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TESTING 21ST CENTURY SKILLS IN A CHANGING NATURE OF WORK: THE CONSTRUCT VALIDITY OF COMPLEX PROBLEM SOLVING AND ORGANIZATIONAL LEARNING

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Summary

This thesis investigates the empirical assessment and construct validity of complex problem-solving (CPS) skills and organizational learning (OL) in a changing nature of work. Technological and organizational change enlarge the gap between the type of employee required by the market and the employees who are actually being provided by higher education as human capital to the market. Two constructs, CPS and OL, might strengthen human capital to close the emerging gap in a changing nature of work.

CPS describes a set of higher-order thinking skills that enables individuals to solve dynamic, new, and interactive problems, whereas OL is the competency of an organization to enable its individuals and groups to explore new ways of working and to exploit established ways of working. Previous research in education emphasizes, how important CPS is for individuals to succeed in their increasingly complex lives. Simultaneously, previous research in organizations points out, how relevant OL is for whole organizations to not only succeed in their running business, but also to sustain success in their future business in complex, competitive, and dynamically changing markets. Despite their promising roles for success of individuals and organizations in the complex world of the 21st century, comprehensive empirical assessments of CPS and OL only play a negligible role in organizations. This is quite different from the role CPS already plays in education, where two current computer-based CPS assessments, MicroDYN and MicroFIN, have already a proven record of theoretical and empirical validity to predict success. On the side of OL, a comprehensive assessment, the Strategic Learning Assessment Map (SLAM), has been repeatedly shown to predict success in

business by OL of and between individuals, their groups, and organization, but the SLAM remains widely unkown in practice. If researchers were further on reluctant to use these tools in organizations, they could miss out on promising information that has the potential to strengthen human capital by fortifying the understanding of the roots and interplay of occupational and organizational success in the 21st century.

However, as much as CPS is valid in education, it remains yet empirically unclear whether CPS is relevant for success in occupations, instead of being an artifact of general mental ability (GMA) and education, two closely related constructs, and two of the strongest and best researched predictors of occupational success. Likewise, if CPS and its assessments via MicroDYN and MicroFIN are truly relevant in a changing world of work, CPS should predict success in areas of work that are particularly target of technological and organizational change, such as entrepreneurship. On the side of OL, the SLAM has unequivocally been tested in managers, but it remains unclear, whether the SLAM still represents a valid construct if addressed to a diverse set of employees, instead of managers only.

This thesis therefore attempts to answer three complementary research questions targeting the sound assessment and construct validity of CPS and OL at the 21st century workplace. Identifying CPS as a construct critical for occupational success, OL as a construct critical for organizational success, and establishing both as relevant in organizational research and practice would only be warranted, if each construct is comprehensively and reliably measured, empirically distinct from conceptually related constructs, and statistically predictive of relevant outcomes.

Research Question 1 (RQ1) therefore asks with a focus on individual skills whether CPS is relevant for predicting[1] success in the workplace, even above and beyond well-established factors of occupational success. RQ2 asks whether CPS is relevant for predicting success in the early stages of entrepreneurship, even above and beyond a selection of well-established factors of entrepreneurial success. Extending the scope of this thesis to OL as a source of organizational success, RQ3 asks whether OL is distinct for individuals, their groups, and organization and associated with indicators and outcomes of a learning organization. Validating OL in the SLAM for a first time in a sample across the range of occupations opens avenues for future research on the interplay of different sources of success, such as CPS for the individual and OL for the organization. This interplay is a promising avenue for the future of CPS research, as skills that make individuals potentially successful in a changing world of work are also likely to help organizations to be successful in their business in times of accelerating technological and organizational change.

This thesis is informed by theory of social development and human capital in the introduction, occupational gravitation in RQ1, entrepreneurial cognition in RQ2, and organizational learning in RQ3, relies on current computer-based assessments of CPS in RQ1 and 2, a paper and pencil tests of OL in RQ3, and applies multivariate methods in structural equation modeling in RQ1 and 3 and multiple regressions in RQ2. On this backdrop, this thesis is the first extensive investigation of the empirical assessment of

[1] RQ1 and RQ2 ask about predictions merely in the statistical sense of explained variance in the success variables, because this thesis uses a cross-sectional research design that does not allow for temporal predictions or conclusions about of causality.

CPS and OL in the changing world of work and considerably extends the research on their validity.

More specifically, this thesis investigates (RQ1) for the first time in a workplace sample (N = 671) across nations, industries, and occupations whether CPS is relevant in the 21st century work context, in particular even above and beyond GMA and the acquired level of education, two of the strongest and best researched predictors. A pilot study on N = 245 employees of a German automobile manufacturer preceded the main study in RQ1. This is followed by (RQ2) a study of CPS in the dynamic context of entrepreneurship. Testing 113 Dutch entrepreneurship students, this study relates CPS for the first time to the early entrepreneurial activity of identifying business opportunities beyond their prior knowledge and problem-solving self-concept. Given that also whole organizations have to readily respond to a changing nature of work, this thesis investigates (RQ3) in a diverse employee sample (N = 434) whether OL in the SLAM is empirically distinguishable on the level of the individual, the group, and the organization, and whether OL associates with the conceptually close indicators and outcomes of a learning organization, including education, job satisfaction, and innovative behavior on the job.

Chapter 1 introduces the societal need in a changing nature of work that motivated this research, as well as the theoretical and empirical foundation that informed this research. This detailed section is followed by a brief description of the four empirical papers on RQ1-3. Constituting the main body of this thesis, these full papers are located in full length in the Chapters 2 to 5. Except Paper 1, which was published in 2015 in the *International Journal of Lifelong Education*, all Papers are currently under peer-review in the *Journal of Vocational Behaviour* (Paper 2), Education Research International (Paper 3), and the Journal of Knowledge Management (Paper 4). Chapter 1 and Chapter 6 refer to two additionally published papers, both conceptual, which further inform this thesis. These works are listed as “additional papers” of the author of this thesis on page 12.

The first two papers (cf. Chapter 2 + 3) introduce the assessment of CPS to the context of work. These papers contribute to research on CPS and CPS assessment as they show with comprehensive methods an incremental contribution of CPS to explain success in the changing nature of work.

The third paper (cf. Chapter 4) introduces the assessment of CPS to the dynamic and technology-infused context of entrepreneurship. This paper contributes to research on CPS and CPS assessment as it shows with comprehensive methods an incremental contribution of CPS to explain activities in the early stages of entrepreneurship, an area of work that is particularly complex.

The fourth paper (cf. Chapter 5) applies a comprehensive assessment of firms' OL for a first time to employees, instead of managers only. This paper contributes to research on OL and its assessment in the SLAM as it attempts to validate for a first time a short form of the SLAM in a diverse employee sample.

Chapter 6 provides a general discussion of this research and its implications. Paper 1, Paper 2, and Paper 3 show that CPS is reliably measured, empirically distinguished from related constructs, and incrementally predictive of relevant outcomes in the context of work. Together, they support CPS as a valid construct that is critical for occupational success. Paper 4 gives preliminary and restricted evidence that the SLAM can validly assess OL in the view of employees. Taken together, whether to apply the

SLAM on employees is warranted requires further research, which then also can address a possible interplay between CPS and OL as sources of success of the individual and the organization.

After this summary of results, strengths of the papers are outlined and shortcomings combined with an outlook for future research are discussed. In summary, this thesis advances the empirical understanding of two construct that are considered critical to master work in times, when technology and organizational change are racing ahead and education is under increasing pressure to provide the required human capital.

Contents

Publication list for this cumulative dissertation

Paper 1:

Mainert, J., Kretzschmar, A., Neubert, J. C., & Greiff, S. (2015). Linking complex problem solving and general mental ability to career advancement: Does a transversal skill reveal incremental predictive validity? *International Journal of Lifelong Education*, *34*, 393–411. doi: 10.1080/02601370.2015.1060024

Paper 2:

Mainert, J., Niepel, C., Murphy, K. R., & Greiff, S. (2017). The Incremental Contribution of Complex Problem Solving Skills in Predicting Occupational Gravitation. *Journal of Vocational Behaviour*, submitted.

Paper 3:

Baggen*, Y., Mainert*, J., Kretzschmar, A., Niepel, C., Lans, T., Biemans, H., & Greiff, S. (2017). Complex Problems in Entrepreneurship Education: Examining Complex Problem Solving in the Application of Opportunity Identification. *Special Issue "Entrepreneurship Education with Impact: Opening the Black Box" of the journal Education Research International,* submitted.

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Paper 4:

Mainert, J., Niepel, C., Lans, T., & Greiff, S. (2017). How employees perceive organizational learning: Construct validation of the 25-item short form of the Strategic Learning Assessment Map (SF-SLAM). *Journal of Knowledge Management*, submitted.

Additional Papers

Baggen, Y., Mainert, J., Lans, T., Biemans, H. J. A., Greiff, S., & Mulder, M. (2015). Linking complex problem solving to opportunity identification competence within the context of entrepreneurship. *International Journal of Lifelong Education*, *34*, 412–429. doi: 10.1080/02601370.2015.1060029

Neubert, J. C., Mainert, J., Kretzschmar, A., & Greiff, S. (2015). The Assessment of 21st Century Skills in Industrial and Organizational Psychology: Complex and Collaborative Problem Solving. *Industrial and Organizational Psychology: Perspectives on Science and Practice*, *8*, 1–31. doi: 10.1017/iop.2015.14

1

Introduction

1.1 Introduction

In the course of technological and organizational change, tasks at work have shifted to become less routine and more complex - affecting skill requirements, skill measurements, and their conceptualizations. This thesis sets out to advance research on skills in the changing nature of work with vital theoretical perspectives on complex problem-solving skills (CPS; Frensch & Funke, 1995; Osman, 2010) and organizational learning (OL; March, 1991), frameworks for their assessment, innovative instruments, and –at the core of this thesis – their empirical validation. This thesis describes, how skill requirements have been changing in ways that enlarge the gap between the type of employee required by the market and the employees who are actually being provided by higher education, and how two constructs, CPS and OL, might contribute to close this gap in the changing nature of work.

The nature of work changes rapidly and individuals are supposed to accomplish more complex tasks than ever, since computers take over their routines (Autor et al., 2003; Cascio, 1995) and other routines are being offshored to low wage countries (e.g., Autor, Katz, & Kearney, 2006; Baumgarten, Geishecker, & Görg, 2010; Becker et al., 2013). Both, computers and offshoring sophisticate work in ways that what individuals largely do does not follow rules that computers could perform or requires higher education than offshore economies provide (Autor et al., 2003; Levy & Murnane, 2004).

Drucker (1954, p. 22) predicted that computers would do rule-based, routine work, so that complex, nonroutine work requiring higher education and lifelong learning would remain for people. Following this logic, the job market would nowadays require much more people than ever to *manage* what computers should do, and to *do* what computer cannot do. The Current Population Survey for the US (Economic Policy Institute, 2016a) supports Drucker's (1954) prediction: Over the last decades, the job market had been demanding more and more educated people who could handle complex tasks that require learning on all levels of an organization as is the case for technicians, professionals, managers and many more. This expansion of higher level occupations is ongoing (Acemoglu & Autor, 2011; Autor & Dorn, 2013) and the European Centre for the Development of Vocational Training [CEDEFOP] (European Center for the Development of Vocational Training, 2011, p. 14) has observed similar trends for Europe. In this current world of work with new and ever changing technologies, organizations, and workplaces, CPS and OL become increasingly critical for occupational and organizational success (Bontis, Crossan, & Hulland, 2002; Neubert, Mainert, Kretzschmar, & Greiff, 2015).

CPS is considered important in everyday life (Funke, 2010) and has been identified by leading scientific and policy agencies as critical for success in one's education, work, and other areas of adult responsibility in the 21st century (National Research Council, 2012; Organization for Economic Co-operation and Development [OECD], 2013). CPS involves solving genuinely new problems that do not have well understood, rule-based solutions. Examples include running new industrial equipment with nonintuitive, new control desks, learning new project and HR management software in fluctuating, digital translation teams, diagnosing an illness of a patient with symptoms that do not fit computer-based diagnostics, or repairing a bad-running car that the board computer diagnosed intact.

OL is considered important for an organization to stay atop in rapidly changing markets, where organizations are in demand of ambidextrous activities of exploring and learning new ways while concurrently exploiting established ways of working (Crossan, Lane, & White, 1999; March, 1991; Wong & Huang, 2011). OL takes place, when employees build a shared understanding of a complex task with their co-workers, when a group of engineers convince their management to redesign their control desks according to their needs as experts, or when managers motivate their employees to follow the best practice in the organization.

Skills that make individuals successful in their jobs are likely to be the same ones that help organizations to be successful in their endeavors (Judge, Higgins, Thoresen, & Barrick, 1999). That is, organizations that rely on their OL activities as a source of sustained success through learning in changing markets are likely to take advantage of those individuals, who can solve complex problems. However important and established CPS and OL might conceptually be, the greatest next challenge remains their empirical validation at the workplace by means of comprehensive assessments, before a joint research of CPS and OL can be kicked-off.

Assessments are key to capture, establish, and distinguish underlying constructs from theory for the purpose of their empirical validation (Hodgkinson & Healey, 2008). To this end, assessments serve to examine a construct's ultimate criteria of importance for organizations: Whether it is a distinct construct that predicts something meaningful (De Fruyt, Wille, & John, 2015). While there are extensive validations of CPS in education (e.g., Greiff, Fischer, Wüstenberg, Sonnleitner, Brunner, & Martin, 2013) and at least some validations of OL in management (e.g., Bontis et al., 2002), there is barely any such effort in and across the range of occupations.

Surprisingly, neither the assessment of CPS, nor the assessment of OL receive the attention in organizational research and practice that their importance would require. That is, to speak of CPS and OL as constructs critical for occupational and organizational success would only be warranted, if each is comprehensively and reliably measured, empirically distinct from conceptually related constructs, and predictive of relevant outcomes in ways that theory would suggest.

One step further, if assessments of CPS and OL proved to be valid for workers as they are for students in the case of CPS and managers in the case of OL, then future research could be set on solid grounds to investigate the interplay of different factors of success across the levels of an organization, such as CPS for the individual and OL for the organization. Skills of the individual might help organizations to succeed, as much as they make individuals successful (Judge et al., 1999). Vice versa, OL activities of the organization might help individuals to develop skills to solve complex problems and become more successful on the job.

This thesis will address the construct validity of CPS and OL at the 21st century workplace in order to pave the way for increasing attention on CPS and OL in organizational research and future research on their interplay. The aim of this thesis is to validate CPS and OL as relevant constructs in the changing nature of work on the basis of comprehensive assessments along three research questions in four corresponding papers:

Research Question 1: Is CPS relevant for predicting success in the workplace, even above and beyond well-established factors of occupational success?

As continuous technological and organizational changes create an increasingly dynamic, nonroutine, and interactive working environment in the 21st century, jobs increasingly demand higher-order thinking skills to plan, actively explore, execute, and monitor one's work tasks (Autor, Levy, & Murnane, 2003; Cascio, 1995; Neubert, Mainert, Kretzschmar, & Greiff, 2015). CPS is an important representative of these higher-order thinking skills that are considered critical for success (National Research Council, 2012; Organization for Economic Co-operation and Development [OECD], 2013). Correspondingly, recent research in the field of education revealed that CPS is relevant for success in a wide range of outcomes even above and beyond the well-established and closely related general mental ability (GMA; Sonnleitner, Keller, Martin, & Brunner, 2013; Stadler, Becker, Greiff, & Spinath, 2015). Since these research results were derived from educational contexts, it remains largely unclear whether CPS is also relevant for predicting success in work contexts (see, Danner et al., 2011; Ederer, Nedelkoska, Patt, & Castellazzi, 2015; Mainert, Kretzschmar, Neubert, & Greiff, 2015), in particular beyond established and associated factors such as GMA or education (Neubert, Mainert, et al., 2015). Paper 1 and Paper 2 aim to fill this research gap. Paper 2 investigates for the first time in a workplace sample ($N = 671$) across nations, industries, and occupations whether CPS is relevant in the work context, in particular even above and beyond GMA and the acquired level of education, two of the strongest and best researched predictors of occupational success (e.g., Gottfredson, 2002; Ng, Eby, Sorensen, & Feldman, 2005; Schmidt & Hunter, 2004, 1998). Paper 1 was a pilot a study on $N = 245$ employees at a large German automobile company that prepared Paper 2.

Research Question 2: Is CPS relevant for predicting success in the early stages of entrepreneurship, even above and beyond well-established factors of entrepreneurial success?

From the earliest stages of entrepreneurship on, when individuals identify business opportunities in continuous technological and organizational change, they must be able to solve complex problems (Baggen et al., 2015). In fact, entrepreneurs work in an extremely dynamic, nonroutine, and interactive working environment of the 21st century that demands key efforts to solve complex problems (Nickerson & Zenger, 2004). However, empirical studies have not yet investigated CPS skills in the early stages of entrepreneurship. Previous research found evidence that CPS is related to performance in school (e.g., Greiff, Fischer, et al., 2013), university (Stadler et al., 2015), and the workplace (Danner et al., 2011; Ederer et al., 2015; Mainert et al., 2015). Extending the assessment of CPS to entrepreneurship, Paper 3 investigates whether CPS skills are relevant to master entrepreneurial activities to identify opportunities beyond the established constructs of prior knowledge and problem-solving self-concept. For this purpose, this paper presents an empirical study on University students that relates CPS to the identification of opportunities. For this paper, more than 100 masters' students were tested who took entrepreneurship or career development courses and mostly intended to start or get involved in a new venture. The objective was to ask: To what degree does CPS relate to opportunitiy identification?

Research Question 3: Is OL distinct on different levels of an organization, and associated with other indicators of a learning organization?

Organizations that operate in continuous technological and organizational change offer broader and more complex jobs to get the work done (Brynjolfsson & McAfee, 2016; Noe, Hollenbeck, Gerhart, & Wright, 2015). In this context, individuals more and more get their jobs done discretely and make their own decisions about what to learn and what not (Parker & Wall, 1998). What individuals learn can affect their organization's balance between explorative and exploitative learning activities, also termed ambidexterity (Tushman & O'Reilly, 1996). As ambidexterity is the source of a sustainable competitive advantage for profit and success in rapidly changing markets (Crossan & Berdrow, 2003), the perspective of employees on OL indicating ambidexterity increasingly matters. This paper investigates therefore for a first time in an employee sample ($N = 434$), whether OL that indicates ambidexterity can be reliably and validly assessed on the Strategic Learning Assessment Map (SLAM; Bontis, Crossan, & Hulland, 2002). The SLAM assesses OL on different levels, indicated by explorative and exploitative learning activities of and between individuals, groups, and their organization. The objective of this paper is to examine the SLAM whether its different levels of OL are empirically distinguishable in a diverse workplace sample and whether OL relates with conceptually close indicators and outcomes of a learning organization. Based on our own theorizing and previous literature (Bontis, 1999; Liu et al., 2002), these indicators include innovation-related learning activities, innovative behavior on the job, education, intelligence, and job performance.

Each paper addresses one of these research questions in the Chapters 2-5. Prior to that, an introduction to the constructs of CPS and OL as well as to their assessments is given in section 1.2 and 1.3. A preview of the four individual papers closes the introduction in section 1.4.

1.2 Complex Problem Solving (CPS)

1.2.1 The Construct of Complex Problem Solving

Buchner (cited in Frensch & Funke, 1995, p. 14) defines CPS as follows:

> “Complex problem solving (CPS) is the successful interaction with task environments that are dynamic (i.e., change as a function of 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.”

Complex problems share the ambiguity of how to approach the task and the lack of transparency of how the task variables function; that is, variables of a complex problem are interconnected, change dynamically over time and with interaction, and some variables might be relevant, while others are not, but non of these three aspects (i.e., connectivity, dynamics, and relevance) is obvious at the beginning (Fischer et al., 2012).

That is, CPS targets situations that are characterized as dynamic, nonroutine, and interactive, which have become a permanent aspect at many workplaces (e.g., Autor, Levy, & Murnane, 2003; Becker, Ekholm, & Muendler, 2013; Goos, Manning, & Salomons, 2009) thus requiring the complex interplay of basic cognitive and noncognitive processes and higher-order thinking skills (e.g., Fischer, Greiff, & Funke, 2012; Funke, 2010; Greiff, Fischer, Stadler, & Wüstenberg, 2014). With a focus on the latter (i.e., higher-order thinking skills), CPS is geared toward problem situations across content domains that feature a multitude of interrelated and varying elements that must be actively explored to find and apply a solution, thus requiring knowledge acquisition and application of this knowledge (e.g., Greiff, Holt, & Funke, 2013; Funke, 2010; Gonzalez, Vanyukov, & Martin, 2005; Osman, 2010).

These two conceptually central CPS components, knowledge acquisition and knowledge application, describe closely intertwined cognitive processes that matter for success across different life domains, such as work and education (Funke, 2001). They root back to theory of sound problem representation in early Gestalt psychology (Duncker, 1945), current cognitive psychology (Markman, 1999), and research on fast and frugal decision-making (Gigerenzer & Brighton, 2009; Novick & Bassok, 2005; Osman, 2010). Essentially, acquiring new knowledge to understand a novel task and applying this knowledge to control this task are the two necessary steps to master dynamic, nonroutine, and interactive problem situations which increasingly occur at the workplace (see above, e.g., Autor et al., 2003; Greiff et al, 2014).

