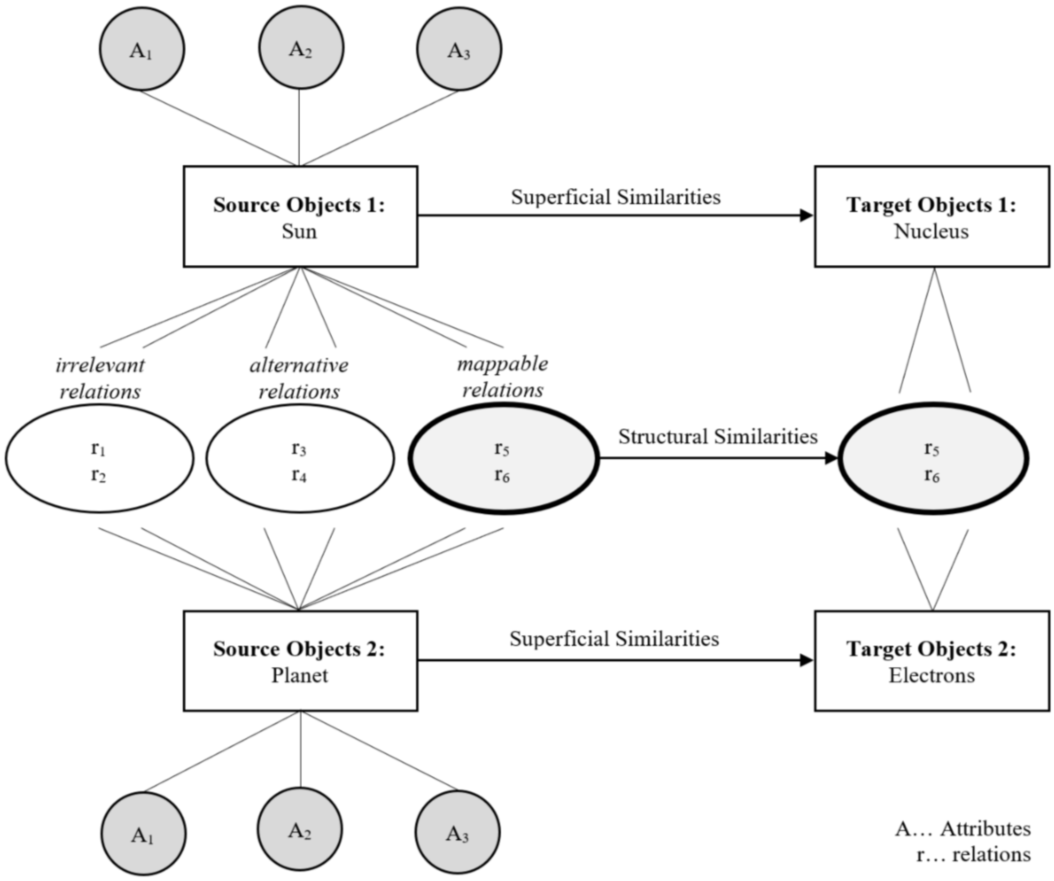

Figure 5: A Schematic Summary of Structure-Mapping Theory and the Difference between Superficial and Structural Similarities; Source: Own rendering based on Zook & Maier (Zook and Maier (1994): 590)

tron share superficial commonalities; both have, to name a superficial similarity, a circular form.

Superficial similarities are major elements in mental processes which facilitate the retrieval of analogies and the perception of its significance. For Grégoire and Shepherd (Grégoire and Shepherd (2012): 759), superficial similarities represent the "default mode" of reasoning. In the same vein, Gentner et al. (1993a) claimed that superficial similarities are the dominant source for analogies. From a cognitive perspective, superficial elements are easier to recognize because they are attached to the idea rather than the context (Gentner and Loewenstein (2003)) and provide plausible interferences (Koedinger and Roll (2012)). Indeed, researchers have shown that superficial similarities positively affect the retrieval and the access of analogies (Blanchette and Dunbar (2000); Gregoire et al. (2010); Keane et al. (1994)). This positive effect has been proven in many empirical studies. In an experimental investigation, Gick and Holyoak (1980) examined if problem-solving by analogy was enhanced by semantically similar task and solution descriptions. The authors thereby illustrated from a cognitive perspective that the retrieval of an analogy is easier contrivable if the stated problem resembles a suggested solution. In a similar study on problem-solving with analogies, Keane (1987) found that semantically distant analogies, i.e. objects with superficial dissimilarity, are tougher to retrieve than superficial similar objects. Also, in the field of educational science, scholars discovered that analogical reasoning and superficial similarities influence the learning outcome. In this regard, the scientific community consents that learners tend to rely on superficial similar elements during the acquisition of new concepts (Gentner and Loewenstein (2003); Namy and Gentner (2002)). In business research, the effects of superficial similarities were empirical confirmed in the adoption of new products (Moreau et al. (2001)), strategic change (Cornelissen et al. (2011)), new technologies (Grégoire and Shepherd (2012); Gregoire et al. (2010)) and new ventures (Cornelissen and Clarke (2010)).

From the abovementioned evidence, I conclude that superficial similarities between a revealed solution and a target market enhance the opinion of a technological gatekeeper the potentials of a collaborative opportunities for the incumbent firm. The higher the level of superficial similarities between a revealed solution and its market, the less uncertainty will a gatekeeper have about the opportunity. Thus, I propose the following hypothesis for this research:

> H1a: Individuals perceive a novel collaborative opportunity that arises through selective reveal-

> ing more positively if there is a high superficial similarity between the revealed solution and the market compared to a low superficial similarity between the revealed solution and the market.

2.2.2. The effects of aligning structural relationships

Two objects or situations are structurally similar if they have a resemblance in their relational logic, i.e. if there is an underlying relation between the components or the surface elements between two objects or situations (Gentner (1983); Gentner and Markman (2006)). An example for structural similarities between two objects is again exemplified in Figure 5 with the comparison of the solar system and at atom: both possess a core (sun vs. nucleus) and both are, due to their gravitation, surrounded by bodies (planets vs. electrons). Structural similarities can be seen as a complementary to superficial similarities (Blanchette and Dunbar (2000)).

Whereas researchers often refer to "near analogies" when analogical transfer is induced by superficial similarities, analogies which are induced by structural similarities are called "far analogies" (Schwartz and Nasir (2003)). Notwithstanding its difficult retrieval (Keane et al. (1994)), far analogies can result in very creative outcomes (Smith and Ward (2012)). This is especially the case, if structural relationships span over many different objects (Gregoire et al. (2010)). In this regard, researchers speak of higher order relationships, i.e. a world in which individuals form a complex world of interdependent and mutual structural relationships (Gentner (1983)).

From a cognitive perspective, the significance of structural similarities lies in the deduction of interferences and the fostering of evaluation and understanding (Colhoun and Gentner (2009); Grégoire and Shepherd (2012)). The relevance of structural similarities is also evident in many empirical findings. Many of these studies confirm that analogical reasoning is facilitated by higher structural relations in semantic stimuli (Blanchette and Dunbar (1997); Blanchette and Dunbar (2000);Green et al. (2008)). When confronted with both superficial and structural relations between two objects, individuals even prefer, despite of reasons unknown, to draw upon more difficult structural relations in analogical reasoning (Gentner (1989)). However, relying upon structural features is not always self-evident: Novick (1988) for instance found that analogical interferences from structural relations are facilitated by prior knowledge.

In the context of this research, a structural relation between a revealed solution and the target market of a technological gatekeeper exists, if the revealed solution fits the latent demands of the market. Similar to the notion of Grégoire and Shepherd (Grégoire and Shepherd (2012): 760), the structural similarity between a target market and the revealed solution increases with its "intrinsic capabilities", i.e. the underlying mechanisms and functions which could satisfy the market's needs and overcome its pain points.

From the presented evidence, I imply for my second hypothesis of this research that structural similarities between the revealed solutions and the target market positively affect the evaluation of a collaborative opportunity for technological gatekeepers. Solutions, whose descriptive elements are structurally more similar to the target market may enhance the inducement of different schemata and aid in the processing of the information. The following hypothesis is thus posited in the following way:

> H1b: Individuals perceive a novel collaborative opportunity that arises through selective revealing more positively if there is a high structural similarity between the revealed solution and the market compared to a low structural similarity between the revealed solution and the market.

2.2.3. Effects in the nexus of structural and superficial similarities

While the last two sections regarded both types of similarities separately, this chapter examines the interplay of superficial and structural similarities and its effects. This perspective is necessary as two of the four treatment scenarios in the online experiment hold divergent levels of superficial and structural similarities (i.e. a scenario with high superficial and low structural similarities and vice versa).

Albeit both types of similarities are crucial in the development of analogical thinking, the scientific community consents that the human mind has a preference towards structural similarities as it induces the transfer and mapping of analogies (Gentner et al. (1993b); Holyoak and Koh (1987)). Evidence from a neuroscientific perspective amplifies this claim by showing that structural similarities cause more brain activity than superficial similarities (Blanchette and Dunbar (2000)). Holyoak and Thagard (1989) even argued superficial similarities are mere disruptive factors and that only structural properties serve as cues for analogies. This finding coincide with observations by Shane (2000), who alleged that an entrepreneurs ability to identify a new opportunity in a different target markets is not related to an opportunity's "obviousness". Because of their expertise, entrepreneurs were still able to recognize the value of such an nonobvious opportunity (i.e. opportunities which feature high structural but low superficial similarities) due the structural commonalities that were drawn between the market and the technology (Grégoire and Shepherd (2012)).

Similarly to Grégoire and Shepherd (2012), I will subsequently compare the scenario with low superficial and high structural similarity, i.e. the nonobvious opportunity, to the other scenarios. From the abovementioned evidence, I imply that scenarios with high structural similarities compared to scenarios with low structural similarities will receive more positive evaluations.

> H1c: Evaluations about a novel collaborative opportunity with low superficial and high structural similarity between the revealed solution and the market are more positive compared to a solution-market combination with low superficial and low structural similarity.

> H1d: Evaluations about a novel collaborative opportunity with low superficial and high structural similarity between the revealed solution and the market are more positive compared to a solution-market combination with high superficial and low structural similarity.

Despite of the importance of structural similarities, researchers have also agreed that superficial similarity facilitate the creation of analogical thinking (Blanchette and Dunbar (2000); Holyoak and Thagard (1995)). Superficial similarities help to retrieve a source for the analog, and are hence a precondition for an analogy (Holyoak and Thagard (1989)). The less prior knowledge one possesses about a situation, the more important superficial similarity consequently becomes in order to retrieve sources for an analogy. The lack of superficial similarities may thereby cause faulty reasoning and hence has an effect of the soundness of an analogy (Gentner et al. (1993b)). This evidence triggers the hypothesis that, compared to the default scenario (the nonobvious opportunity), the scenario with high superficial and high structural similarity between the solution and the market is superior in terms of the individual perception. Thus, the last hypothesis in this section is formulated as following:

> H1e: Evaluations about a novel collaborative opportunity with low superficial and high structural similarity between the revealed solution and the market are less positive compared to a solution-market combination with high superficial and high structural similarity.

2.3. The effects of creativity

Creativity is a very diverse phenomenon that necessitates a multiplicity of approaches to comprehend it. As neuroscientific research suggests, creative outcome depends on an interplay of individual, social and cultural criteria during a certain situation (Ward and Kolomyts (2010)) and involves cognition (Mumford and Antes (2007)). While creativity is usually seen as a process in which novel ideas are produced (Drazin et al. (1999)), scholars now argue that creativity is increasingly recognized as a crucial mindset when it comes to make sense of novel innovations or technologies (Maitlis and Christianson (2014)) and to identify new opportunities (Gielnik et al. (2012); Heinonen et al. (2011)).

Thus, by building on the fourth assumption in section 2.1., creativity may be seen in the context of this study as a facilitating element during the recognition of a collaborative opportunity in selective revealing. The aim of this chapter is to review the major contemporary theories on creativity and to close with a hypothesis that refers to the moderating effect of creativity on superficial and structural similarities and analogical reasoning. Due to the myriad of complex and diverse theories in the field of creativity research, this review commences with the conceptual and comparative elements of the different theories, followed by the introduction of the two most important theories for this research and the presentation of empirical evidence for the elaboration of the hypothesis.

In order to compare the different theories of creativity, researchers often distinguish different levels of creative magnitude (Kozbelt et al. (2010)). The different levels of creative magnitude are summarized in Table 1. Creative magnitude is according to Kaufman and Beghetto (Kaufman and Beghetto (2009): 10) “important to have a specific understanding and categorization of what it means to be creative.”. Thus, it helps researchers to gain a better comprehension of the nature, the extent and the restrictions of each theory in the field of creativity.

By looking at the four-c models of creativity, one could rightly assert that all four levels of magnitude are relevant for a technological gatekeeper. However, as this research is mostly concerned with the evaluation of technological opportunities, I will subsequently focus on theories which are related to the little-c and/or big-c level.

Apart from different levels of creative magnitude, creativity can also be categorized according to the research’s reference point (Kozbelt et al. (2010)). Runco (2014) created a framework in which he classified the different aspects of creativity research consisting of five elements: person, product, process, place and persuasion. Theories that emphasize the person for instance, try to apprehend how traits and characteristics of a person, e.g. motivation or openness, affect his or her creative ability. Theoretical approaches of creativity focusing on products usually scrutinize the creative outcome such as inventions, patents or publications. Regarding the cognitive aspect of this thesis, the most important category is process. Creativity research that focuses on this aspect aims to understand how thinking affects creative ability and which mental processes appear during that process (Runco (2014)). Analogously, I aim to understand how different formulated solutions affect the perception of such a solution given divergent levels of creative abilities.

The previous section hence clarified that theories of creativity should with regard to this research focus on the process and creative magnitudes from little-c to big-c. From Kozbelt et al. (2010), who provide an extensive review of ten different theories of creativity, several them match these specifications. In the next phase, I will focus on one category of theory that not only fits the process focus and the creative magnitude, but is also consistent with the cognitive aspect of this research: creative cognition.

