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Research Article

Complex Problems in Entrepreneurship Education: Examining Complex Problem-Solving in the Application of Opportunity Identification

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In opening up the black box of *what* entrepreneurship education (EE) should be about, this study focuses on the exploration of relationships between two constructs: opportunity identification (OI) and complex problem-solving (CPS). OI, as a domain-specific capability, is at the core of entrepreneurship research, whereas CPS is a more domain-general skill. On a conceptual level, there are reasons to believe that CPS skills can help individuals to identify potential opportunities in dynamic and nontransparent environments. Therefore, we empirically investigated whether CPS relates to OI among 113 masters students. Data is analyzed using multiple regressions. The results show that CPS predicts the number of *concrete* ideas that students generate, suggesting that having CPS skills supports the generation of detailed, potential business ideas of good quality. The results of the current study suggest that training CPS, as a more domain-general skill, could be a valuable part of *what* should be taught in EE.

1. Introduction

Acquiring entrepreneurial skills can help in preparing students for a working life characterized by uncertainty and complexity [1]. Accordingly, entrepreneurship education (EE) receives attention as a means to close the gap between the type of young talent required by the market and the talent that is actually being provided by higher education. EE is in this study broadly defined as the "[c]ontent, methods, and activities that support the development of motivation, skill and experience, which make it possible to be entrepreneurial, to manage and participate in value-creating processes" ([2], p. 14). In this definition, EE is not only about new start-up creation; it also includes other value-creation processes which are more and more present in daily (working) life. However, many empirical studies do not apply the broad definition of EE but solely focus on teaching skills that are required in independent entrepreneurship [3]. Rideout and Gray [4] in their review on EE conclude that research on EE is still in an early stage and that it is unclear *whether* and *how* EE works. The wide debate about EE results in a *black box* of *what* EE should be about.

In this manuscript, we aim to contribute to opening up this black box by explaining an important entrepreneurial capability of which the role in entrepreneurship is widely agreed upon, namely, opportunity identification (OI; [5]). OI is at the conceptual heart of the entrepreneurship literature, as opportunities and their identification are part of the defining start of the entrepreneurial process. Explaining variables behind OI are widely discussed. For instance, Gielnik et al. [6] found that divergent thinking explained the number and originality of generated business ideas. Wang et al. [7] found that self-efficacy, prior knowledge, social networks, and perceptions about opportunities in the industrial environment significantly explained OI of research and development managers. Although these and other studies have significantly improved our understanding of OI, research on OI is still in an early phase [8, 9].

Hsieh et al. [10] argue that in OI individuals search for or stumble upon problems to solve. Identifying opportunities involves decision-making processes and information-seeking activities to bring facts and relationships between facts to bear in problem-solving [10, 11]. Seeking information and making decisions in systematic ways result in more identified opportunities [12]. A set of skills that supports individuals to systematically seek information and make decisions in the complex world around them is complex problem-solving (CPS; [13]). CPS targets tasks that are characterized as dynamic, nonroutine, and interactive, as they are likely to occur in OI. These tasks require higher-order thinking skills of CPS that cover cognitive (e.g., fluid reasoning; [14, 15]) and noncognitive (e.g., self-management; [13, 16]) processes. Moreover, CPS aligns with the broad definition of EE because CPS can, as a more generic skill, help in managing to act entrepreneurial. Despite the linkages at the conceptual level, the relationship between OI and CPS has not been empirically investigated yet [11].

The importance of CPS for current and future generations of working individuals is best reflected by the decision made by the Organisation for Economic Co-Operation and Development (OECD) to incorporate CPS into the Programme for International Student Assessment (PISA; [17]) and to include the closely related skill of problem-solving in technology-rich environments in the Programme for the International Assessment of Adult Competencies (PIAAC; [18]). In general, these initiatives have assessed the CPS of tens of thousands of students and adults under controlled conditions using computer-based assessment [17, 18]. Using similar methodologies, several empirical studies have identified CPS as a relevant skill that has been found to be related to school and university success (e.g., [19–21]). A small number of studies suggest CPS to be relevant for success in work settings [22–24]. On a theoretical basis, Neubert et al. [25] discussed CPS as a promising skill for improving the prediction of workplace performance in complex and nontransparent tasks.

In short, when entrepreneurs identify opportunities, then they ideally solve complex problems in systematic ways on their journey to create new value. On the basis of this theoretical understanding, we investigate whether skills to solve complex problems are relevant to identify opportunities in the early stages of entrepreneurship. For this purpose, we present an empirical study that relates CPS to OI. We tested 113 masters students who took entrepreneurship or career development courses and mostly intended to start or get involved in a new venture. The objective of this study was to test whether CPS plays an empirical role in OI by using a standardized setting and established tasks from different research areas.

1.1. Complex Problem-Solving. In their essence, problems to solve are barriers to overcome between a given situation and an intended goal state. These barriers occur if the functioning of the underlying system is unknown to the individual [26, 27]. For example, an engineer who works on appliances for the rapidly developing Internet of Things faces barriers if the technical functioning develops too fast for the engineer to stay up to date without constant use and interaction. A lack of knowledge about the functioning of only one component can be considered a barrier that prevents a solution. Accordingly, Buchner (cited in Frensch and Funke [28], p. 14) defined CPS as follows.

Complex problem-solving (CPS) is the successful interaction with task environments that are dynamic (i.e., change as a function of the user's intervention and/or as a function of time) and in which some, if not all, of the environment's regularities can only be revealed by successful exploration and integration of the information gained in that process.

CPS targets tasks that are characterized as dynamic, nonroutine, and interactive and thus require more than domain-specific prior knowledge. These characteristics are what makes the barriers complex, or, in other words, that makes a task a complex problem requiring active exploration to find and apply a new solution. To overcome complex barriers requires generic skills for knowledge acquisition and application of this knowledge [16, 29–31]. Knowledge acquisition and knowledge application are domain-general processes of CPS that are distinct from domain-specific prior knowledge (i.e., expert knowledge or expertise; [32–34]).

If, for example, an engineer with vast experience in the Internet of Things faces a previously unknown problem with the dimming of light-emitting diodes (LEDs) in the home automation system that she manages, she is only then likely to solve this problem on the basis of her prior knowledge, once she has gathered new knowledge in order to model the problem in terms that she is familiar with, such as electric circuits. Solving could even mean for her to be entrepreneurial to the extent that she might identify a business opportunity, if her solution is genuinely new and advantageous. In contrast, solving a problem of a system she knows perfectly well, such as the dimming of traditional light bulbs in home automation systems, the electric engineer would very likely have previously known the procedure needed in order to arrive at the solution—she would solve the problem routinely, not entrepreneurially. However, to arrive at a solution for dimming a new technology, such as LEDs, engineers face a complex problem that surpasses their prior knowledge. Her complex problem is to tap into new grounds of successfully manipulating LEDs in ways she has never done before (i.e., dimming) without undesired side effects (e.g., flickering). She must learn how to properly dim LEDs in the first place. That is, arriving at the electric circuit model of her new problem is a complex issue that requires domain-general processes of knowledge acquisition and knowledge application about the functioning of LEDs.

In general, complex problems share the ambiguity of how to approach the task and a lack of transparency in the task environment; the task structure is complex and the environment is dynamic. Variables in the system are interconnected; they change over time and interaction; whether they are relevant or not is unclear at the beginning [13]. Hence, in order to arrive at her circuit model, domain-general processes enable her to explore, recombine, and utilize new knowledge about LEDs in electric circuitries. These processes are especially helpful when prior knowledge is not available or insufficient, as is usually the case with new technology, such as, for example, LEDs in home automation systems. In short, domain-general processes lead to knowledge structures about how a previously unknown system works (e.g., LEDs in home automation) and how to seize control (e.g., dimming) within such a system [31]. These processes constitute the core of the domain-general construct of CPS [21, 29].