1.2.2 The Process of Complex Problem Solving

The domain-general processes knowledge acquisition and knowledge application lead to knowledge structures about how a previously unknown system works and how to seize control within such a system (Osman, 2010). To this end, the problem solver ideally acquires new knowledge, builds an internal problem representation, applies the newly acquired knowledge, and strategically interacts with her nonroutine, dynamically changing task (Novick and Bassok, 2005).

In such a task, knowledge acquisition begins as the solver retrieves information; it continues as she reduces the information in order to keep a set of relevant pieces that lead her to an actionable problem representation. Markman (1999) emphasizes how important a sound and actionable problem representation is for simplifying complex task environments. Before a solution is found, this representation contains problem elements (i.e., the represented world) and processes by which these elements can be related to each other (i.e., the representing world; Markman, 1999). In order to find a solution, the connections between the elements (the representing world) need to be established by acquiring new knowledge and applying this knowledge to solve the problem. As knowledge acquisition precedes knowledge application (and vice versa, knowledge application leads to the disclosure of new information), these processes mutually depend on each other. Together, they constitute the core of the domain-general construct of CPS (Greiff, Wüstenberg, et al., 2013; Greiff, Holt, & Funke, 2013). Knowledge acquisition and knowledge application have been repeatedly validated as distinguishable CPS components in empirical research (e.g., Fischer et al., 2012; Funke, 2001; Wüstenberg et al, 2012), and together they indicate that CPS (for details, see Greiff, Wüstenberg et al., 2013) is likely to be critical for success in the workplace (e.g., Neubert, Mainert, Kretzschmar, & Greiff, 2015).

1.2.3 Complex Problem Solving in the Workplace

CPS has in fact been identified by leading scientific and policy agencies as critical for success in the workplace of the 21st century (National Research Council, 2012; OECD, 2013b), in large part because they are characterized by an increasing amount of dynamic, interactive, and nonroutine tasks and a decreasing amount of well-defined organizational practices and routines (e.g., Middleton, 2002). That is, a high level in CPS skills are thought to better equip students for their future work lives in terms of dealing with increasingly dynamic, nonroutine, and interactive tasks on the job.

Many jobs require incumbents to solve complex problems. For instance, operating demanding machinery in engineering or managing a translation project in a digital team with a broad set of rules and patterns requires cognitive ability to fulfill associated cognitive information processing demands and also requires higher educational levels to bring in the necessary knowledge base. But if the machinery improves, adds, and alters triggers, functions, and settings, and if the translation project gains and loses team members, and updates and substitutes software and management procedures, then dynamics and interactions are more likely to be important determinants of success than working within the constraints of existing rules and patterns.

According to the O*NET (2016b) summary report for industrial engineers, incumbents not only record and maintain routine machinery (often with the aid of robots and computers), but are also in demand to operate, maintain, and repair advanced, previously unknown, and varying machinery, and deal with extensive, but at times cumbersome electronic assistant systems that do not build on their routines or knowledge (O*Net, 2016b). Similarly, managers of a translation project are not only involved in text translation and HR tasks, but are also in demand to coordinate digital teams of changing subcontractors and handle permanently improving translation and HR software (O*Net OnLine, 2016a). This type of tasks lacks obvious rules and patterns that lead to desirable outcomes, for example, on how to successfully repair new, but malfunctioning industrial equipment or on how to best instruct and manage new and varying digital team members of different ethnicity, educational levels, and experience. Knowledge acquisition manifests in actively exploring and generating new information about how to handle nonintuitive, new control desks in engineering, or how to use new project and HR management software in fluctuating, digital translation teams. Knowledge application manifests in applying newly generated information to control changing technology, teams, and procedures toward the task accomplishment.

1.2.4 The Measurement of CPS

Computerized measures of CPS have been included in what is arguably the most important large-scale assessment worldwide, the Programme for International Student Assessment (PISA). The 2012 PISA cycle assessed for the first time CPS skills of tens of thousands of 15-year-old students in 44 countries and economies worldwide using a similar design to the tests used in this thesis, administered to those, who represented the next generation of workers (i.e., 15-year-old students; OECD, 2012, 2014).

In PISA, as well as in Paper 1, Paper 2, and Paper 3 of this thesis CPS was measured in a number of short problem tasks that build on the concept of Microworlds. Microworlds are empirical realizations to assess CPS skills on computers (Gonzalez, Vanyukov, & Martin, 2005). Microworlds are simulations of complex problems that have been constantly refined in the last decades to allow a detailed and psychometrically sound task analyses of knowledge acquisition and knowledge application (Greiff, Wüstenberg, & Funke, 2012; see section 1.2.1).

Two of the most recent Microworlds, MicroDYN and MicroFIN, are based on the multiple complex systems (MSC; Greiff, Fischer, et al., 2014) using linear structural equations (LSE) in MicroDYN and finite state automata (FSA; Buchner & Funke, 1993) in MicroFIN. While LSE describes relations between quantitative variables, for example, the influence of training intensity on speed and accuracy in sports, FSA describes relations between qualitative variables, for example, the differing cleanliness of laundry triggered by the chosen washing program. Both MSC frameworks, LSE and FSA, consist of entire batteries of relatively short CPS tasks with varying difficulties and semantics that have consistently revealed high reliability and validity in educational contexts Grei(Greiff et al., 2012; Neubert, Kretzschmar, Wüstenberg, & Greiff, 2014; Schweizer, Wüstenberg, & Greiff, 2013; Sonnleitner, Keller, Martin, & Brunner, 2013). Alternative assessments consist of only a single task (e.g., Tailorshop; Funke, 2003). Single task designs bear various psychometric problems ranging from a lack of variation in task difficulty, low reliability, and heavily compounded performance due to a single random error (see Greiff et al., 2014). In order to ensure reliable and valid assessments, this thesis' empirical studies in Paper 1, Paper 2, and Paper 3 were conducted with the MSC frameworks, LSE and FSA.

MicroFIN is the most recent one of the employed fully computer-based CPS assessments that has been empirically validated (Neubert et al., 2014). It features multiple, dynamic tasks on the basis of FSA. FSA tasks have been found to facilitate a greater heterogeneity than previous instruments (e.g., Greiff et al., 2012; Sonnleitner et al., 2012), share a general layout of input variables that influence output variables, and are in accordance with the theoretical understanding of CPS as outlined in section 1.2.1. That is, the test items change dynamically with the user's interaction and the underlying relationships between input and output are not clear at the onset (Fischer et al., 2012).

For instance, users of MicroFIN face the challenge of planning a city while considering the needs of very different interest groups ("Plan-o-Mat" task; see Figure 4). The goal in this task is to achieve well being through a balance the interests of various parties (e.g., families and industries) by improving their locations in the urban landscape.

The parties' neighbourhood lead to discrete states of well-being, which can 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 vs. Rock'n'Roll), price level, and atmosphere (indoor vs. outdoor), or (b) the challenge of successfully harvesting a new kind of pumpkin that varied according to the season and the amount of fertilizer.

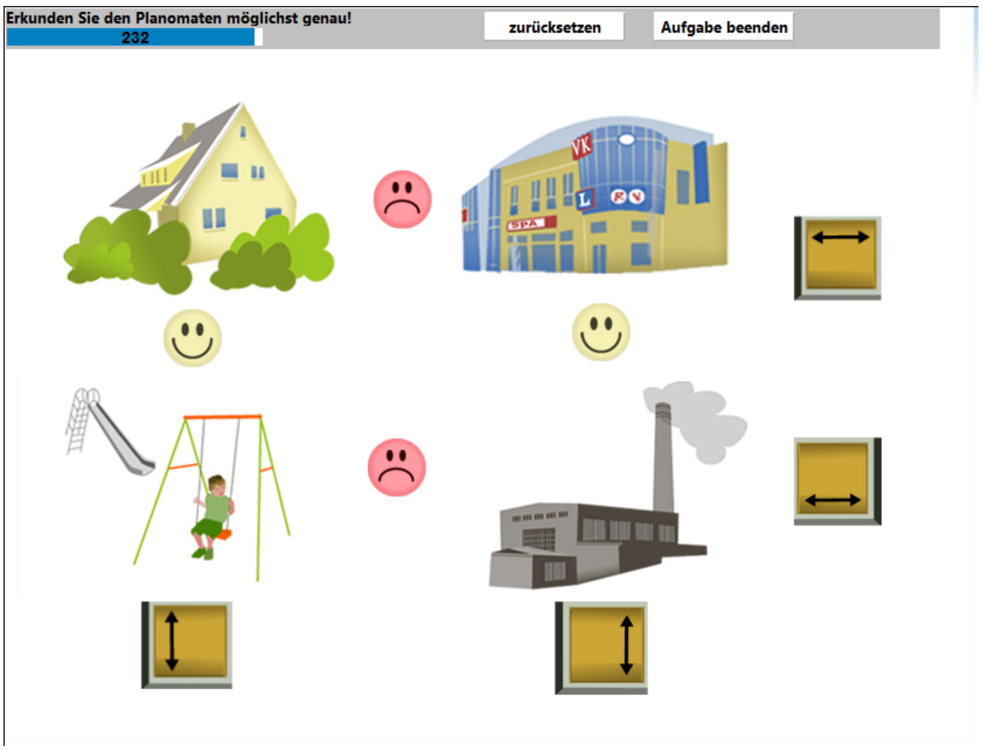

Figure 4. Screenshot of the MicroFIN item “Plan-o-mat” (Neubert et al., 2014). Problem solvers have to balance the interests of various parties in a city by making alterations in the urban landscape. The keys for altering the location of the interest groups are located along the bottom and the right side. In principle, two stakeholders change places when triggered. A city mall and a factory are situated on the right side, and a family home and a playground are situated on the left side. Between these parties, smiley faces are presented to indicate the atmosphere. The problem solver has to acquire knowledge about how to

change the atmosphere (knowledge acquisition) and has to find one of several optimal setups (knowledge application).

Two items per task ask participants to explore several states and relations, and from there, to derive the causal structure of the task (i.e., knowledge acquisition). Subsequently, one more item per task ask participants to apply their knowledge to manipulate each task toward 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 takes approximately 5 min to complete and contributes to a *general* CPS performance score. The corresponding Paper 1, Paper 2, and Paper 3 of this thesis both contain more detailed descriptions of the design and scoring, as well as an introduction of the LSE approach in MicroDYN. While the construct of CPS describes skills on the individual level, the next section introduces OL as a construct of learning in organizations spanning from the individuum, over groups and towards the organization.

1.3 Organizational learning (OL)

As CPS is considered a factor of success for individuals in the workplace of the 21st century, OL is considered as a promising response of organizations to their need for strategic renewal in the changing nature of work (Crossan & Berdrow, 2003). In contexts of change, organizations need strategic renewal in order to anticipate future events around new product developments, changes in job descriptions, technological advances, market trends, and so forth. Building channels for OL to exchange ideas, viewpoints, and procedures triggers a virtuous cycle of strategic renewal through multilateral knowledge transfer from the individual to its organization and back (Nonaka & Takeuchi, 1995).

OL has a strong scientific, mostly conceptual, basis departing from the organization as the level of analysis (Huber, 1991). Central is the notion that OL activities can be more explorative or more exploitative in nature (Crossan et al., 1999; March, 1991; Wong & Huang, 2011). Ideally, individuals, work groups, and whole organizations *explore* and learn new ways of working and concurrently *exploit* established ways of working in order to stay competitive in a changing nature of work. To be progressive and profitable at the same time in rapidly changing markets requires organizations to balance the learning activities of their employees and work groups between explorative and exploitative learning, because learning activities generally tie up limited human capital that might be needed elsewhere (March, 1991).

1.3.1 The Construct of OL

Exploration and exploitation are at the core of OL (Crossan et al., 1999). Explorative learning emphasizes search, variation, risk taking, experimentation, play, flexibility, and discovery. Exploitative learning is about refinement, choice, production, efficiency, selection, implementation, and execution. As learning activities in organizations can either be more explorative or more exploitative in nature, explorative and exploitative learning create conflict with respect to how individuals and groups should explore and learn new ways while concurrently exploiting established ways of working (Crossan et al., 1999; March, 1991; Wong & Huang, 2011).

A balance between explorative and exploitative learning provides a way to develop a sustainable competitive advantage for profit and success in the market in as much as this balance unveils new business opportunities that can be exploited to create value that others in the market cannot immediately capture or copy (Crossan & Berdrow, 2003). Tushman and O'Reilly (1996) labeled the desirable balance between explorative and exploitative learning ambidexterity. Taken together, ambidexterity is an organizational level construct that is central for the understanding, examination and management of learning in organizations and roots in theory of OL in a context of strategic renewal (Bontis et al., 2002; March, 1991).

1.3.2 Measurement of OL

The Strategic Learning Assessment Map (SLAM; Bontis et al., 2002) assesses OL activities that indicate ambidexterity on different levels of an organization. The SLAM captures the ambidexterity issue in organizations by emphasizing the interplay between learning activities at the individual level, the group level, and the organizational level. Individual learning, group learning, and organizational learning occur on these three ontological levels, and explorative learning and exploitative learning occur between the levels. In sum, the SLAM includes five learning dimensions on and between three organizational levels resulting in five subscales of individual learning, group learning, organizational learning, explorative learning, and exploitative learning.

The individual learning subscale assesses to what extend individuals build "a clear sense of direction in their work," "break out of traditional mindsets," have a "high energy level," and feel "a strong sense of pride in their work." Group learning captures to what extend groups build, for example, a "shared understandings of issues," “learn from each other,” have the "right people involved in addressing the issue," and hold "productive meetings." Learning on the organizational level captures to what extend organizations build competitive, adaptive, and innovative organizational systems, structures, and procedures that prepare the organization for the future, allowing employees to work efficiently and facilitating innovation. Explorative learning and exploitative learning assess to what extend individuals, groups, and the organization learn from each other across levels (Bontis et al., 2002, pp. 443–444). Explorative learning is also termed *feed-forward* learning and occurs, if individuals actively share new knowledge and insights with their work group and management in order to improve products, strategies, and procedures (Crossan et al., 1999). Vice versa, exploitative learning is interchangeably called *feedback* learning and occurs if product lines, strategies, and procedures guide individuals and groups in what they do, how they do it, and what they learn in the workplace (Crossan et al., 1999). The corresponding Paper 3 (section 4) of this thesis contains a detailed description of the questionnaire's design and scoring.

1.4 Preview of the individual papers

1.4.1 Preview of Paper 1 and Paper 2

As dynamic, nonroutine, and interactive demands on the job increasingly require complex cognition that is represented in CPS (Funke, 2010), we expect that CPS is related to job level, job complexity, and salary as markers of occupational success, and hypothesize that people with a higher level of CPS will be located higher up the occupational hierarchy. Simultaneously, the salary usually rises with the job level; thus higher CPS levels should be associated with higher salary. In addition, higher levels of CPS that enable incumbents to perform well on complex jobs with increasingly dynamic, nonroutine, and interactive tasks should be associated with higher levels of job complexity.

CPS is conceptually and empirically related to GMA and the level of education (Funke, 2010; Molnár et al., 2013; Schweizer et al., 2013), and there is ample evidence that GMA and the level of education are related to job level, job complexity, and salary (e.g., Burrus, Jackson, Xi, & Steinberg, 2013; Converse et al., 2014; Ng et al., 2005). Thus, beyond the assumed relations of CPS to job level, job complexity, and salary, it is crucial to determine whether the contribution of CPS in explaining these outcomes is incremental, instead of merely being an artifact of GMA and the level of education. Further, the skills required by jobs represent one of the key determinants of incumbents' salary, job level, and job complexity levels (Guthrie, Dumay, Massingham, & Tam, 2015; Jensen, 1980; Milkovich et al., 2013; Murphy, 1989). Therefore, if CPS skills are indeed required by jobs in the 21st century, CPS skills ought to make a unique contribution to the prediction of occupational success, or in other words, they ought to also make a unique contribution to explaining job levels, job complexity levels, and salary.

Informed by theory of occupational gravitation, CPS theory, and previous empirical findings on the role of CPS in educational context, we examined in Paper 1 and Paper 2 the hypothesis that CPS made an incremental contribution to occupational success after controlling for GMA (and education in Paper 2). As Paper 1 pilotted and prepared Paper 2, this thesis inequivocally focuses on Paper 2 in the Introduction and Discussion, referring the interested reader of Paper 1 directly to the published work on page xxx ff.

In Paper 2, $N = 671$ employees across jobs and educations in 21 EU-based organizations ($M_{Age} = 37.06$ years, $SD = 12.46$; 32.9% female) completed computerized tests of GMA and CPS and self-reports about job level, job complexity, and salary as indicators of occupational success. A regression model on the basis of latent structural equation modeling served to test H1: Measures of CPS will predict job complexity beyond GMA and the level of education. And H2: Measures of CPS will predict job level and salary beyond GMA and the level of education.

We found 4% and 8% of incrementally explained variance by CPS in job complexity and salary beyond GMA and education. We found no increment of CPS in predicting the job level. Taken together, CPS appears to be linked to job complexity and salary in a range of occupations, and this link cannot be explained as an artifact of GMA and education.

Although these findings are interesting and important for our understanding of CPS in occupational contexts, precaution is imperative towards several limitations. For example, the convenience sample, high rates of missings, a narrow GMA measure, and cross-sectional data restricted inferences and generalizability. As CPS occurs within these restrictions to be relevant for occupational success even beyond GMA and education, an implication for research and practice in personnel selection and development could be that CPS is a valuable complement measure over and above GMA and educational achievements to evaluate candidates and develop employees for complex positions. Taken together, this paper contributes to research on CPS and CPS assessment as it shows with comprehensive methods an incremental contribution of CPS to explain success in the world of work, where technology and organizational change are racing ahead.

1.4.2 Preview of Paper 3

This paper introduces the assessment of CPS to the dynamic and technology-infused context of entrepreneurship. In the early stages, entrepreneurs have to handle the complexity and dynamics of technological change in order to identify business opportunities. Theoretically, higher-order thinking skills, such as CPS, target the complexities and dynamics of early entrepreneurial challenges. Surprisingly, the assessment of these skills plays yet a negligible role in entrepreneurship research. Hence, we examined in this paper whether CPS predicts, how well individuals identify business opportunities beyond the factors prior knowledge and problem solving self-concept.

Informed by theory of entrepreneurial cognition, CPS theory, and CPS assessments of previous studies in educational context, we tested in this paper the hypothesis that CPS predicted opportunity identification even when controlling for established predictors from previous research.

To this end, we applied multiple regressions on data of 113 Dutch entrepreneurship students (M_{Age} = 23.55 years; *SD* = 2.00; 68.1% female). The computer-based test MicroFIN assessed participants' CPS skills. Questionnaires on 5-point-Likert-scales served to assess participants' prior knowledge and problem solving self-concept. A case-based test assessed, how well participants identified business opportunities.

In support of our hypothesis, CPS statistically predicted the identification of *concrete* business opportunities, explaining 5.9% incremental variance beyond prior knowledge and problem-solving self-concept. Despite a small effect size and non-siginificant results for predicting other aspects of opportunity identification, this is first empirical evidence for the role of CPS in the early entrepreneurial activities of identifying business opportunities. However, with the cross-sectional data at hand and in the absence of a GMA measure, which is closely related to CPS, conclusions about causality were as much impossible as conclusions about incremental contributions above GMA.

As CPS occurs in this paper to be at least to some extent relevant for early entrepreneurial activities of students in simulation tasks, future research should examine the role of CPS for the real-life performance of experienced entrepreneurs. This direction might further clarify whether and how CPS is involved in individual and interactive activities in the early stages of entrepreneurship. As a preliminary practical implication, assessing CPS skills in the entrepreneurial classroom could be a very first step towards weaving CPS into entrepreneurship education. Taken together, this paper contributes to research on CPS and CPS assessment as it shows with comprehensive methods an incremental contribution of CPS to opportunity identification in the early stages of an area of work that is strongly affected by the complex and rapidly developing technological advancements of our times.

1.4.3 Preview of Paper 4

This paper applies for a first time a comprehensive assessment of the ambidexterity issue in OL to employees across the board, instead of managers only. Originally, the Strategic Learning Assessment Map (SLAM) assesses explorative and exploitative learning that address the ambidexterity issue in OL by asking managers. However, in a rapidly changing nature of work, where employees increasingly make their own decisions, the employees' view on OL increasingly matters. Hence, we investigated in this paper the validity of a short-form SLAM (SF-SLAM) by asking employees.

This paper is informed by theory of OL in a context of strategic renewal of organizations. On this backdrop, we examined in this paper whether the SLAM is construct valid even if addressed to a diverse set of employees, instead of managers only.

To validate the SF-SLAM for employees, $N = 434$ participants ($M_{\text{age}} = 34.92$ years, $SD = 11.76$; 21.9% female) of 11 German companies rated their individual learning, group learning, organizational learning, feed-forward learning, and feedback learning. Together, these five learning dimensions address the ambidexterity issue in OL. On this empirical basis, we tested the SF-SLAM's reliability, factorial validity, and for a first time its nomological network. The respective research questions were whether the SF-SLAM maps OL activities on five corresponding dimensions, and whether the SF-SLAM correlates with engaging in innovation related learning activities, behaving innovatively on the job, and showing higher educational level, intelligence, and individual job performance. We analyzed data using structural equation modeling.

The SF-SLAM revealed good reliability, constrained factorial validity, and few relations of its five dimensions with variables of its nomological network. Individual learning is the only among these five learning dimension that can be truly distinguished in our employee sample. As a limitation this paper solely tested individual level constructs as part of the SF-SLAM's nomological network, despite the fact that its network also includes business performance and many more group and organizational level constructs. Thus, whether an application of the SF-SLAM in research and practice is warranted requires further research. However, this paper closes a research gap on the ambidexterity issue in OL in the perspective of employees by shortening the valid, but lengthy SLAM and validating for a first time the resulting SF-SLAM's nomological network in an diverse employee sample. Taken together, this SF-SLAM occurs to be quick, useful, reliable and valid to examine individual learning, while the validity of group, organizational, feed-forward, and feedback learning is restricted limiting a comprehensive assessment of OL.