The cognitive theory of creativity , which is mostly referred to creative cognition, attempts to clarify the impact of cognitive processes on knowledge and memories during the ideation and evaluation of novel situations (Kozbelt et al. (2010); Ward and Kolomyts (2010); Ward et al. (1998)). Creative cognition is thus strongly interrelated to cognitive science and asserts that individual creative ability depends on knowledge and its accession and combination (Feldhusen (1995); Ward (2007)). One of the most important models which illustrates the mental processes of creative cognition is the Geneplore framework of Finke et al. (1992). Exhib-

Table 1: Levels of Creative Magnitude

Model	Level of Magnitude	Scope
Systems model of creativity	Small c	Personal creativity, i.e. subjective qualities that count as creativity (Csikszentmihalyi (1998); Csikszentmihalyi (2013))
	Larger c	Cultural creativity, i.e. social qualities that count as creativity (Csikszentmihalyi (1998); Csikszentmihalyi (2013))
Four-C Model of Creativity	Little c	Creativity that takes place in everyday situations (Kaufman and Beghetto (2009); Stein (1953))
	Big c	Creativity which has the outcome of an eminent contribution, i.e. the work of a creative genius (Kaufman and Beghetto (2009); Stein (1953))
	Mini c	Creativity that occurs during a learning process (Kaufman and Beghetto (2009))
	Pro c	Creativity that arises due to expertise (Kaufman and Beghetto (2009))

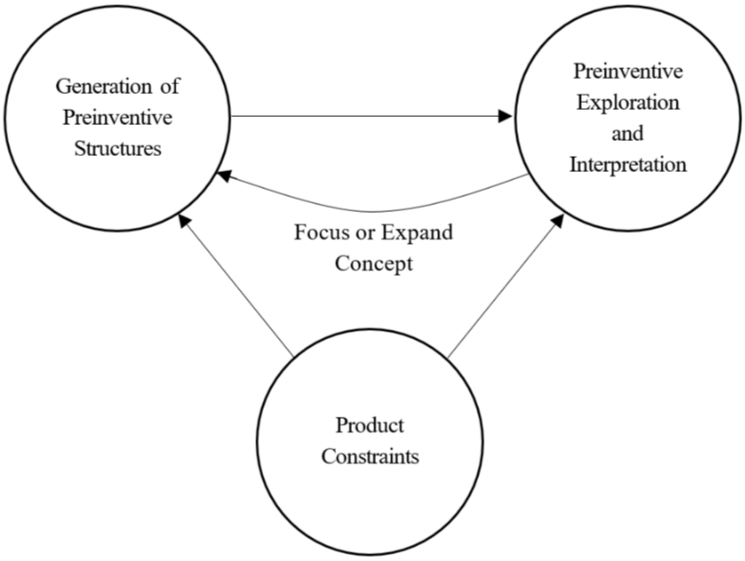

Figure 6: Geneplore Framework; Source: Own rendering based on Ward, Smith, and Finke (Ward et al. (1998): 193)

ited in Figure 6, the Geneplore Framework views creativity as a two-tier process, consisting of a generative and an explorative phase.

In the generative phase, several preinventive structures, i.e. the forerunner of an idea which is usually only an image or a sound, with a varying degree of creative potential are elaborated (Ward and Kolomyts (2010)). During this generative phase, several cognitive processes take place such as the retrieval of knowledge, images, schemata, features, concepts, analogies or a combination of those (Finke et al. (1992); Ward et al. (1998)). During the second stage of the Geneplore framework, selected preinventive structures are further elaborated with the aim to find a creative solution to an issue. Finke et al. (1992) thereby argued that preinventive structures may be chosen by certain aspects such as novelty or aesthetic factors. However, the last step is also seen as iterative, meaning that preinventive structures are permanently discarded or explored (Ward et al. (1998)).

To conclude, creative cognition views creative ability as a matter of employing or combining specific cognitive processes (Runco and Chand (1995); Ward and Kolomyts (2010)). The Geneplore framework stresses that an understanding of how creative outcomes are generated requires the appreciation of the underlying cognitive processes and their operation on existing knowledge and memories.

Despite its strong recognition in research, creative cognition has one major limitation which is worth a closer look in the context of this research: it conceptualizes creativity as a single entity and disregards the environment of an individual and its impact on individual creative ability (Kozbelt et al. (2010)). A remedy are the systems theories of creativity, which claim that "creativity results from a complex system of interacting and interrelated factors" (Kozbelt et al. (2010): 28). Gruber and Wallace (1998) and Csikszentmihalyi (1998), both pioneers in this field of research, claimed that multiple factors in one's environment such as network enterprise, belief systems or the professional milieu contribute to the creative ability. Creativity hence results from an interplay of socio-cultural factors (Kozbelt et al. (2010)). In this context, Csikszentmihalyi (1998) especially highlighted gatekeeper as the typical representative of system theories. Thus, systems theorist dramatically deemphasized the significance of individual contributions to creativity and is in stark contrast to the previous illustrated approach of creative cognition.

As the last section showed, creativity is a highly complex and divers theoretical model that requires to situate and to select existing theories according to the respective circumstances of the researched phenomenon. By acknowledging that collaborative opportunity recognition in gatekeeping falls into the categories of system theories and creative cognition, this review section will now exploit the empirical landscape of this domain. In entrepreneurial research, scholars already recognized the strong ties between creativity and opportunity recognition (Baron and Tang (2011); DeTienne and Chandler (2004)). Some researchers even tend to say that "opportunity recognition is a creative process itself" (Corbett (2005): 483; Hills et al. (1999): 217). Indeed, Ward (2004) proposed that opportunity recognition in entrepreneurial endeavors might be explicated by the Geneplore framework. Additionally, empirical examples have confirmed the positive relation between creativity and opportunity recognition among entrepreneurs. Ardichvili et al. (2003) have shown that entrepreneurs which successfully recognized opportunities tend to be more creative than other entrepreneurs. In another study, Heinonen et al. (2011) found evidence that creativity is positively associated with the perceived viability of the business idea. As a result, the implication of a positive association between opportunity recognition and creativity may be extrapolated to technological gatekeepers and the context of this research. Technological gatekeeper execute similar tasks as entrepreneurs (Bjerke and Hultman (2004); Boari and Riboldazzi (2014)).

The assertion that technological gatekeeping is a creative process like the Geneplore framework leads us to the assumption that the recognition of collaborative opportunities in selective revealing is also affected by different formulations of the revealed solutions. But to what extent does individual creativity moderate the effect of superficial and structural similarities in analogical reasoning?

As a matter of fact, creativity and analogical reasoning are strongly interrelated; for many researchers, analogical reasoning is a creative process itself (Finke et al. (1992); Ward and Kolomyts (2010)). Nevertheless, individual traits such as creative ability are also predictors of analogical transfer (Jones and Estes (2015)). Creativity enables individuals to find far analogies resulting in more creative interferences and outcomes (Holyoak and Thagard (1995); Smith and Ward (2012)). Studies from Corkill and Fager (1995) or Vendetti et al. (2014) have shown that semantic distance, i.e. superficial and structural similarities between a source and a target, influence the extent to which creativity is used during analogical reasoning. The authors discovered that higher semantic distances between the source and a target promoted the creation of more far analogies. These findings coincide with the claims of Gielnik et al. (2012) and Runco and Chand (1995), who proposed that the amount and the diversity of information triggers and enhances creative processes. Also from a neuroscience perspective, it has been confirmed that far semantic distance triggers creativity (Green (2016)).

From the presented evidence, I propose that the individual creativity of gatekeepers not only affects their ability to recognize collaborative opportunities, but also affects the generation of analogies. By acknowledging that low superficial and structural similarities trigger creativity, I infer that creativity positively affects opportunity recognition when there is a high semantic distance between the revealed solution and the target market of the gatekeeper. The hypothesis is thus posited in the following way:

> H.2.: Creativity moderates the relationship between superficial and structural similarities and the recognition of collaborative opportunities from selective revealing such that technological gatekeepers with high levels of creativity evaluate collaborative opportunities with dissimilar descriptive characteristics higher than gatekeepers with low levels creativity.

2.4. The effects of prior knowledge

2.4.1. Prior knowledge

The effects of prior knowledge in opportunity recognition have received much attention since the ground-breaking essay of Hayek (1945), who argued that as a result of unevenly dispersed information, decisions should be made by those who possess the most of it. Based on this argument, many scholars concluded that prior knowledge has, amongst others, a significant positive effect on the recognition of opportunities (Ardichvili et al. (2003); Arentz et al. (2013);Canavati et al. (2016); Hajizadeh and Zali (2016); Shane (2000)).

According to different studies, gatekeepers also need to be savvy in the domain they are acting in (Macdonald and Williams (1993); Scheiner et al. (2015)). Consequently, this section builds on the third cognitive assumption and aims to understand how prior knowledge from a specific domain affects technological gatekeepers in the evaluation and identification of novel opportunities. Thereby, a review on the underlying theories on domain-specific knowledge as well as a connection to cognitive abilities will be illustrated. At the end of this section, the latest empirical evidence paves the way for the elaboration of a hypothesis.

Prior to the introduction of the main theoretical approaches, this section commences with a disambiguation of domain-specific knowledge and expertise. Both terms are coherent, but it is easy to misspend them for the right context. An expert is a person "whose judgements are uncommonly accurate and reliable, whose performance shows certain types of rare or tough cases... and who acquired special skills or knowledge derived from extensive experience." (Chi (2006): 22). As this definition suggests, an expert possesses a great amount of domain-specific knowledge that is attained from past experiences. What distinguishes an expert from a non-expert is the ability to detect solutions to problems, generate the best solutions and to retrieve knowledge with a minimum cognitive effort (Chi (2006)). However, while extensive prior knowledge and experience is a prerequisite to become an expert in a specific domain, it is not the only element that makes somebody an expert (Ericsson et al. (2007)). Becoming an expert is according to Feltovich, Prietula, and Ericsson (Feltovich et al. (2006): 57) not only a matter of prior knowledge and skills, but also of "mechanisms that monitor and control cognitive processes". Nevertheless, domain-specific knowledge and related experiences largely contribute to becoming an expert and have, correspondingly, a major impact.

From a psychological and cognitive perspective, it is generally accepted that domain-specific prior knowledge enhances problem solving in a particular domain (Newell and Simon (1972)). Also in the entrepreneurial research, prior knowledge is seen to be positively associated with opportunity recognition (Corbett (2005); Shane (2000)). According to Tricot and Sweller (2014), domain-specific knowledge even affects the most basic cognitive abilities such as learning. Comparisons between chess players and non-chess players have even shown that domain-specific knowledge affects the use of domain-general skills and memory strategies (Chi (1981)).

Cognitive research offers several explanations for the effects of domain-specific knowledge. First, the acquirement of domain-specific knowledge leads to the circumstance that more and larger integrated cognitive units or so called chunks are formed (Feltovich et al. (2006)). A chunk, which is situated in the LTM, is a memory structure with many elements (Gobet et al. (2015)). These chunks, whose existence was discovered by Chase and Simon (1973), facilitate individuals in the retrieval of information and in the recognition of patterns.

Inspired by research of Chase and Simon (1973), many scholars followed their lead and undertook further investigations in the specific cognitive processes that are affected by domain-specific knowledge. One major finding in the subsequent research was that domain-specific knowledge causes more abstracted and functional knowledge representations (Engle and Bukstel (1978); Hinds et al. (2001); Zeitz (1994)). Thus, compared to people with no knowledge in a specific domain, experts tend to represent domain-specific knowledge structures at a deeper level (Feltovich et al. (2006)). Thereby, the level of abstraction in mental representations increases with the amount of domain-specific knowledge and expertise (Hinds et al. (2001)). Abstract mental presentations facilitate experts to think in terms of relationships between elements of a specific knowledge structures. This in turn enhances the evaluation, reasoning and monitoring of a specific situation or problem (Ericsson et al. (2000)). In the contrast, individuals lacking domain-specific knowledge leads to a concreter, more isolated view on a special situation (Bingham and Eisenhardt (2011)).

When it comes to evaluate a novel situation, the evidence from the last sections illustrated that a person with domain-specific knowledge is supported by chunks and more abstract representations. However, a major issue lies in the question which of the acquired mental representations from domain-specific experience should be activated for a specific situation (Feltovich et al. (2006)). According to Hill and Schneider (2006) selectivity is the remedy which inhibits limited cognitive capacity (Feltovich et al. (2006)) and helps one to distinguish between general and domain-specific tasks. True expertise hence not only consists of domain-specific knowledge, but also the ability to apply the knowledge and cognitive processes for the right situations.

To conclude the theoretical review, I assert that the recognition of collaborative opportunities in selective revealing differs among individuals' due to their prior knowledge (Venkataraman (1997)). Consequently, gatekeepers with prior knowledge are better able to identify and evaluate novel collaborative opportunities that arise from selective revealing. Many studies have also confirmed that prior knowledge and schemata facilitate analogical transfer and reasoning (Gentner (1989); Holyoak (2012)). As demonstrated in Figure 3, a greater amount of prior knowledge provides more sources and hence increases the number of possible maps and transfers for better interferences. Even though superficial and structural similarities in analogical reasoning simplifies information proceeding (Kao and Archer (1997)), the magnitude of the impact is also steered by amount of the prior knowledge (Collins and Burstein (1989)). Schwanenflugel and Shoben (1983) have shown that similarities in representations are easier to understand if they respond to a suitable context. One very important feature that facilitates analogical transfer is the abstract and functional nature of knowledge representations, which is usually found in individuals with high levels of domain-specific knowledge. Novick (1988) argues that especially structural features of different objects are easier conceivable by people with prior domain-specific knowledge. This is attributed to the abstracted and functional knowledge representations, which allows individuals with prior knowledge to perceive relationships between elements of certain objects or situations. Empirical findings from Grégoire and Shepherd (2012) did confirm this suggestion.