1.2. Opportunity Identification. Suddaby et al. [8] recently published a special issue of *the Journal of Business Venturing* on OI, underlining the importance and relevance that OI has in the field of entrepreneurship. Scholars tend not to agree on what opportunities are and how the process underlying opportunities evolves (e.g., [35, 36]). For instance, some authors argue that opportunities emerge in the economic environment and can be *discovered* by alert individuals [37]. Yet, others argue that opportunities are *created* by individuals in interaction with their (social) environment [36]. Recently, authors tend to agree that the different views on opportunities and the process underlying opportunities can coexist [8, 9]: ideas can be "found" in the economic environment or be generated by individuals who are willing to become an entrepreneur.

In this manuscript, we follow Suddaby et al. [8] and Vogel [9] by acknowledging that different views towards opportunities and their underlying process can coexist. Still, the discussion around opportunities in this manuscript mostly hits (but is not limited to) the discovery perspective towards opportunities, having its roots in cognitive psychology [38]. This perspective is considered to have the most connections with CPS. In this article, the capability to identify opportunities is defined as "the ability of individuals to identify ideas for new products, processes, practices or services in response to a particular pain, problem, or new market need" ([11], p. 417).

From a discovery point of view, the market is seen as continuously changing, offering new information all the time, making it possible for individuals to continuously acquire new information that can help in identifying opportunities [36]. The role of information is a first determining factor explaining why some individuals identify an opportunity that others do not identify. It is assumed that information is not evenly distributed over individuals [39]. As a result, it is important (1) to have access to relevant information and (2) to have prior knowledge so that new information can be used adequately. In the example of the engineer who aims to dim LEDs, which is new to her, it helps if she knows experts in light dimming or when she is a digital native, who has the capability to systematically search for relevant information. Regarding the second, prior knowledge can support in interpreting new information. When the engineer already has prior knowledge on the dimming of traditional light bulbs, this helps her to connect new information to what she already knows and, as a result, to give meaning to the information on a deeper and richer level [40]. Consequently, being able to access relevant information and having prior knowledge in a certain domain explain why some individuals identify an opportunity while others do not, without actively searching for it: individuals value information or events differently, because of the prior knowledge they have [41].

Second, uncertainty plays a large role in OI [36]. Individuals have to collect information from relevant stakeholders. Those stakeholders value information in a certain way, may share some information but not all, or could even share wrong information. It is up to the individual to integrate and merge the, often unstable, collection of information into expectations about future events (i.e., the opportunity). It is only ex ante possible to determine the eventual value of an opportunity after an idea has been exploited and tested for its potential [40]. The degree of uncertainty has influence on the opportunity beliefs of the individual—individuals can be more or less certain about the opportunity potential of ideas. These beliefs have their impact on whether or not individuals act upon an opportunity [40]. In sum, individuals have to be able to deal with uncertainties about the potential of opportunities and are challenged to collect relevant information from stakeholders.

Third, in their empirical study, Costanzo et al. [39] explain OI based on structural alignment. Structural alignment is "a cognitive tool that people use to compare things—and to draw implications from the comparison" ([39], p. 416). Individuals make sense of new information by comparing it to what they already know and by detecting similarities that can help them to understand and give meaning to the situation at hand. They found that individuals consider alignment with both superficial features and higher-order structural relationships in order to identify opportunities. Superficial features are basics, such as the materials a new technology consists of. Higher-order structural relationships are more complex and abstract, such as cause-effect relationships contributing to understanding how and why consumers behave in a certain way [39, 40].

The study of Costanzo et al. [39] showed that particularly similarities in higher-order structural relationships helped to identify new opportunities.

1.3. Integrating Complex Problem-Solving and Opportunity Identification. The elaboration on CPS and OI reveals several potential connections between the field of cognitive psychology and entrepreneurship, namely, regarding (1) the usage and distribution of (prior) knowledge and information, (2) dealing with uncertainty, and (3) the role of CPS in structural alignment.

First, scholars tend to agree that domain-specific prior knowledge is necessary but not sufficient for identifying opportunities. In more complex situations, individuals need skills to apply and expand on their prior knowledge. An increase of knowledge makes it likelier that a person solves a complex problem that then can lead to OI [42]. For instance, the engineer from the example taps into a complex problem when she has the idea of dimming LEDs and realizes that this is not as simple as dimming traditional light bulbs. In this situation, being able to identify opportunities and having high level CPS are both valuable: dimming LEDs has the characteristics of a complex problem (i.e., being dynamic, nonroutine, and interactive; [16]) and, at the same time, has opportunity potential by exploring solutions for dimming in home automation. More specifically, LEDs start flickering when dimmed like conventional light bulbs, but their application in home automation is new, and appropriate dimming of LEDs might not have been taken care of in advance. Here, having prior knowledge on the dimming of traditional light bulbs is not enough to explore the potential of the opportunity; the engineer also needs the skills to deal with the complex problem situation that requires the domain-general processes of acquiring and applying new knowledge in order to seize control of the dimming of LEDs. Being able both to successfully acquire knowledge and to apply this knowledge to the problem situation at hand is needed to solve the complex problem and explore the opportunity potential of dimming LEDs. As stated, it is only ex ante possible to determine the value of an opportunity, when the engineer has used her CPS to develop dimming LEDs and succeeds (or not) in developing means so that LEDs do not flicker [40].

Eventually, differences in the resulting knowledge distinguish those who see opportunities in complex environments and those who do not [43–45]. Similar to entrepreneurs, successful complex problem solvers actively acquire knowledge by assuming that the information around them is incomplete or false [32]. In other words, entrepreneurs and successful complex problem solvers both reveal a great deal of willingness to challenge information. This willingness or tendency might be what facilitates the ability to access information, an ability that can lead to differences in knowledge between those who see opportunities in complex environments and those who do not.

Second, regarding uncertainty, in applying CPS [28], individuals generally overcome complex barriers between a given state and a desired goal state. In entrepreneurship, uncertainty of opportunity beliefs [40], for instance, about how technology, user needs, and whole markets develop, represents such a complex barrier [46]. In this sense, individuals who attempt to create new value need to overcome complex barriers between, on the one hand, a given state of yet-to-be-connected information about technology and user needs and, on the other hand, a desired future state that involves a product or service that does not yet exist. Processes of knowledge acquisition and knowledge application can lead to collecting relevant, correct information that can help (1) to overcome complex barriers, (2) to reduce the amount of uncertainty about the opportunity potential, and, as a result, (3) to increase the opportunity beliefs of the individual [40]. That is, as soon as the engineer of the previous example overcomes the complex barrier of how to dim LEDs in home automation systems in a way that prevents flickering, she succeeded in reducing uncertainty and, as a result, in identifying and exploring opportunities of dimming LEDs in new, efficient ways. To be able to overcome such barriers, the engineer needs to be able to deal with uncertainty and to deal with dynamic, nonroutine, and interactive tasks.

A process that can be applied to support such activities is to simplify the diverse amount of information in the environment so that it becomes manageable (cf. [5, 13]). One way to simplify is to first observe how a problem evolves without interference and next to explore the problem step-by-step by varying only one variable at a time. To vary only one variable at a time is a strategy to overcome complex barriers, gain control, and eventually solve a complex problem (VOTAT strategy; [47]). However, VOTAT is not sufficient to solve a complex problem that requires a whole set of strategies and their adaptive use (see [48]). The VOTAT strategy is therefore a specific one among many different exploration strategies that might help to simplify knowledge acquisition in the real world as well as in current CPS tests that have been applied in the present study [49, 50].

Third, the supportive role of CPS skills in identifying opportunities can also be argued for when considering the role of cognitive alignment in OI, as investigated by Costanzo et al. [39]. When individuals face a complex task in a dynamic situation, the process of structural alignment can be very demanding, especially when detecting similarities in higher-order relationships with the problem situation at hand. Costanzo et al. [39] argue that individuals need to detect and process relevant signals on a deeper level. Just as in dealing with (new) information and uncertainty, structural alignment could be traced back to the integral processes of CPS: knowledge acquisition and knowledge application [32]. These closely intertwined and equally important processes for solving complex problems [13] lead to knowledge structures about how a previously unknown system works on a deeper level and how to seize control within such a system [31]. Knowledge acquisition begins as a problem solver retrieves information in an environment, where it is yet unclear what is important and what not; it continues as the solver reduces the information in order to keep a set of relevant pieces, thus leading to an actionable problem representation (see above; [34]). Supporting the identification of an opportunity in a real market, an actionable representation ideally contains a sufficient number of pieces of the puzzle by which to identify customers' needs and the ways in which such needs can be met. This actionable representation is the foundation for applying the acquired knowledge to a set goal and, thus, to gradually gain control over the variables of the problem in order to successfully solve the problem, or, in other words, to identify an opportunity.