2

Complex problem solving in careers

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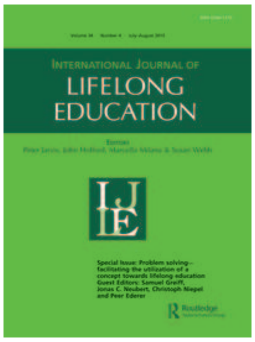

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Linking complex problem solving and general mental ability to career advancement: Does a transversal skill reveal incremental predictive validity?

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Linking complex problem solving and general mental ability to career advancement: Does a transversal skill reveal incremental predictive validity?

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Transversal skills, such as complex problem solving (CPS) are viewed as central twenty-first-century skills. Recent empirical findings have already supported the importance of CPS for early academic advancement. We wanted to determine whether CPS could also contribute to the understanding of career advancement later in life. Towards this end, we conducted a study ($n = 245$) at a large German automobile company in which we predicted career advancement and related criteria with CPS in addition to general mental ability (GMA). A computer-based assessment served as a measure of CPS. The dependent variables were the participants' job level in accordance with the international standard classification for occupations (ISCO-08) and the number of professional training days as a proxy for lifelong learning efforts. The data were analysed using a structural equation modelling approach. CPS and GMA showed correlations (from .18 to .26, $p < .01$) with indicators of career advancement. All regression models showed good fit and indicated that CPS explained incremental variance in one of two indicators (β was .14 for trainings, $p < .05$). Our findings suggest an increment of CPS for predicting career advancement

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beyond GMA. Hence, CPS could complement GMA in methodologies for the study of professional development.

Keywords: complex problem solving; general mental ability; career advancement; lifelong learning; predictive validity

Understanding and predicting aspects of individual occupational careers has significant relevance for policy-making, company strategy and individual life-course planning, and therefore is of high interest for research in lifelong education and human capital practices in the twenty-first century. Occupational careers reflect developments across individuals' life courses and are strongly related to lifelong learning as a social-personal process and lifelong education as an educational provision (Billett, 2010). When considering predictors of occupational careers on an individual level, cognitive science has contributed meaningful results. Comprehensive research has shown that general mental ability (GMA) is one of the best predictors of career advancement and performance (cf. Schmidt & Hunter, 1998).

However, these results show a need to be reworked due to the manifold changes in the world of work in the twenty-first century (Neubert, Mainert, Kretzschmar, & Greiff, in press). The skill set and flexibility of the individual are increasing in their importance to careers in comparison with the traditional career factors of vertical mobility and reasonable stability in one and the same organization (Arthur & Rousseau, 1996; Hall & Mirvis, 1996). Simultaneously, jobs have increasingly involved nonroutine tasks across the last few decades. Previously repetitive and routine work has been supplemented with nonroutine work or even eventually dissolved (Autor, Levy, & Murnane, 2003; Cascio, 1995). These developments have opened a new chapter of research on the prediction of career advancement and assessments of the skill sets required for human capital practices. For the first time, Wüstenberg, Greiff, and Funke (2012) have revealed the empirical strength of complex problem solving (CPS) in predicting early indicators of successful careers (e.g. school achievement in primary and secondary education) above and beyond GMA. Although these relationships have also been critically discussed (Sonnleitner, Keller, Martin, & Brunner, 2013), it could be substantiated by Greiff et al. (2013), and extended by Kretzschmar, Müller, and Greiff (2015). We investigated whether this predictive strength of CPS above and beyond GMA would persist for career advancement in a person's later working life. Skills to solve complex problems portray a general (i.e. not bound to a domain; cf. Neubert et al., in press) understanding of problem solving, and are considered so-called transversal skills and integral parts of twenty-first century skills with high relevance for professional lives (Binkley et al., 2012). Initiatives looking for the facilitation of these so-called twenty-first century skills stress that these skills are relevant for lifelong learning and are adapted to the changing career demands in the working lives of adults (National Research Council, 2012; Neubert et al., in press; Binkley et al., 2012).

Changes in the working world and higher education

In modern work environments, so-called boundaryless or protean career paradigms emphasize individuals' transversal skill sets and release careers from being defined by status and hierarchy as the building blocks of traditional assumptions about careers (Arthur & Rousseau, 1996; Bird, 1994; Greenhaus, Callanan, & Godshalk, 1994; Hall & Mirvis, 1996). Boundaryless and protean careers imply that a general increase in project-based work and changes in employment confront individuals with the need to constantly learn and transfer their skill sets to different working environments (Anakwe, Hall, & Schor, 2000). Modern workplaces are characterized by an increase in nonroutine tasks, a larger number of ill-defined problems and a broader range of tasks; consequently, career demands have shifted (Autor et al., 2003). Automotive engineers in the research and development department of a car manufacturer and professional translators for an international publisher are very different occupations that require the execution of very different tasks. Nonetheless, both are exposed to a multitude of increasing complexities, contradictions and ever-changing task environments. Automotive engineers are in demand every time their organization encounters technical, electronic or even economic issues and this involves aspects of sales, logistics, quality or project management, marketing or consulting. For example, they have to invent, implement and explain innovations in the areas of passenger safety and engine efficiency. The levels of qualification required for this job have increased accordingly, and on top of a Master's degree in engineering and training on the job, modern engineers often complete further educational requirements in electronics and IT. Their knowledge of marketing, finances, mathematics and many other subjects allows them to look at projects from different points of view, to integrate the different aspects of a project into a cohesive whole, and hence to enable them to evaluate the different phases of a project and the progress made in each phase. With regard to the job of a translator, because translations can now be implemented by computers, the focus of the jobs of language translators have tended to shift towards handling sophisticated software and coordinating outsourced translation projects with changing subcontractors. What these examples of very different industries have in common is that the work is done in projects that change in unpredictable ways, and the tasks tend to be nonroutine and involve the need to solve new, previously unknown problems. Thereby their work tasks have become dissociated from the expertise they acquired during their educations and have continued to intensify on the job.

As a political reaction, the Bologna process complemented the development of domain-bound expertise with that of transversal skills in its mission to facilitate employment opportunities in Europe (Bologna, 1999). To this end, Bologna (1999) encouraged systems of higher education to integrate instruments for the development of transversal skills applicable across domains and occupations in an attempt to close the gap between the type of employee required by the market and the employees who were actually being provided by higher education (Rocha, 2012). In the eyes of Rocha (2012), this political response indicates that European educational policy and society have shifted towards a goal of employability by extending their focus to include lifelong learning and transversal skills.

For example, adults executing the aforementioned or other expert jobs are considered to be functioning at the maximum of their expert capacity to handle highly complex work environments (Smith & Reio, 2006). But with the shift towards nonroutine tasks, the limits of sheer expertise are revealed. Expertise is domain-specific and does not necessarily translate to problems outside the domain (Rybash, Hoyer, & Roodin, 1986). Hired as a well-educated translator by a publisher, an employee might be confronted with problems he or she has not been prepared for, either by education, on-the-job training or job experience. If the publisher decides to change the software system or to outsource whole parts of the actual translation process, the translator must adapt quickly and take on the new and previously unknown roles of coordinator, planner and manager. As a consequence of increasingly being faced with nonroutine and unexpected tasks, experts in some work situations may not even be better off than novices (Ericsson & Charness, 1995). Expertise cannot prepare a person for nonroutine tasks. In other words, a high educational degree and experience on the job are no longer sufficient for ensuring reasonable long-term career advancement.

GMA, CPS and occupational careers

In order to connect CPS with a lifelong perspective on occupational careers, it is necessary to bring CPS of working adults into perspective, disentangle them from GMA and delineate previously existing empirical evidence for the importance of CPS in individual careers.

According to Buchner (cited in Frensch & Funke, 1995), CPS reveals itself in the successful interaction with dynamic and previously unknown task environments that change as a function of the individual's intervention or over time. The intransparency and novelty of the problem task require the individual to strategically explore the environment's regularities and to integrate any information that is obtained in order to successfully tackle the problem via the selection and application of an adequate solution strategy. That is, CPS involves *knowledge acquisition*, which leads to a representation of the problem space (e.g. Klahr & Dunbar, 1988), and *knowledge application*, which, if appropriate, delivers a solution to the problem (Novick & Bassok, 2005). In an attempt to integrate theoretical considerations on the process of CPS, Fischer, Greiff, and Funke (2012) portrayed knowledge acquisition and knowledge application as the core processes of CPS.

Empirical work shows that CPS performance can be best accounted for by facets of GMA, such as working memory capacity (Wittmann & Süß, 1999), but also that CPS remains a relevant predictor of academic achievement, after controlling for GMA (Greiff et al., 2013; Schweizer, Wüstenberg, & Greiff, 2013). These findings contribute to a continuous debate whether the core processes of CPS, knowledge acquisition and knowledge application are fully accounted for by GMA, or not (cf. Fischer et al., 2012).

As Fischer et al. (2012) exemplify, CPS includes processes that are typically not included in conceptualizations of GMA, such as paying attention to the side effects of actions or adjusting cognitive operations to changes in the task environment (Fischer et al., 2012). In accordance with Fischer and colleagues' (2012) argument that GMA be expanded to include aspects of problem solving, we therefore expect an assessment of CPS to have the potential to enrich the assessment of GMA with new task features that might be important in the context of today's changing world of work (cf. Neubert et al., in press).

In contradistinction to GMA tests, assessments of CPS must be predominantly computer based due to the dynamic nature of the tasks. To mimick nonroutine tasks and interactions, these dynamics include changes made by the system itself or by the testee (Funke & Frensch, 2007), and these require immediate adaptions to the task environment. So far, efforts to utilize transversal skills such as CPS in research and practice have mostly been restricted to primary and secondary education. Lifespan or educational research on the role of CPS as a transversal skill for learning later in life is scarce at best, and practices in adult education have failed to fully tap into the requirements of the reality of the work environment, which is defined by uncertainties, contradictions and dynamic changes (Smith & Reio, 2006). CPS as a transversal skill is considered to be important for occupational performance (e.g. Danner et al., 2011), and lifelong learners, 'who can handle unfamiliar situations where the effect of their interventions is not predictable' (OECD, 2014, p. 26). However, CPS-related skills have been underrepresented in research and practice targeting life after formal education in school (for an overview, see Griffin, Barry, & Care, 2012). To overcome this lack of research, the goal of this study was to empirically evaluate whether CPS could be meaningful predictors of occupational careers on an individual level in comparison with GMA. Towards this end, we investigated cognitive predictors of occupational careers as an evaluation of the potential of CPS in adult education and human capital development. The explored constructs consisted of GMA and CPS as predictors of occupational careers.

The literature has unequivocally demonstrated the importance of GMA as a predictor of numerous life outcomes. Many authors have confirmed GMA's predictive value for careers (for reviews, see Brand, 1987; Gottfredson, 2002). Various studies have demonstrated strong positive correlations between GMA and academic achievement (e.g. Kuncel, Hezlett, & Ones, 2004; Linn & Hastings, 1984), work skill acquisition (e.g. Ackerman, 1987, 1992; Lohman, 1999) and successful job training outcomes (for reviews, see Ree & Carretta, 1998; Schmidt, 2002). In particular, Schmidt and Hunter (1998) argued that GMA can be considered the primary personnel measure for hiring decisions. In fact, assessment centres that do the hiring for companies of oftentimes include measures of GMA (e.g. Gaugler, Rosenthal, Thornton, & Bentson, 1987), and additional assessments have shown only a moderate incremental validity above GMA for predicting job performance (e.g. a 2% increase of explained variance in job performance by biographical information; Schmidt & Hunter, 1998). Even further, Schmidt and Hunter (2004) presented evidence suggesting that GMA alone predicts career advancement, such as the occupational level attained, income received and performance. In sum, it seems beyond doubt that GMA is a powerful predictor of performance and career advancement in both the educational and work domains.

Looking for an overlap of CPS with GMA, recent research on convergent and discriminant validity has revealed that CPS is substantially related to GMA and working memory capacity, but that the constructs are still distinct (Greiff et al., 2013; Rigas, Carling, & Brehmer, 2002). For example, CPS has been shown to improve the prediction of school grades beyond GMA and working memory capacity in different scholastic domains (Kretzschmar et al., 2015; Schweizer et al., 2013; Wüstenberg et al., 2012). Extending the scope to real-world criteria in an occupational context, Danner et al. (2011) related CPS performance to supervisory ratings beyond GMA. These and more results (also see Abele et al., 2012; Kersting, 2001) point toward the practical value of CPS measures for explaining professional achievement also when accounting for GMA (Danner et al., 2011).

Previous research has not included considerations on the role of CPS for career advancements, even though the conceptual overlap seems straightforward in light of the developments towards boundaryless and protean careers. In the following, we will therefore investigate connections between CPS and several indicators of career advancement. Derived from personnel psychology, the most common measures of career advancement in personnel selection were previously comprised of information about salary, promotions and job level (Schmidt & Hunter, 1998). A commonly used group of personnel selection procedures revealed that the acquisition of job knowledge in professional trainings is also closely related to career advancement (McDaniel, Schmidt, & Hunter, 1988). These procedures are comprised of systematic methods that are used to evaluate previous training and experience and to assess, amongst other experiences, a person's exposure to professional trainings as relevant indicators of career advancement (McDaniel et al., 1988; Schmidt & Hunter, 1998).

For the purpose of this study, we had access to information about job level and the exposure to professional trainings, and used these as indicators of career advancement. We chose job level in accordance to the International Standard Classification of Occupations (ISCO-08; International Labour Office, 2012) to represent job complexity because more complex jobs are typically on a higher hierarchical level in organizations (International Labour Office, 2012). Furthermore, we consider the measure of professional trainings to represent lifelong learning efforts. To our knowledge, no previous investigations have related CPS to career advancement while controlling for GMA.

The present study

Building on the rich body of research on the impact of GMA on diverse life outcomes (see above; e.g. Schmidt & Hunter, 1998), the development of the working world towards emphasizing nonroutine tasks, and the promising results on the validity of CPS in predicting academic achievement (e.g. Wüstenberg et al., 2012) and occupational performance (e.g. Danner et al., 2011) beyond GMA, we hypothesized:

> H1: Both GMA and CPS will be positively correlated with current job level and the exposure to professional training.

> H2: CPS will predict current job level and the exposure to professional training over and above GMA.

H1 addresses the relations between GMA, CPS and occupational careers and establishes an empirical basis for H2, which states that career advancement indicators can be predicted by GMA and CPS.

Methods

Participants

The sample consisted of 245 employees of a German automobile manufacturer (between the ages of 45 and 49 years; 91% male). Participation was voluntary, and participants received no financial reimbursement.

Measures

To assess CPS, we used a set of tasks within the MicroDYN approach. MicroDYN is a computer-based assessment tool with good psychometric qualities (consistent Cronbach's $\alpha > .70$) and validity (Greiff et al., 2013; Schweizer et al., 2013; Wüstenberg et al., 2012).

In line with the theoretical understanding presented above, the measurement of CPS within MicroDYN (e.g. the *Wind Power Station* task in figure 1) allowed us to assess the two core aspects of CPS: knowledge acquisition and knowledge application (cf. Fischer et al., 2012). To this end, problem-solvers have to detect causal relations between several variables in the exploration phase (knowledge acquisition). After acquiring information about the system, problem-solvers are asked to reach certain target values in the control phase (knowledge application). Figure 1 explains how these two phases are implemented in the MicroDYN *Wind Power Station* task.

In this study, we implemented one instruction task (excluded from the analyses) and nine MicroDYN tasks. Furthermore, each task had a different semantic embedding (i.e. cover story; e.g. fabric, marketing, sport). To prevent the uncontrolled impact of domain-specific prior knowledge, input or output variables were labelled fictitiously or without deep semantic meaning (e.g. component Z in figure 1; also see Beckmann & Goode, 2013).

The scoring of the performance variables for knowledge acquisition and knowledge application followed Wüstenberg et al.'s (2012) recommendations.

The purpose of this study was to examine the impact of CPS on career advancement on a general level. Therefore, we combined the two facets of knowledge acquisition and knowledge application into a general CPS factor (i.e. a latent second-order factor).

As a measure of GMA, we used a standardized test of reasoning with figural material (CFT-20-R; Weiß, 2006); the test is a German adaption of the Culture Fair Intelligence Test (Cattell & Cattell, 1960). The paper-and-pencil test contained 56 multiple-choice items. All items were scored dichotomously as specified in the manual (Weiß, 2006).

We used two career measures; first, we employed an indicator of occupational advancement; and second, a measure of exposure to professional training. These will be explained in detail below.

Figure 1. Screenshot of the MicroDYN Wind Power Station task. Left side: Exploration phase. *X*, *Y* and *Z* influence noise and costs. Participants are asked to draw their acquired knowledge about the relations in an onscreen causal diagram (Funke, 1985, 2001; see bottom of figure, left side). Right side: Control phase (cf. Wüstenberg et al., 2012). Target values for each output variable (red areas and numbers in brackets) have to be met within a maximum of four steps

First, we asked about participants' current job position. The answers were categorized and ranked according to the International Standard Classification of Occupations (ISCO-08; International Labour Office, 2012). ISCO-08 is a hierarchically structured four-level classification of all jobs in the world; it allows different jobs to be aggregated into 10 major groups of decreasing skill levels and many more subgroups and minor groups. The first major group consists of managers (1), followed by professionals (2), technicians (3), clerical support workers (4), service and sales workers (5), skilled agricultural workers (6), craft and trade workers (7), plant and machine operators and assemblers (8) and so forth. For example, technicians are described as performing complex technical and practical tasks in specialized fields (International Labour Office, 2012). In sum, ISCO-08 maps job levels according to job complexity. Thereby the rank in ISCO-08 indicates the advancement of an individual's career. Our sample contained the five major groups of technicians, clerical support workers, service and sales workers, craft and related trade workers, and machine operators and assemblers. Due to the diversity of job positions in our sample, and thus a low number of participants in some categories, we aggregated the job levels into three categories: plant and machine operators and assemblers (major group 8), craft and related trade workers (major group 7), and we combined the service and sales workers, clerical support workers and technicians into one group (major groups 5, 4 and 3).

Second, as an indicator of the individual's exposure to professional training, and thus the current level of professional development, we asked participants to report the number of days they spent in professional training last year. This variable was assessed using four categories consisting of (a) 0, (b) 1, (c) 2 and (d) 3 or more working weeks that each consisted of 5 workdays.

Procedure

The study was administered at the company's factory locations. Participants were assessed in groups of up to 20 people. Single sessions lasted approximately 120 min in total with short breaks between the three parts. First, participants filled out the background questionnaire by providing demographic information and information on their career efforts. Afterwards, each participant worked on the MicroDYN test presented on a laptop. Finally, the CFT-20-R test was administered. Test sessions were supervised by research assistants who had been thoroughly trained in test administration.

Statistical methods

We used the structural equation modelling approach (SEM; Bollen, 1989) to examine our research questions. Therefore, the results and coefficients were measured on a latent level, thus accounting for measurement error. Within SEM, confirmatory factor analyses (CFA) were used to examine the MicroDYN and CFT-20-R measurement models. To reduce the number of parameters to be estimated, the items of the CFT-20-R were aggregated into four parcels according to Little, Cunningham, Shahar, and Widaman (2002) recommendations.

The Weighted Least Squares Mean and Variance adjusted (Muthén & Muthén, 2012) estimator for categorical outcomes was used for analyses with categorical parameters, otherwise standard maximum likelihood (ML) estimation was employed. In order to ensure high statistical power for the detection of small effects, we applied the full information ML estimation method to adjust for missing data. The software package Mplus 7.0 (Muthén & Muthén, 2012) was used for all analyses.

To evaluate model fit in the CFA and SEM analyses, we applied standard fit indices such as Pearson's χ^2, the comparative fit index (CFI), the Tucker-Lewis Index (TLI), the root mean square error of approximation (RMSEA) and the weighted root mean square residual (WRMR). The cut-off values followed the recommendations of Hu and Bentler (1999); that is, CFI > .95, TLI > .95, RMSEA < .08, and WRMR < .80.

For Hypothesis 1, we computed latent correlations (i.e. the correlations were adjusted for measurement error) to analyse the relations between CPS, GMA, job level and exposure to professional training. For Hypothesis 2, we computed latent regressions with GMA as predictor (Model 1), and CPS and GMA as predictors (Model 2) as well as job level and exposure to professional training as criteria that indicated career advancements. In these models, the path coefficients from the predictors to the criterion variables indicated the corresponding degree of explained variance of the criteria by CPS and GMA.

To clarify the incremental validity of CPS beyond GMA, we used an approach similar to stepwise regression on a latent level (see Wüstenberg et al., 2012, for more details about the specific regression procedure). We first regressed CPS on GMA, and then we used the corresponding residuals as well as GMA to predict the criterion (e.g. job level). That is, we first controlled for the impact of GMA on CPS before we examined the incremental validity of CPS beyond GMA. If the path coefficients of the CPS residuals were significant, this would indicate that CPS explained additional variance above and beyond GMA.

Results

Descriptive statistics for the dependent variables job level and exposure to professional training are presented in table 1.