From this evidence, I imply for the following hypothesis that gatekeeper who possess prior knowledge are better able to perceive the structural features between revealed solutions and the target market. the As this study differentiates between prior knowledge about the market and prior knowledge about the technology, I adopt the insight of Grégoire and Shepherd (2012) that only prior knowledge about the technology has a moderating effect on the recognition of technological opportunities for revealed solution. The hypothesis is hence formulated as following:

> H.3.a: Prior knowledge of technologies moderates the effect of structural similarities on the evaluation of collaborative opportunities in selective revealing such that technological gatekeepers with higher levels of prior knowledge

> evaluate collaborative opportunities with similar structural descriptive characteristics higher than with dissimilar structural characteristics.

2.4.2. Peripherical knowledge

With the deduction of the last hypothesis, it was clearly demonstrated that domain-specific knowledge is a salient element in the identification and evaluation of opportunities of selectively revealed solutions. By talking of domain-specific knowledge, I simultaneously referred to core knowledge, i.e. knowledge that refers to a distinctive area of expertise (Simonton (2009)). However, researchers reckon that not only core knowledge, but also peripherical knowledge is increasingly important for the analogical reasoning process (Gavetti and Ocasio (2015); Haas and Ham (2015)). Some scholars even claim, that breakthrough innovation is more probable if peripherical knowledge is recombined and applied on a core domain (Fleming (2001); Kaplan and Vakili (2015); Savino et al. (2017)).

With peripherical knowledge, researchers often refer to knowledge from domains that is seemingly irrelevant to a given task at the beginning (Haas and Ham (2015)). However, according to Gavetti and Ocasio (2015), analogies can be also driven by peripherical knowledge. If the peripheral knowledge is in any sense related to the core problem, analogies will be formed that connect ideas from peripheral knowledge with the problem. In this case, the peripheral knowledge is the basis of the analogical transfer (Haas and Ham (2015)). Similar to the last findings about prior knowledge, peripheral knowledge enables individuals to find more potential sources and hence increases the number of possible maps and transfers for better interferences. By assuming that the distance between core-knowledge and peripherical knowledge domains is highly subjective and difficult to assess (Glaser et al. (2016)) and adopting the claims of Novick (1988), I assert that especially structural similarities between a revealed solution and the target market are easier conceivable by persons with deeper peripheral knowledge.

From these insights, I posit that peripheral knowledge of gatekeepers moderates the effect of structural similarities between the revealed solution and the target market. The second hypothesis in this second is thus stated as following:

> H.3.b: Peripheral knowledge moderates the effect of structural similarities on the evaluation of collaborative opportunities in selective revealing such that technological gatekeepers with higher levels of peripheral knowledge evaluate collaborative opportunities with similar structural descriptive characteristics higher than with dissimilar structural characteristics.

2.5. Conceptual framework and summary of the hypotheses

To conclude the current state of research, all hypotheses are again summarized in Table 2. The dimensions are consistent with the research questions and the dichotomy of optimal information flows: superficial and structural similarities investigate the bearings of the revealing instance, whereas creativity and prior knowledge address the potential issues of the receiving instance.

With the hypothesis being deducted, Figure 7 gives an overview on the dependent and independent variables and their interaction. I infer that the ability of analogical thinking presumably impacts how a collaborative opportunity is recognized. In keeping with the research questions, analogical thinking is affected by the structure of the information, i.e. superficial and structural similarities between the solution and the market, and individual traits, such as creativity and prior knowledge. Whether the interrelations between the dependent and independent variables are additive and/or interactive will emerge in the fourth section of this thesis.

3. Approach and method

To test the proposed hypothesis and to prove a causal relationship between the variables, I conducted a within-subject experiment (Bryman and Bell (2011); Mitchell and Jolley (2004)) with two revealed solutions, each formulated in four different scenarios. As illustrated in Table 3, the procedure to obtain the stimuli for the experiment, i.e. the different scenarios of the market-technology combination, was partly derived from Grégoire and Shepherd (2012) and conducted in a collaborative effort with industry experts.

The experimental approach allowed to test the causal and direct effect of superficial and structural similarities on the recognition of a novel collaborative opportunity. In addition, this set-up provided evidence through illustrating the relationship between creativity, prior knowledge, superficial and structural similarities, and the recognition of collaborative opportunities. The data collection was conducted through a web experiment (Reips (2002)) on Qualtrics (www.qualtrics.com). Table 4 exhibits a detailed design of the experiment.

3.1. Setting and participants

The experiment was conducted on the web-based platform Qualtrics in which the participants had to assess and evaluate different scenarios of selectively revealed solutions. The access to the platform was granted by the WU. In an attempt to make a case for external validity (Mitchell and Jolley (2004)), a real-world setting was achieved within the experiment by illustrating two revealed solutions from the "European Enterprise Network" (EEN). The EEN is a market platform in which firms have the opportunity to reveal their intellectual property and technologies in order to find new collaboration partners. For the study, the participants evaluated two selectively revealed solutions from the EEN that originated from the timber and wooden industry. The specific domain was chosen because more than half of Austria's area is covered with forest. This makes the local wood and timber industry a strong domestic economic force. Due to its specialization, the Austrian wood industry is seen as one of

Table 2: Summary of Hypothesis

Dimension	#	Hypothesis
Superficial and Structural Similarities	H_{1a}	Individuals evaluate a novel collaborative opportunity that arises through selective revealing higher if there is a high superficial similarity between the technology and market compared to a low superficial similarity of technology and market.
	H_{1b}	Individuals evaluate a novel collaborative opportunity that arises through selective revealing higher if there is a high superficial similarity between the technology and market compared to a low superficial similarity of technology and market.
	H_{1c}	Evaluations about a novel collaborative opportunity with low superficial and high structural similarity between the revealed solution and the market are more positive compared to a solution-market combination with low superficial and low structural similarity.
	H_{1d}	Evaluations about a novel collaborative opportunity with low superficial and high structural similarity between the revealed solution and the market are more positive compared to a solution-market combination with high superficial and low structural similarity.
	H_{1e}	Evaluations about a novel collaborative opportunity with low superficial and high structural similarity between the revealed solution and the market are less positive compared to a solution-market combination with high superficial and high structural similarity.
Creativity	H_2	Creativity moderates the effect of superficial and structural similarities on the evaluation of collaborative opportunities in selective revealing such that individuals with high levels of creativity evaluate collaborative opportunities with similar descriptive characteristics higher than with dissimilar characteristics.
Prior Knowledge	H_{3a}	Prior knowledge of technologies moderates the effect of structural similarities on the evaluation of collaborative opportunities in selective revealing such that individuals with higher levels of prior knowledge evaluate collaborative opportunities with similar structural descriptive characteristics higher than with dissimilar structural characteristics.
	H_{3b}	Peripheral knowledge moderates the effect of structural similarities on the evaluation of collaborative opportunities in selective revealing such that individuals with higher levels of peripheral knowledge evaluate collaborative opportunities with similar structural descriptive characteristics higher than with dissimilar structural characteristics.

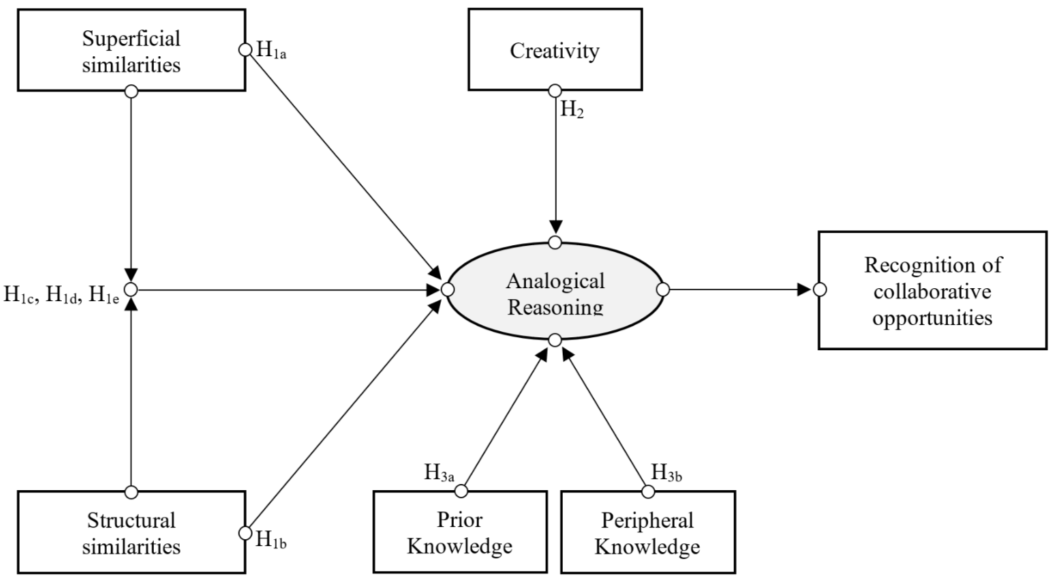

Figure 7: Conceptual framework and corresponding hypothesis

Table 3: Preparation of the Stimuli for the Experiment

	1. Selection	2. Manipulation	3. Manipulation-Check
Creation of two stimuli	Selecting two revealed solutions from the EEN according to their novelty and usefulness through a survey with industry experts.	In cooperation with three experts, four opportunity scenarios for each revealed solution were created. To come up with the scenarios, the superficial and structural similarities were manipulated.	Validating the manipulations of the technology-market pairs in a survey with university students.

the technological leaders in Europe (Hollersbacher (2010)). Many of Europe's leading wood processing companies and institutions are based in Austria. As a consequence of the of the timber industry's presence in Austria, both the stimuli creation and the access to potential participants was facilitated. Due to the specificity of the revealed solutions, I decided to execute the whole experiment in German. Consequently, the elaboration of the stimuli with industry experts was considerably simplified. Additionally, potential communication biases that would have arisen from the use of a non-native language were kept on a minimum level. This procedure was aligned with the sampling strategy, which destined to obtain participants solely from German-speaking countries.

Due to restrictions in time and resources, finding technological gatekeepers to participate in the experiment was constrained. However, students from technical and science degrees resemble gatekeepers very well, as both receive tertiary education (Allen (1970)). As a result, invitations to the experiment were sent to colleges and universities that have strong and weak ties with the wood industry in order to control for prior and peripheral knowledge in the sample. The sampling strategy, illustrated in Table 33 in the Appendix, reveals all contacted university departments and the communication channels used for the experiment. The maxim to attract as many participants as possible was supported by an incentive scheme. In total, vouchers with a total value of € 100 were raffled among all participants.

Eventually, data points from 653 participants were collected. With a completion rate of 40.5%, and the elimination of outliers according to Schlosser and Höhne (2016), the final number of participants for this analysis was 216. This number thereby did almost fulfill the requirements calculated from a power analysis (Cohen (2013)). The latter indicated that for the given research design and the desired effect the sample size should approximately count 62 participants in each treatment group. The sample characteristics are further illustrated in Table 5. In the quintessence, the participants originated from public universities and had a diverse background in natural science, engineering or business.

3.2. The manipulation of the stimuli

The creation of the stimuli for the experiment was an integral part of this study. As already mentioned, the stimuli consisted of four differently formulated scenarios from two revealed solutions from the EEN. The formulation of the stimulus was conducted in collaboration with industry experts from the Holztechnikum Kuchl. As summarized in Table 3, the creation of the stimuli for the experiment consisted of three phases.

Prior to the manipulation itself, the selectively revealed solutions were chosen in the first phase. To create a realistic setting, the revealed solutions which originated from wood- and timber-industry were selected from the EEN. The EEN is used by companies and institutions to unveil their intellectual property to find new partnerships. From a pool of 30 technologies available, ten distinctive solutions were chosen for a pre-selection. An overview of all technologies is provided in Table 20 in the appendix. The aim of the pre-selection was to identify technologies which were perceived novel and useful. For the assessment, alumnus from the Holztechnikum Kuchl evaluated the idea quality of the ten different solutions similar to O'Quin and Besemer (1989). The assessment of the idea quality consisted of the two dimensions novelty and usefulness (O'Quin and Besemer (1989)) and assess whether an idea represents an implementable solution to a problem (Dean et al. (2006)). An exact scheme of the questionnaire can be found in Table 21 in the appendix. With this pre-selection, I controlled for novelty and different levels of usefulness of the revealed solutions. By providing different solutions with diverging perceptions, I attempted to avoid potential framing biases during the experiment and to enhance the generalizability of this research.

Overall, 17 professionals from the wood industry evaluated the ten technologies in the survey. As a result, the following technologies were chosen for the further manipulation: "T15 - Bioethanolherstellung von Holzabfällen" and "T23 - Holztrocknung mit Infrarotstrathlung". The calculation of Cronbach's alpha confirmed the high internal validity of the survey ($\alpha_{Novelty} = 0{,}86$ and $\alpha_{Usefulness} = 0{,}83$). Both chosen technologies exhibited high levels of novelty. With respect to providing different solutions, the technologies varied significantly in their perceived usefulness ($t = 2{,}12 > 1{,}96$). While the solution for drying wood via infrared technologies was perceived less useful, the solution which described the process of producing bioethanol from wood was rated very useful. The two chosen solutions were subsequently further adjusted for the experiment by manipulating the superficial and structural similarity between the revealed solution and the target market. The aim of the second phase of the stimp

Table 4: Procedure of the Experiment

1. Technology Scenarios		2. Measurement dependent variables	3. Measurement prior knowledge	4. Measurement creativity	5. Measurement control variables
Randomization	High structural similarity High superficial similarity	a) Opportunity-recognition belief	a) Knowledge about technology	a) Wallach & Kronach Divergent thinking test (1965)	a) Recording demographic and socio-demographic data about participants
	High structural similarity Low superficial similarity	b) Collaborative opportunity evaluation	b) Knowledge about market	b) Creative self-efficacy	
	Low structural similarity High superficial similarity		c) Peripheral Knowledge		
	Low structural similarity Low superficial similarity				

Table 5: Sample Characteristics

	Business science		Law		Timber & Forestry		Math & Sciences		Engineering		Σ
	N	%	N	%	N	%	N	%	N	%	
Number of Participants	96	45.5	34	16.1	27	12.7	25	11.8	29	13.7	211
Pursued Degree											
Bachelor	65	47.8	30	22.1	13	10.1	11	8.1	17	12.5	136
Master	29	41.4	4	5.7	14	20.0	13	18.6	10	14.3	70
PhD	2	40.0	-	-	-	-	1	20.0	2	40.0	5
Gender											
Female	39	49.4	17	21.5	6	7.6	11	13.9	6	7.6	79
Male	57	43.2	17	12.9	21	15.9	14	10.6	23	17.4	132
	Business science		Law		Timber & Forestry		Math & Sciences		Engineering		Σ
	μ		μ		μ		μ		μ		μ
Age	24.5		23.9		25.4		25.1		24.1		24.5
Job Tenure	4.0		3.6		3.6		3.3		3.3		3.7

uli creation was to develop revealed solution-market pairs with different similarity characteristics. All scenarios were conducted with the aid of three specialists in the wood and timber sector in order to prevent individual schemata from affecting the formulation of the different scenarios (Kao and Archer (1997)). Prior to the manipulation of the technology, each expert received a short introduction on superficial and structural similarities and further instructions about the format. Each stimulus consists of around 150-200 words. Hence, after the definition of a target market and the description of the technology, which were very similar to the original version on the EEN, the superficial and structural elements between the revealed solutions and the markets were identified. Superficiality is understood as shared basic features of two objects or concepts (Grégoire and Shepherd (2012); Holyoak and Thagard (1995)). Overall, two scenarios of the technology with high superficial similarity and low superficial similarity were generated. Subsequently, the same procedure was repeated for the structural similarities, i.e. a logical relationship between the components of two objects (Grégoire and Shepherd (2012); Holyoak and Thagard (1995)). Eventually, all traits of superficial and structural similarity were combined, resulting in four scenarios. A summary of the manipulations is presented in Table 23 in the appendix. Furthermore, a detailed illustration of all different scenarios for both technologies is depicted in Table 24 (for the technology "Holztrocknung mit Infrarotstrathlung") and Table 25 (for the technology "Bioethanolherstellung von Holzabfällen") in the appendix.