2. The Present Study

The goal of the present study was to empirically evaluate whether CPS plays a significant role in OI. Investigating the linkages between CPS and OI has the potential of contributing to opening up the *black box* of what EE should be about. As stated in the Introduction, in this study, EE is broadly defined, having new-value creation as common core [3]. By comparing a more domain-specific capability, namely, OI, with a more generic skill, namely, CPS, we aim to contribute to a better understanding of what students should learn in EE that is directed towards preparing students on a career full of complexity and uncertainty [1]. From a conceptual point of view, the importance of CPS in OI seems reasonable. As discussed above, CPS (1) helps to adequately acquire and apply new relevant information in the OI process, (2) helps to deal with uncertainty, and (3) supports demanding structural alignment processes. Subsequently, the main research question of this manuscript is, *To what degree does CPS relate to OI?*

3. Method

3.1. Sample and Procedure. The sample consisted of 113 Dutch students who were doing their masters studies in the field of life sciences and were enrolled for two semesters in the weekly courses *Entrepreneurial Skills* and *Career Development and Planning* (this sample was also used for a different study with a different purpose, namely, to develop the measurement of OI; see [51]). *Entrepreneurial Skills* addressed important personal characteristics of entrepreneurial individuals, and the students created mind maps of their own entrepreneurial characteristics, goals, and intentions. As part of the course, the students pitched their own venture ideas. In *Career Development and Planning*, students reflected upon and described their career goals and created an action plan towards the realization of these goals. The students were between 21 and 31 years of age (M = 23.55 years, SD = 2.00), and 68.1% were female. When asked "What is the likelihood that you will be involved in an entrepreneurial venture sometime in your lifetime?," almost all of the students (96.2%) stated that they had the intention, at least to some degree, of getting involved in an entrepreneurial venture ("maybe" [30.8%], "probably will" [38.5%], and "definitely will" [26.9%]); 70.2% of the students even stated the intention to get involved within the next 5 years ("maybe" [37.5%], "probably will" [26.0%], and "definitely will" [6.7%]); 7.7% of the sample were currently involved in an entrepreneurial venture, and 12.5% had undertaken an entrepreneurial venture in the past (questions adapted from DeTienne and Chandler [52]).

Split into four almost even groups, the participants rotated between a session in which OI and the control variables were assessed (Session A; see next paragraph), a session in which CPS was assessed in a computer-based format (Session B; see next paragraph), and a course with content that was unrelated to the assessments. Sessions A and B each lasted 45 minutes, whereas the course lasted 1.5 hours, so the first two groups switched between Sessions A and B for the first 1.5 hours while Groups 3 and 4 took the course. Then, Groups 3 and 4 switched between Sessions A and B while Groups 1 and 2 took the course. Switching the groups between separate seminar rooms for each different session resulted in two 10–15-minute breaks for each group.

3.2. Measures

3.2.1. Opportunity Identification. An earlier developed performance assessment on OI by Baggen et al. [51] was used. In the assessment, the participants were asked to generate business ideas related to sustainable development, as a case closely related to the background of the participants (who were students from a university in the life sciences domain). In the case, examples of problems in the area of sustainable development were given, such as education and climate change. The participants were asked, "Imagine that you are asked to give input for business ideas for new start-ups in the area of sustainable development. These business ideas can concern people, planet, and/or profit, and may lead to social, environmental and/or economic gains. What ideas for new start-ups come up in your mind?" Furthermore, it was stated that "You do not have to worry about whether the ideas have a high or low potential for success. Do not limit yourself; the more ideas you can list, the better."

The generated ideas were scored on (1) comprehensibility, (2) concreteness, and (3) flexibility. The scoring criteria were derived and adopted from earlier work of Guilford [53], who developed criteria to score the results of creativity tasks. Comprehensibility refers to responses that actually correspond to the question (1 = comprehensible; 0 = incomprehensible). Concreteness encompasses the extent to which it was possible to visualize or apply the idea (1 = concrete; 0 = not concrete). Per participant, the percentage of comprehensible ideas that were also concrete was calculated. Flexibility refers to the amount of categories in which the participants could generate business ideas. Each idea was scored into one category, corresponding to the examples given in the case on sustainable development. In total, six categories were defined: food, decent housing, energy, climate change, education, and personal health and safety. The flexibility score was calculated by dividing the number of scored categories by the total number of categories (i.e., six).

In order to develop the codebook, two raters (from the team of authors) scored 10% of the ideas in three scoring rounds, which is an acceptable percentage when scoring such large dataset [54]. After each scoring round, they compared and discussed their results and refined the codebook until acceptable levels of interrater reliability were reached for the scoring procedure, Cohen's Kappa .78 (flexibility), and for the dichotomous variables agreement of 82.9% (concreteness) and 94.7% (comprehensibility). Please refer to Baggen et al. [51] for a more specific elaboration on the analysis of the business ideas.

3.2.2. Complex Problem-Solving. We employed one introduction task and a set of six complex task simulations from the fully computer-based CPS assessment test MicroFIN [49, 50]. MicroFIN features multiple, dynamic tasks that are based on a formal framework called "Finite State Automata" [55]. Based on this framework, MicroFIN aims to counter limitations in the breadth of problems included in previous CPS instruments (e.g., MicroDYN; [56]) and facilitate a greater heterogeneity in tasks [49, 50, 57]. MicroFIN was recently found to have convergent validity with an established CPS instrument and discriminant validity with different measures of general mental ability (GMA; [49, 58]). MicroFIN tasks share a general layout of input variables that influence output variables and are in accordance with the theoretical background as outlined in the Introduction (i.e., test items contain (a) values that change with the user's interaction and (b) various nontransparent interactions between variables, such as threshold or equilibrium states in the input variables; [13]).

For instance, our participants faced the challenge of planning a city while considering the needs of very different interest groups ("Plan-o-Maton" task; see Figure 1). The goal in this nontransparent task was to balance the interests of various parties (e.g., families and industries) by improving their

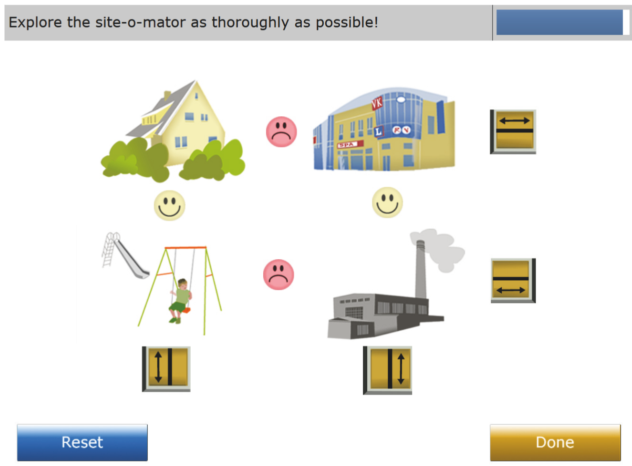

Figure 1: Screenshot of the MicroFIN item "Plan-o-Maton" [49, 50]. Problem solvers have to balance the interests of various parties in a city by making alterations in the urban landscape. Along the bottom and the right side: the keys for altering the location of the interest groups. In principle, two stakeholders change places when triggered. On the right side: a city mall and a factory. On the left side: a family home and a playground. Between these parties, smiley faces indicate the atmosphere. The problem solver has to improve the atmosphere by finding one of several optimal setups.

locations in the urban landscape. The parties' interactions led to discrete states of well-being, also called equilibrium, which could be achieved through various ways of interacting. Similar but different tasks consisted of, for example, (a) the challenge of successfully managing a concert hall that varied according to the type of music (e.g., classical versus Rock'n'Roll), price level, and atmosphere (indoor versus outdoor) or (b) the challenge of successfully harvesting a new kind of pumpkin that varied according to the season and the amount of fertilizer.