Table 1. Descriptive statistics for job level and training days

Variable	Frequency	Percent
Job level		
Machine operators and assemblers	98	40.0
Craft and related trade workers	87	35.4
Service and sales workers, clerical support workers, and technicians	60	24.6
Training		
No training	95	38.8
One week	67	27.3
Two weeks	30	12.3
Three or more weeks	53	21.6

Note: Job level is based the ISCO-08; Training = Number of professional training days within the last year.

The results confirmed H1, in which we predicted substantial correlations between CPS, GMA and the indicators of career advancement. Applying bivariate latent correlations for Hypothesis 1, we discovered that GMA was positively correlated with job level and the exposure to professional trainings. The correlations between CPS and exposure to professional trainings were moderate to small ($r = .26$, $p < .01$). By contrast, the correlation between CPS and job level was small and nonsignificant. All correlations are displayed in table 2. These results were a first step towards the statistical models tested in Hypothesis 2.

According to H2, we expected that CPS would predict current job level and the exposure to occupational training over and above GMA. For this purpose, we first built Model 1 with only GMA as a predictor and compared this model with Model 2, which represented all variables including a residual for CPS, which was independent of GMA by definition (see Methods section). Both models showed good model fit (Model 1: $c^2 = 7.41$, $df = 8$, $p > .05$; CFI = 1.00, TLI = 1.00; RMSEA = .00; WRMR = .29; Model 2: $c^2 < 352.67$, $df = 246$, $p < .01$; CFI = .98; TLI = .97; RMSEA = .04; WRMR = .86). The chi square statistic did not support Model 2. However, according to Hu and Bentler (1999), the combination of different model fits indicated a good model fit for Model 2.

Model 1 showed significant paths overall and explained 6% of the variance in exposure to professional trainings with $\beta = .24$ ($p < .01$), and 4% in job level with $\beta = .19$ ($p < .01$). Model 2 with GMA and CPS as predictors additionally revealed significant paths between the CPS residual and professional trainings. The path between the CPS residual and job level remained nonsignificant. The CPS residual predicted professional trainings with $\beta = .14$ ($p < .05$). The total amount of variance explained in the exposure to professional trainings by Model 2 showed a small increase over Model 1 of 2% ($\Delta R^2 = .02$). No increase was found for job level. Thus, the increase in explained variance with Model 2 provided evidence for a small increase of the prediction of one out of two career advancement indicators above and beyond GMA (figure 2).

In summary, the correlations of CPS and GMA with indicators of career advancement partially confirmed H1, indicating substantial relations between the two constructs and indicators of career advancement with the exception of the relation of CPS to job level. H2 was also only partly supported by our results. CPS predicted career advancement only to a limited extent, and did not explain incremental variance in occupational status. We compared two empirical

Table 2. Latent correlations between measures used in H1

	(1)	(2)	(3)
(1) GMA			
(2) CPS	.68**		
(3) Job level	.18**	.07	
(4) Training	.24**	.26**	.18*

Note: GMA = General mental ability; CPS = Complex problem solving; Training = Number of professional training days within the last year.
*$p < .05$; **$p < .01$.

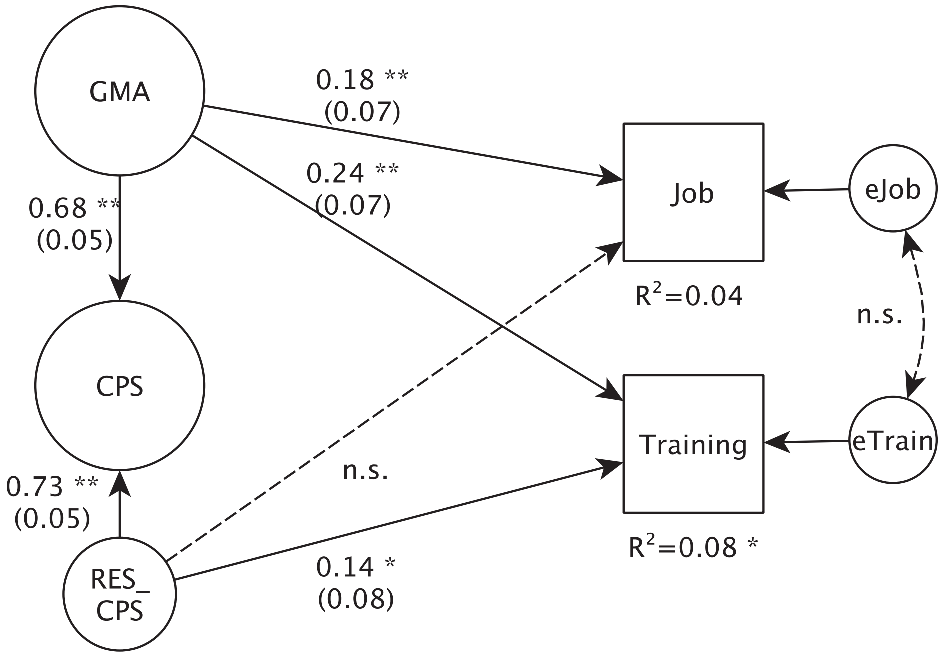

Figure 2. Model 2 for H2. CPS was regressed on GMA. The CPS residuals (RES_CPS) in this regression as well as GMA were used to predict job level (Job) and number of professional trainings (Trainings). eJob and eTrain are the uncorrelated residuals of Job and Training. The numbers in parentheses are the standard errors (SE; e.g. SE = .08 for $\beta = .14^{*}$ between RES_CPS and number of professional trainings). $^{*}p < .05$; $^{**}p < .01$

models: Model 1 with only GMA as a predictor, and Model 2, which contained all variables including a residual for CPS. In this way, we were able to specify the role that CPS might play in occupational careers. In Model 2, CPS explained additional variance in the exposure to professional training (i.e. professional training days) over Model 1. Conversely, occupational status (i.e. job level) was explained only by GMA in both models.

Discussion

In this study, we examined cognitive predictors of occupational careers in working adults in general, and we looked for evidence for the predictive value of CPS above and beyond reasoning as a measure of GMA in particular. We investigated a sample of 245 employees of a large German automobile manufacturer who held various positions, such as machine operators, trade workers and service staff. We assessed their CPS and GMA levels in relation to their job level and exposure to professional training as indicators of career advancement. The results were both promising and constrained. In the following section, we will take a closer look at the relation between CPS and career advancement; we will discuss reasons for this; and finally, we will make an attempt to position

CPS within the realm of lifelong education and the development of human capital.

The results partially supported H1 and partly H2. Firstly, the results confirmed manifold previous findings on the predictive validity of GMA for measures of occupational success (cf. Schmidt & Hunter, 1998). Secondly, the results provided a general indication of an as-yet-to-be-defined role of CPS in matters of career advancement. CPS appeared to be no less associated with the exposure to professional training than GMA, whereas job level was not related with CPS. To our surprise, the empirical data did only partly support our assumptions about the links of CPS to career advancement. This contrasts to studies that found an increment of CPS which might have selected a more specific criterion for professional success than the status of occupation. For example, Kersting (2001) and Danner et al. (2011) showed incremental predictive validity of CPS measures for supervisory ratings about how the candidates performed on their job, whereas the candidates individual income could not be predicted by CPS. This finding suggests that income as an indicator of occupational success might rather be valid within occupations, but not between occupations. Since occupational status as used in our study does not inform about variance within categories of occupations, or even within specific jobs, all the possible relations between CPS and occupational success might not have been accounted for.

Does the process of CPS relate to complexity in the job?

Using the developments in the working realities of automotive engineers and professional translators as examples, we can see that modern-day work increasingly emphasizes nonroutine tasks instead of the execution of organizational routines and expert knowledge. Without doubt, expertise and GMA are necessary, but they do not appear sufficient for covering the needs of a sophisticated workplace in the twenty-first century (cf. Neubert et al., in press). The literature on protean and boundaryless careers, which emphasizes the transferability of skills and acknowledges that individuals need to take responsibility for managing their own careers, identified self-knowledge, interpersonal knowledge and environmental knowledge as the key factors of new careers (e.g. Anakwe, Hall, & Schor, 2000). Hall defined these skills as the skills that are needed to prepare an individual 'for learning how to learn' (Hall, 1996, p. 11). Such skills enable the individual to manage his or her career effectively. We believe that our findings on the relation between CPS and the exposure to professional training can contribute to our understanding of the key factors of new careers that are constantly changing and more and more depend on lifelong learning.

In fact, our empirical results reveal that CPS leverages the understanding and prediction of career aspects, at least to some extent. Applying the core processes of knowledge acquisition and knowledge application in these workplaces, CPS can be considered a facilitator of the acquisition and application of knowledge required for the completion of nonroutine tasks. For a successful professional translator, in order to deal with new IT-solutions and the coordination of translation work that often does not have a clear target and comprises multiple obstacles, it might not be sufficient to have high GMA and a well-founded background in translating. In addition, the translator might also have to bring along a number of transversal skills such as CPS to enable a readiness for lifelong learning and to be able to familiarize him/herself with a variety of project-specific topics.

However, according to the empirical results, CPS significantly explained efforts towards professional training and hence lifelong learning as an indicator of career advancement, but not occupational status. In theory, CPS could be viewed as the foundation of many other job-specific skills that are necessary for a successful performance in a complex and demanding job. The contrasting finding of occupational status not being related to CPS seems somewhat puzzling in light of this theoretical relevance. The results at hand suggest that CPS does not contribute to the prediction of occupational status, which was supposed to inform about job complexity. Our measure of occupational status following ISCO-08 could have resulted in a too broad measure of job complexity, thus resulting in a lack of relations. The relation of CPS and job complexity might be more specific than a broad classification of occupational status can potentially reveal (i.e. CPS might account for variance in specific occupations, but not in others). This assumption is supported by studies on the predictive validity of CPS for academic success (e.g. Kretzschmar et al., 2015). CPS explains variance in school grades only for natural science classes, which mainly demand analytic thinking and use of technology, whereas not for social science classes. The finding could mean that CPS might show predictive validity in particular for those jobs that involve complex technology and scientific thinking, rather than complex social problems, such as direct customer service, which was also represented in our sample.

CPS as a complement to GMA

After exploring the relation between CPS and career advancement, it would still be worthwhile to integrate CPS into the realm of the assessment of cognitive ability in the twenty-first century. When nonroutine and interactive tasks increasingly determine occupations, then domain-general transversal skills are presumably separately important.

Obviously, CPS is not able to supersede GMA as the better predictor of career outcomes, and our results unquestionably supported this important role of GMA. Rather, CPS complements GMA in defining and assessing the cognitive processes involved in solving complex real-world problems, and such skills can be relevant for contemporaneous career advancement. Facing escalating complexities in the workplace and considering the Bologna process as an educational response made by society, researchers and practitioners might benefit from the added predictive value of CPS assessments above and beyond the strongest factor for employee performance (i.e. GMA). Including CPS in the realm of cognitive assessments in education and the development of human capital could be considered a palpable next step towards improving employee development and selection processes, leveraging human capital growth paths (i.e. careers). Increases in employee performance and a dedication to learning job-relevant skills are potential benefits.

Limitations

Several limitations of the present study should be considered. First, the sample was drawn from a single automotive company. This fact highly restricts the representativeness of the results for other industries and sectors and might also have led to the restricted variance in the criterion variables. CPS might play a larger role in companies with a structurally higher rate of nonroutine tasks due to, for example, changes in technology or when comparing jobs and occupations between companies.

Second, applying SEM to cross-sectional data did not allow for temporal predictions or conclusions about causality. Thus, when considering the additional predictive value of CPS, we referred to the increases in the variance explained in the dependent variables.

Third, one could argue that there is more to the large construct of GMA (see Horn & Noll, 1997) than only reasoning. Just to name two, fluid intelligence and working memory were not assessed in our study. However, reasoning indicates fluid intelligence, which itself is a good indicator of GMA (cf. Cattell–Horn–Carroll theory; McGrew, 2009). Schmidt and Hunter (1998) also used reasoning as a measure of GMA. In addition, research has tended to find similar results for reasoning, working memory capacity and even aspects of personality (Barrick & Mount, 1991; Brand, 1987; Gottfredson, 2002; Schmidt & Hunter, 1998).

We did not account for job knowledge as a proxy for expertise, given that it is likely to be an additional most relevant predictor. Moreover, one might criticize the limited range and control of indicators of career advancement. However, we wanted to include concrete indicators of careers and the use of normed job levels is an established estimate of career advancement (International Labour Office, 2012), and the exposure to professional trainings provides information about aspects of lifelong learning.

On the downside, we did not collect information on who initiated the trainings; how the organization supported the trainings; or what kinds of barriers were encountered with regard to the trainings. Not knowing who is the initiator—either the employee, a supervisor or the human resource department—undermines the empirical relations between CPS, GMA and the career indicators, just as missing information about the organizational learning culture does. Information on whether the organization either restricted or facilitated the trainings and information on whether there were certain other barriers that prevented employees from participating in trainings (e.g. the supply, visibility and information about trainings) are relevant pieces of information that were missing from our study. Moreover, we did not control for factors of occupational status at the organizational level, and doing so may have produced different results. Therefore, we suggest that future research controls for these factors, which may have also contributed to the missing relation between job level and CPS, when investigating predictors of career advancement indicators on an individual level. Even further, job knowledge is an indispensable task for future research, it should be included in order to paint a more complete picture of what determines advancement in careers.

In sum, the most prevailing points of improvement are the limitations to the predictive validity due to the cross-sectional research design; the specific sample, which may conceivably have underestimated the underlying relations; as well as the lack of control variables and more detailed outcome variables.

Conclusions

Our goal was to shed light on predictors of modern occupational careers. Towards this end, we attempted to empirically substantiate the connections of transversal skills to solve complex problems and GMA with indicators of occupational career advancement. Results on the relation of CPS to the changing working realities of adults are our contribution to this special issue. We found that both CPS and GMA were substantially related to career-relevant criteria and, at least partly, contributed to the explanation of variance in job level and exposure to professional training as criteria that indicated career advancements. Against the background of increasing complexity, uncertainty and ever-changing challenges at work, we suggest that CPS can complement the use of GMA in existing methodologies for the study of professional development and can specifically extend assessments that have previously used only GMA in research and practice.

Larger test batteries and more representative samples should be used to underpin these preliminary findings, and longitudinal assessments should be conducted to confirm predictions over time. In the long run, we hope that future research will substantiate our findings and provide further empirical arguments to convince assessment practitioners of the added value of CPS as a transversal cognitive skill for the development and selection of human capital.

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3

Solving complex problems at work

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Abstract: As work life becomes increasingly complex higher-order thinking skills, such as complex problem-solving skills (CPS), are becoming critical for occupational success. It has been shown that individuals gravitate to jobs and occupations that are commensurate with their level of general mental ability (GMA). Based on theory of occupational gravitation, CPS theory, and previous empirical findings on the role of CPS in educational contexts, we examine whether CPS makes an incremental contribution to occupational choice and success after controlling for GMA and education. Administering computerized tests and self-reports in a multinational sample of 671 employees, and analyzing data with structural equation modeling, we found 4% and 8% of incrementally explained variance by CPS in job complexity and salary beyond GMA and education. We found no increment of CPS in predicting the job level. Taken together, CPS appears to be linked to job complexity and salary in a range of occupations, and this link cannot be explained as an artifact of GMA and education. Thus, CPS incrementally predicts success, potentially contributes to theory of job gravitation, and elucidates a better understanding of complex cognition in the workplace.

***Title Page**

The Incremental Contribution of Complex Problem Solving Skills in Predicting Occupational Gravitation

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Abstract

As work life becomes increasingly complex higher-order thinking skills, such as complex problem-solving skills (CPS), are becoming critical for occupational success. It has been shown that individuals gravitate to jobs and occupations that are commensurate with their level of general mental ability (GMA). Based on theory of occupational gravitation, CPS theory, and previous empirical findings on the role of CPS in educational contexts, we examine whether CPS makes an incremental contribution to occupational choice and success after controlling for GMA and education. Administering computerized tests and self-reports in a multinational sample of 671 employees, and analyzing data with structural equation modeling, we found 4% and 8% of incrementally explained variance by CPS in job complexity and salary beyond GMA and education. We found no increment of CPS in predicting the job level. Taken together, CPS appears to be linked to job complexity and salary in a range of occupations, and this link cannot be explained as an artifact of GMA and education. Thus, CPS incrementally predicts success, potentially contributes to theory of job gravitation, and elucidates a better understanding of complex cognition in the workplace.

Keywords: complex problem solving, general mental ability, occupational gravitation, salary, job complexity

The Incremental Contribution of Complex Problem Solving Skills in Predicting Occupational Gravitation

There is extensive evidence that, over time, individuals gravitate to jobs and occupations that are commensurate with their general cognitive ability (also referred to as general mental ability, or GMA; Desmarais & Sackett, 1993; Gottfredson, 1986; Jensen, 1980; Sorjonen, Hemmingsson, Deary & Melin, 2015; Wilk, Desmarais & Sackett, 1995). As a result, jobs and occupations can be reliably scaled in terms of the GMA levels of incumbents (Gottfredson, 1986; Wonderlic, 2002). That is, individuals with higher levels of cognitive ability are more likely than individuals with lower ability levels to fill and succeed in jobs that involve more demanding, intense or frequent information processing requirements (McCormick, DeNisi & Shaw, 1979; McCormick, Jeanneret, & Mecham, 1972; Murphy, 1989; Wilk et al., 1995). The mental demands of jobs are consistently correlated with the general cognitive ability levels of job incumbents (Jensen 1980; Murphy, 1989), and successfully holding and ascending in cognitively demanding jobs is associated with higher cognitive ability levels (Judge, Klinger, & Simon, 2010), even post retirement (Smart, Gow & Deary, 2014).

The role of general cognitive ability versus specific abilities and skills in predicting performance and success in the workplace has long been debated. The effect of general cognitive ability on job performance and job success is so strong and consistent that some researchers (e.g., Ree, Caretta & Teachout, 2015; Ree, Earles, & Teachout, 1994) have argued that specific abilities offer very little incremental information as predictors of these criteria. In a similar vein, tests of gravitation hypotheses have focused almost exclusively role of general cognitive ability in sorting people into more or less cognitively demanding jobs and occupations; the possibility that other cognitive abilities or skills might play an independent role in understanding the way individuals are sorted into jobs has not been examined to date. In this study, we examine the hypothesis that there are specific skills, in particular complex problem solving (CPS) skills, that play a role in understanding occupational choice and success over and above the important role that has already been demonstrated for general cognitive ability.

The Nature CPS Skills

Complex Problem Solving (CPS) has been defined as "… the successful interaction with task environments that are dynamic (i.e., change as a function of 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" (Buchner, cited in Frensch & Funke, 1995, p. 14). CPS involves both the acquisition and the application of new knowledge in situations that must be actively explored to find and apply a solution (Greiff, Holt, & Funke, 2013; Funke, 2010; Gonzalez, Vanyukov, & Martin, 2005; Osman, 2010). CPS has been identified by leading scientific and policy agencies as critical in the workplace of the 21st century (National Research Council, 2012; OECD, 2013a, b), in large part because an increase in the number of jobs require employees to solve complex problems in real time and corresponding decrease in the number of jobs that involve executing well-defined organizational practices and routines (Autor, Levy, & Murnane, 2003; Goos, Manning, & Salomons, 2009; Middleton, 2002; Neubert, Mainert, Kretzschmar, & Greiff, 2015).

Computerized measures of CPS have been successfully included in what is arguably the most important large-scale assessment worldwide, the Programme for International Student Assessment (PISA). Starting in 2012 PISA administered computerized tests of CPS to tens of thousands of 15-year-old students in 44 countries and economies worldwide (OECD, 2012, 2014). The results of the CPS tests in PISA have been instrumental for the creation of policies in education and lifelong learning to prepare individuals for the challenges of the 21st century workplace.

Relationship between CPS and GMA. CPS skills involve cognitive processes that are linked to general cognitive abilities, such as fluid intelligence (McGrew, 2009) and working memory capacity (e.g., Ackerman, Beier, & Boyle, 2005), and measures of CPS are often strongly correlated with measures of general cognitive ability. For example, a recent meta-analysis (Stadler, Becker, Gödker, Leutner, & Greiff, 2015) suggested that the most widely-used measures of CPS are highly correlated (uncorrected mean $r = .585$) with measures of general mental ability, with even higher correlations for measures of fluid intelligence. However, there are a number of reasons to believe that CPS is both theoretically and empirically distinct from these more general cognitive abilities (e.g., Wüstenberg, Greiff, & Funke, 2012; Sonnleitner, Keller, Martin, & Brunner, 2013).

First, unlike cognitive abilities, skills like CPS are modifiable through practice and training (Weinert, 2001). Unlike GMA, which tends to be highly consistent over time and relatively resistant to change through the age ranges where individuals are most likely to be employed (Jensen, 1980; Rönnlund, Sundström & Nilsson, 2015), CPS can be developed over relatively short periods of time with appropriate instruction, practice and feedback (Bakken, 1993; Jensen, 2005; Kretzschmar & Süß, 2015; Tomic, 1995; Weinert, 2001). There is also evidence that CPS skills can be improved through workplace experience (Zaccaro et al., 2015), in particular through experience in solving complex problems in the workplace (Ohlott, 2004). Measures of CPS are consistently correlated with assessments of experience with complex tasks in the workplace and in training ($r = .40$, $p < .01$; Zaccaro, et al., 2015).