Even though the scenarios were constructed with experts – thereby confirming the face-validity of the stimulus – it was still necessary to conduct a manipulation check of both solution-market pairs. This manipulation check was conducted with 32 participants, mostly students, through an online survey on Qualtrics and yielded 64 evaluations of similarities and dissimilarities. A detailed description about the survey statistics is provided in the appendix in Table 26 and Table 27.

For the manipulation check, the participants were randomly assigned to one of the four scenarios of each solution. The sequence of the technologies was randomized to prevent order effects. After a short introduction to the problem, every participant was asked to list the similarities and dissimilarities of the illustrated scenarios between the revealed solution and the market. Once the listing was finished, the prior knowledge about the solution-market pair as well as socio-demographic details were collected. The rendered answers were later qualitatively categorized according to the prior defined manipulations standards (see Table 23). To verify the internal validity of the manipulations, a two-sample t-test for each scenario and technology was conducted. In this analysis, a p-value for the listed similarities of two opposing scenarios (e.g. high superficial similarity versus low superficial similarity) was computed. For both technologies, the participants listed more similarities in scenarios with high similarities and more dissimilarities in scenarios with low similarities (for detailed results, please consult Table 28 and Table 29 in the appendix). With a confidence interval of .95, all p-values confirm that the scenarios are significantly distinctive from each other. The results, which are summarized in Table 6, thus affirmed that the manipulations feature the desired effect and can be used in the online-experiment.

3.3. Experimental Design

For the experimental phase, I employed a 2*2 within-subject online-experiment on Qualtrics, consisting of six phases as illustrated in Table 4. The average participation time of the experiment was 14.67 min. In the first phase, every participant received a short introduction about the experiment. Particularly, they were informed about the role of technological gatekeepers in firms and of selective revealing. For this purpose, the participants were also asked to put themselves in the position of a gatekeeper in a firm, and

Table 6: Results of the Manipulation Check

Technology/Characteristic		Superficial Similarities [p-value]	Structural Similarities [p-value]
Holztrocknung mit Infrarotstrathlung			
	Similarities	2.75E-07	1.85E-05
	Dissimilarities	2.63E-03	8.08E-04
Bioethanolherstellung von Holzabfällen			
	Similarities	9.37E-05	4.87E-07
	Dissimilarities	7.42E-03	7.64E-04

in the following, to evaluate a novel opportunity that was recently revealed.

The second phase of the experiment emphasized the evaluation of collaborative opportunities. In this phase, the participants were randomly assigned to one scenario for each solution-market pair. In order to control for order effects, the sequence of technologies was randomized. After each solution-market pair was illustrated, the participants had to assess the solution-market pair according to the opportunity-recognition belief and the attractiveness of the collaborative opportunity (more details will be provided in section 3.4). Lastly, every solution-market block also consisted of the assessment of a participant's prior knowledge. Four questions were provided to assess a participant's prior knowledge about the previously presented solution-market pair.

After the fourth phase came the evaluation of individual creativity. The creativity assessment was conducted through a divergent thinking test. Every participant was asked to take part in a Wallach and Kogan (1965) divergent thinking test which was limited to two minutes (for further details, please see section 3.4.2). Similar to Grégoire and Shepherd (2012), another proxy for creativity in this research was creative self-efficacy. This variable was measured with a three-item scale developed by Tierney and Farmer (2002). Eventually, selected demographic and socio-demographic data about participants were collected. This data was necessary to control for differences in educational levels (i.e. degree, type of university and field of study), work experience, age and gender.

3.4. Operationalization of the experiment

With the operationalization, I intend to define the means of measuring the variables for this experiment. Summarized in Table 7, the theoretical constructs refer to corresponding elements in the conceptual framework. Each theoretical construct may consist of multiple variables to measure the desired effects. A detailed examination of all measurement scales is provided in the sub-sections below.

As illustrated in Table 7, most of the scales were derived from established academic literature. However, as this study was conducted in German, all items also had to be translated. In order to provide comparable questions and to avoid contortions of the questions, a re-translation was conducted (Smith (2003); Su and Parham (2002)). With a re-translation, an individual (in this case a student), who was unfamiliar to the original question, translated the German question back into English. The re-translated questions were compared with the original question to see if the German question had to be adapted. The process of re-translation is iterative and ensures that meaning of the original question is conveyed appropriately (Bernard (2012)).

3.4.1. Measurement of the dependent variable: collaborative opportunity evaluation and opportunity-recognition belief

In order to measure the dependent variable of this experiment, I used two distinct series of questions from Grégoire et al. (2010) as well as Tyler and Steensma (1995) to evaluate the recognition of collaborative opportunities. For each technology, the evaluation of the opportunity directly took place after the revealed solution was presented. A detailed extract about the operationalization of the dependent variables is illustrated in Table 30 in the appendix.

The first series of questions targeted the participants' opportunity-recognition beliefs, i.e. the belief whether the presented opportunity is of value and achievable (Shepherd et al. (2007)). The measurement of a participants opportunity-recognition belief on a seven-point Likert-scale is based on Grégoire et al. (2010), who established and validated a method which is appropriate to examine the recognition of several kinds of opportunities in different contexts. According to the researchers, there are two categories which contribute to an individual's opportunity-recognition belief: the fit between a novel opportunity and the market requirements, and the feasibility of the novel opportunity. In this context, the dimension of fit consisted of three items and mirrors the ability of a revealed solution to offer qualities that match a market's needs and requirements. On the other hand, the notion of feasibility captures one's belief about the achievability of the revealed solution and captures two items. By deploying the opportunity-recognition belief measure of Grégoire et al. (2010) I ensured that the target items are internally consistent. The Cronbach alpha of the two categories also confirmed internal consistency, with acceptable values of $\alpha_{Fit} = 0.786$ and $\alpha_{Feasibility} = 0.646$.

With the second series of questions, I attempted to find out how the participants assess the attractiveness of a col-

Table 7: Operationalization of the Analyzed Variables

Theoretical construct	Variables	Categories	Items	Source
Recognition of collaborative opportunities	Opportunity-recognition belief	Fit Feasibility	2 3	Grégoire and Shepherd (2012) Gregoire et al. (2010)
	Collaborative opportunity evaluation	Attractiveness	2	Tyler and Steensma (1995)
Prior Knowledge	Prior knowledge	Technology Market	2 2	Grégoire and Shepherd (2012); Shane (2000)
	Peripheral knowledge	Educational background	3	-
Creativity	Divergent thinking	Elaboration Flexibility Fluency Originality	1	Runco (2010); Runco and Acar (2012); Wallach and Kogan (1965)
	Creative self-efficacy	Self-efficacy	3	Beghetto (2006); Tierney and Farmer (2002); Tierney and Farmer (2011)

laborative opportunity which would arise through the revealed solution. This measurement was derived from Tyler and Steensma (1995), who evaluated the attractivity of a technological collaborative opportunity. The variable consisted of two items: (1) the direct assessment of the attractivity of a potential collaboration and (2) the probability that they would recommend the opportunity. This variable measured the answers – similar to the questions about opportunity-recognition belief – on a seven-point Likert-scale from 1 (strongly disagree) to 7 (strongly agree). The internal consistency was confirmed with a Cronbach alpha for this scale of $\alpha_{CE} = 0.883$.

3.4.2. Measurement of prior and peripheral knowledge

The third stage of the procedure of the experiment served as a mean to determine the individual level of prior knowledge about the presented solution-market combination. It controlled for a possible impact of prior knowledge during the evaluation of an opportunity and consisted of two sub-measurements.

In the first sub-measure - the assessment about the prior knowledge - each participant had to self-evaluate one's knowledge about the presented technology and about the concerned market. Similar to Grégoire and Shepherd (2012), the assessment about the prior knowledge consisted of two categories which in turn included two items as illustrated in Table 7. In the technology dimension, the participant was asked how familiar one is with the presented technology and the underlying scientific principles. In order to assess prior knowledge about the market, each participant was asked about the prior knowledge of the market and its latent needs and issues. All four items were captured on a 7-point Likert-Scale. A detailed listing of all items is depicted in Table 31 in the appendix.

In addition to this self-assessment, all participants were asked about their field of study in the last stage of the online experiment. This question does not only help to assess the relationship between prior knowledge and the study field, but also support the determination of the peripheral knowledge. In this regard, I will distinguish between close knowledge (i.e. participants with a background in timber science and forestry), analogous knowledge (i.e. participants whose study fields cover the technical principles of the revealed solutions, i.e. students with a background in engineering and natural science) and distant knowledge (participants with no relation to the revealed solutions, i.e. students with a background in business and law)

3.4.3. Measurement of creativity: divergent thinking and creative self-efficacy

In this experiment, individual creativity was assessed through a divergent thinking test and a questionnaire about creative self-efficacy. Both measurements have been adopted from the scientific literature.

Even though divergent thinking is only seen as a part of creativity (Runco (2010)), it is generally accepted that divergent thinking tests serve as an overall indicator for creative potential (Berg (2016); Runco (2010); Runco and Acar (2012); Zeng et al. (2011)). In the context of this study, a Wallach/Kogan test was carried out (Wallach and Kogan (1965)). Despite its maturity, this test is still very esteemed among researchers due to its reliability and validity (Runco and Acar (2012)).

In the Wallach & Kogan assessment of creativity, examinees are asked to come up with many possible ideas for a specific element (Wallach and Kogan (1965)). In this experiment, the item was a brick stone, similar to the suggestions of Wallach and Kogan (1965). The response time for the test was limited to two minutes to ensure that every participant had the same preconditions. Due to the time limit, a picture of a brick stone was illustrated so that every participant could put oneself as quickly as possible into the exercise. The analysis of the results was carried out post experiment. Scores were allotted according to four criteria: originality, fluency, flexibility and elaboration. Eventually, individual creativity was determined through a proportional summative score in the Wallach & Kogan test (Runco and Acar (2012)). The objectivity of the divergent thinking assessment was guaranteed through a two-folded examination through the author and a student assistant. A deeper insight about the scoring mechanism and its criteria are specified in the appendix in Table 32.

Creative self-efficacy was another proxy for individual creative ability in this research. This variable was measured through a self-assessment of "one's imaginative ability and perceived competence in generating novel and adaptive ideas, solutions and behaviors" (Beghetto (2010): 457). According to researchers, the perceived creative competences are connected to the specific situational context (Jaussi et al. (2007)). In addition, creative self-efficacy also reflects one's personal value of creativity (Randel and Jaussi (2003)). Even though the interrelations between divergent thinking and creative self-efficacy have yet to be clarified (Plucker and Makel (2010)), this variable was integrated into this experiment. The measurement of creative self-efficacy is very brief and consists only of three items. The scales, derived from Tierney and Farmer (2002), Tierney and Farmer (2011) and Beghetto (2006), exposed evidence of reliability and validity due to the extent of scrutiny in scientific articles. In addition, the Cronbach alpha for this scale was $\alpha_{CreativeSelf-Efficacy} = 0.832$.

3.5. Data analysis

The analysis of the data gathered during the experiment was fragmented in seven phases as illustrated in Figure 8. After the raw data was obtained, a data cleaning was conducted. In this step, the aim was to convert the raw data into technical correct and consistent data (Dasu and Johnson (2003); De Jonge and van der Loo (2013)). During this step, necessary adaptions such as dummy creation, data alignment, replacement of missing values or dropping of obsolete columns were carried out. In addition to that, parts of the data were sorted out according to different pre-decided criteria. Thus, all participants with non-completed surveys as well as all non-students were rejected for the later analysis. In addition, response time outliers (i.e. the 5th and 95th percentile) were eliminated according to Schlosser and Höhne (2016). Once all outliers were eliminated, the divergent thinking scores, which were analyzed separately, were allocated to the participants. Lastly, it was manually controlled if each participant correctly assigned him-/herself to the right group in the field of study variable.

The third stage of the analysis comprised a check of the effectiveness of the randomization. By testing the difference between means of various sample-characteristics of each scenario (i.e. a two-sample t-test), it was determined if the randomization was successful. This step was necessary to ensure that all participants were equal with respect to all conditions except for the different solution-market pair scenarios. Once the success of the randomization was ensured, the analysis advanced to the sample characteristics and the internal reliability. While the sample characteristics were comprised of descriptive data, the internal reliability was computed through the calculation of the Cronbach Alpha, a coefficient that determines the interrelatedness of all items of a category in a measurement scale (Cortina (1993)).