Participants were to explore a previously unknown problem in order to derive knowledge about the causal structure of the task and the possibilities of interventions. Next, four items per task were used to assess the participant's knowledge about the problem (i.e., knowledge acquisition). Subsequently, one more item per task asked participants to apply their knowledge to manipulate each task towards achieving a previously set goal to thereby gain control over the system or, in other words, to solve the complex problem (i.e., knowledge application). Overall, each MicroFIN task took approximately 5 minutes to complete (for a more detailed description of the different MicroFIN tasks and items, see [49, 50]).

In detail, to determine participants' scores on knowledge acquisition, they received credit for a correct summary of the previously unknown relations within a task (e.g., the Plan-o-Maton) and no credit if they failed to do so. The score was an average of the four items for knowledge acquisition per task. To determine participants' scores on the knowledge application item, they received credit for reaching the target state on each task (e.g., different states of well-being for families and industries in the Plan-o-Maton), and no credit was given when participants failed to do so. The scores for knowledge acquisition and knowledge application were further aggregated across all tasks and finally collapsed into one *general* CPS score according to a procedure used by Kretzschmar et al. [58]. Due to a software issue, the data for one MicroFIN task was not saved and, thus, our analyses were based on five tasks. Cronbach's alpha was calculated as an indicator for the reliability and was based on the approach proposed by Rodriguez and Maeda [59]. Cronbach's alpha of MicroFIN was .57.

In sum, MicroFIN provided a measure of skills to solve complex problems that stemmed from theoretical considerations of CPS and has been empirically validated [49, 50, 58, 60].

3.2.3. Control Variables. In order to measure the unique relation between CPS and OI, we additionally assessed and controlled for two variables that might relate to either CPS or OI: problem-solving self-concept and prior knowledge. Problem-solving self-concept is one's self-perceived ability to solve problems [61] in addition to the actual problem-solving performance covered by CPS. Self-concept measures should be associated with performance scales of a corresponding ability [61]. As CPS and problem-solving self-concept correspond, controlling for this area of self-concept allows us to show whether it is either the belief in one's ability or one's ability itself or both that potentially leverage OI. Prior knowledge about a market or topic has an impact on the development of new venture ideas (i.e., OI) in a specific domain (e.g., [62]). As argued in the section on OI, knowledge is not evenly distributed among people. Those who have prior knowledge in a specific domain are more likely to identify an opportunity [41].

Problem-Solving Self-Concept. We used six problem-solving items from the Self-Description Questionnaire III (SDQ III; [61]) to assess problem-solving self-concept. The SDQ III was designed to measure 13 self-concept factors, of which problem-solving is one factor. An example item is "I am good at problem solving," which participants answered using a similar 5-point Likert scale. Cronbach's alpha of the scale was .75.

Prior Knowledge. The participants had to come up with as many business ideas as possible on the basis of a case that was related to sustainability. Therefore, we aimed to control for the sustainability-related prior knowledge of the participants. We asked the participants how much they knew about several sustainability-related topics such as climate change using a 5-point Likert scale (8 questions) before they took the main survey. Cronbach's alpha was .76.

3.3. Data Analysis. All statistics were calculated using the R software [63]. We applied multiple imputations using the mice package [64] in combination with the miceadds package [65]. In detail, we used 10 imputed datasets (100 iterations; method: predictive mean matching) to account for up to 28% of missing data for two MicroFIN tasks, which were the result of technical issues that occurred in the computer-based

Table 1: Descriptive statistics for the assessment of OI, CPS, prior knowledge, and problem-solving self-concept.

Variable	Minimum	Maximum	M	SD
Opportunity identification				
Number of comprehensible ideas	0	23	6.27	3.55
Number of concrete ideas	0	16	5.77	3.20
Flexibility	0.17	1	0.53	0.18
CPS	0.75	5	3.3	0.87
Prior knowledge	1.50	4.88	2.91	0.67
Problem-solving self-concept	1.50	4.83	3.66	0.62

Note. Statistics are based on raw data (i.e., nonimputed). CPS: complex problem-solving; PS self-concept: problem-solving self-concept. The control variable ratings ranged from 1 *(strongly disagree)* to 5 *(strongly agree)*.

Table 2: Pearson's correlations between variables.

Measure	1	2	3	4	5
(1) Number of comprehensible ideas					
(2) Proportion concrete	−.01				
(3) Flexibility	.71***	.03			
(4) CPS	.18	.29**	.20*		
(5) Prior knowledge	.05	−.14	−.12	−.10	
(6) PS self-concept	.21*	.12	.15	.20*	.09

Note. $N = 113$ (imputed data). Manifest correlations are reported. Proportion concrete: proportion of concrete ideas; CPS: complex problem-solving; PS self-concept: problem-solving self-concept. Two-tailed p values: $^{*}p \leq .05$, $^{**}p < .01$, and $^{***}p < .001$.

assessment at the end of the testing of the second group of participants. Although the technical issues were solved in a short amount of time, not all participants were able to work on all tasks due to external time restrictions. For all other tasks, the amount of missing data was less than 9%. Checking for patterns in missing data, Little's test indicated that data were missing completely at random (MCAR; χ^2 [579] = 633.5625, $p = .057$). In the following, we report the results computed on the imputed data ($n = 113$).

In preliminary analyses, we calculated descriptive statistics for our variables as well as bivariate Pearson correlations to provide information about the basic data structure. To test whether CPS explained variance in (1) the number of comprehensible ideas, (2) the proportion of concrete ideas, and (3) flexibility beyond prior knowledge and problem-solving self-concept, we computed multiple regression analyses and compared different models. In Model 1a, we regressed the number of comprehensible ideas on our control variables, and in Model 1b, we included CPS as a statistical predictor in addition to our control variables. Simultaneously, in Models 2a and 3a, we, respectively, regressed the proportion of concrete ideas and flexibility on the control variables, and in Models 2b and 3b, we additionally included CPS.

4. Results

4.1. Preliminary Analyses. The participants revealed an average total number of 6.27 comprehensible ideas and 5.77 concrete ideas in the OI task. On average, the flexibility score of the participants was .53, indicating that they generated ideas in about three of the six categories (see Table 1).

CPS was not significantly correlated with the number of comprehensible ideas ($r = .18$, $p = .071$) and was weakly but significantly correlated to the proportion of concrete ideas ($r = .29$, $p = .005$) and the flexibility score ($r = .20$, $p = .047$) The control variables showed correlations with OI that were very weak and nonsignificant (see Table 2). Problem-solving self-concept significantly correlated with the number of comprehensible ideas ($r = .21$, $p = .031$) and CPS ($r = .20$, $p = .050$). A correlation of .71 ($p < .001$) between the number of comprehensible ideas and flexibility indicated that they were substantially associated.

4.2. Tests of Hypotheses. In the basic Model 1a in which the control variables were used to predict the number of comprehensible ideas, only problem-solving self-concept ($\beta = .20$, $p = .037$) was a significant predictor. Prior knowledge ($\beta = .01$, $p = .908$) remained nonsignificant. Model 1b with CPS as an additional predictor (see Table 3) revealed that CPS ($\beta = .12$, $p = .174$) and the control variables problem-solving self-concept ($\beta = .18$, $p = .073$) and prior knowledge ($\beta = .03$, $p = .775$) remained nonsignificant in predicting the number of comprehensible ideas. In comparison with Model 1, CPS explained an additional 1.7% (adjusted: 0.8%) of the variance in the number of comprehensible ideas.

The basic Model 2a, which included problem-solving self-concept ($\beta = .13$, $p = .184$) and prior knowledge ($\beta = -.17$, $p = .143$), did not predict the proportion of concrete ideas. However, Model 2b (see Table 3) revealed that CPS ($\beta = .24$, $p = .016$) significantly predicted the proportion of concrete ideas. Problem-solving self-concept ($\beta = .08$, $p = .402$) and prior knowledge ($\beta = -.14$, $p = .235$) remained nonsignificant. CPS incrementally explained 5.9% (adjusted: 5.4%) of the variance in the proportion of concrete ideas in comparison with the basic Model 2a (see Table 3), which included only the control variables.