Second, several studies of the construct validity of contemporary CPS measures have demonstrated the discriminant validity of these measures and have shown that aspects of CPS that are completely independent of general mental ability predict performance and success in educational settings (Greiff, Fischer, Sonnleitner, Brunner, & Martin, 2013; Sonnleitner et al., 2013; Schweizer et al., 2013; Stadler et al., 2015; Wüstenberg et al., 2012). A few recent studies have suggested that measures of CPS may also have incremental value for predicting job performance and occupational success. Ederer, Nedelkoska, Patt, and Castellazzi (2015) estimated the market value of CPS in an econometric human capital model and found that CPS was a significant predictor in Mincer-style wage regressions when added to a model that included GMA and work experience.[1] Danner, Hagemann, Schankin, Hager and Funke (2011) showed that measures of dynamic decision making (which are similar to widely-used CPS measures) predicted both self-reports of occupational success and supervisory assessments of performance, even after holding general mental ability constant.

Do CPS Skills Play a Distinct Role in Occupational Choice and Success?

There are several reasons to believe that skills in solving complex problems play a distinct and incremental in understanding the types of occupations individuals are drawn to, remain in and succeed in. These can be grouped under three headings: (1) changes in jobs, (2) demonstrations of incremental contributions in other settings, and (3) evidence for the relevance of related skills in the workplace.

Changing jobs. Jobs in the modern economy are becoming increasingly complex (Hoffman, 2015; Scherbaum, Goldstein, Yusko, Ryan, & Hanges, 2012), and this complexity has increased demands upon cognitive skills that are related to, but not fully subsumed under general cognitive ability. Both the National Research Council (2012) and the OECD (2013a, b) have identified CPS skills as critical for success in tasks workers need to perform when carrying out their duties in the 21st century. As continuous technological and organizational changes create an increasingly dynamic, nonroutine, and interactive workplace, jobs increasingly demand higher-order thinking skills to plan, actively explore, execute, and monitor associated tasks in the workplace (Autor et al., 2003; Becker et al., 2013; Cascio, 1995; Goos et al., 2009; Middleton, 2002).

Jobs are changing in terms of the equipment and procedures they require (see Autor et al., 2003; Cascio, 1995) as well as the organizational structures and teams that support them (see also Middleton, 2002), while at the same time there is an increase in the offshoring of routine tasks (e.g., Autor, Katz, & Kearney, 2006; Goos et al., 2009). As jobs become more complex, higher-order thinking skills including CPS, creativity, and information and communication technology literacy will be needed to perform well on the job (Binkley et al., 2012). GMA is critically important for, and sometimes sufficient to allow workers to perform tasks that do not change quickly over time or do not require repeatedly active interaction to learn how they work (Funke, 2010; Raven, 2000; Wüstenberg et al., 2012), but jobs that involve nonroutine problem solving are likely to require the higher-order cognitive skills (National Research Council, 2012) that are neither fully subsumed under GMA (Funke, 2010) nor provided by higher education (Rocha, 2012).

Incremental contributions of CPS. Several studies have shown that CPS skills make an incremental contribution, above general cognitive ability, in predicting school achievement (e.g., Greiff, Fischer et al., 2013; Schweizer et al., 2013) and University success (Stadler, Becker, Greiff, & Spinath, 2015). There is some evidence such that CPS skills make an incremental contribution to predicting workplace performance (e.g., Neubert, et al., 2015), but workplace studies are at present few in number and incomplete in terms of what criteria they cover to allow researchers to draw firm conclusions. The present study is designed to help fill the gap in research on the role of CPS in the workplace.

Relevance of related skills in the workplace. There is evidence that skills that appear to be related to modern conceptions of CPS are related to performance and success in a range of occupations. For example, assessment centers and high-fidelity simulations often include exercises that require participants to solve complex and challenging problems (Lievens & Patterson, 2011; Thornton & Rupp 2006). Indeed, the precursors of modern assessment centers, developed to assess candidates for the Office of Strategic Services (OSS) during World War II often required candidates to work in groups to solve complex and difficult problems, sometimes even inserting non-cooperative confederates or other impediments to achieving solutions to these problems (Wiggins, 1973).

Second, there is evidence that CPS skills play an important role in leadership success and continuance (Zaccaro et al., 2015). One of the role of leaders is to provide structure and support for their subordinates, and it is possible that CPS skills help leaders to acquire and apply knowledge and understanding that individuals and teams require to solve complex problems at work.

Is There Room for an Incremental Contribution?

It is important to note that industrial-organizational (I-O) psychology has, over decades, unequivocally reported relatively small increments, above and beyond GMA, when predicting success on the job using specific cognitive skills and abilities. Given the extensive body of evidence that general cognitive ability predicts performance across most jobs (for an overview, see Ng, Eby, Sorensen & Feldman, 2005; Salgado et al., 2003; Schmidt & Hunter, 1998, 2004), some researchers have suggested that not much more than GMA is needed to predict job success (e.g., Ree et al., 2015; Ree et al., 1994; Schmidt & Hunter, 1998, 2004). Existing research on the role of cognitive skills in occupational gravitation has focused on GMA, and it is very possible that similar outcomes will be observed for specific cognitive skills in this research area. That is, it is possible that the incremental contribution of CPS in predicting measures of occupational choice and success could be similarly limited, especially given conceptual and empirical overlap between CPS and GMA (e.g., Funke, 2010; Wüstenberg et al., 2012). Given current recommendations that substantial investments be made in the development of CPS skills (National Research Council, 2012; OECD, 2013b), it is both theoretically and practically important to ask whether this specific set of skills does, in fact, make a distinct contribution to understanding occupational choice and success. In this study, we empirically examine the hypothesis that CPS makes a distinct and incremental contribution, over and above GMA, in predicting occupational choice and success.

In addition to GMA, education is a well-established empirical predictor of occupational choice and success (Converse et al., 2014; Ng et al., 2005; Sorjonen et al., 2015). More educated individuals fill more managerial positions (Tharenou, Latimer, & Conroy, 1994), receive more promotions (Sheridan, Slocum, & Buda, 1997), and their salaries rise faster (Bretz & Judge, 1994). Education aims to both provide knowledge and to build career-relevant skills and strategies needed to solve complex problems on the job (Molnár, Greiff, & Csapó, 2013), and it is possible that assessments of CPS could simply serve as proxies for education level. Correspondingly, reaching higher educational levels is associated with greater success on the job (e.g., Converse et al., 2014; Ng et al., 2005). Given that CPS improves with years of schooling (Molnár et al., 2013), and that education itself is widely used as cost-efficient proxy for career-relevant skills and abilities (Ng & Feldman, 2010) predicting occupational success, it is important to demonstrate that CPS makes an incremental contribution to understanding occupational success over and above not only GMA, but also the level of education.

Importance of incremental contribution of CPS. This study tests that hypotheses that individuals CPS skills predict the likelihood that they will be drawn to and succeed in jobs that have require them to deal with complex, unstructured problems, independent of their level of education or general mental ability. An empirical test of this hypothesis is important for several reasons. First, both the National Research Council and the OECD have recommended substantial investment in developing CPS skills. If these skills are so tightly bound to GMA that they do not make a difference once GMA is taken into account, this recommendation may not be a sound one. Second, this hypothesis has important implications for recruitment, selection and placement. If CPS skills do have incremental value for identifying which occupations individuals are likely to be drawn to and to succeed in, including measures of these skills in vocational counseling, personnel selection and placement is likely to improve the quality of individual and organizational decisions.

The Present Study

We were able to obtain data in large multi-national studies to link CPS with the type of job and occupation incumbents hold and with measures of success in those jobs and occupations. In this study, we test two hypotheses. First, as described above, we predict that CPS levels will make an incremental contribution to predicting the likelihood that individuals hold jobs that require higher levels of complex problem solving and decision-making. Because CPS skills are correlated with both GMA and with level of education (Funke, 2010; Molnár et al., 2013; Schweizer et al., 2013), we control for both variables and test the hypothesis that:

H1: CPS will predict measures of job complexity beyond GMA and the level of education

Next, we predict that CPS will make an incremental contribution to predicting the likelihood that individuals achieve job success, measured both in terms of job level and salary. The skills required by jobs represent a key determinant of individuals' job level and salary (Guthrie, Dumay, Massingham, & Tam, 2015; Jensen, 1980; Milkovich et al., 2013; Murphy, 1989). The job level attained is one indicator job success (International Labour Office, 2012) and the higher the job level the higher the salary; thus, salary is often used as a monetary indicator of success (Jaskolka, Beyer, & Trice, 1985). If CPS skills are indeed required to succeed on the job, they ought to make a unique contribution to the prediction of occupational success (e.g., job levels and salary). We test the hypotheses that:

H2: Measures of CPS will predict job level and salary beyond GMA and the level of education.

Method

To test our hypotheses, we obtained measures of CPS skills using multiple tests modeled in the highly successful PISA assessments (OECD 2012, 2014).[2] We also obtained measures of GMA using a well-validated, widely respected measure of fluid intelligence (Raven's Progressive Matrices). Finally, we used multiple items from the Federal Institute for Vocational Education and Training Survey (BIBB; Rohrbach-Schmidt, & Hull, 2013) to classify incumbents' jobs in terms of their complexity, and developed and tested structural models to test our hypotheses.

Sample and Procedure

The data reported here were obtained as part of a larger project (LLLight in Europe, 2015a) that involved both standardized on-site and unproctored online assessments of employees, students, and entrepreneurs at companies, social enterprise community centres, and universities in 13 different countries in Africa, Europe, and South America. The LLLight in Europe dataset (*N* = 1,167) has been used in EU policy (LLLight in Europe, 2015a, b, c) project and in a recent article examining the relationship between CPS and salary (Ederer et al., 2015).

The current study involves a subsample of the LLLight in Europe study, specifically data from 671 EU-based employees who were assessed on-site during company visits in the seven participating European Union (EU) countries (Denmark, France, Germany, Netherlands, Slovakia, Spain, and United Kingdom) and Switzerland.[3] This sample of working adults (M_{Age} = 37.06 years, *SD* = 12.46; 32.9% female) included responses from incumbents across various job and educational levels of 21 organizations across Europe. Frequencies of country origin, educational level, and job level are displayed in Appendix 1.

The current study differs from the broader LLLight in Europe (2015a) study in terms of its objectives and in terms of the variables examined. In particular, previous studies using LLLight in Europe (2015a) data have not examined the incremental contribution of CPS over GMA and education in a straightforward way. Nevertheless, in parts of the current study where we report results based on data that has been previously analyzed (i.e., in Ederer et al. 2015; LLLight in Europe, 2015a, b, c), we explicitly note this overlap.

The European subsample used in this study was economically, geographically, and socially more homogenous than the full global LLLight in Europe sample of 1,167 employees, entrepreneurs, and students, distributed on three continents. Further, in this study, trained test administrators collected all CPS data during company visits, whereas the larger LLLight in Europe project relied on a mix of on-site and online assessments. In our subsample, 671 company-employed participants completed computerized test batteries of cognitive abilities and skills, as well as self-reports measures assessing job characteristics and salaries. Testing took approximately 100-145 minutes, depending on slightly differing test batteries used in different organizations, and testing included one 10-15 minute break.

Measuring CPS

We employed two established computer-based CPS performance tests (MicroDYN - Greiff, Wüstenberg, & Funke, 2012, and MicroFIN - Neubert, Kretzschmar, Wüstenberg, & Greiff, 2014), both modeled on assessments included in the PISA assessment, and both administered on tablets. MicroDYN and MicroFIN have already been proven to reliably and validly measure CPS for the prediction of success in a variety of educational settings (e.g., Greiff, Fischer et al., 2013). Both measure CPS in a number of short problem tasks (approx. 5 min per task; 14 tasks in total in the current study).

MicroDYN. These tasks are divided in the two conceptually distinguished phases of knowledge acquisition and knowledge application (e.g., Funke, 2010). MicroDYN tasks are designed within the framework of linear structural equations (LSE; Funke, 2010) that allow examinees to interact via slide controls for the inputs that, when applied, influence the outputs in quantitative ways that are dynamic, nonroutine, and interactive according to CPS theory (Funke, 2010). For instance, several technical components (e.g., A, B, and C) might gradually influence the noise and maintenance costs in the exemplary MicroDYN task "Wind Power Station" (see Appendix 2). As the relationships between inputs and outputs in the "Wind Power Station" are not apparent when the task begins, examinees need to actively engage to control the task (e.g., if the examinee increases slide control A, the "Wind Power Station's" noise may be lowered, but this relation becomes only apparent during interaction). The labeling and the nature of the inputs, such as A, B, and C, eliminate effects of expert knowledge (i.e., even wind power engineers should not have an advantage in solving this problem with arbitrary labeled inputs of A, B, and C). In a knowledge acquisition phase, examinees are first requested to freely explore the task, learn relations, and draw connections between inputs and outputs (e.g., between A and noise) for 3 minutes, and then in a knowledge application phase to reach defined thresholds (e.g., of lowering noise and costs) within a time frame of 1.5 minutes. The task contents range, for example, from handball coaching, to the transportation of logistics of goods by road, to the illustrated "Wind Power Station" (for more details on MicroDYN, see Greiff et al., 2012).

After excluding the first task, which served as an introduction and practice, the six remaining tasks were scored with respect to their underlying two phases of knowledge acquisition and knowledge application. In phase 1 of knowledge acquisition, we gave full credit of (1) for correctly drawing all connections between variables (e.g., between input A and output noise in the "Wind Power Station") and a credit of (0) for incorrect connections.

In phase 2 of knowledge application, we gave full credit of (1) for correctly controlling target values on all outputs toward a requested goal state (e.g., down-regulating noise and costs of the "Wind Power Station" to a target value) and a credit of (0) for not reaching the requested goal state.

MicroFIN. These tasks also consist of a knowledge acquisition and a knowledge application phase. MicroFIN tasks are designed as so-called finite state automata (FSA; Funke, 2001). FSA are complex systems with levers, switches, and buttons that change the system from one state to another in dynamic, nonroutine, and interactive ways according to CPS theory (Funke, 2010). Within FSA, examinees are requested to press buttons in order to transfer an undesired finite state of a system (i.e., an automaton, such as a smart phone) into a desired goal state. Formally, levers, switches, and buttons are a finite set of inputs that change the state of the automaton in qualitative ways. For instance, pressing a button in MicroFIN's "Plan-o-mat," activates changes in the urban landscape that directly influence states of well-being of four urban interest groups (families, playgrounds, malls, and industry; see Appendix 2). The knowledge acquisition and application phases are conceptually similar to MicroDYN. Apart from the urban planning task "Plan-o-mat", typical MicroFIN tasks included in the current study demand, for example, to manage concerts of classical versus rock and roll music that depend of the type of audiences, ticket price, and venues ("Concert-o-mat"), or to harvest a new pumpkin species that grows depending on the season and various fertilizers ("Green-o-mat," for more details on the MicroFIN tasks, see Neubert et al., 2014). MicroFIN was scored similarly to MicroDYN.

Additional Measures

In addition to CPS, we measured GMA, educational level, job level, salary and job complexity.

GMA. A computerized version of Raven's Standard Progressive Matrices (SPM; Raven, Raven, & Court, 1998) was administered on tablets as a measure of GMA. The Raven's SPM is widely accepted as one of the best measures of fluid intelligence, and scores on this test have consistently been shown to exhibit high loadings on GMA factors (Jensen, 1998; Raven et al., 1998; Ree et al., 2015).

Level of education. Respondents indicated their level of education using the international standard classification for education (ISCED; UNESCO Institute for Statistics, 2012) shown in Appendix 1.

Job level. Respondents provided descriptions of their general job level. The international standard classification for occupations of 2008 (ISCO-08; International Labour Office, 2012) served as a template to measure job level. First, we inverted the ISCO-08 ranking for the sake of clarity of results (i.e., high job levels score high in the current study). Next, we merged adjacent job levels on the low end of the scale with small sample sizes (e.g., elementary occupations $n = 12$) into larger categories. As a result, jobs were coded as 1 = Skilled agricultural workers, craft and related trades workers, plant and machine operators and assemblers, and elementary occupations ($n = 160$), 2 = Service and sales workers and clerical support workers ($n = 85$), 3 = Technicians and associate professionals ($n = 83$), 4 = Professionals ($n = 241$), and 5 = Managers ($n = 70$, missing $n = 32$; Appendix 1).

Job level as measured by the ISCO-08 is an ordinal-level variable that sorts jobs in terms of their content, salary levels and opportunities for advancement.[4]

Salary. Salary was assessed by directly asking respondents to indicate their total annual net income. To assure comparability across different countries and currencies, income was transformed into normalized US Dollars per year, employing the purchasing power parity conversion factor (World Bank, 2015). In this sample, the mean and standard deviation of the salary distribution were \$35,434 and \$25,474, respectively. A relatively small number of very high salaries (the maximum salary observed was $174,638), created a relatively large standard deviation and a slight skew, but the salary distribution, excepting a few outliers, was reasonably normal.

Job complexity. Examinees rated the frequency of different tasks that were related to the level of job complexity on a 5-point-Likert scale, with 1 (never), 2 (*less than once a month*), 3 (*less than once a week but at least once a month*), 4 (*at least once a week but not every day*), and 5 (*every day*). All six items were derived from the Federal Institute for Vocational Education and Training Survey (BIBB; Rohrbach-Schmidt, & Hull, 2013) and asked respondents if they (1) make difficult decisions independently and without instructions, (2) collect, investigate, or document information at work, (3) have to recognize and close own knowledge gaps, (4) have to perform many different tasks, (5) have to keep an eye on different work processes or sequences at the same time, and (6) face new tasks which they have to think through and become familiar with. Ratings on these six items were combined to reflect the complexity of each incumbent's job. The distribution of job complexity was reasonably normal, with a mean and standard deviation of 3.62 and .88, repectively

Statistical Analyses

To derive measurement models and evaluate our hypotheses we used structural equation modeling (SEM; Bollen, 1989). First, we derived latent measurement models for all latent constructs (i.e., CPS, GMA, and job complexity) on the basis of confirmatory factor analyses. Then we calculated latent regression models in SEM for Hypotheses 1 and 2. In particular, we calculated a latent CPS residual that represented the portion of the CPS factor that that was independent of the two other predictors, GMA and the level of education. Because the latent CPS, GMA and education measures are on average more highly intercorrelated than their observed counterparts, the creation of latent CPS residual scores as predictors that are independent of GMA and education provides a conservative and rigorous version of the same hypothesis that can be tested in hierarchical multiple regression using observed variables (i.e., that CPS makes a unique and independent contribution). The SEM-based methods used here allow us to evaluate both incremental contribution (as in hierarchical regression) and the fit of a model that lays of an incremental role for CPS. We followed up this SEM-based test with more traditional hierarchical regression analyses to allow readers to more easily compare our results with previous regression-based studies and to provide interpretable effect size estimates.

Evaluating model fit and model parameters. Examining all models' goodness of fit with the robust weighted least squares estimator (WLSMV) or the robust maximum likelihood estimator (MLR), we evaluated the comparative fit index (CFI), the Tucker-Lewis index (TLI), the root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR) (the latter only for MLR) with respect to their recommended cutoff values (Hu & Bentler, 1999). The WLSMV was applied as this estimator is appropriate for measurement and structural models with binary manifest data; for measurement models with categorical data of five or more categories (e.g., Job Complexity), we used the MLR (Rhemtulla, Brosseau-Liard, & Savalei, 2012). To calculate scale reliabilities, used McDonald's ω_H (Zinbarg, Revelle, Yovel, & Li, 2005).

There is a nested data structure, with data collected within the 21 organizations. Intraclass correlations (ICC) of our measures ranged from .485 for salary to .547 for educational level. To account for this nested data structure, we used the MPlus 7.1 option TYPE=COMPLEX that avoids biases in standard errors and removed clustering effects (Muthén & Muthén, 1998-2014).

Missing Data

Because this study relied on tailored assessment suites (we tailored different subsets in accordance to each organization’s interests, data protection regulations, and time restrictions; e.g., Ravens SPM was administered to approximately 50% of our subjects) there was a substantial amount of missing data built into our design. There was also a small amount of missing data due to software errors during tests or saving data.

In a check for patterns in missing data, we evaluated models treating data as missing completely at random (MCAR) or as missing at random (MAR). Little's test resulted in a better fit for MAR ($\chi^2 = 407.712$, $p < .001$), indicating that there were not systematic relationships between the other variables studied here and whether or not particular assessments were missing. To account for missing data, we applied multiple imputations in the MPlus 7.1 software package for categorical variables and missing data. Facing high rates of missing data, we imputed 40 times, as recommended by Graham (2009). Multiple imputation is the method of choice that is thought to be always as good as more traditional methods (e.g., listwise deletion), but typically better and often very much better (Graham, 2009).

The proportion of missing data in the various measures ranged from 2.3% for the ISCED to 43.6% for the SPM. Data of CPS was missing for 6.2% of all participants, SPM scores were missing for 43.6% of participants (i.e., examinees who were not administered this particular test), and job complexity questionnaire responses were missing for 43.1% of participants. Job complexity, SPM, and salary data were largely missing, because either they were not part of the assessment suit or the testing ran out of time and participants could not finish. Data on salary was missing for 31% of all participants, on the job level for 4.7%, on educational level for 2.3%, and organizational membership information was missing for 2.4% of participants.

Results

Measurement Models and Reliabilities

We tested the measurement models of our latent variables CPS, GMA, and job complexity, and calculated the corresponding McDonald's ω_H. We used single manifest measures for level of education, salary, and job level that did not require these preliminary analyses.