The descriptive statistics of the data took up a major part of the analysis. In order to use these parametric methods, all variables which were of ordinal nature during the experiment (i.e. all Likert-Scales) were converted into numerical values by averaging the multiple Likert items (Allen and Seaman (2007)). The results from the correlation matrix or the calculation of the means within the different scenarios or different levels of prior knowledge/creativity represented a first indicator of the correctness of the hypothesis. In order to prove the hypothesis, however, a generalized linear model, or GLM, was conducted in the last stage of the analysis. Such a model is especially useful in repeated measurements. In the context of this research, this was necessary because every participant of the survey provided multiple data points by evaluating two out of four solution-market scenarios during the experiment. The GLM model was preferred over a repeated ANOVA (analysis of variance) due to missing values (i.e. participants only evaluated revealed solutions in two out of four scenarios) (McLean et al. (1991)).

The peculiarity of a GLM is that it analyzes both fixed and random effects of a dependent variables (Sachs and Hedderich (2006)). Fixed effects are effects that are only assignable to the treatment of the experiment and constant across all individuals. On the other hand, random effects are effects that are assignable beyond the treatment of the experiment. In this experiment, I used the common assumption that all random effects are independent (i.e. heterogenous variance structure), which allows parameters to vary (i.e. the slopes or intercepts of a model).

As two out of four treatments were carried out on the same participant, the GLM aimed at explaining the within-variance of the dependent variables. In particular, this analysis helped to differentiate whether the variance in the evaluation of a revealed solution was caused by individual differences (random effects) or the experimental manipulation that was carried out on the same persons (fixed effects), i.e. the effects of superficial and/or structural similarities (Field et al. (2012)). During the analysis, I applied the linear mixed-effect model of Pinheiro and Bates (2009) with a maximum likelihood estimation. This model belongs to the applications of multilevel modeling and assumes that the coefficients of a model are no longer fixed but random, meaning that both intercept and slope of a model can change (Hoffman and Rovine (2007)). The use of such a multi-level model allowed to relinquish the assumptions of sphericity (i.e. the requirement that the variance across the scenarios must be symmetrical) and homoscedasticity (i.e. the notion that variances are homogenous) compared to a conventional repeated ANOVA method (Quené and van den Bergh (2004)). Simi-

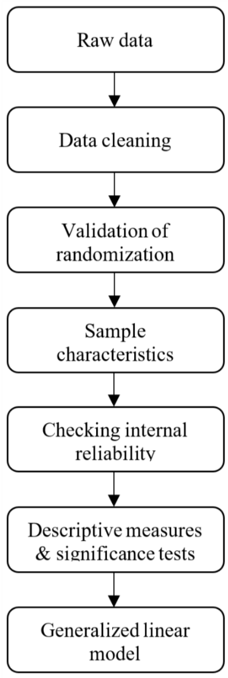

Figure 8: Process of the Data Analysis

lar to Judd et al. (2017), I used orthogonal contrasts to control for the treatment effects during the analysis. With the aid of these contrasts, I not only captured and isolated the main effects of superficial and structural similarities which were nested within each participant (Field et al. (2012)), but also assessed the different interactive effects. In addition, the other independent variables were added to the model in order to evaluate if their effect varied across the treatment variables. By deploying various models with different covariance structures, I ensured that the model with the highest fit compared to the base model (i.e. with superior Akaike's information criterion (AIK) and Schwarz's Bayesian criterion (BIC)) was chosen to test the previously elaborated hypotheses (Field et al. (2012)).

4. Results

4.1. Examining the effectiveness of the randomization

Even though randomization was operated through Qualtrics, the effectiveness of the randomization had to be revised due to the inability to monitor the allocation of participants to the scenarios during the experiment. In addition, there was a risk that the immense data cleaning that was carried out on the whole sample blurred the composition of the treatment groups. An initial check - summarized in Table 8 - illustrates that the number of participants in each scenario was approximately the same.

In Table 9, the most important participant characteristics are broken down for each scenario. It shows, that most participants in each scenario are currently undergraduates (with 1 = Bachelor, 2 = Master and 3 = Ph.D.). Furthermore, most participants originated from business studies (with 1 = Distant knowledge fields, i.e. Business and Law; 2 = Peripheral knowledge fields, i.e. Engineering and Natural Science; 3 = Close knowledge fields, i.e. Forestry and Wood Science). Regarding the gender, which was assigned in the data as a dummy for female, the proportion of female participants amounted from 33% to 44% between the solution-market scenarios.

To assess whether the treatment groups differed significantly from each other, I used a paired t-test to examine the differences in the characteristics across all scenarios. The p-values exhibited in Table 10, indicate for all but one (i.e. the studied field between the scenario High Superficial and Structural Similarities and High Superficial and Low Structural Similarities) comparison, that there is insufficient evidence to claim that the sample characteristics between the solution-market scenarios are different as they exceed the confidence interval of $\alpha = .05$. Due to the ordinal nature of the variables studied degree and studied field, I also computed a chi-squared test to assess if there is a significant difference in the distribution of the data among the scenarios. For both variables, the test-statistic was below the critical value ($\chi^2_{SD} = 5.26 < \chi^2_{(0.95;6)} = 12.59$ and $\chi^2_{SF} = 6.80 < \chi^2_{(0.95;12)} = 21.03$), which means that there is enough evidence to accept the null hypothesis (i.e. that the variables in the scenarios are independent from each other). Hence, both statistical tests allow the inference that the randomization was successful.

4.2. Descriptive data of the experimental outcome

In Table 11 and Table 12 the descriptive statistics for both dependent variables, ORB and CE are exhibited. Table 11 illustrates that the effects of superficial and structural similar-

Table 8: Number of Participants in Each Scenario

	High Structural Similarity	Low Structural Similarity
High superficial similarity	109	108
Low superficial similarity	104	101

Table 9: Characteristics of Sample within Treatment Groups

Solution-Market Scenario	Studied Degree		Studied Field		Age		Gender	
	μ	σ	μ	σ	μ	σ	μ	σ
High superficial similarity, High structural similarity	1.45	0.55	1.43	0.67	24.72	6.44	0.38	0.49
High superficial similarity, Low structural similarity	1.37	0.54	1.64	0.75	24.52	5.39	0.32	0.47
Low superficial similarity, High structural similarity	1.33	0.53	1.45	0.70	24.25	4.48	0.44	0.50
Low superficial similarity, Low structural similarity	1.37	0.50	1.52	0.72	24.63	4.58	0.36	0.48

Table 10: P-Values Comparing the Sample Characteristics of the Treatment Groups

	Studied Degree [p-value]	Studied Field [p-value]	Age [p-value]	Gender [p-value]
HSU/HST ⟷ HSU/LST	0.287	0.033	0.807	0.423
HSU/HST ⟷ LSU/HST	0.100	0.825	0.593	0.328
HSU/HST ⟷ LSU/LST	0.255	0.331	0.915	0.768
HSU/LST ⟷ LSU/HST	0.555	0.062	0.693	0.078
HSU/LST ⟷ LSU/LST	0.956	0.263	0.868	0.624
LSU/HST ⟷ LSU/LST	0.586	0.461	0.545	0.211

ities are positively reflected in the average ORB of the sample. In scenarios with high superficial and structural similarities, participants assessed the revealed solution on average by 0.07, and 0.12 respectively, higher. Table 12 shows similar, though smaller effects for CE. The correlation matrix further discerns the relationships between the variables. Except for some few exceptions, the correlations among the variables are low. However, the correlation matrix shows in both cases, that the superficial and structural similarities are slightly positively correlated with the dependent variables. A significance test was conducted to verify the monotonic relationship between the variables. This test showed that some correlation coefficients, such as the coefficient between structural similarity and the dependent variables, were statistically significant given a pre-defined confidence interval. A computation of the variance inflation factor by Fox and Monette (1992) further indicated that multicollinearity did not influence the results of both correlation matrices (values ranged from 1.02 to 2.14 and were under the critical value of 7).

Even though the information of both tables already provides interesting insights, the results must be treated very cautiously as correlation does not imply causality (cum hoc non est propter hoc). Whereas some findings deserve further examination (i.e. the positive correlation of structural and superficial similarities on opportunity-recognition belief and collaborative opportunity evaluation; or the negative significant correlations of divergent thinking and study fields on the dependent variables), other insights are either intuitive (such as the positive relationship between prior knowledge of markets and technologies and the studied field or the positive relation between divergent thinking and self-efficacy) or hard to interpret (such as the significant positive correlation between studied field and divergent thinking or creative self-efficacy). By means of a GLM, the next sub-sections will scrutinize selected relationships to detect causal and meaningful relationships between the variables and to prove or reject the elaborated hypotheses.

Table 11: Means, Standards Deviations, and Correlations of Opportunity-Belief Recognition and Independent Variables; * $p \leq .05$, ** $p \leq .01$

Variables	Mean	s.d.	1	2	3	4	5	6	7	8	9
1. Average opportunity belief	4.80	0.96									
2. Effect of superficial similarities	4.88	0.88	0.08*								
3. Effect of structural similarities	4.91	0.97	0.11**	-0.01							
4. Prior knowledge of markets	2.36	1.00	-0.03	0.04	-0.04						
5. Prior knowledge of technologies	2.46	1.01	-0.01	0.04	-0.03	0.56**					
6. Divergent thinking	1.52	0.45	-0.08*	0.00	-0.02	0.05	-0.03				
7. Creative self-efficacy	4.77	1.06	-0.01	0.02	-0.09*	0.25**	0.11*	0.19**			
8. Job tenure	3.73	2.75	-0.07	-0.05	-0.01	0.03	-0.01	-0.05	-0.01		
9. Studied degree	1.38	0.53	-0.08	0.06	0.02	-0.04	-0.19**	0.16	0.05	0.13**	
10. Studied field	1.51	0.71	-0.10*	0.03	-0.10*	0.40**	0.30**	0.25**	0.15**	-0.07	0.20**

Table 12: Means, Standards Deviations, and Correlations of Collaborative Opportunity Evaluation and Independent Variables; * $p \leq .05$, ** $p \leq .01$

Variables	Mean	s.d.	1	2	3	4	5	6	7	8	9
1. Av. Collaborative opportunity evaluation	4.78	1.33									
2. Effect of superficial similarities	4.81	1.28	0.02								
3. Effect of structural similarities	4.90	1.30	0.09**	-0.01							
4. Prior knowledge of markets	2.38	1.01	-0.04	0.04	-0.04						
5. Prior knowledge of technologies	2.47	1.01	0.03	0.04	-0.03	0.56**					
6. Divergent thinking	1.49	0.50	-0.10*	0.00	-0.02	0.05	-0.03				
7. Creative self-efficacy	4.79	1.05	-0.03	0.02	-0.09*	0.25**	0.11*	0.19**			
8. Job tenure	3.80	2.83	-0.03	-0.05	-0.01	0.03	-0.01	-0.05	-0.01		
9. Studied degree	1.74	1.01	-0.07	0.06	0.02	-0.04	-0.19**	0.16	0.05	0.13**	
10. Studied field	2.32	1.48	-0.04	0.03	-0.10*	0.40**	0.30**	0.25**	0.15**	-0.07	0.20**

4.3. The effects of different similiarity characteristics on the evaluation of a revealed solution

This section further examines how the induced superficial and structural similarities in the solution-market pairs influenced the perception of the revealed solutions. Figure 9 illustrates the average opportunity-recognition belief and collaborative opportunity evaluation across all scenarios. This illustration points out the distinctive differences in the evaluations across the four scenarios. As demonstrated, the evaluations for both evaluations were highest in the scenario with high superficial and high structural similarity ($\mu_{ORB-High/High}$ = 5.02 and $\mu_{CE-High/High} = 5.03$). On the opposite side, the ratings for ORB were the lowest in the scenario with low superficial and low structural similarity ($\mu_{ORB-Low/Low} = 4.65$). However, this was not the case for the CE rating, which was the lowest in the scenario with high superficial and low structural similarity ($\mu_{CE-High/Low} = 4.60$). For both variables, ratings in the scenarios with high superficial and high structural similarity and low superficial and high structural similarity were above the average, whereas the ratings in the other two scenarios were below average.

Table 13 shows the p-value of a two-sample test and summarizes whether the differences of both dependent variables across the four scenarios are statistically significant. With varying confidence intervals, the differences in mean for both dependent variables between high superficial and high structural similarity, and low superficial and low structural similarity and high superficial and low structural similarity respectively are statistically significant.

The differences reported above were further examined through the linear mixed-effect model from Pinheiro and Bates (2009). The fixed effects on opportunity-recognition belief and collaborative opportunity evaluation are illustrated in Table 14. The latter shows, that for both dependent variables, the coefficient for structural similarity was positive and significant ($b_{ORB} = .10$, $p \leq .05$; $b_{CE} = .12$, $p \leq .10$). This result not only coincides with positive significant correlation coefficient, but also confirms the hypothesis that technological gatekeepers perceive a novel collaborative opportunity that arises through selective revealing more positively if there is a high structural similarity between the revealed solution and the market. On the other hand, the coefficient for superficial similarity is positive, however insignificant for both ORB and CE (bORB = .08, p = .12; bCE = .03, p = 0.58). This means that there's not enough evidence to support the first hypothesis H1a, which claimed that that technological gatekeepers perceive a novel collaborative opportunity that arises through selective revealing more positively if there is a high superficial similarity between the revealed solution and the market. The results for both coefficients were confirmed by a post-hoc test, a log-likelihood ratio statistic (see Table 34 and Table 35 in the appendix) and the F-Values (calculated through ANOVA in Table 14).

During the course of the analysis, different models including varying manipulations of explanatory factors were tested; however, all of them were not only inferior in terms of fit, but also showed no statistical significance in the added interaction terms. The random effects in the linear mixed-effect model are reported in Table 15. The first three columns exhibit the random effects between the treatment groups, i.e. variability between individuals and between superficial and structural similarity. The standard deviation in the residual states the variance within the treatment. Whereas variability between individuals and superficial similarities strongly varied across both outcomes, the between standard variance of structural similarity and the within-variance were equally high in both cases.