Table 3: Regression analyses with (1) the number of comprehensible ideas, (2) the proportion of concrete ideas of comprehensible ideas, and (3) flexibility as dependent variables.

Predictor	Number of comprehensible ideas		Proportion concrete		Flexibility	
	Model 1a	Model 1b	Model 2a	Model 2b	Model 3a	Model 3b
Intercept						
PS self-concept	.20*	.17	.13	.08	.16	.12
Prior knowledge	.01	.03	−.17	−.14	−.16	−.14
CPS		.12		.24*		.16
R^2	0.042	0.059	0.041	0.101	0.044	0.072
ΔR^2	—	0.017	—	0.059	—	0.027

Note. $N = 113$ (imputed data). Standardized regression coefficients and R^2 values are reported. PS: problem-solving; CPS: complex problem-solving. ΔR^2 represents the comparison between models (a) and (b) for each dependent variable. Two-tailed p values: $^{*}p \leq .05$ and $^{**}p < .01$.

Finally, in the basic Model 3a, problem-solving self-concept ($\beta = .16$, $p = .106$) and prior knowledge ($\beta = -.16$, $p = .100$) did not predict the flexibility score. In Model 3b, CPS was not a significant predictor of flexibility ($\beta = .16$, $p = .096$); the control variables problem-solving self-concept ($\beta = .12$, $p = .209$) and prior knowledge ($\beta = -.14$, $p = .154$) remained nonsignificant. Compared to Model 3a, the model including CPS (Model 3b) explained an additional 2.7% (adjusted: 1.9%) of the variance in the flexibility score. In summary, CPS only significantly predicted the proportion of concrete ideas in Model 2.

5. Discussion

With this study, we set out to examine the role of CPS in OI by administering standardized performance tasks of CPS and OI to a sample of 113 students, most of whom had an interest in independent entrepreneurship. We found that CPS incrementally predicted the proportion of concrete ideas beyond the control variables problem-solving self-concept and prior knowledge. These results can be interpreted as the first empirical evidence for a significant role of CPS in entrepreneurial activities and suggest that training CPS skills could be a valuable addition to defining "*what*" should be taught in EE. Below, we first elaborate on the findings, before we reflect on the (practical) meaning of our results for EE.

5.1. The Role of Complex Problem-Solving in Opportunity Identification. CPS solely contributed to statistically predicting the proportion of concrete ideas, whereas here all control variables remained irrelevant for this prediction. The correlations between CPS and the three indicators for OI ranged between .18 and .29, which can be considered small [66] to medium effects [67]. This means that CPS processes matter at least to some extent in the application of OI in a standardized entrepreneurial task context. By contrast, our results suggest that prior knowledge does not play any role in the application of such tasks, whereas one's problem-solving self-concept matters in the number of comprehensible ideas. One may assume that, in a real market, individuals with high levels of CPS are more likely to perform the necessary steps of exploring, simplifying, and controlling complex tasks in order to eventually identify concrete and readily applicable opportunities better than others.

Regarding the sizes of the effects, (a) the overall small effect sizes for CPS actually confirm the pattern of results reported in previous studies with cognitive and noncognitive predictors of entrepreneurial outcomes (e.g., [68, 69]). For example, GMA and the Big Five (i.e., broad personality traits) are two well-researched predictors that both matter but nonetheless do not specifically match the context of entrepreneurship. Gielnik et al. [68] found no significant relation between GMA and OI and only a moderate relation between OI and divergent thinking. In their meta-analysis, Rauch and Frese [69] reported correlations that were close to 0 between domain-general predictors and entrepreneurial outcomes, particularly in studies using the Big Five. Conversely, other studies of their meta-analysis that matched traits with entrepreneurial outcomes reported relatively small to moderate and heterogeneous relations. Rather than resembling specifically entrepreneurial traits, these predictors remained domain-general. As it is not bound to a specific domain either, CPS also does not specifically match the context of entrepreneurship.

Furthermore, (b) as the applied computer-based CPS and paper-and-pencil-based assessments on OI were genuinely different methods, the relations between OI and CPS were invariably due to the particular constructs that were measured and could not be attributed to a common method in accordance with Podsakoff et al. [70]. Hence, in light of (a) previous findings and (b) the use of different measures of CPS and OI in the present study, the direct relations between CPS and OI were not exceptionally small but rather drew a picture of meaningful results that support CPS as a predictor of entrepreneurial activities.

The results suggest that CPS predicts the concreteness of the generated business ideas (i.e., OI). Furthermore, CPS and flexibility were correlated ($r = .20$). Although CPS was not a significant predictor of flexibility, the correlation between flexibility and CPS on the one hand and the relationship between CPS and concreteness on the other hand offer reasons to believe that CPS is of value for generating ideas *of good quality*. This result might be explained based on the process of knowledge acquisition and knowledge application. As stated, differences in (prior) knowledge distinguish those who identify certain opportunities and those who do not [43–45]. More specifically, those who have higher levels of CPS might be able to identify concrete opportunities, which are visualizable and applicable, in complex environments. Entrepreneurs and successful complex problem solvers both reveal a great deal of willingness to challenge information. This willingness or tendency might be what facilitates the ability to access information, an ability that can lead to differences in knowledge between those who see concrete opportunities in detail and those who do not. In sum, effective problem solvers and entrepreneurs arrive at a higher level of concreteness by (a) reducing uncertainty and recombining resources to solve relevant complex problems, (b) using a range of processes to simplify complex environments, and (c) sharing the tendency to question the relevance and completeness of information. This way, knowledge acquisition processes leverage the applicability of business ideas; when individuals engage more with the task, they give more concrete answers. On the side of knowledge application, someone high in CPS proved to be better than others in applying new knowledge. In OI, this advantage might translate into concrete ideas that are more ready to apply. Taken together, the results of the present study support the idea that CPS advances explanations for how entrepreneurs deal with uncertainty and recombine resources, why they differ from other people, and, eventually, how they identify concrete opportunities that are ready to apply.

Regarding problem-solving self-concept and prior knowledge, our results deviated from our expectations and previous research. Regarding problem-solving self-concept, we expect it to significantly correlate with CPS, such as what Marsh and O'Neill [61] have shown for other areas, where self-concept and ability corresponded. The problem-solving self-concept solely contributed to explaining the comprehensiveness of ideas, neither their concreteness nor flexibility. This pattern might suggest that the belief in one's problem-solving ability supported—at least to a small extent—coming up with ideas at all but did not affect how concrete or flexible the ideas were. As we have shown for CPS, at least for the concreteness of ideas, it is rather one's ability itself than one's self-concept that makes a difference.

Regarding prior knowledge, Shane [41] distinguishes three types of prior knowledge: (1) prior knowledge on markets, (2) prior knowledge on how to serve markets, and (3) prior knowledge of customer problems. The results of his study show that many types of prior knowledge influence the process of identifying opportunities, which can be developed in different functions and roles. As Costanzo et al. [39] argue, the resulting idiosyncratic prior knowledge advantages individuals not only to recognize opportunities at hand, but also to draw parallels between markets by *connecting the dots* between relevant, complicated information from one market to another. The items measuring prior knowledge in this study only related to the content of the case from the OI task. The role of prior knowledge and, accordingly, its measurement might be way more complex and extended, which might explain the lack of relationships between prior knowledge and the three outcomes of OI as used in this study.

5.2. Strengths and Limitations. We administered computer-based simulations of complex and dynamic problems to obtain a performance measure of CPS in order to clarify the relation between OI and CPS. Conversely, previous quantitative research has employed self-assessment questionnaires instead of cognitive performance measures (for a recent review, see [71]) or has obtained performance measures from paper-and-pencil-based assessment tests (e.g., [68]). What these very different approaches have in common is that they cannot account for complex and dynamic tasks as they occur during entrepreneurial activities (e.g., [62, 72, 73]). Neither self-reports nor paper-and-pencil-based performance measures assess the interaction between a person and a dynamically changing task. However, if such complex interactions with dynamic tasks play a role in implementing entrepreneurial activities, as repeatedly proposed in this article, research cannot spare the advantage of computer-based assessments to simulate such problems under controlled conditions. In fact, our results support the application of computer-based assessments to examine and better understand entrepreneurial activities.