CPS. We aimed to build CPS as a hierarchical factor in which CPS was represented by two assessments, MicroDYN and MicroFIN. First, we examined theoretically plausible models of MicroDYN and MicroFIN separately, testing solutions for each of the two, which were represented by their knowledge acquisition and knowledge application items (see, Funke, 2010) against more parsimonious solutions, which did not distinguish between knowledge acquisition and knowledge application items. For MicroDYN, the theoretically expected two-factor solution fitted significantly better to the data than a one-factor solution ($\Delta\chi^2 = 316.021$, $p < .001$; see absolute fit indices in Table 1), confirming previous research (e.g., Greiff, Fischer et al., 2013). For MicroFIN, a two-factor solution was not significantly better than a more parsimonious one-factor solution ($\Delta\chi^2 = 3.178$, $p = .075$; see absolute fit indices in Table 1). Second, we combined the measurement models for MicroDYN and MicroFIN into one overarching, second-order CPS factor. This second-order CPS factor model was reliably measured ($\omega_H = .89$), fitted the data well (see Table 1), and is depicted in Appendix 3.[4]

GMA. A single GMA factor fit the 31 items of the SPM well (see Table 1). We used parceling to reduce the number of parameters in this model, by assigning items to three balanced parcels using the item-to-construct balance recommended by Little, Cunningham, Shahar, and Widaman (2002). All parcels showed significant and substantial factor loadings on the GMA factor ($\lambda > .85$; with all ps < .001) in a just-identified model. An unparceled solution also indicated good model fit; the fit of this model is shown in Table 1. Reliability was high ($\omega_H = .98$).

Job complexity. Exploratory principal component analysis (PCA) in a previous study (Nedelkoska, Patt, & Ederer, 2015) using the full LLLight in Europe dataset suggested that the job complexity items could be grouped into a single scale. We applied confirmatory factor analysis to the job complexity scale and found that single job complexity factor fit the data well (see Table 1). Reliability was acceptable (ω_H = .83).

Latent correlations. Manifest correlations as well as latent correlations showed that all variables (CPS, GMA, level of education, job level, job complexity, and salary) were positively and significantly correlated in line with the hypothesized relations (Table 2). For instance, on the (latent) construct level, CPS was associated to salary (r = .34, p < .001), job complexity (r = .31, p < .001), and job level (r = .23, p = .023), and it also correlated with the level of education (r = .41, p = .004) and to GMA (r = .85, p < .001).

The observed correlation between GMA and CPS (r = .68) is high, but is consistent with meta-analytic estimates (Stadler et al., 2015 report a meta-analytic mean correlation of .58 between CPS tests of the sort used here and measures of GMA), and consistent with the results of several previous studies that show that CPS be meaningfully distinguished from GMA (Sonnleitner et al., 2013; Stadler et al., 2015; Wüstenberg et al., 2012). While the latent variable correlation between GMA and CPS is very high (r = .85), it is still the case that almost 30% of the variance in latent CPS scores is unrelated to latent GMA, leaving substantial room for a potential incremental contribution.

Latent Regressions. We hypothesized a unique contribution of CPS in predicting job complexity (H1), job level, and salary (H2) beyond GMA and the level of education, two highly established and also very efficient predictors. In order to investigate and quantify a unique contribution, we regressed CPS on GMA and educational level, and used the resulting CPS residual, which represented the variance of CPS that is not shared with GMA and the level of education, as a predictor variable. We employed this latent residual CPS score to predict the three criteria in H2, setting the direct effect of CPS on the criteria to zero, following the approach chosen by Wüstenberg and colleagues (2012). This latent regression model fit the data well (see Table 1) and is illustrated in Figure 1. The resulting SEM model allowed us to quantify the incremental statistical effect of CPS on the criteria as specified in H1 and H2.

Preliminary analyses of control variables. First, GMA strongly predicted CPS ($\beta_{CPS} = .83$, $SE = .05$, $p < .001$), whereas the level of education did not predict CPS when GMA was taken into account ($\beta_{CPS} = .04$, $SE = .07$, $p = .305$; Figure 1). This link of CPS and educational level in our regression model was weak in comparison to the moderate zero-order between CPS and educational level ($r = .41$, $p = .004$; depicted in Table 2), suggesting that a large part of this overlap was due to GMA.

Secondly and in line with previous research, the level of education predicted job level ($\beta_{job\ level} = .81$, $SE = .10$, $p < .001$), job complexity ($\beta_{job\ complexity} = .28$, $SE = .10$, $p < .001$), and salary ($\beta_{salary} = .27$, $SE = .09$, $p = .001$). When taken into account simultaneously with level of education, GMA neither predicted job level ($\beta_{job\ level} = -.05$, $SE = .05$, $p = .168$) nor job complexity ($\beta_{job\ complexity} = .09$, $SE = .10$, $p = .147$), and only weakly predicted salary ($\beta_{salary} = .08$, $SE = .045$, $p = .03$; Figure 1). These links weakened in the statistical prediction of our criteria by GMA, compared to the small to moderate correlations in the preliminary analysis between GMA and salary of .20 ($p < .001$), job complexity of .22 ($p = .005$), and job level of .32 ($p < .001$; depicted in Table 2). This decrease is likely due to shared variance with educational level ($r = .41$, $p = .005$) in this prediction.

H1: CPS Predicts Job Complexity Beyond GMA and the Level of Education

The latent residual of CPS incrementally predicted job complexity, with $\beta_{complexity} = .21$ ($SE = .12$, $p = .047$) beyond the level of education and GMA, supporting H1. As this CPS residual was statistically independent of GMA and educational level, the square of its path coefficient indicated the amount of uniquely explained variance in the criteria by CPS, revealing significant effect size of 4% ($R^2 = .04$) of uniquely explained variance in job complexity.

H2: CPS Predicts Job Level and Salary Beyond GMA and the Level of Education

Job level and salary indicate job success and if CPS matters in job success, it should be related to job level and salary beyond cognitive ability and education. The latent residual CPS score predicted salary with $\beta_{salary} = .29$ ($SE = .05$, $p < .001$) above and beyond the level of education and GMA, supporting H1 (in contrast, in an analysis of observed measures by Ederer et al., 2015 for CPS did not predict salary when controlling for GMA, education, and a number of additional variables). In opposition to H2, CPS failed to account for incremental variance in the job level ($\beta_{job\ level} = -.11$, $SE = .10$, $p = .15$; see Figure 1). Taken together, predictions regarding the incremental contribution of CPS beyond GMA and the level of education in predicting occupational success were supported for salary, but not for the job level.

The incremental contribution of CPS is not an artifact of job level. As higher-level jobs usually pay better (e.g., Guthrie et al., 2015; Jensen, 1980; Milkovich et al., 2013; in the current study, the observed correlation between job level and salary is $r = .30$), it is possible that the relationship between residual CPS and salary is an artifact of job level. To determine whether the incremental contribution of CPS in predicting salary was an artifact of the different salaries and job duties associated with jobs at higher vs. lower level jobs, we calculated the latent partial correlation between the CPS residual and those parts of salary that are independent of the job level. There is a significant latent partial correlation between residual CPS and salary independent of job level ($r = .39$, $p < .001$) suggested that even after controlling for both GMA and the level of education on the predictor side and for occupational level on the side of criteria, CPS still a contribution to the prediction of salary.

Relative weights analyses. Because the residualized SEM methods used here have not been widely used in similar studies, we also assessed the predictions in H1 and H2 using hierarchical regression and applied relative weights analyses on a manifest level. First, the criteria (complexity, level, salary) were regressed on GMA and the level of education as controls (step 1), before entering CPS (step 2). Similar to our latent regression model reported above, CPS significantly explained additional variance in salary (β = .25, t(252) = 2.90 , p = .004) and job complexity (β = .30, t(213) = 3.46 , p = .001) with significant $\Delta R^2_{\text{salary}} = .03$ ($\Delta F(1, 252) = 8.43$, p = .004) and $\Delta R^2_{\text{complexity}} = .05$ ($\Delta F(1, 225) = 42.64$, $p < .001$). The incremental contribution of CPS over GMA and education was small for the job level variable (β = -.12, t(352) = 2.93 , p = .004) with $\Delta R^2_{\text{job level}} = .01$ ($\Delta F(1, 352) = 8.62$, p = .004).

In a last step, we examined the importance of CPS relative to GMA and the level of education. We evaluated importance of each predictor using relative weights analysis (Fabbris 1980; Johnson 2000), a method that is useful for partitioning variance to the predictors when they are correlated. This analysis shows that CPS contributes 55% of a total R^2 of .10 by all predictors to explain salary, 61% of a total R^2 of .11 to explain job complexity, and 4% of a total R^2 of .65 to explain job level (see Appendix 4). These analyses suggest that, compared to GMA and education, CPS is relatively important in explaining job complexity and salary and relatively unimportant for predicting job level.

Discussion

It has been suggested (e.g., OECD, 2013a, b) that CPS skills are important in the workplace. The current study uses rigorous and conservative tests to evaluate the incremental contribution of CPS skills in predicting occupational choice (in particular, the choice of jobs that involve tasks that require incumbents to solve unstructured problems) and occupational success (job level and salary). We used the best available measures of CPS, modeled on the highly successful PISA assessments, and one of the best pure measures of fluid intelligence and figural reasoning (i.e. Raven's SPM. See Greiff, Fischer et al., 2013; Schweizer et al., 2013; Stadler, et al, 2015; Wüstenberg et al., 2012 as illustrations of similar methods in educational settings), and used a set of job-analytic questions to classify jobs in terms of complexity. Our results suggest that CPS skills play a distinct and incremental role in occupational gravitation. Individuals with stronger CPS skills are more likely to occupy and to succeed in jobs that require complex problem solving, and this effect is independent of the effects of both general mental ability and education.

Going beyond previous studies, such as Ederer and colleagues (2015), we used SEM to construct a latent CPS residual score that is fully independent from GMA and the level of education, and showed that CPS makes a unique and relatively important contributions, above GMA and the level of education in predicting salary and job complexity. Our pattern of results are consistent the assumption that CPS represents unique aspects of complex cognition in the form of higher-order thinking skills to deal with dynamic, nonroutine, and interactive tasks that: (1) are characteristic of modern jobs, and (2) are not fully captured by such strong predictors as GMA and the level of education (Funke, 2010).

A number of studies have shown that GMA can be used to sort individuals into jobs that are more or less cognitively demanding (Desmarais & Sackett, 1993; Gottfredson, 1986, 2003; Jensen, 1980; Wilk et al., 1995). Our results suggest a comparable role for CPS skills; individuals with higher CPS skills are more likely to be found in and to be successful in jobs that require complex problem solving. Taken together, our results provide empirical support for the recommendations of the OECD and the National Research Council that investment in the development of CPS skills is likely to have payoffs in the workplace. In contrast to GMA, a well-established predictor of occupational gravitation, career success and job performance, CPS skills can be meaningfully enhanced with training and practice, and the development of these skills may open more doors for students who are entering job markets in which an increasing proportion of jobs require them to successfully solve complex and unstructured problems.

Strengths and Limitations

The present study is the first to link skills in CPS to multiple indicators of occupational success, while unambiguously controlling for both GMA and education in a large and diverse multinational sample of employees that spanned a range of jobs and occupations. Our statistical approach allowed us to directly evaluate the contribution of the part of CPS that is strictly independent of GMA and the level of education to a number of occupational criteria not examined in previous studies (Ederer et al., 2015). There are, however, limitations to the conclusions that we have drawn from the present study.

First, with a latent correlation of .85 between CPS and GMA, one might question, whether these constructs are separable. The strong overlap between CPS and GMA measures observed here is consistent with previous research that demonstrate strong g-loadings for CPS tests (Kretzschmar, Neubert, Wüstenberg, & Greiff, 2016; Stadler et al., 2015), but our findings are also consistent with the conclusions reached in several previous studies that GMA and CPS are both conceptually and empirically distinct (Wüstenberg et al., 2012; Sonnleitner et al., 2013). In particular, despite the substantial correlation between latent GMA and CPS measures, we were still able to demonstrate significant increases in predictive power when CPS was added to regression models that already included both GMA and education.

Second, the effect sizes for the residual CPS scores here are in relatively small, with increments in R^2 of 8% for salary and 4% for job complexity. It is, of course, notable to find *any* incremental contribution beyond GMA and the level of education at all (e.g., Ree et al., 2015; Ree et al., 1994), given that: (1) GMA and the level of education are among the most powerful single predictors of occupational outcomes (e.g., Ng et al., 2005; Schmidt & Hunter, 1998), and (2) measures of GMA usually subsume measures of other specific cognitive abilities (e.g., Ree et al., 2015). Nevertheless, it is important to recognize that while the incremental contribution of CPS is statistically significant, it is not necessarily large.

Third, the data presented here clearly do not allow us to fully test the gravitation hypothesis, because a cross-sectional research design does not allow for temporal predictions or conclusions about causality. Our results are consistent with, but not confirmative of theories that assign a causal role to CPS in gravitation to specific types of jobs (e.g., Murphy, 1989). For example, there is evidence that complex jobs stimulate and facilitate the development cognitive skills up until old age (Schooler, Mulatu, & Oates, 1999; Smart et al., 2014), and it is possible that causation runs in the opposite direction suggested by a gravitation model (i.e., being in a complex job leads to higher CPS skills). Thus, there may be considerable payoff in further research to collect longitudinal data that allow researchers to track movement in the job market over time (cf. Wilk et al., 1995) in relation to CPS skill levels, and to more fully test causal and reciprocal relationships between CPS and the likelihood of occupying well-paying, complex jobs higher up in the occupational hierarchy.

Fourth, applying SEM to cross-sectional data also assumes linear relations between variables, a presumption that might not hold true in a working world that has been repeatedly criticized for paying disproportionally high wages for managers (thus establishing nonlinear relationships between job characteristics and salary; Neal & Rosen, 2000). We excluded extraordinary wages in the current study, but it is possible that including a larger number of individuals at the highest job levels in this study would reveal nonlinear as well as linear trends.

Finally, our results may not be representative. We were not able to draw a randomized sample, but instead had to rely on companies willing to participate in a time-consuming research project, a circumstance that resulted in a large, but selective convenience sample with a high rate of missing data by design.

Conclusions

Our study provides first evidence that CPS is relevant in the workplace, partly independent of GMA and the level of education, two of the best predictors of success in the work life (for reviews, see Brand, 1987; Gottfredson, 2002; Ng & Feldman, 2010). The unique links of CPS to success presented here are an important exception to the frequent claim in I-O psychology that not much more than GMA is needed to make predictions about performance on the job and career success (Ree et al., 2015). Also, CPS skills represent more than a simple set of strategies learned during formal education. Our data suggests that the construct of CPS includes unique higher-order thinking skills to acquire and apply particularly new knowledge that matter in increasingly complex and nonroutine jobs and that have previously not been captured in I-O psychology (Neubert et al., 2015). Thus, CPS may contribute to a more comprehensive picture of complex cognition at the workplace. If technology and organizational change continue race ahead, the increasing complexity of jobs is likely to further enhance the role CPS skills in the workplace, possibly creating an increasingly important set of employment opportunities for individuals who manage to develop these skills.

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[1] Ederer and colleagues' (2015) study served as a starting point of the current study, and used a subsample (*N* = 399) with less than 50% overlap with the sample used here. More important, the current study includes two dependent variables, occupational level and job complexity, not examined by Ederer and colleagues (2015) and frames the analysis in terms of a multivariate model with multiple dependent variables, in contrast to the univariate wage regression model in Ederer and colleagues (2015).

[2] Several of the authors of the current paper were part of the team that developed the computerized CPS assessments used in PISA.

[3] We collected data from 676 respondents but dropped five employees who reported unusually high or low wages relative to the median (with a cut-off of more than 2.5 times the Median Absolute Deviation [MAD; Hampel, 1974] around the median; as recommended by Leys, Ley, Klein, Bernard, & Licata, 2013). As a result, our sample included *N* = 671 working individuals

[4] Mean salary per job level were $ 1495.84 (SD = 292.27) on level 1, $ 2044.72 (SD = 1740.99) on level 2, $ 2929.71 (SD = 1565.23) on level 3, $ 2907.23 (SD = 1377.89) on level 4, and $ 5916.80 (SD = 3371.15) on level 5 of Managers.. This finding largely supports that ISCO-08 sorts jobs by salary levels, as suggested by the OECD, 2013a).

Table 1

Goodness of Fit Indices for all Models, Including One- and Two-Factor Solutions for CPS, Solutions for GMA, and Job Complexity, as well as the Latent Correlation and Regression Models that Tested our Hypothesis (N = 671).

Model	χ2	*df*	*p*	CFI	TLI	RMSEA	SRMR
1. MicroDYN 1-dimensional	124.042	55	<.001	.974	.969	.059	-
2. MicroDYN 2-dimensional	104.591	54	<.001	.981	.977	.051	-
3. MicroFIN 1-dimensional	196.969	135	<.001	.955	.949	.027	-
4. MicroFIN 2-dimensional	195.936	134	<.001	.955	.949	.027	-
5. CPS	521.442	404	<.001	.977	.976	.021	-
6. GMA	426.393	377	.04	.957	.953	.018	-
7. Job Complexity	11.22	8	<.001	.998	.997	.032	.023
8. Latent correlations	895.434	805	.01	.965	.963	.013	-
9. Latent regression of CPS	747.679	660	.01	.969	.967	.014	-
10. Latent regression of GMA, Education, and CPS	909.029	806	.006	.96	.957	.014	-

Note. MicroDYN-1 = one-factor solution of the MicroDYN test; MicroDYN-2 = two-factor solution of the MicroDYN test; MicroFIN-1 = one-factor solution of the MicroFIN test; MicroFIN-2 = two-factor solution of the MicroFIN test; CPS = complex problem solving modeled as a second order hierarchical factor; GMA = general mental ability; unparceled solution; df = degrees of freedom; CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; CI = confidence interval; SRMR = standardized root mean square residual (only for MLR); χ^2 and df estimates are based on MLR (model 7: Job Complexity) or WLSMV (all other models).

Table 2

SEM-Based Latent Correlations and Manifest Correlations Between Observed Measures, and Reliability (ω_H)

	(1)	(2)	(3)	(4)	(5)	(6)
(1) CPS	(.89)	.68**	.40**	.27**	.36**	.15**
(2) GMA	.85**	(.97)	.44**	.35**	.21**	.16**
(3) Education	.41**	.45**	-	.79**	.30**	.18**
(4) Job Level	.23*	.32**	.79**	-	.46**	.23**
(5) Salary	.34**	.20**	.30**	.46**	-	.15**
(6) Job Complexity	.31***	.22**	.33***	.33**	.31***	(.83)

Note. N = 671 for latent constructs and N between 276 and 645 for observed measures. Correlations of observed measures are reported above the diagonal. Model-based latent correlations are reported below the diagonal. If applicable, also McDonald's ω_H is reported in parentheses as measure of reliability; ω_H of CPS as a hierarchical factor (see Appendix 3); CPS = complex problem solving; Education = international standard classification for education (ISCED); Job Level = international standard classification for occupations of 2008 (ISCO-08 [inverse scoring]); Salary = total yearly net income normalized with purchasing power parity conversion factor (World Bank, 2015); Job Complexity = latent variable of 7 complexity items (see Method). Two-tailed p-values: *$p < .05$. **$p < .01$. ***$p < .001$.

Figure

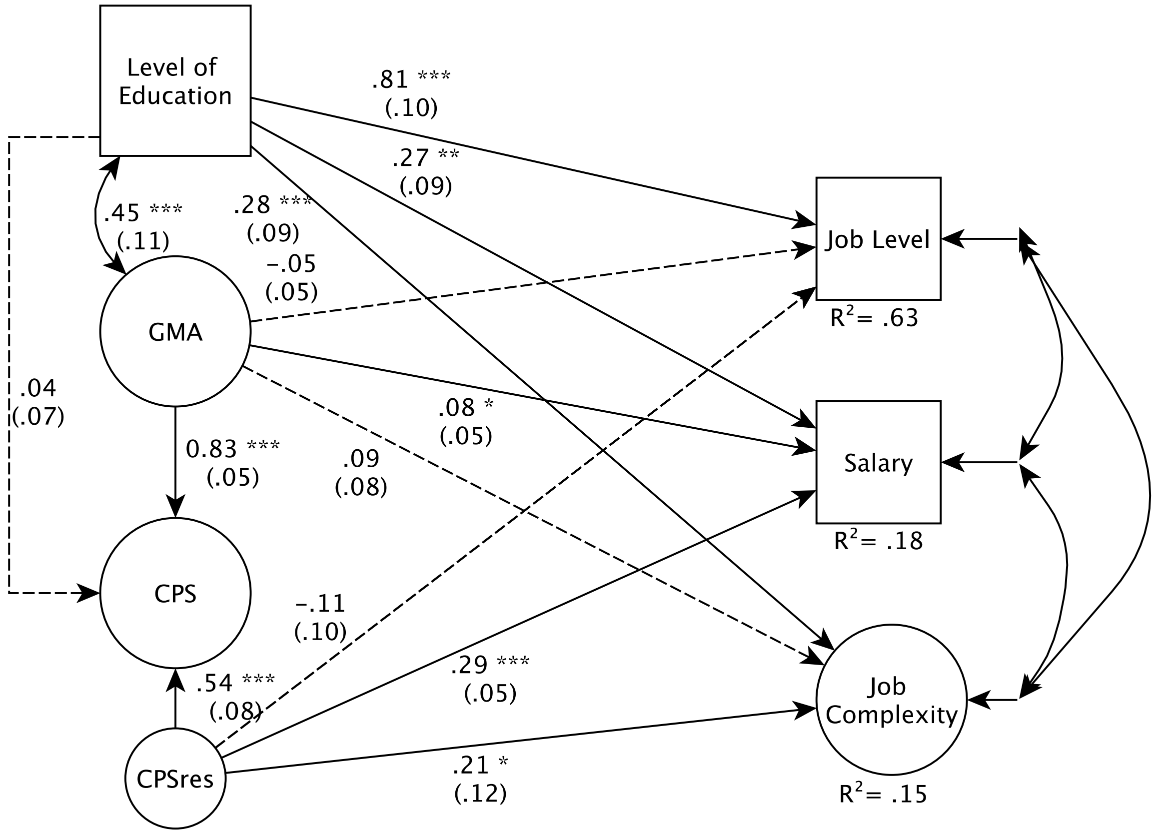


Figure 1. Incremental contribution of CPS = complex problem solving over GMA = general mental ability and Level of Education in predicting Job Level, Salary, and Job Complexity. *N* = 671. Level of Education, GMA, and the residual of CPS (CPSres) that is unrelated to GMA and the Level of Education are statistical predictors of Job Level, Salary, and Job Complexity. The numbers in parentheses are the standard errors. One-tailed p-values: *$p < .05$, **$p < .01$, ***$p < .001$.