In addition to the computation of the random effects, the analysis also included several checks aiming at the identification of carry-over effects during the experiment. Neither a two-sample t-test nor the inclusion of a dummy in the GLM, which indicated the sequence of the illustrated technologies during the experiment, indicated a significant effect of carry-over effects.

The last part of this sub-section compares opportunity-recognition belief and collaborative opportunity evaluation across the scenarios with divergent levels of superficial and structural similarities. Table 16 reports the outcomes of the comparison of the "default-scenario" (i.e. the scenario with low superficial but high structural similarities) with the other scenarios. Again, it shows slightly divergent results across opportunity-recognition belief and collaborative opportunity evaluation. Only for the comparison between low/high and high/high the result is similar across both dependent variable. The results ($b_{ORB-L/Hvs.H/H} = .19, b_{CE-L/Hvs.H/H} = .22, p \leq .0.05$) confirm that the average evaluations for scenarios with high superficial and structural similarities ($\mu_{ORB} = 5.00$ and $\mu_{CE} = 5.01$) were higher than for scenarios with low superficial and high structural similarities ($\mu_{ORB} = 4.81$ and $\mu_{CE} = 4.79$). Consequently, these findings provide support for H1e. As Table 16 further exhibits, there is also partial support for hypothesis H1c. For this hypothesis, I assumed that scenarios with high structural similarities, but low superficial similarities will receive more positive evaluations than scenarios with low structural and superficial similarities. During the comparison of the default scenario ($\mu_{ORB} = 4.81$ and $\mu_{CE} = 4.79$) with the scenario with both low superficial and structural similarities (μ_{ORB} = 4.63 and $\mu_{CE} = 4.71$), the results from the linear-mixed effect model yielded a negative significant value for ORB ($b_{ORB-L/Hvs.L/L} = -.17, p \leq .0.5$). It gives partial support to the hypothesis that non-obvious opportunities receive more positive evaluations than opportunities with low levels of superficial and structural similarities. However, the latter effect was non-significant in CE. For the hypothesis H1d, this analysis yielded a negative, but non-significant coefficient in both dependent variables ($b_{ORB-L/Hvs.H/L} = -.04, p = 0.61; b_{CE-L/Hvs.H/L} = -.16, p = .0.17$). Even though scenarios with low levels of superficial but high levels of structural similarity ($\mu_{ORB} = 4.81$ and $\mu_{CE} = 4.79$) received more positive evaluations than scenarios with high levels of superficial similarities and low levels of structural similarities ($\mu_{ORB} = 4.76$ and $\mu_{CE} = 4.61$), the data provided insufficient

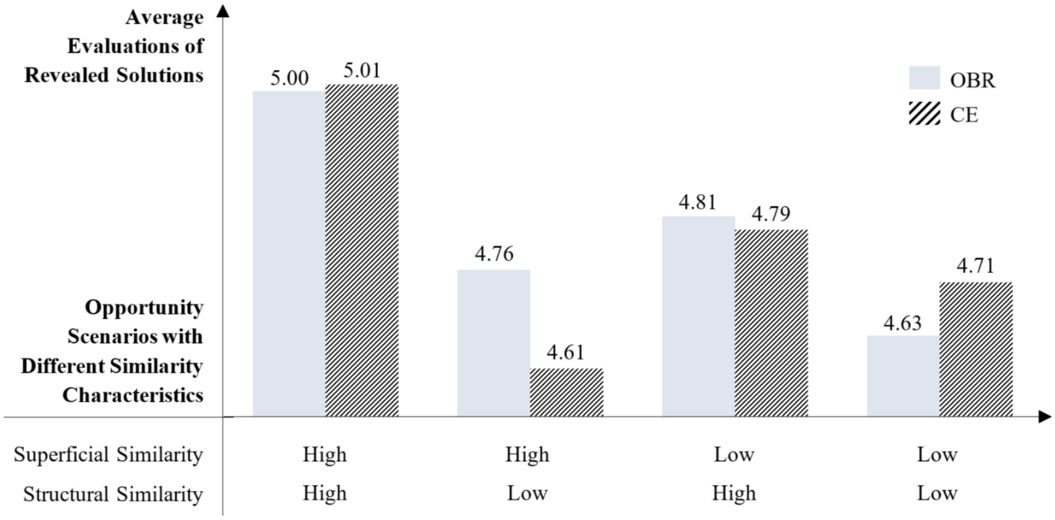

Figure 9: Evaluation of Scenarios across Different Similarity Characteristics

Table 13: P-Values Comparing the Sample Characteristics of the Treatment Groups; * p ≤ .1, ** p ≤ .05, *** p ≤ .01

	ORB			CE		
	High-High	High-low	Low-High	High-High	High-low	Low-High
High-low	0.24**			0.40**		
Low-High	0.19	0.05		0.22	0.18	
Low-Low	0.37***	0.13	0.18	0.30*	0.10	0.08

Table 14: Fixed Effects on Opportunity-Recognition Belief and Collaborative Opportunity Evaluation; * p ≤ .1, ** p ≤ .05

	ORB				CE			
	Value	Std. Error	denDF	F-Value	Value	Std. Error	DF	F-Value
Superficial similarities	0.08	0.05	102	2.30	0.04	0.07	102	0.24
Structural similarities	0.10**	0.05	55	4.91**	0.12*	0.07	55	3.29*
Prior knowledge (markets)	0.02	0.06	50	0.15	-0.09	0.08	50	0.64
Prior knowledge (technologies)	-0.02	0.06	50	0.01	0.08	0.08	50	2.12
Divergent thinking	-0.11	0.11	205	1.87	-0.24	0.16	205	2.87*
Creative self-efficacy	0.01	0.05	205	0.03	0.00	0.07	205	0.00
Job tenure	-0.02	0.02	205	2.02	-0.01	0.02	205	0.51
Studied field	-0.11	0.08	205	2.71*	0.01	0.11	205	0.02
Studied degree	-0.10	0.10	205	1.00	-0.13	0.14	205	0.87

Table 15: Random Effects on Opportunity-Recognition Belief and Collaborative Opportunity Evaluation

	ORB	CE
	Std. Dev.	Std. Dev.
Participant (Intercept)	2.33E-04	1.64E-01
Superficial (Intercept)	1.65E-01	2.18E-04
Structural (Intercept)	5.30E-01	7.07E-01
Residual	7.57E-01	1.09E+00

evidence to support the hypothesis.

4.4. The effects of prior knowledge

This section attempts to shed further light on hypotheses H3a and H3b. First, I address the claim that prior knowledge about the technology positively moderates the effects of structural similarities in the evaluation of collaborative opportunities. The results provided in Table 14 show direct effects of both types of prior knowledge on the dependent variables. Specifically, it shows that the direct coefficient for prior technological knowledge for variable of ORB is negative and non-significant ($B_{PKT} = -.02$; $p = .75$) and the coefficient for CE is positive and non-significant ($b_{PKT} = .08$; $p = .32$).

In order to get a better understanding of these results, the effects of structural similarities were partitioned in Figure 10 by the participants' prior knowledge of technologies. The partition was carried out through three groups, viz. low prior knowledge (all participants who were below the threshold mean minus standard deviation), moderate knowledge (all participants with levels of knowledge centered around the mean +/- the standard deviation) and high prior knowledge (participants with levels of knowledge above the threshold mean plus standard deviation). However, this illustration only gives an ambiguous picture on the effects of prior knowledge. For both evaluation types, the scores across high and low structural similarities were not coercively higher when prior knowledge was at hand.

Even though Figure 10 provides an interesting perspective on the effect of prior knowledge, it does not distinguish between within-subject and between-subject differences. A cue to this issue is offered in Table 17. The latter shows the interactive coefficients between structural similarity and prior knowledge of technologies. It does not only confirm the conjecture from the upper illustration that prior knowledge has no moderating effect for structural similarities, but also does render statistical evidence that prior knowledge of technologies has no significant moderating effect on structural similarities. Additionally, other ratios that recheck the significance of the model (i.e. the F-Value or the log-likelihood ratio) reaffirm that the effect is non-significant. This insight allows the conclusion that there is insufficient statistical evidence to support H3a, i.e. that prior knowledge about the technology positively moderates the effect of structural similarity.

Next, I address the claim that peripheral knowledge positively moderates the effects of structural similarities in the evaluation of collaborative opportunities. A look at the correlation matrix shows that the field of study is negative correlated with both dependent variables – however only significantly with the variable of ORB. With values from 1 (distant knowledge domains) to 3 (close knowledge domains), this correlation index indicates that the scores for ORB and CE decrease with the degree of studied expertise. Results from the GLM provided in Table 14 indicate similar, yet insignificant effects: the direct coefficient for ORB is negative and non-significant ($b_{PKT} = -.11$; p = .18) and the coefficient for CE is positive and non-significant ($b_{PKT} = .01$; p = .92).

As before, the effects of structural similarities were partitioned in Figure 11 by the field of study. The partition was carried out through three groups: distant knowledge (all participants who studied business or law), peripheral knowledge (all participants who studied engineering or natural science) and close knowledge (participants who studied timber science and forestry). With this illustration, no positive moderation of peripheral knowledge on the effects of structural similarity is visible. Contrariwise, it seems that participants from distant knowledge domains gave more positive evaluations for both levels of structural similarity. A look at the interactive effects of field of study and structural similarity confirmed this view for low structural similarities. As Table 18 clarifies, the interactive effect of low structural similarity and study field is negative and significant for the dependent variables of ORB ($b_{ORB:HST:PKT} = -.11$; $p \leq .05$) and negative and non-significant for the variable of CE ($b_{CE:HST:PKT} = -.10$; $p \leq .10$). Other ratios like the F-Value or the log-likelihood ratio confirm this result. The results hence contradict hypothesis H3b, which assumed that the field of study, or peripheral knowledge, positively moderates the effects of structural similarity on the evaluation of a collaborative opportunity.

4.5. The effects of creativity

This present section aims to examine the effects of creativity on the perception of a collaborative opportunity. The proxy for creativity in this analysis is the divergent thinking score from the Wallach & Kogan test. In contrast to the second proxy for creativity in this experiment, creative-self efficacy, the correlation coefficient and the GLM coefficient for divergent thinking are both significant. As divergent thinking and creative self-efficacy significantly correlate ($\rho_{DT/CSE} = .19$; $p \leq .01$), the variable for divergent thinking is solely used to assess the effects of creativity.

Consequently, both, the descriptive measures and fixed effects of the linear mixed-effect model, demonstrate a negative and significant effect of divergent thinking on ORB ($\rho_{DT/ORB} = -.10; b_{DT} = -.15; p = .12$) and CE ($\rho_{DT/ORB} = -.12; b_{DT} = -.27;\ p \leq .10$). This effect is further apparent in Figure 12, which depicts that the average evaluations of the revealed solutions decrease with creativity. In this figure, participants were, depending on their divergent thinking score, partitioned into three groups: low creativity (all participants who were below the threshold mean minus standard deviation), moderate creativity (all participants with levels of DT-scores centered around the mean +/- the standard deviation) and high creativity (participants with levels of DT above the threshold mean plus standard deviation).

In addition to the abovementioned effects, the interactive effects of divergent thinking on superficial and structural similarities were examined. The results, illustrated in Table 19, show that divergent thinking has across all levels of low superficial and structural similarities significant negative moderating effects. For high levels of superficial and structural similarities, the effects of divergent thinking are negative, yet

Table 16: Comparing the Effects of Different Scenarios on Opportunity-Recognition Belief and Collaborative Opportunity Evaluation; * p ≤ 0.10, ** p ≤ 0.05

Fixed Effects	ORB				CE			
	Value	Std. Error	denDF	F-Value	Value	Std. Error	DF	F-Value
Low/High vs. Low/Low	-0.17**	0.08	156	2.39*	-0.08	0.12	156	1.57
Low/High vs. High/Low	-0.04	0.08	156		-0.16	0.11	156	
Low/High vs. High/High	0.19**	0.08	156		0.22**	0.11	156	
Random Effects	Std. Dev.				Std. Dev.			
Participant (Intercept)	0.13				0.17			
Group (Intercept)	0.56				0.71			
Residual	0.76				1.10			

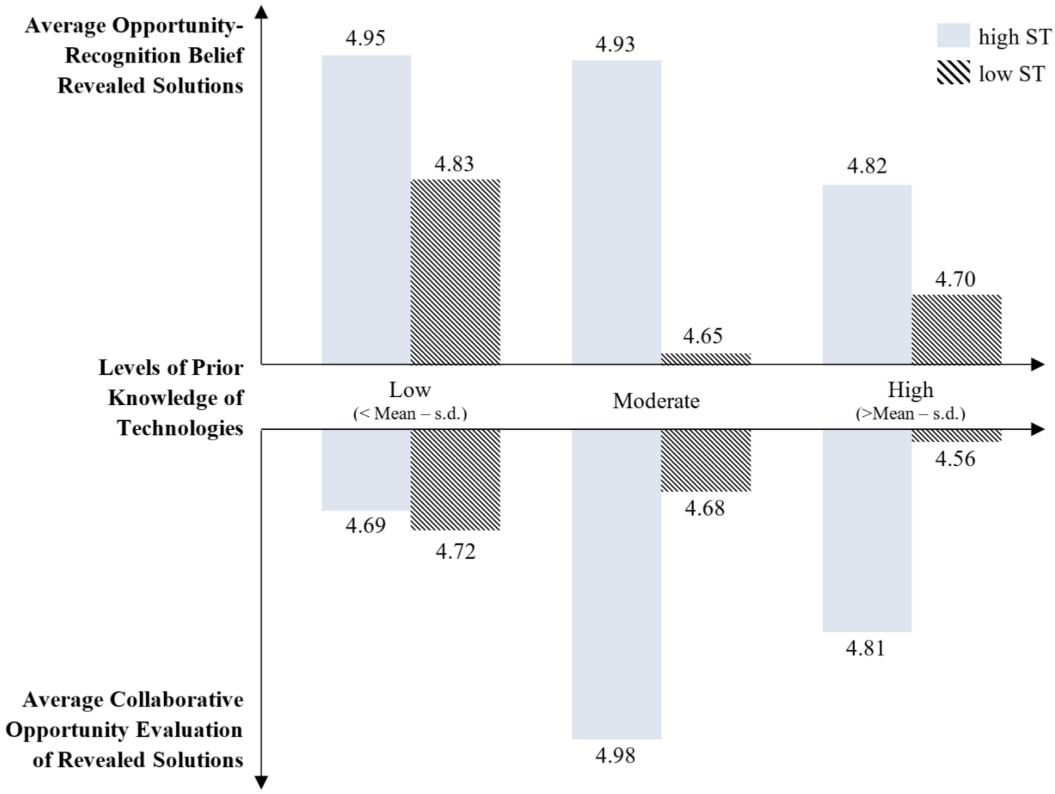

Figure 10: Effects of Structural Similarity by Levels of Prior Knowledge of Technologies