Simultaneously, this study revealed several limitations and the need to modify scales and procedures in future research. First of all, except for a measure of problem-solving self-concept and prior knowledge, cognitive covariates and moderators (e.g., GMA and divergent thinking) were not included in our empirical study, although these abilities influence how people process information in general [74] and have previously been examined in the context of entrepreneurship outcomes (cf. [68]), such as OI.

Second, deviating results could be due to the choice of (a) sample or (b) instruments. (a) The sample size was rather small, and, consequently, the power was small. Therefore, the significant results have to be interpreted with care. The age and experience ranges in our student sample were restricted, which may have disguised stronger empirical relations as the sample was composed of young would-be entrepreneurs between 21 and 31 years of age who, due to their lack of practical entrepreneurial experience, could not provide additional information on entrepreneurial success or number of innovations. (b) The independent variable (i.e., CPS) and the dependent variables (i.e., the number of comprehensible ideas, concreteness, and flexibility) were merely indicators for real-life performance in solving complex problems or in identifying opportunities. These constraints came along with detriments to external validity and generalizability and thus reduced the interpretability of the results. However, as the real-world performances of experts in CPS and entrepreneurial tasks are rare and are hardly observable events [39, 75], the observation of fictional task performance in students who are being prepared for entrepreneurial careers was a feasible means for obtaining the first empirical evidence of a relation between CPS and entrepreneurial activities.

5.3. Future Research. First of all, in terms of research design, other variables could be included in the research design of which earlier research has shown that they are related to either CPS or OI, such as GMA and divergent thinking [68, 74]. Furthermore, the relationship between CPS and OI could be investigated among different groups of people, such as independent entrepreneurs and entrepreneurial employees. Such research would provide insight into the relationship between OI and CPS in different settings.

Second, future study designs should use longitudinal data and intervention studies in order to enable the study of temporal dynamics or conclusions about causality and training effects on CPS and entrepreneurial activities (cf. [76, 77]). In their experimental study, DeTienne and Chandler [52] found that creativity training had a stronger effect on the innovativeness of generated ideas by students, compared to the number of generated ideas. Apparently, creativity influenced the quality of the generated ideas, which is in line with the results of the current study that carefully suggest that CPS also impacts the quality of ideas. In future research, the influence of training CPS on the OI capabilities of students could be tested in order to investigate whether CPS has a similar effect as creativity on OI capabilities.

5.4. Practical Implications. As stated, it is difficult to disentangle what should be taught in EE when following the broad definition [3]. As a response to critique of that kind, educators increasingly engage students in alternative ways of learning, such as experimentation and real-world start-up practices (for details, see [78]). If solving complex problems is part of what individuals do on their journey towards new-value creation, as the present study suggests, CPS could possibly contribute valuable skills to EE. Per definition, skills are modifiable through practice and training [79]. It follows that CPS skills are precisely what the name implies—a set of skills that can possibly be sharpened with instruction and practice. Previous empirical findings point to the possibility of increasing CPS and related skill with instruction and practice, at least in the research lab [80–85].

More specifically, educating CPS skills could be part of the so-called progression models. In a progression model, learners gradually learn to act entrepreneurially over levels and grades in the educational system [3]. Such progression model could start at primary education, where learners can develop their CPS skills by actively engaging in everyday problems and challenges of society and technology that are in particular dynamic and change over time and with interaction. Later, in secondary and higher education, teaching gets a stronger focus on learning curriculum knowledge. Accordingly, then, more domain-specific entrepreneurial capabilities, such as OI, could be taught.

However, dating back to the beginnings of institutionalized education, initiatives to enhance CPS are still in their infancy without a unified underlying conceptual framework and valid instructional methods [86]. A significant obstacle hindering more practical considerations of CPS in assessment and education has been the absence of valid, reliable measures of the underlying construct. This hindrance has recently been overcome as the application of CPS tests in PISA 2012 [17] and first validation studies on CPS in the educational sector reveal (e.g., [19–21, 58]). Accordingly, assessing CPS skills in EE could be a very first step towards weaving CPS into EE.

6. Conclusions

Our empirical research identified weak but significant statistical relations supporting that CPS plays a role in the application of OI in the early stages of entrepreneurship. With the study's limitations in mind, the results pointed towards CPS as a domain-general predictor of entrepreneurial activities. Starting from the preliminary evidence we have, we suggest that whether an individual successfully identifies an entrepreneurial opportunity and thereby solves a complex problem in a dynamic and previously unknown task environment will depend in part on his or her CPS level. However, our findings also need to be replicated and substantiated in the future. For the time being, our contribution to entrepreneurship research is an empirical study in which we evaluated whether CPS plays a role in the application of OI of students who are presumably much affected by the complex and rapidly developing technological advancements of our times. Accordingly, integrating CPS skills in EE would be highly valuable as it is a generic skill that has potential linkages with a crucial entrepreneurial capability, namely, OI, and that fits the broad definition of EE with value creation at its core.

Conflicts of Interest

Samuel Greiff is one of two authors of the commercially available COMPRO test that is based on the multiple complex systems approach and that employs the same assessment principle as MicroDYN. However, for any research and educational purpose, a free version of MicroDYN is available. Samuel Greiff receives royalty fees for COMPRO.

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References

[1] A. Gibb, "Creating conducive environments for learning and entrepreneurship. living with, dealing with, creating and enjoying uncertainty and complexity," *Industry and Higher Education*, vol. 16, pp. 135–148, 2002.

[2] K. Moberg, H. Barslund Fosse, A. Hoffman, and M. Junge, *Impact of entrepreneurship education in Denmark*, 2014, http://eng.ffe-ye.dk/media/637847/effektmacc8alingen20201520eng-online.pdf.

[3] M. Lackéus, "Entrepreneurship in education: What why, when how. Entrepreneurship360 background paper," http://www.oecd.org/cfe/leed/BGP_Entrepreneurship-in-Education.pdf.

[4] E. C. Rideout and D. O. Gray, "Does entrepreneurship education really work? A review and methodological critique of the empirical literature on the effects of university-based entrepreneurship education," *Journal of Small Business Management*, vol. 51, pp. 329–351, 2013.

[5] S. A. Shane and S. Venkataraman, "The promise of entrepreneurship as a field of research," *Academy of Management Review*, vol. 25, no. 1, pp. 217–226, 2000.

[6] M. M. Gielnik, M. Frese, J. M. Graf, and A. Kampschulte, "Creativity in the opportunity identification process and the moderating effect of diversity of information," *Journal of Business Venturing*, vol. 27, pp. 559–576, 2012.

[7] Y. L. Wang, A. D. Ellinger, and Y. C. J. Wu, "Entrepreneurial opportunity recognition: An empirical study of RD personnel," *Management Decision*, vol. 51, pp. 248–266, 2013.

[8] R. Suddaby, G. D. Bruton, and S. X. Si, "Entrepreneurship through a qualitative lens: Insights on the construction and/or discovery of entrepreneurial learning," *Journal of Business Venturing*, vol. 30, pp. 10-10, 2015.

[9] P. Vogel, "From Venture Idea to Venture Opportunity," *Entrepreneurship: Theory and Practice*, 2016.

[10] C. Hsieh, J. A. Nickerson, and T. R. Zenger, "Opportunity discovery, problem solving and a theory of the entrepreneurial firm," *Journal of Management Studies*, vol. 7, pp. 1255–1277, 2007.

[11] Y. Baggen, J. Mainert, T. Lans, H. J. A. Biemans, S. Greiff, and M. Mulder, "Linking complex problem solving to opportunity identification competence within the context of entrepreneurship," in *Proceedings of the International Journal of Lifelong Education*, vol. 34, pp. 412–429, 2015.