Appendices

Appendix 1

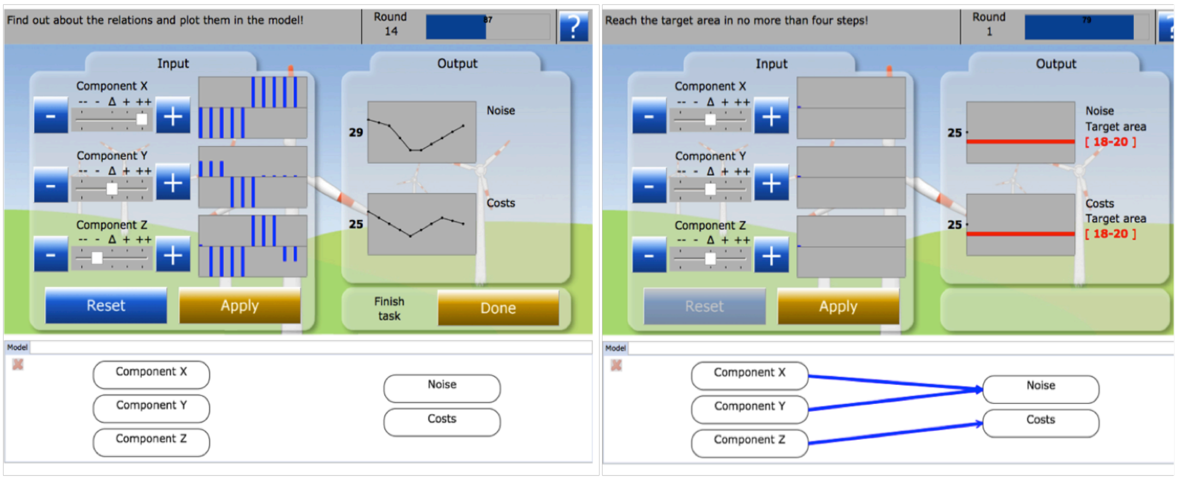
Sample Characteristics

Country	%	Educational Level [a]	%	Job Level [b]	%
Denmark	3.0	Primary	1.3	Lower-level [c]	23.6
Germany	63.2	Lower Secondary	20.0	Clerical	12.7
France	1.5	Upper Secondary	9.8	Technician	12.4
Netherlands	0.1	Post Secondary, Non Tertiary	13.9	Professional	35.6
Slovakia	6.0	Bachelors or equivalent	13.6	Manager	10.4
Spain	22.7	Masters or equivalent	37.9	Missing	5.3
Switzerland	1.8	Doctorate or equivalent	3.6		
UK	1.8				

Note. N = 671. [a] for educational level, an adjusted version of the international standard classification for education (ISCED) was used. [b] for job level, an adjusted version of the international standard classification for occupations of 2008 (ISCO-08) was used. [c] lower-level jobs included service and sales workers, skilled agricultural workers, craft and related trades workers, plant and machine operators and assemblers, and elementary occupations.

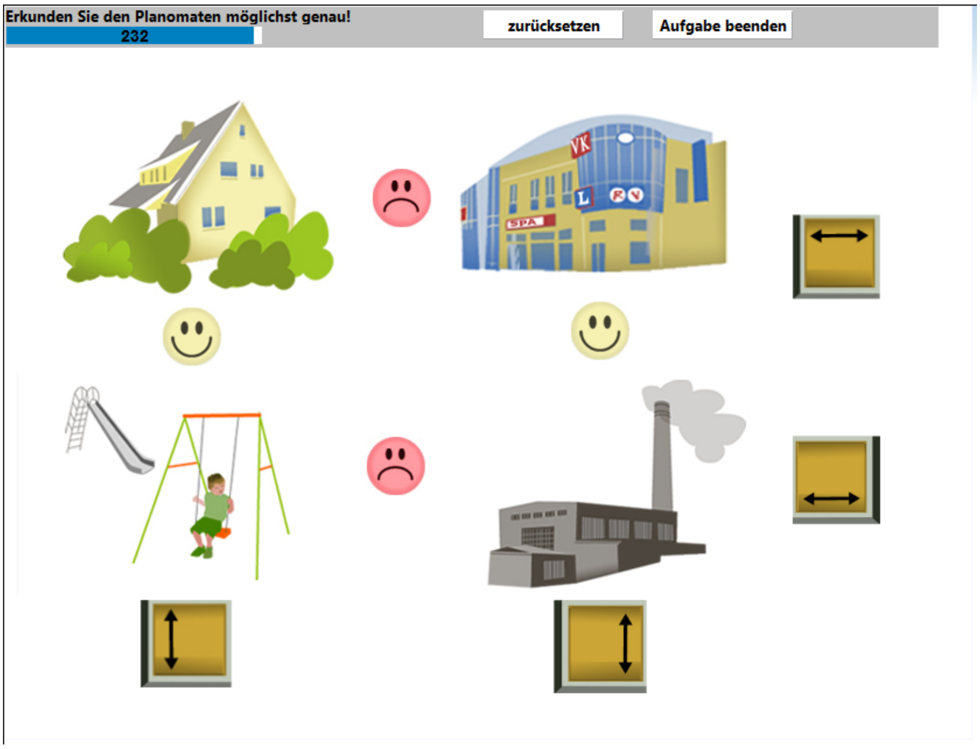
Appendix 2

MicroDYN Wind Power Station task



Screenshot of the MicroDYN Wind Power Station task (Greiff et al., 2012). Left side: Knowledge acquisition. X, Y, and Z influence noise and costs. Examinees are asked to draw their acquired knowledge about the relations in an onscreen causal diagram (Funke, 2001; see bottom of this Figure, left side). Right side: Knowledge application (cf. Wüstenberg et al., 2012). Target values for each output variable (red areas and numbers in brackets) have to be met within a maximum of four steps to gain control over the system.

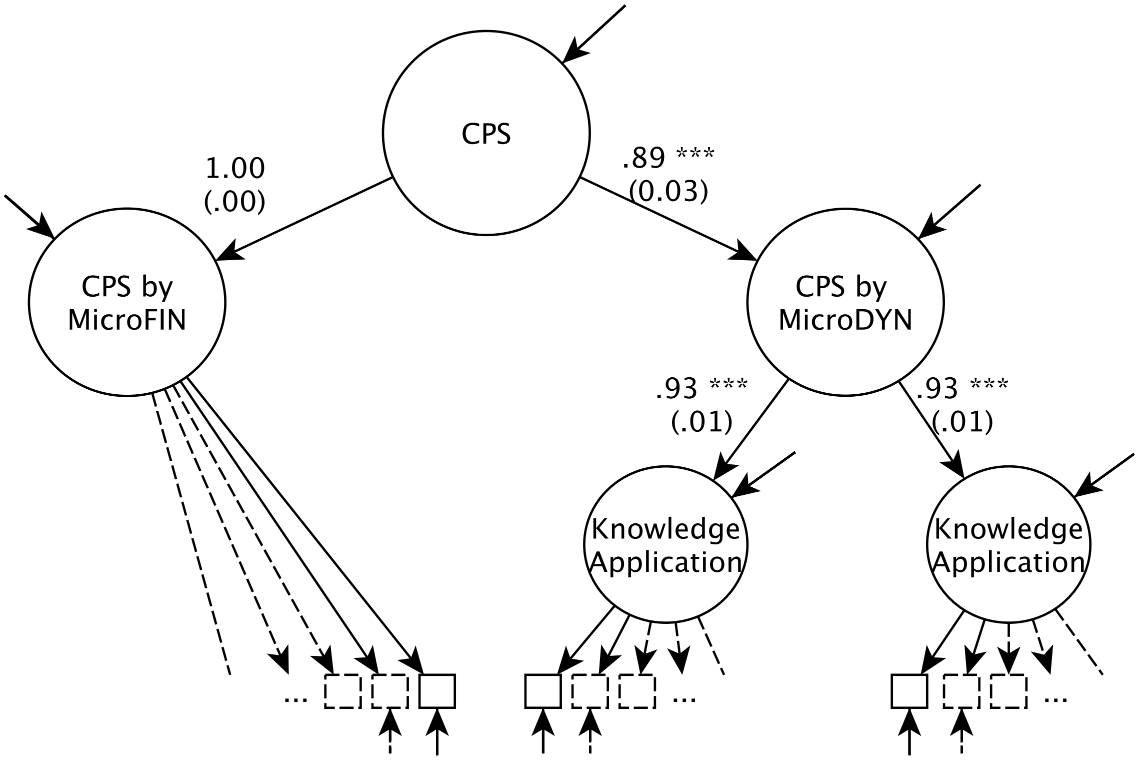
MicroFIN task "Plan-o-mat"



Screenshot of the MicroFIN task "Plan-o-mat" (Neubert et al., 2014). Problem solvers have to balance the interests of various parties in a city by making alterations in the urban landscape. The keys for altering the location of the interest groups are located along the bottom and the right side. In principle, two stakeholders change places when triggered. A city mall and a factory are situated on the right side, and a family home and a playground are situated on the left side. Between these parties, smiley faces are presented to indicate the atmosphere. The problem solver has to acquire knowledge about how to change the atmosphere (knowledge acquisition) and has to find one of several optimal setups (knowledge application).

Appendix 3

Hierarchical factor of CPS



Hierarchical factor of CPS on the basis of MicroDYN and MicroFIN. $N = 671$. The path coefficient between the hierarchical CPS and the CPS factor of MicroFIN is set to 1 and its variance to 0 to allow for a stable model estimation (for details see Method). CPS = complex problem solving modeled as a second order hierarchical CPS factor; CPS by MicroFIN= one-factor solution on the basis of MicroFIN; CPS by MicroDYN= two-factor solution on the basis of MicroDYN. Two-tailed *p*-values: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Appendix 4

Relative weights analysis for job level, job complexity, and salary regressed on the level of education, GMA, and CPS,

Criteria	Predictors	ε	CI (ε)	rescaled ε
Job Level	Education	.57*	.50 – .63	87.42
	GMA	.05*	.03 – .08	8.33
	CPS	.03*	.01 – .04	4.25
		R^2 =. 65		Σ = 100.00
Job Complexity	Education	.03	.00 – .08	25.85
	GMA	.01	.00 – .03	12.46
	CPS	.07*	.02 – .13	61.69
		R^2 =. 11		Σ = 100.00
Salary	Education	.02	.00 – .06	23.57
	GMA	.02	.00 – .04	20.89
	CPS	.06*	.01 – .10	55.54
		R^2 =.10		Σ = 100.00

Note. N = 671. Education = level of education CPS = complex problem solving. GMA = general mental ability. ε = Raw relative weight values; CI (ε) = Confidence Interval; rescaled ε = rescaled weights (scaled as a percentage of predictable variance); sum of the raw relative weights is equal to the value of the R^2; Σ = the sum of the rescaled relative weights is 100%.

p-values: $^*p < .05$.

4

Complex Problems in Entrepreneurship Education

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

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Abstract

In opening-up the black box of *what* entrepreneurship education (EE) should be about, this study focusses 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-generic 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 master students. Data is analyzed using multiple regressions. The results show that CPS predicts the number of *concrete* ideas students generate, suggesting that having CPS skills support the generation of detailed, potential business ideas of good quality. The results of the current study suggest that training CPS, as a more domain-generic skill, could be a valuable part of *what* should be taught in EE.

Keywords: entrepreneurship; complex problem solving; entrepreneurial opportunity; opportunity identification; business idea.

Complex Problems in Entrepreneurship Education:

Examining Complex Problem Solving in the Application of Opportunity Identification

1. Introduction

Acquiring entrepreneurial skills can help in preparing students on 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, but 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, Frese, Graf, and Kampschulte [6] found that divergent thinking explained the number and originality of generated business ideas. Wang, Ellinger and Wu [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, Nickerson and Zenger [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, non-routine, 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 non-cognitive processes (e.g., self-management; [13, 16]). 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, 20]). A small number of studies suggest CPS to be relevant for success in work settings [21, 22, 23]. On a theoretical basis, Neubert, Mainert, Kretzschmar and Greiff [24] 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.

1.2. 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 [25, 26]. 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 [27], 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 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, non-routine, and interactive, and thus require more than domain-specific prior knowledge. These characteristics are what make the barriers complex, or in other words, that make 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, 28, 29, 30]. 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; [31, 32, 33].

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 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 [30]. These processes constitute the core of the domain-general construct of CPS [34, 28].

1.3. Opportunity identification

Suddaby et al. [8] recently published a special issue of *the Journal of Business Venturing* on OI, underlining the importance and relevance 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 co-exist [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 its underlying process can co-exist. 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 manuscript, 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 explains 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].

Secondly, 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.

Thirdly, in their empirical study, Grégoire 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 which 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 Grégoire et al. [39] showed that especially similarities in higher order structural relationships helped to identify new opportunities.

1.4. 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 realises that this is not as simple as dimming traditional light bulbs. It is here that being able to identify opportunities and having CPS is both valuable in a single situation: dimming LEDs has the characteristics of a complex problem (i.e., being dynamic, non-routine, 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 an 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. Both being able 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 skills 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, 44, 45]. Similar to entrepreneurs, successful complex problem solvers actively acquire knowledge by assuming that the information around them is incomplete or false [31]. 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 [27] 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 and (2) reduce the amount of uncertainty about the opportunity potential, and, as a result, (3) 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, non-routine, 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. [13, 5]). 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].

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 Grégoire 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. As Grégoire et al. [39] argue, 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 [31]. 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 [30]. 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; [33]). 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* or *Career Development and Planning*[2]. *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 [50]).

[2] This sample was also used for a different study with a different purpose, namely to develop the measurement of OI (see [51]).

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 hour, so the first two groups switched between Sessions A and B for the first 1.5 hour 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 minutes 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 [52], 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 (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 [53]. After each scoring round, they compared and discussed their results, and refined the codebook until acceptable levels of interraterreliability 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 read 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]. MicroFIN features multiple, dynamic tasks that are based on a formal framework called “Finite State Automata”. Buchner and Funke [54] introduced this framework in order to counter limitations in the breadth of problems included in previous instruments (e.g., MicroDYN; [55]) and facilitate a greater heterogeneity in tasks [56]. 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, 57]). 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-Mat" 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 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 vs. Rock'n'Roll), price level, and atmosphere (indoor vs. outdoor), or (b) the challenge of successfully harvesting a new kind of pumpkin that varied according to the season and the amount of fertilizer.

Please insert Figure 1 about here

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 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 toward 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 [58, 49]).

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-Mat) 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-Mat), 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. [57]. 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]. The Cronbach's alfa 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, 57, 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. The 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 data sets (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 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 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 Model 2a and 3a, we respectively regressed the proportion of concrete ideas and flexibility on the control variables, and in Model 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).

Please insert Table 1 about here

CPS was not significantly correlated with the number of comprehensible ideas (r = .18, p = .071), and weakly but significantly correlated to the proportion 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.

Please insert Table 2 about here

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.

Please insert Table 3 about here

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 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.

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 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 IO 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 thought 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 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 non-cognitive 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 to resemble 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 the 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, 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, 44, 45]. More specifically, those who have higher levels of CPS skills, might be able to identify concrete opportunities, which are visualisable 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 with 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 Marsh and O'Neill [61] have shown for other areas, where self-concept and ability corresponded. The level of problem-solving self-concept solely explained variance in comprehensive ideas, and neither in concreteness, nor in flexibility. This pattern might suggest that the belief in one's problem-solving ability supported – at least to a small extent – to come 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] distincts 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 been developed in different functions and roles. As Grégoire 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.

Secondly, 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 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 [75, 39], 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.

Secondly, 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 [50] found that creativity training had a more 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 skills 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 toward 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, 81, 82, 83, 84, 85].

More specifically, educating CPS skills could be part of 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, 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, 49]). 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 toward 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.

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8. 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.

Tables and Figures

Table 1
Descriptive Statistics for the Assessment of OI, CPS, Prior Knowledge, and Problem-Solving Self-Concept

Variable	Minimum	Maximum	*M*	*SD*
Opportunity identification				
No. comprehensible ideas	0	23	6.27	3.55
No. concrete ideas	0	16	5.77	3.20
Flexibility	.17	1	.53	0.18
CPS	0.75	5	3.3	.87
Prior knowledge	1.50	4.88	2.91	.67
Problem-solving self-concept	1.50	4.83	3.66	.62

Note. Statistics are based on raw data (i.e., non-imputed). CPS = Complex Problem Solving; PS self-concept = Problem-solving self-concept. The control variable ratings ranged from 1 (*disagree strongly*) to 5 (*agree strongly*).

Table 2
Manifest Correlations between Variables

Measure	*1*	*2*	*3*	*4*	*5*	*6*
1. No. 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 concrete of comprehensible ideas; CPS = Complex Problem Solving; PS self-concept = Problem-solving self-concept.
Two-tailed p-values: $^{*}p \leq .05$. $^{**}p < .01$. $^{***}p < .001$

Table 3

Regression Analyses with (1) the Number of Comprehensible ideas, (2) The Proportion Concrete Ideas of Comprehensible Ideas, and (3) Flexibility as Dependent Variables, including Beta's

	No. comprehensible ideas		Proportion concrete		Flexibility	
Predictor	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. The ΔR^2 represents the comparison between Models (a) and (b) for each dependent variable.

Two-tailed p-values: *$p < .05$. **$p < .01$.

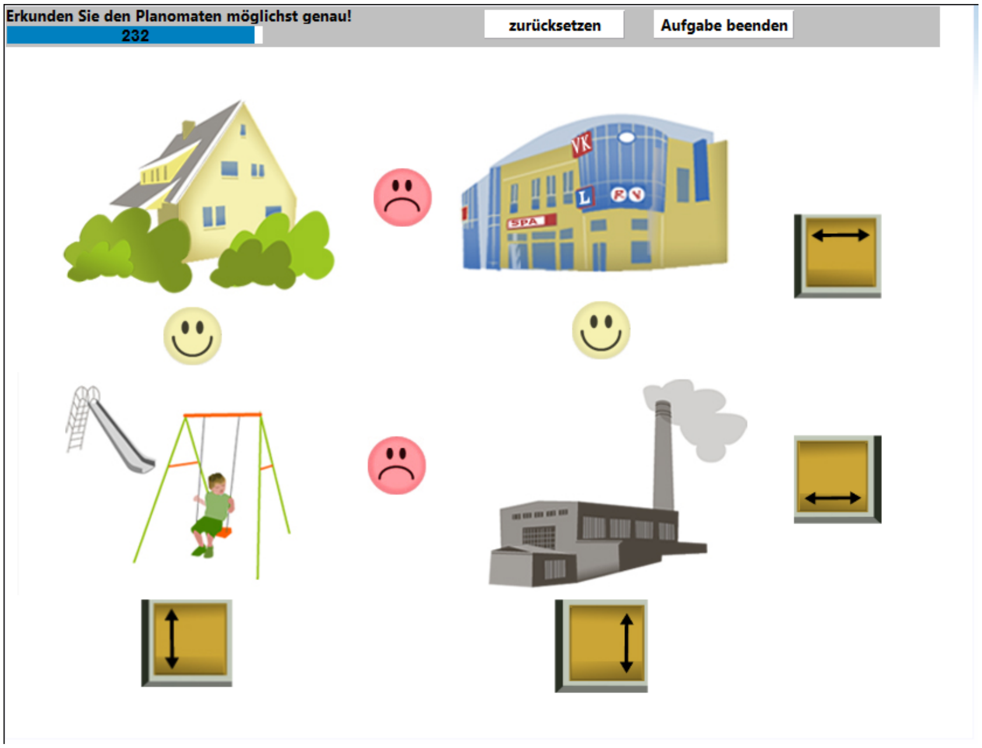

Figure 1. Screenshot of the MicroFIN item "Plan-o-mat" [49]. Problem solvers have to balance the interests of various parties in a city by making alterations in the urban landscape. Along the bottom and the right side: the keys for altering the location of the interest groups. In principle, two stakeholders 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.

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How employees perceive organizational learning

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How Employees Perceive Organizational Learning: Construct Validation of the 25-Item Short Form of the Strategic Learning Assessment Map (SF-SLAM)

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Abstract

Purpose. The Strategic Learning Assessment Map (SLAM) originally assessed organizational learning (OL) at the level of the firm by addressing managers, who rated OL on five dimensions of individual learning, group learning, organizational learning, feed-forward learning, and feedback learning. However, as employees are getting their jobs done discretely and are increasingly making their own decisions, their perspective on OL genuinely matters. Hence, we assessed OL at the level of the individual by addressing employees on all levels, who rated OL in a short form of the SLAM (SF-SLAM).