Table 17: Fixed Effects of Interaction of Structural Similarities and Prior Knowledge of Technologies; * p ≤ 0.10

Fixed Effects	ORB				CE			
	Value	Std. Error	denDF	F-Value	Value	Std. Error	denDF	F-Value
HST : PKT	0.02	0.05	50	1.72	0.10	0.07	50	1.68
LST : PKT	-0.04	0.05	50		0.01	0.07	50	

mostly insignificant. Having these results confirmed by the F-ratio and the log-likelihood ratio, I imply that the statistical evidence supports the rejection of hypothesis 2. Instead of being a positive moderating factor, the results of this analysis suggest that creativity has rather a negative impact on the effects of superficial and structural similarities in the evalua-

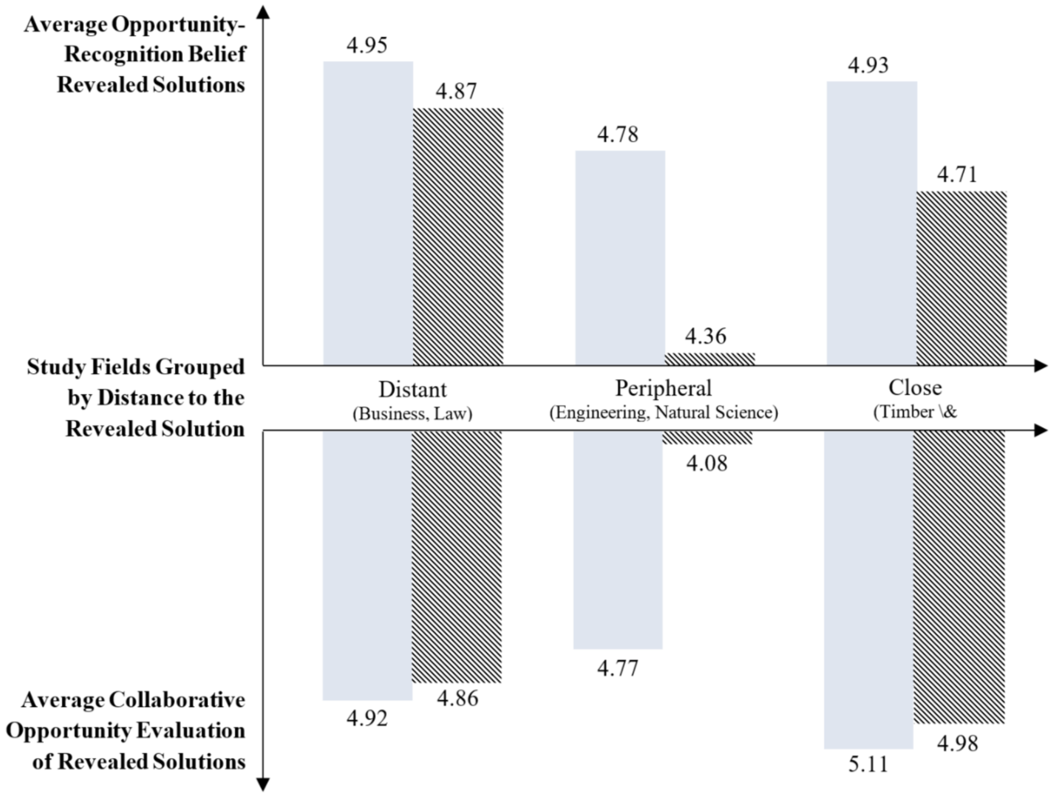

Figure 11: Effects of Structural Similarity by Field of Study

Table 18: Fixed Effects of Interaction of Structural Similarities and Field of Study; * p ≤ 0.10, ** p ≤ 0.05

Fixed Effects	ORB				CE			
	Value	Std. Error	denDF	F-Value	Value	Std. Error	denDF	F-Value
HST : SF	-0.05	0.08	54	4.38*	0.02	0.11	54	2.35
LST : SF	-0.18**	0.07	54		-0.13	0.10	54	

tion of a collaborative opportunity.

5. Discussion

Despite missing evidence for some hypotheses, the prior section gave important insights and serves as a fundament for the upcoming discussion, in which the results are going to be discussed from different perspectives. In the following, implications about the results will be drawn from a practical and a theoretical angle. Additionally, the last part of this chapter critically reflects on potential limitations and discusses options to mitigate them in future research.

5.1. Theoretical implications

To commence an impactful discussion on the theoretical aspects of this experiment, it is expedient to revisit and recall the original theoretical motivations of this research. With the first research question, I questioned whether different formulations of selectively revealed solutions influence the recognition of collaborative opportunities by technological gatekeeper. The second research question was closely related to the first research question and examined if creativity and prior knowledge of technological gatekeepers impact the identification of collaborative opportunities in selective revealing. Naturally, both research questions - which take interest in each end of the dichotomy of optimal information flows in selective revealing - involve different perspectives and theories. As a result, this chapter is divided in two subsections with a focus on each research question.

A general, but major implication that can be drawn from this research - before I deep dive into the implications for each research question - is that opportunity recognition is a cognitive process (Baron (2004); Baron (2006); Gregoire et al. (2010); Mitchell et al. (2002)). Many studies in entrepreneurial research both of theoretical and empirical nature confirm this view. By drawing on the commonalities between an entrepreneurial opportunity and a collaborative opportunity arising from selective revealing, this study was the

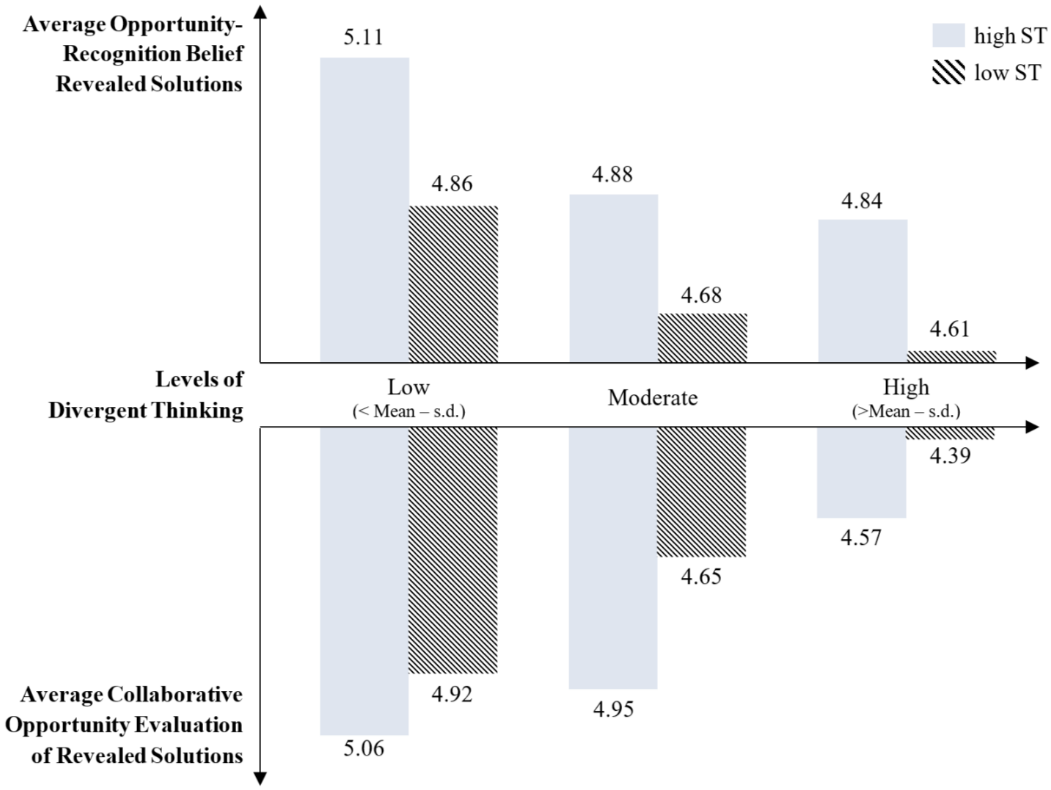

Figure 12: Effects of Structural Similarity by Divergent Thinking Score

Table 19: Fixed Effects of Interaction of Superficial and Structural Similarities and Divergent Thinking; * p ≤ 0.10, ** p ≤ 0.05, *** p ≤ 0.01

Fixed Effects		ORB				CE			
		Value	Std. Error	DF	F-Value	Value	Std. Error	DF	F-Value
Superficial Similarity	HSU : DT	-0.11	0.11	101	1.86	-0.27*	0.15	101	1.97
	LSU : DT	-0.19*	0.11	101		-0.30**	0.15	101	
Structural Similarity	HST : DT	-0.08	0.11	54	3.48**	-0.21	0.15	54	3.46**
	LST : DT	-0.22*	0.11	54		-0.36**	0.15	54	

first to take a cognitive perspective in the considerations of selective revealing. At the same time, my inquiries provided a felicitous answer to the concerns of Alexy et al. (2013) on the formulation of selectively revealed solutions and a complement to the idiosyncratic focus on problem formulation in hitherto existing research (Baer et al. (2013); Simon (1973)).

5.1.1. Implications for the formulation of revealed solutions

Based on the theory of structure-mapping, this study reflected that analogical thinking is inherent in all mental processes and partly determines how we conceive our environment (Fauconnier (2001)). Consequently, analogical thinking is also a crucial explanatory factor in the perception of selectively revealed solutions. The major process that triggers analogical thinking lies in the alignment of structures and elements between a source and a target (Gentner (1983)). By performing an alignment of superficial and structural similarities between a revealed solution and its market, this thesis demonstrated that different formulations affect the perception of such a solution. In this case, perception refers to the belief that the opportunity is valuable (Grégoire et al. (2010)), as well as to the willingness to assume a collaboration with the revealing instance (Tyler and Steensma (1995)).

Analogies can hence be utilized by firms who reveal their intellectual property to frame a technological gatekeeper's perception about an opportunity. In keeping with previous research on analogical thinking and structural alignment, the carried-out study has affirmed that the alignment of especially structural relationships prevails sense-making about selectively revealed solution. With such an alignment, each individual's mental proximity between a market - with all its characteristics and needs - and the revealed solutions - with its underlying mechanisms and cause-effect principles - was reduced (Gregoire et al. (2010)). Most notably, the results have shown that high-order relationships are of ample significance when individuals encounter novel opportunities. Instead of relying on superficial similarities, the participants of this study rather made sense of an opportunity through structural similarities. Therefore, scenarios with high levels of structural similarities but low levels of superficial similarities were persistently rated better. Taken together, the results confirm that even though superficial similarities are an important part in the recognition of opportunities, their identification is mostly driven by structural relationships. These findings match the predominant view that analogies are particularly sensitive to structural commonalities and that, despite the involved high cognitive efforts in their retrieval, high-order relations can result in highly creative outcomes (Blanchette and Dunbar (2000); Keane et al. (1994)).

It is however also important not to misinterpret the effects of superficial similarities. Unlike to Grégoire and Shepherd (2012), who identified superficial similarities as a significant stand-alone impact factor in the recognition of entrepreneurial opportunities, my findings confirm the view of Blanchette and Dunbar (2000), which asserts that superficial similarities facilitate the retrieval of analogies from structural commonalities. This insight becomes obvious by comparing ratings between scenarios with both high superficial and structural similarities and scenarios with low levels of superficial and high levels of structural similarities. Dunbar (2001) ascribes such changing effects to more naturalistic environments. Such environments, in which information is illustrated more sophisticatedly, trigger the retrieval conditions in favor of structural relations and higher order relations.

While the results contribute to a better understanding of the formulation of selectively revealed solutions, the latest insights should also encourage future researchers to dig deeper in this field of study. In this respect, I suggest three levers for future research. First, an interesting element for prospective studies would be different scopes of solution formulations, ranging from varying levels of superficial and structural similarities to formulations with diverging levels of length and/or sophistication. Besides, subsequent research on this topic could, like in real-life settings, solely illustrate a revealed solution and relinquish a corresponding market in the formulation to increase generalizability. However, such a setting would complicate the manipulation of scenarios due to the ex-post identification of each individual corresponding market, which is shaped by prior knowledge and experience (Gruber et al. (2010)). Lastly, prospective studies should investigate the role of the environmental context on opportunity-beliefs and the willingness to collaborate ceteris paribus superficial und structural similarities between solutions and markets. Such investigations would shed light on concurrent view that the value of an opportunity is highly impacted by a myriad of factors such as its newness, its available alternatives or its underlying industry conditions (Hansen et al. (2016)).

5.1.2. Implications in regard of individual factors in selctive revealing

By regarding optimal information flows in selective revealing as a dichotomy, this thesis offers implications about the recipient instance, and in particular, how personal traits impact the perception of selectively revealed solutions. As the conceptual framework in Figure 7 exhibited, analogies are not only induced through the descriptive elements of a revealed solution formulation, but are also moderated through personal traits. In my argumentation, I followed the notion from cognitive science that the retrieval of analogies is facilitated through prior knowledge and expertise (Arentz et al. (2013); Hajizadeh and Zali (2016)). This rationale was additionally extended by the claim that creativity allows individuals to be more flexible in the retrieval of analogies, which leads in turn to more sound decision-making when one encounters a novel opportunity (Vendetti et al. (2014)).