[12] D. A. Shepherd, T. A. Williams, and H. Patzelt, "Thinking About Entrepreneurial Decision Making: Review and Research Agenda," *Journal of Management*, vol. 41, no. 1, pp. 11–46, 2015.

[13] A. Fischer, S. Greiff, and J. Funke, "The process of solving complex problems," *The Journal of Problem Solving*, vol. 4, pp. 10–7771, 2012.

[14] K. S. McGrew, "CHC theory and the human cognitive abilities project: Standing on the shoulders of the giants of psychometric intelligence research," *Intelligence*, vol. 37, no. 1, pp. 1–10, 2009.

[15] J. Raven, J. C. Raven, and J. H. Court, *Manual for Ravens Progressive Matrices and vocabulary scales: Section 4. The standard progressive matrices*, Oxford Psychologists Press, 1998.

[16] J. Funke, "Complex problem solving: A case for complex cognition?" *Cognitive Processing*, vol. 11, no. 2, pp. 133–142, 2010.

[17] "Assessing problem-solving skills in PISA 2012," in *PISA 2012 Results: Creative Problem Solving (Volume V)*, PISA, pp. 25–46, OECD Publishing, 2014.

[18] *OECD Skills Outlook 2013*, OECD Publishing, 2013.

[19] A. Kretzschmar, J. C. Neubert, and S. Greiff, "Komplexes Problemlösen, schulfachliche Kompetenzen und ihre Relation zu Schulnoten [Complex problem solving, school competencies and their relation to school grades," *Zeitschrift für Pädagogische Psychologie*, vol. 28, no. 4, Article ID a000137, pp. 205–215, 2014.

[20] M. Stadler, N. Becker, S. Greiff, and F. M. Spinath, "The complex route to success: complex problem-solving skills in the prediction of university success," *Higher Education Research Development*, vol. 115, pp. 10–1080, 2015.

[21] S. Greiff, S. Wüstenberg, G. Molnár, A. Fischer, J. Funke, and B. Csapó, "Complex problem solving in educational contexts-something beyond g: Concept, assessment, measurement invariance, and construct validity," *Journal of Educational Psychology*, vol. 105, no. 2, pp. 364–379, 2013.

[22] D. Danner, D. Hagemann, D. V. Holt et al., "Measuring Performance in Dynamic Decision Making: Reliability and Validity of the Tailorshop Simulation," *Journal of Individual Differences*, vol. 32, no. 4, pp. 225–233, 2011.

[23] P. Ederer, L. Nedelkoska, A. Patt, and S. Castellazzi, "What do employers pay for employees' complex problem solving skills?" *International Journal of Lifelong Education*, vol. 34, no. 4, pp. 430–447, 2015.

[24] M. Kersting, "Zur Konstrukt- und Kriteriumsvalidität von Problemlöseszenarien anhand der Vorhersage von Vorgesetztenurteilen über die berufliche Bewährung," *Diagnostica*, vol. 47, no. 2, pp. 67–76, 2001.

[25] J. C. Neubert, J. Mainert, A. Kretzschmar, and S. Greiff, "The assessment of 21st century skills in industrial and organizational psychology: Complex and collaborative problem solving," in *Industrial and Organizational Psychology: Perspectives on Science and Practice*, vol. 8, pp. 31-10, 1-31, 8, 2015.

[26] J. R. Sampson, *Adaptive Information Processing*, Springer Berlin Heidelberg, Berlin, Heidelberg, 1976.

[27] J. Funke, "Human Problem Solving in 2012," *The Journal of Problem Solving*, vol. 6, no. 1, 2013.

[28] P. A. Frensch and J. Funke, *Complex problem solving: The European perspective*, L. Erlbaum Associates, Hillsdale, N.J, 1995.

[29] S. Greiff, D. V. Holt, and J. Funke, "Perspectives on problem solving in educational assessment: Analytical, interactive, and collaborative problem solving," *Journal of Problem Solving*, vol. 5, no. 2, pp. 71–91, 2013.

[30] M. Karavidas, N. K. Lim, and S. L. Katsikas, "The effects of computers on older adult users," *Computers in Human Behavior*, vol. 21, no. 5, pp. 697–711, 2005.

[31] M. Osman, "Controlling Uncertainty: A Review of Human Behavior in Complex Dynamic Environments," *Psychological Bulletin*, vol. 136, no. 1, pp. 65–86, 2010.

[32] J. Funke, "Dynamic systems as tools for analysing human judgement," *Thinking & Reasoning*, vol. 7, no. 1, pp. 69–89, 2001.

[33] D. Klahr and K. Dunbar, "Dual space search during scientific reasoning," *Cognitive Science*, vol. 12, 148, pp. 10–1016, 1988.

[34] P. A. Argenti, "Book Reviews : Organizational Public Relations: A Political Perspective. By Christopher Spicer. Mahwah, NJ. Lawrence Erlbaum, 1997 324 pages," *Journal of Business Communication*, vol. 36, no. 3, pp. 305-306, 1999.

[35] D. F. Kuratko, "The emergence of entrepreneurship education: development, trends, and challenges," *Entrepreneurship: Theory and Practice*, vol. 29, no. 5, pp. 577–597, 2005.

[36] S. D. Sarasvathy, N. Dew, S. R. Velamuri, and S. Venkataraman, "Three views of entrepreneurial opportunity. In," in *Handbook of entrepreneurship research*, Z. J. Acs and D. B. Audretsch, Eds., Springer, Boston, 2010.

[37] Y. E. Companys and J. S. McMullen, "Strategic entrepreneurs at work: The nature, discovery, and exploitation of entrepreneurial opportunities," *Small Business Economics*, vol. 28, pp. 301–322, 2007.

[38] D. R. DeTienne, "Entrepreneurial exit as a critical component of the entrepreneurial process: theoretical development," *Journal of Business Venturing*, vol. 25, no. 2, pp. 203–215, 2010.

[39] M. Costanzo, A. Baryshnikova, J. Bellay et al., "The genetic landscape of a cell," *Science*, vol. 327, no. 5964, pp. 425–431, 2010.

[40] D. A. Grégoire, D. A. Shepherd, and D. A. Grégoire, "Technology-market combinations and the identification of entrepreneurial opportunities: An investigation of the oppor-

tunity-individual nexus," *Academy of Management Journal*, vol. 55, pp. 753–785, 2012.

[41] S. Shane, "Prior knowledge and the discovery of entrepreneurial opportunities," *Organization Science*, vol. 11, no. 4, pp. 448–469, 2000.

[42] D. Dimov, "Beyond the single-person, single-insight attribution in understanding entrepreneurial opportunities," *Entrepreneurship: Theory and Practice*, vol. 31, no. 5, pp. 713–731, 2007.

[43] L. W. Busenitz, "Research on entrepreneurial alertness: sampling, measurement, and theoretical issues," *Journal of Small Business Management*, vol. 34, no. 4, pp. 35–44, 1996.

[44] C. M. Gaglio and J. A. Katz, "The psychological basis of opportunity identification: entrepreneurial alertness," *Small Business Economics*, vol. 16, no. 2, Article ID 1011132102464, pp. 95–111, 2001.

[45] J. Rank, V. L. Pace, and M. Frese, "Three avenues for future research on creativity, innovation, and initiative," *Applied Psychology: An International Review*, vol. 53, pp. 518–528.

[46] J. S. McMullen and D. A. Shepherd, "Entrepreneurial action and the role of uncertainty in the theory of the entrepreneur," *Academy of Management Review*, vol. 31, pp. 132–152, 2006.

[47] Z. Chen and D. Klahr, "All other things being equal: acquisition and transfer of the control of variables strategy," *Child Development*, vol. 70, pp. 1098–1120, 1999.

[48] S. T. Levy and U. Wilensky, "Mining students' inquiry actions for understanding of complex systems," *Computers and Education*, vol. 56, pp. 556–573, 2011.

[49] J. C. Neubert, A. Kretzschmar, S. Wüstenberg, and S. Greiff, "Extending the assessment of complex problem solving to finite state automata - Embracing heterogeneity," *European Journal of Psychological Assessment*, vol. 31, Article ID a000224, pp. 181–194, 2015.

[50] A. Kretzschmar, L. Hacatrjana, and M. Rascevska, "Re-evaluating the psychometric properties of MicroFIN: A multidimensional measurement of complex problem solving or a unidimensional reasoning test?" *Psychological Test and Assessment Modeling*, vol. 59, no. 2, pp. 157–182, 2017.

[51] Y. Baggen, J. K. Kampen, A. Naia, H. J. A. Biemans, T. Lans, and M. Mulder, "Development and application of the opportunity identification competence assessment test (OICAT) in higher education," *Innovations in Education and Teaching International*, 2017.

[52] D. R. DeTienne and G. N. Chandler, "Opportunity identification and its role in the entrepreneurial classroom: a pedagogical approach and empirical test," *Academy of Management Learning and Education*, vol. 3, pp. 242–257, 2004.

[53] J. P. Guilford, *The Nature of Human Intelligence*, McGraw-Hill, New York, NY, USA, 1967.

[54] K. A. Hallgren, "Computing inter-rater reliability for observational data: an overview and tutorial," *Tutorials in Quantitative Methods for Psychology*, vol. 8, no. 1, pp. 23–34, 2012.

[55] A. Buchner and J. Funke, "Finite-state automata: Dynamic task environments in problem-solving research," *The Quarterly Journal of Experimental Psychology*, vol. 46, Article ID 14640749308401068, pp. 83–118, 1993.

[56] S. Greiff, S. Wüstenberg, J. Funke, and S. Wüstenberg, "Dynamic problem solving a new assessment perspective," *Applied Psychological Measurement*, vol. 36, Article ID 0146621612439620, pp. 189–213, 2012.

[57] J. C. Müller, A. Kretzschmar, S. Greiff, and J. C. Müller, "Exploring exploration: inquiries into exploration behavior in Complex Problem Solving assessment," in *Proceedings of the 6th International Conference on Educational Data Mining*, S. K. DMello, R. A. Calvo, and A. Olney, Eds., pp. 336-337, Memphis, Tenn, USA, 2013.

[58] A. Kretzschmar, J. C. Neubert, S. Wüstenberg, and S. Greiff, "Construct validity of complex problem solving: A comprehensive view on different facets of intelligence and school grades," *Intelligence*, vol. 54, pp. 55–69, 2016.

[59] M. C. Rodriguez and Y. Maeda, "Meta-analysis of coefficient alpha," *Psychological Methods*, vol. 11, no. 3, pp. 306–322, 2006.

[60] S. Greiff, A. Fischer, M. Stadler, S. Wüstenberg, and S. Wüstenberg, "Assessing complex problem-solving skills with multiple complex systems," *Thinking and Reasoning*, vol. 21, pp. 356–382, 2014.

[61] H. W. Marsh and R. O'Neill, "Self-description questionnaire III: The construct validity of multidimensional self-concept ratings by late adolescents," *Journal of Educational Measurement*, vol. 21, pp. 153–174, 1984.

[62] A. Ardichvili, R. Cardozo, and S. Ray, "A theory of entrepreneurial opportunity identification and development," *Journal of Business Venturing*, vol. 18, no. 1, pp. 105–123, 2003.

[63] R Core Team, *R: A Language and Environment for Statistical Computing*, R Foundation for Statistical Computing, Vienna, Austria, 2016.

[64] S. van Buuren and K. Groothuis-Oudshoorn, "Mice: multivariate imputation by chained equations in R," *Journal of Statistical Software*, vol. 45, no. 3, pp. 1–67, 2011.

[65] A. Robitzsch, S. Grund, and T. Henke, *Miceadds, Some Additional Multiple Imputation Functions, Especially for mice*, 2017, https://CRAN.R-project.org/package=miceadds.

[66] J. W. Cohen, *Statistical Power Analysis for The Behavioral Sciences*, Erlbaum, Hillsdale, NJ, USA, 1988.

[67] G. E. Gignac and E. T. Szodorai, "Effect size guidelines for individual differences researchers," *Personality and Individual Differences*, vol. 102, pp. 74–78, 2016.

[68] M. M. Gielnik, A.-C. Krämer, B. Kappel, M. Frese, and A.-C. Krämer, "Antecedents of business opportunity identification and innovation: Investigating the interplay of information processing and information acquisition: Business opportunity identification," *Applied Psychology: An International Review*, vol. 63, pp. 344–381.

[69] A. Rauch and M. Frese, "Let's put the person back into entrepreneurship research: A meta-analysis on the relationship between business owners' personality traits, business creation, and success," *European Journal of Work and Organizational Psychology*, vol. 16, no. 4, pp. 353–385, 2007.

[70] P. M. Podsakoff, S. B. MacKenzie, J.-Y. Lee, and N. P. Podsakoff, "Common method biases in behavioral research: a critical review of the literature and recommended remedies," *Journal of Applied Psychology*, vol. 88, no. 5, pp. 879–903, 2003.

[71] J. C. Short, D. J. Ketchen, J. G. Combs, and R. D. Ireland, "Research methods in entrepreneurship: opportunities and challenges," *Organizational Research Methods*, vol. 13, Article ID 1094428109342448, pp. 15-10, 2010.

[72] R. A. Baron and M. D. Ensley, "Opportunity recognition as the detection of meaningful patterns: Evidence from comparisons of novice and experienced entrepreneurs," *Management Science*, vol. 52, pp. 1331–1344, 2006.

[73] S. A. Shane, *A general theory of entrepreneurship: The individual-opportunity nexus*, Elgar, Cheltenham, UK, 2007.

[74] T. B. Ward, "Cognition, creativity, and entrepreneurship," *Journal of Business Venturing*, vol. 19, no. 2, pp. 173–188, 2004.

[75] J. Funke, "Complex Problem Solving," in *Encyclopedia of the Sciences of Learning*, M. Seel, Ed., pp. 682–685, Springer, Boston, MA, USA, 2012.

[76] K. Kraiger, J. K. Ford, and E. Salas, "Application of cognitive, skill-based, and affective theories of learning outcomes to new methods of training evaluation," *Journal of Applied Psychology*, vol. 78, no. 2, pp. 311–328, 1993.

[77] P. Warr and D. Bunce, "Trainee characteristics and the outcomes of open learning," *Personnel Psychology*, vol. 48, pp. 347–375, 1995.

[78] H. M. Neck and P. G. Greene, "Entrepreneurship Education: Known Worlds and New Frontiers," *Journal of Small Business Management*, vol. 49, pp. 55–70, 2011 (Chinese).

[79] F. E. Weinert, "Concept of competence: A conceptual clarification," in *Defining and Selecting Key Competencies*, D. S. Rychen and L. H. Salganik, Eds., pp. 45–65, Hogrefe, Seattle, WA, USA, 2001.

[80] B. E. Bakken, *Learning and transfer of understanding in dynamic decision environments*, Massachusetts Institute of Technology, 1993.

[81] L. S. Fuchs, D. Fuchs, K. Prentice et al., "Explicitly teaching for transfer: Effects on third-grade students' mathematical problem solving," *Journal of Educational Psychology*, vol. 95, no. 2, pp. 293–305, 2003.

[82] E. Jensen, "Learning and transfer from a simple dynamic system," *Scandinavian Journal of Psychology*, vol. 46, no. 2, pp. 119–131, 2005.

[83] A. Kretzschmar and H.-M. Süß, "A Study on the Training of Complex Problem Solving Competence," *Journal of Dynamic Decision Making*, vol. 1, pp. 16-10, 2015.

[84] W. Putz-Osterloh and M. Lemme, "Knowledge and its intelligent application to problem solving," *German Journal of Psychology*, vol. 11, pp. 286–303, 1987.

[85] W. Tomic, "Training in inductive reasoning and problem solving," *Contemporary Educational Psychology*, vol. 20, no. 4, pp. 483–490, 1995.

[86] S. Greiff, S. Wüstenberg, B. Csapó et al., "Domain-general problem solving skills and education in the 21st century," *Educational Research Review*, vol. 13, pp. 74–83, 2014.