Whereas previous scientific evidence has shown that the deepness and richness of prior knowledge and the capability to think divergently fosters the ability to notice opportunities (Shepherd et al. (2017); Walsh (1995)), the results in this study could not substantiate these arguments. Contrarily, the findings from my experiment illustrated that both, the field of study and the divergent thinking ability, had to some extent a negative significant impact on the opportunity-recognition belief and the evaluation of the collaborative opportunity.

The study design captured the variable of prior knowledge through two proxies: (a) a self-assessment of the knowledge about the illustrated technologies and markets and (b) a determination of prior knowledge through the participant's field of study. Regarding the self-assessment of prior knowledge, my findings do not confirm the results of previous empirical investigations (c.f. Grégoire and Shepherd (2012)) which proved that prior knowledge of technologies is positively affiliated with the development of analogies. It is even more surprising, that effects between the two proxies (prior knowledge of technologies and field of study) considerably deviate from each other. The effects from the field of study even illustrate a negative significant effect on the evaluation of a collaborative opportunity that arises from selective revealing. One cue for these results may lie in the newness of the presented technologies. Studies have shown that experienced entrepreneurs favour familiar technologies over unique and new solutions (Baron (2006)). The newness of the illustrated technologies might have increased the perceived uncertainty of students from "close fields of studies" (i.e. timber science and forestry) about the future success of the revealed technologies in the market (Butler et al. (2010)).

Similar to the previous section, the results might be also attributed to the naturalistic environment of the experiment. Dunbar (Dunbar (2001): 330) reflected that in such a testing environment, "subjects must have a minimal amount of understanding of the source and target, but do not need the extensive knowledge of experts to use higher-order structural relations naturalistic environment". This might explain the reason, why neither prior knowledge of markets nor prior knowledge of technologies significantly affected the perception of a selectively revealed opportunity. Even though prior knowledge alters the cognitive processes (Ericsson and Charness (1994)), analogies do not require prior knowledge to develop. Additionally, Eggers and Kaplan (Eggers and Kaplan (2013): 308) found that the "encoding experience", i.e. the sense-making of opportunities, highly depends on routine which is acquired through repetition and resemblance. As students usually lack experience in the recognition of opportunities, this could be an explanatory factor for these results too.

In addition, past research on expert knowledge has shown that prior knowledge and expertise is not always associated with positive effects. A review on contemporary research on expert characteristics by Chi (2006) provided the insight that specialist knowledge also has its drawbacks. Among them are cognitive inflexibility, context dependency and functional fixedness. Individuals with high know-how accordingly have issues in recognizing opportunities if the information starkly deviates from standard applications in this domain (Chi (2006)). Apparently, it seems that students with training and education in the relevant domain of this experiment (i.e. timber and forestry) were more averse towards the revealed opportunities as they did not represent standard solutions in the domain. This aversion could also not be explained by a difference in the technology (i.e. infrared drying vs. bioethanol production) or higher job tenure.

Creativity, which was the second personal trait that was under scrutiny in this study, also significantly diverged from the initial assumptions. Being regarded as a key concept in creativity (Welling (2007)), analogies were in the set-up of this research considered to be positively moderated by individual creative ability. By drawing on the Geneplore framework (Finke et al. (1992)), I argued that creativity, which was assessed through a DTT, enhances the generation of preinventive structures and the transfer of existing knowledge to a new context. So why do the results of this study differ to such an extent from the theoretical opinion? One argument that could explain this deviation is that creativity is domain specific (Amabile (1983); Baer (2010); Runco and Sakamoto (1999)). Even though there is still disagreement among academics about the nature of creativity, evidence from Kaufman et al. (2009) has shown that creative ability in opportunity recognition is composed of general and domain specific skills. Considering that an analogy is constructed on prior knowledge (Welling (2007)), the effects of creativity, derived from a general DTT, could consequently loose its explanatory power to assess its effect on opportunity recognition in a specific domain. Evidence for this rationale may be found in the interaction term of structural similarity and divergent thinking: in scenarios with low structural similarities between the solution and the market, individual creativity seemed to be an impediment due to missing context. This view is substantiated through a significant interaction term combining structural similarity, divergent thinking and prior knowledge of technologies. Under these circumstances, it would have also been interesting to understand participants' intrinsic motivation and attention spans during the experiment (Baer (2010)). In theory, a lack in both traits is often seen as an impediment to creative ability (Runco and Sakamoto (1999)). Apart from the issue of domain specifity in creativity, the insights from my experiment are consistent with previous findings from Benedek et al. (2014). The researchers found that creativity, measured through a DTT, is unrelated to the cognitive process of shifting, i.e. "the process of switching between different tasks and mental sets" (Benedek et al. (2014): 74). As a result, creativity would not facilitate the creation of analogies, as it is unrelated to shifting knowledge from one domain to another.

Even though the results didn't deliver the desired results, this study yielded important insights on individual differences in the evaluation of selectively revealed solutions. Besides, my master thesis provides important recommendations for future studies in this field of research. Most importantly, prospective studies should take place in a different setting than an online-experiment to better control for individual differences. Additionally, prospective research should include other individual factors such as personal motivation (c.f. Molden and Higgins (2012)), alertness (c.f. Goh (2002); Shane and Eckhardt (2003)), risk adversity (c.f. LeBoeuf and Shafir (2012)), or cognitive adaptiveness (c.f. Haynie and Shepherd (2009)) in order to help explain potential differences in the results. At last, studies which involve tests about creative ability should consider the strong impact of domain specifity on creativity and should focus on assessments which establish a domain-specific context.

5.2. Practical Implications

By examining both ends of the information flows in selective revealing, this study addresses all operating firms in open innovation and notably all firms which reveal their intellectual property to appeal to potential new collaboration partners. The findings offer a blueprint on how revealed solutions should be formulated and which recipients should be addressed.

To fully tap into the potentials of reaching new collaboration partners with selective revealing, this thesis has demonstrated that a revealed solution should be formulated in a way so that it induces analogical thinking in the recipients' mind. Analogies evolve through observed similarities from old objects to understand a new context. As the results of the thesis confirmed, firms should emphasize structural commonalities between the revealed solution and target markets to trigger analogical thinking. The communication efficacy of a selectively revealed solution is further maximized through an interplay of superficial and structural similarities.

As in communication science or marketing, where a good deal of success depends on the message and on its recipients

(Vesanen (2007)), practioners in selective revealing should hence focus more on the content of their revealed solutions and on the individuals and firms they want to target. As some personal traits, such as individual creativity or prior knowledge, are significant impact factors in the recognition of a collaborative opportunity, the revealing instance should consider - prior to the release of its intellectual property - the characteristics of the potential recipient and the context of the transfer (Goh (2002)). This would render the possibility to tailor the descriptions of a revealed solution to the recipient's requisites, i.e. the target market. Despite its advantages, such a procedure would also involve more effort in revealing a firm's intellectual property.

This study holds important implications for potential recipients of revealed solutions and for firms, who employ technological gatekeepers in its R&D departments, too. I demonstrated that high creativity, and prior knowledge to a certain extent, are no compulsory prerequisites to recognize technological opportunities and hence challenges the common opinion that gatekeepers need to be technologically proficient and highly experienced (Macdonald and Williams (1993)).While highly experienced and knowledgeable gatekeepers will nonetheless be indispensable in the future, my findings make clear that multiple gatekeeping, in which a diverse team connects a firm's R&D department with the external environment, may be the key to enhance the innovative potential of a firm.

5.3. Limitations and future research

The methodology and the drawn implications also bring limitations. Albeit no empirical work is perfect, and one could objurgate the choice of the variables, I will emphasize the limitations which stemmed from the methodical strategy and most affected the quality of the insights and the capability to answer the research questions. Lastly, this section will also respond to analytical limitation that arose during this research.

The first limitation concerns the stimulus for the effect. Even though the stimuli highly resembled the original versions from the EEN in their dictions, it can be questioned whether such a collaborative opportunity would occur in a real-life setting. Visual elements, such as schemes or imagery, for example, are commonly used in many patents and revealed solutions because they facilitate the inducement of analogic thinking and foster understanding (Holyoak and Thagard (1995)). Yet, visual elements were deliberately omitted because they would have complicated matters for the manipulation of scenarios with high and low superficial/structural similarities. On these grounds, future research in opportunity recognition and/or open innovation should include visual objects and examine its effects on the perception of a novel opportunity.

Through focusing on the semantic elements in the illustrated opportunities, the manipulation of the different scenarios was facilitated. The manipulation of scenarios was carried out with the utmost effort in order to meet the theoretical requirements. Nevertheless, it entailed the consequence that the stimuli were framed in a subjective manner. As a remedy, three experts were involved during the creation of the manipulations. It helped to prevent that individual schemas affect the formulation of the scenarios (Kao and Archer (1997)). In addition, a pre-experimental manipulation check was carried out to verify whether the different scenarios featured the desired effect. Future research on this topic could nonetheless improve the creation of such a stimulus in two ways. First, the involvement of linguists could help to reconcile the effect of language on perception (Klemfuss et al. (2012)). Second, a greater extent of technologies and manipulations could enable researcher to benchmark the different scenarios and ensure to choose "substantively equivalent" manipulations (Grégoire and Shepherd (2012): 767).

Another alleged limitation represents the domain from which the solution-market combinations originated. The decision to choose manipulations from a similar domain partly stemmed from the design of the experiment. Due to the within-subject, the deployment of technologies from one domain, i.e. the timber industry, tended to minimize the error variance associated with individual difference. With the illustration of two technologies that are rooted in the same industry I also aimed to reduce the carry-over effect. This carry-over effect was additionally diminished through a randomization in the sequential arrangement of the technologies. A single domain also made it easier to control for prior knowledge and studied field. Nevertheless, future studies could employ more diverse stimuli, similarly to the article of Grégoire and Shepherd (2012). This would probably represent a more realistic experimental setting, as technological gatekeepers daily encounter technologies from different domains. Such a setting would also be especially interesting for the field of rapid cognition and first impressions, i.e. how attention spans change depending on what one sees (Gladwell (2005)).

The third limitation concerns the participants of the experiment. Despite the fact that students and technological gatekeepers have a tertiary education in common (Allen and Cohen (1969)), students lack other important characteristics such as gut feeling or professional experience (Scheiner et al. (2015)). Even though both types of prior knowledge were significantly correlated with the studied field of the participants, its extent is not comparable to that of a gatekeeper. This is probably also the reason, why the effects of prior knowledge were not statistically significant in the recognition of a collaborative opportunity. Though the facilitated mobilization of participants justifies the choice to use students as a proxy for gatekeeper, future empirical studies in this topic should target real gatekeepers.

The last limitation refers to an analytical issue, namely to the problem of fitting a model. In models of high-dimensional and complex data sets like the data in this research, overfitting may often incur. Overfitting refers to the dilemma that the training of the data happens at the expense of generalization to unseen data points, which results in high variance caused by random errors (Bühlmann and Van De Geer (2011)). By attempting to reduce the complexity of a model (i.e. through neglecting variables) the tide can also quickly turn: too simple models, or underfitted models, might not be flexible enough to capture important features, thereby causing a high bias of the analysis. In order to find a model with a good fit (i.e. a balance between bias and variance), modern statistics increasingly rely on an optimization algorithm called "LASSO" (least absolute shrinkage and selection operator). The algorithm, which is based on regularization and selection, applies a penalization factor based on geometrical and Bayesian assumptions on each coefficient on the model (Zou and Hastie (2005)). Simply expressed, this optimization discards futile coefficients (i.e. coefficients whose contributions to the model fit are lower than the penalty factor) from the regression by setting it to a feature to zero (Bühlmann and Van De Geer (2011)). Even though the models in this analysis were selected upon comparisons of performance (i.e. through comparing the AIC and the BIC), future research could deploy LASSO algorithms, which can be also extended to the GLM functions (Schelldorfer et al. (2011)), in order to optimize the predictive power of models used in the analysis.

6. Conclusion

> Discovery is 10% inspiration and 90% perspiration. - Thomas Edison

Already Thomas Edison in 1929 reckoned that innovation is a multi-stage process that requires a myriad of methods and techniques (Acar et al. (2010)). By acknowledging the innovative potential of selective revealing and the recognition of an opportunity being a decisive step, this thesis has contributed to the emergence for more sophisticated solution formulations in this field of study. Indeed, I delivered implications for both ends of the information flow by conjointly examining the effects of selectively revealed opportunities and personal traits, and enriched this area of research through comprehending the drivers of early action in open innovation and strategic renewal. By centering this study around established academic literature from cognition (Gentner (1983); Holyoak and Thagard (1995)), selective revealing (Alexy et al. (2013)) and opportunity recognition (Grégoire and Shepherd (2012); Gregoire et al. (2010); Tyler and Steensma (1995)), I demonstrated that recipients of selectively revealed solutions rely on analogies that are moderated by personal traits in order to make sense of novel information.

This thesis hence affiliates to recent academic work that accentuates the significance of analogic reasoning in opportunity recognition (Gregoire et al. (2010)) and clearly illustrates that different formulations affect the perception of a revealed solution. The fact that opportunities are usually hastily encountered through websites or patents further highlights the need for more sophisticated solution descriptions in selective revealing. Most importantly, the results indicate that solution formulations which induce analogies through relational commonalities are more prone for positive evaluations. Yet, my findings also challenge the conventional presumption about the role of prior knowledge in technology evaluation and add another perspective through the inclusion of individual creative ability. All in all, further research on this topic will be necessary not only to affirm the results, but also to overcome some of the limitations of this work, such as the framing of the opportunity scenarios or the participants' origin. Especially the role of personal traits in the recognition of opportunities requires further examination. To get a better understanding and a more holistic picture of the present results, prospective studies should incorporate more variables that control for personal traits. In doing so, future efforts to understand the recognition of opportunities in selective revealing can hold benefits for individuals and firms alike. With my thesis, I have advanced the understanding of cognitive processes, namely similarity comparisons and structural alignment, in selective revealing and provided a basis for future research that should focus on the factors that facilitate and impede the means of this promising strategic tool in open innovation.

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