Design/methodology/approach. In this paper, we focused on the construct validity of this SF-SLAM by investigated its reliability, factorial validity, and nomological network. First, we asked whether the SF-SLAM reliably measures OL on five dimensions of individual, group, organizational, feed-forward, and feedback learning. Next, we asked whether the SF-SLAM was associated with its nomological network of engaging in innovation-related learning activities, behaving innovatively on the job, and showing higher educational levels, intelligence, and individual job performances. We used a diverse German employee sample of skilled and unskilled workers and managers ($N = 434$) and analyzed the data with structural equation modeling.

Findings. The SF-SLAM was reliable, but revealed both constrained factorial validity and validity on the basis of its nomological network. First, five dimensions found support in our employee sample, but their correlations were high or very high, except for individual learning. Second, the SF-SLAM showed only few differential relations with variables from its nomological network.

Originality/value. Taken together, the SF-SLAM is short, reliable, and only valid for examining individual learning.

Keywords: Strategic Learning Assessment Map (SLAM), organizational learning (OL), ambidexterity, short-form, construct validation

How Employees Perceive Organizational Learning: Construct Validation of the 25-Item Short Form of the Strategic Learning Assessment Map (SF-SLAM)

Introduction

The 50-item Strategic Learning Assessment Map (SLAM; Bontis, Crossan, & Hulland, 2002) was originally designed to explain strategic renewal at the level of the firm by asking managers how they perceived their firm's organizational learning (OL; Huber, 1991). OL in the SLAM describes a set of learning activities on multiple organizational levels. First, individuals intuit and interpret knowledge that is shared in groups and later integrated and institutionalized in systems, structures, or routines (Bontis et al., 2002; Crossan, Lane, & White, 1999). The SLAM was a direct operationalization of the seminal work of Crossan et al. (1999), who delineated OL in their 4I framework, which has been received extensively in theoretical and empirical work (Berson, Da'as, & Waldman, 2015; Crossan et al., 2011; Lloria & Moreno-Luzon, 2014; Real Leal, & Roldán, 2006; Real, Roldán, & Leal, 2014; Vargas & Lloria, 2014). According to Bontis and colleagues (2002), the SLAM is a reliable and valid scale of OL activities for managers. However, as jobs are broader and more complex, and employees are more independent and self-organized than ever (Brynjolfsson & McAfee, 2016; Noe, Hollenbeck, Gerhart, & Wright, 2006), managers might not fully notice the OL activities of their employees. How employees perceive their firm's OL activities through the SLAM might therefore offer a more complete picture of OL and eventually facilitate the study of antecedents of strategic renewal, which is an important topic for researchers and practitioners alike (Bontis et al., 2002; Chadwick & Raver, 2015; Crossan et al., 1999; March, 1991). To this end, we administered a short form of the SLAM to $N = 434$ employees across job levels and investigated its reliability, factorial validity, and nomological network with conceptually and theoretically related variables in assessing OL activities from the employees' perspective.

Theoretical Framework

The OL activities in the SLAM represent drivers of strategic renewal and long-term organizational success with multiple dimensions of and between individuals, groups, and their organization (Crossan et al., 1999). Recently, researchers largely explained how organizational strategy and environment determine the direction of OL activities (Fang & Chen, 2016) and how different learning mechanisms encourage organizational members to gather and apply OL activities for the creation of new knowledge (Cirella, Canterino, Guerci, & Shani, 2016; Chou & Wang, 2003; Coghlan, Shani, & Roth, 2016). Strategy can be proactive or reactive and environments that affect an organization can be stabile or unstable (Fang & Chen, 2016). Building on Shani and Docherty (2008), learning mechanisms can be planned symbols, as for example, promoting a sense of urgency and setting overall organizational goals (Mitki, Shani, & Stjernberg, 2008), structures, as for example, task forces, quality teams, and open workspace layouts (Coughlan, 2012), as well as procedures, such as regular learning meetings, and programs to capture and apply new knowledge and skills (Pedler, 2011). Learning mechanisms, organizational strategy, and business environment are core concepts that contribute different perspectives on OL activities as assessed in the SLAM.

OL activities can be more explorative or exploitative. Concerning strategy, Fang and Chen (2016) found evidence in their multiple case study that a strategy for developing new products or entering into new markets will cultivate explorative OL activities in groups to innovate, whereas a strategy for defending established businesses, centralized authority, and cost control will promote exploitative OL activities of individuals to stay ahead of their market competitors (e.g., Atuahene-Gima, Slater, & Olson, 2005). Moreover, rapidly changing business environments require explorative OL activities to bring in new knowledge to the organization in order to innovate and stay agile, whereas stable environments call for exploitative OL activities to improve, specialize, be profitable, and fulfill aspired benchmarks (Armstrong & Foley, 2003; Chao & Kavadias, 2008). Inspiring visions are a major learning mechanism to focus employees on exploration or exploitation (Berson et al., 2015).

Hence, depending on learning mechanism, strategy and environment, OL activities can be more explorative or more exploitative in nature (Berson et al., 2015; Crossan et al., 1999; March, 1991; Wong & Huang, 2011). Explorative learning emphasizes search, variation, risk taking, experimentation, play, flexibility, and discovery. Exploitation is about refinement, choice, production, efficiency, selection, implementation, and execution. Explorative learning occurs on different levels when individuals and groups learn, for example, during informal conversations with customers how to improve their product or when they have productive meetings in which they share ideas about how to prepare for the future. Exploitative learning occurs on different levels when individuals and groups use their firm's internal strategies to decide, for example, how to meet customers' demands. To be explorative *and* exploitative enables organizations to be agile in rapidly changing markets to the extent that explorative *and* exploitative OL activities make an organization progressive and profitable at the same time. However, to be agile requires firms to balance their OL activities between explorative and exploitative learning, because OL activities tie up limited human resources (March, 1991). Firms must allocate their work force to exploration and exploitation while following fundamentally different learning logics that do not easily go together. That is, in rapidly changing markets, explorative and exploitative learning create conflict with respect to how individuals and groups should explore and learn new ways while concurrently exploiting established ways of working. A balance between explorative and exploitative learning provides a way to develop a sustainable competitive advantage for profit and success in the market in as much as this balance unveils business opportunities that can be used to create value that competitors in the market cannot capture or copy (Crossan &

Berdrow, 2003). This desirable balance between explorative and exploitative OL activities is also termed ambidexterity (Tushman & O'Reilly, 1996).

OL activities in the Strategic Learning Assessment Map (SLAM). As stated in the introduction, the SLAM is a questionnaire of OL activities on different levels that tries to capture ambidexterity. The SLAM's backdrop is Crossan and colleagues' (1999) conceptual work on OL activities. They acknowledged the ambidexterity issue in organizations and emphasized the interplay between OL activities at the individual level, the group level, and the organizational level. Individual learning, group learning, and organizational learning occur on these three ontological levels, and the kinds of learning that Crossan and colleagues (1999) interchangeably called feed-forward learning and feedback learning, or explorative learning and exploitative learning, respectively, occur between the levels. Altogether OL activities include five learning dimensions on and between three organizational levels. In the early 2000s, Bontis and colleagues (2002) attempted to break this conceptual framework down to a measurable degree, which resulted in the SLAM. In line with Crossan and colleagues' (1999) conceptual work, Bontis and colleagues' (2002) SLAM measures OL activities on and between the three ontological levels of individuals, groups, and the organization with five subscales that address individual learning, group learning, organizational learning, feed-forward learning, and feedback learning. Through individual learning, individuals build "a clear sense of direction in their work," "break out of traditional mindsets," have a "high energy level," and feel "a strong sense of pride in their work." Through group learning, groups build a "shared understandings of issues," "learn from each other," have the "right people involved in addressing the issue," and hold "productive meetings." Through organizational learning, organizations build competitive, adaptive, and innovative organizational systems, structures, and procedures that prepare the organization for the future, allowing employees to work efficiently and facilitating innovation. Through feed-forward and feedback learning, individuals, groups, and the organization learn from each other across levels (Bontis et al., 2002, pp. 443–444). Feed-forward learning occurs if individuals actively share new knowledge and insights with their work group and management in order to improve products, strategies, and procedures. Vice versa, feedback learning occurs if product lines, strategies, and procedures guide individuals and groups in what they do, how they do it, and what they learn in the workplace.

The SLAM has repeatedly been awarded potential value for research and management practice, after revealing good reliability, factorial validity, and predictive validity for perceived business performance in management samples (e.g., Bontis et al., 2002; Real et al., 2006, 2014). The key results are that the SLAM's 50 items consistently load on the five-dimensional structure postulated above (Bontis et al., 2002); that OL activities measured with the SLAM are a mediator between a firm's information technology, its entrepreneurial and learning orientation, and its business performance (Real, et al., 2006, 2014); and that OL activities measured with the SLAM also independently predict business performance as perceived by managers (Bontis et al., 2002; Vargas & Lloria, 2014; Prieto & Revilla, 2006; Real et al., 2006, 2014; Wong & Huang, 2011). With an emphasis on its practical value, Bontis and colleagues (2002) and others (e.g., Real et al., 2014) concluded that the SLAM affords companies the potential to monitor, direct, and improve their OL efforts. Bontis and colleagues (2002) argued that the SLAM gives strategic management personnel the opportunity to evaluate individual learning, group learning, organizational learning, feed-forward learning, and feedback learning. Until the present day, the SLAM's theoretical underpinnings and assessment practice have served as a source of inspiration for broader OL scales that complement types and modes of learning with its five dimensions of learning activities for individuals, groups, and organizations (e.g., Lloria & Moreno-Luzon, 2014).

Taken together, the SLAM is a highly recognized, theory-driven, reliable, and valid scale that takes a management perspective on OL.

However, researchers who have been using the SLAM have devoted the majority of their attention to the managers' perspective (see Bontis et al., 2002; Lloria & Moreno-Luzon, 2014; Real et al., 2006, 2014; Vargas & Lloria, 2014), while paying little attention to the view of employees. The common argument is that managers are able to report the core aspects (e.g., OL activities) of all organizational members (Lyles & Schwenk, 1992). This is surprising because current research in this field has acknowledged that employees' views matter (Graham & Tarbell, 2006; John & Björkman, 2015). Paying little attention to the employee view on OL is problematic as managers might not see all of the OL activities of their employees. Organizations have more employees under each manager than ever, increasingly rely on self-organized teams, and offer broader and more complex jobs to get the work done (Brynjolfsson & McAfee, 2016; Noe et al., 2006). In this context, employees get their jobs done discretely and increasingly make their own decisions (e.g., how much time to allocate to learning; Parker & Wall, 1998). The employee view on OL matters for these reasons, and it makes sense to directly administer the SLAM to employees, instead of solely to their managers. Admittedly, Crossan and Hulland (1997), Berson and colleagues (2015), as well as Wong and Huang (2011) administered the SLAM to employees who were not managers but asked these employees how they perceived everyone else's OL activities in their firm. Hence, to the best of our knowledge, there is no study that asked employees how they perceived their own OL activities in the SLAM.

A major reason, why validation efforts that have applied the SLAM directly to employees are scarce is its length. 50 items seem to discourage research efforts that usually assess several constructs in one survey and rely on participants to volunteer when they have only a limited amount of time to answer tests. With its 50 items, the SLAM appears to be too long for widespread research activity. Thus, the SLAM requires a short form that is more feasible to apply in research and practice than its lengthy original. A shorter SLAM should preserve the high reliability and factorial validity of the original measure and should substantiate the construct validity of the original form by revealing discriminant validity between its five dimensions and convergent validity with conceptually related learning constructs in a sample that includes employees on all levels: skilled and unskilled workers and managers alike.

Research Questions

In the present study, we present a 25-item short form of the SLAM (SF-SLAM) that addresses employees directly for the first time and examined its reliability, factorial validity, and construct validity. This validation of the SF-SLAM contributes to research on OL in three ways. First, we shifted the SLAM's perspective from managers to employees. That is, we administered the SF-SLAM to employees across a range of occupations and job levels, instead of solely to managers. This provides a more complete picture of OL activities through the eyes of employees. Second, we tested the SF-SLAM's factorial validity by comparing its five-dimensional measurement structure involving individual learning, group learning, organizational learning, feed-forward learning, and feedback learning against more parsimonious measurement structures (cf. Greiff et al., 2013; Wüstenberg et al., 2012). These comparisons provide information about our first research question (RQ1) on factorial validity, namely, whether the SF-SLAM reveals a five-dimensional measurement structure that corresponds with the original SLAM's measurement structure and with the underlying theory (Bontis et al., 2002; Crossan et al., 1999).

Third, we explored the SF-SLAM's nomological network to shed more light on its construct validity. A nomological network reveals empirical relations with variables that are conceptually and theoretically related to the SF-SLAM (cf. Nunnally & Bernstein, 1994).

Specifically, for the first time, we examined relations with constructs that are conceptually close to the postulated learning activities that indicate OL in the SF-SLAM. Based on our own and previous theorizing (Bontis, 1999; Liu et al., 2002), individual constructs that are conceptually close to OL activities include innovation-related learning activities, innovative behavior on the job, level of education, intelligence, and job performance. These variables and their conceptual relations to OL activities in the SF-SLAM are explained in the following Research Questions 2 to 5 (RQ2 to RQ5), which ask, whether the SF-SLAM empirically relates to its nomological network.

More specifically, in RQ2 we asked whether employees who score high on the SF-SLAM tend to engage in innovation-related learning activities (Liu et al., 2002; OECD, 2010; Støren, 2016). According to the OECD Survey of Adult Skills (PIAAC; OECD, 2013a, 2013b), employees tend to engage in innovation-related learning activities if they enjoy newness, attempt to apply new ideas to real life, and connect new and existing knowledge (also see, Støren, 2016). The literature suggests that these innovation-related learning activities and the OL activities of individuals, groups, and organizations are mutually reinforcing (Crossan et al., 1999; De Spiegelare et al., 2012; Ellström, 2010). Støren (2016) explained that engaging in innovation-related learning activities brings about OL activities, and OL activities in the workplace provide opportunities for the individual to innovate.

In RQ3, we asked whether employees who score high on the SF-SLAM tend to engage in innovative job behavior that is indicated by staying up-to-date, negotiating, and learning from colleagues as well as by handling job complexity. Individuals who stay up-to-date on work matters and who negotiate with others might also engage in individual learning, whereas individuals who learn from colleagues might engage in group and organizational learning, as well as feed-forward and feedback learning. Further, innovative job behavior occurs in jobs with changing task requirements and variety, ambiguous goals, and frequent multitasking activities that resemble job complexity. Job complexity is considered to stimulate learning (Oswald et al., 1999; Wall et al., 1990). Handling job complexity should therefore also be associated with the OL activities of individuals and groups.

In RQ4, we asked whether employees who score high on the SF-SLAM are also better educated and score better on an assessment of intelligence. Essentially, intelligence is the ability to learn in one's daily life and work affairs (Gottfredson, 2002; Hunter & Schmidt, 1996), such as getting the job done, staying knowledgeable, and generating new knowledge. Similarly, a person's level of education reflects the level of skills and abilities that makes him/her attractive for and productive in a job (Colarelli et al., 2012). Individuals in jobs that demand a lot of learning are usually more educated and intelligent than individuals in simpler jobs (Gottfredson, 2002; Ng et al., 2005; Schmidt & Hunter, 2004). Higher SF-SLAM scores should therefore be associated with higher levels of intelligence and education.

In RQ5, we asked whether employees who score high on the SF-SLAM reveal higher *individual* job performance in terms of job level, salary, and job satisfaction. Previous research has already indicated that individuals and their groups and organizations who have higher scores on learning activities in the eye of their managers tend to have higher satisfaction (Bontis et al., 2002) and higher perceived *business* performance (Bontis et al., 2002; Prieto & Revilla, 2006; Real et al., 2006, 2014). We argue that individuals who directly experience strong OL measured in the SF-SLAM typically have higher level jobs, which are usually accompanied by higher salaries, and tend to be more satisfied with their work (International Labour Office, 2012).

Taken together, for the first time in a sample of employees, we explored the SF-SLAM's reliability and factorial validity (RQ1) at the level of the individual. We also explored relations between the SF-SLAM's subscales (i.e., individual learning, group learning, organizational learning, feed-forward learning, and feedback learning) and employees' innovation-related learning activities (RQ2), innovative job behavior (RQ3), intelligence and educational level (RQ4), and individual job performance (RQ5) indicated by job level, salary, and job satisfaction. In summary, we investigated in an employee sample the validity of the SF-SLAM in five RQs, namely:

RQ1: Does the SF-SLAM for employees measure OL reliably on five dimensions of individual learning, group learning, organizational learning, feed-forward learning, and feedback learning?

RQ2: To what extent is the SF-SLAM for employees related to their innovation-related learning activities?

RQ3: To what extent is the SF-SLAM for employees related to their innovative job behavior, such as staying up-to-date, negotiating, learning from colleagues, and handling job complexity?

RQ4: To what extent is the SF-SLAM for employees related to their level of intelligence and education?

RQ5: To what extent is the SF-SLAM for employees related to their job performance in terms of job level, salary, and job satisfaction?

Method

Sample and Procedure

Ranging from lower level positions to the position of manager, $N = 434$ employees ($M_{age} = 34.92$ years, $SD = 11.76$, Range: 18 to 64; 21.9% female) first signed an informed consent form and then completed the SF-SLAM and an intelligence test, answered questionnaires on innovation-related learning activities and innovative job behavior, and gave self-reports on their level of education, job level, salary, and job satisfaction. These employees were from 11 German companies in agriculture, engineering, social entrepreneurship, health care, IT, and the automobile industry. As part of a larger project[1] (LLLight in Europe, 2015), this German-speaking sample allowed us to use a translated German version of the SF-SLAM. An internal back and forth translation process ensured that we were able to maintain the linguistic nuances of the SLAM. Testing was administered on tablets during company visits, and the complete sessions took approximately 90 min.

Measures

SF-SLAM. We built a short form comprised of 25 of the 50 original SLAM items by Bontis and colleagues (2002). Specifically, for each of its five subscales (i.e., individual learning, group learning, organizational learning, feed-forward learning, and feedback learning), the SF-SLAM contained a selection of five of the original 10 SLAM items. In order to preserve the original measure's good psychometric properties, we carefully shortened it on the basis of item content and high factor loadings, as recommended by Stanton, Sinar, Balzer, and Smith (2002). That is, each selected item captured a core aspect of its designated subscale and loaded highly on its latent factor in Bontis and colleagues' (2002) study. For example, the individual learning items captured the five aspects of pride, energy, growth, confidence, and innovation, which, according to Bontis and colleagues (2002), comprise the core of individual learning. In addition, we were able to confirm that the five out of 10 original items from each scale revealed high factor loadings on their respective subscale in Bontis and colleagues' (2002) study. Table 1 shows the specific selection of items we employed. Adapted from the original SLAM, all items were rated on a 7-point Likert scale ranging from 1 (*Not at all*) to 7 (*To a very high extent*). We altered the wording of the items

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[1] This subsample was taken from a larger data set of $N = 1{,}167$ subjects (i.e., students, employees, and entrepreneurs; Ederer et al., 2015) from 13 countries and three continents procured in the LLLight in Europe (2015) project, leading to the publication of EU policy reports (LLLight in Europe, 2015a, 2015b, 2015c). The subsample used in this study consisted of only German-speaking employees, who represented by far the largest subsample. The variables whose relations we assessed in this study have not been previously employed in this manner.

in order to directly address employees on all levels, instead of solely managers who had evaluated their firms' OL activities for everyone else in previous research (e.g., Real et al., 2014). For example, on the SF-SLAM, which targeted employees, participants rated the individual learning item "I feel a sense of pride in my work" (see Table 1) instead of this item targeting managers: "Individuals feel a sense of pride in their work" from Bontis and colleagues' (2002) and other studies. For another example, participants rated the group learning item "We are prepared to rethink group decisions when presented with new information" (see Table 1) instead of this item targeting managers: "Groups are prepared to rethink decisions when presented with new information" (Bontis et al., 2002). As a result, the SF-SLAM is directed toward all employees, from the lower level to management, and takes less time than the original.

Innovation-related learning activities. Adopted from the PIAAC study (OECD, 2010), three items assessed innovation-related learning activities on a 7-point scale from 1 (*Not at all*) to 7 (*To a very high extent*). The items were "When I hear or read about new ideas, I try to relate them to real life situations to which they might apply," "I like learning new things," and "When I come across something new, I try to relate it to what I already know."

Innovative job behavior. Staying up-to-date, negotiating, learning from colleagues, and handling job complexity indicated innovative job behaviors in the current study. Also adopted from the PIAAC study (OECD, 2010), each item assessed staying up-to-date, negotiating, and learning from colleagues, respectively, on a 5-point scale ranging from 1 (*never*) to 5 (*every day*). The three items were "How often does your job involve staying up-to-date with new products or services?" "How often does your job involve negotiating with people?" and "How often do you have the opportunity to learn new work-related things from co-workers or supervisors?" Adopted from the German Federal Institute for Vocational

Education and Training Survey (BIBB; Rohrbach-Schmidt, & Hull, 2013), six items asked about handling job complexity. Example items asked how often "I have to recognize and close my own knowledge gaps" and "I have to face new tasks that I have to think through and become familiar with."

Level of education. The international standard classification for education indicated level of education (ISCED; UNESCO Institute for Statistics, 2012) as shown in Table 2.

Intelligence. The figural reasoning test Raven's Standard Progressive Matrices (SPM; Raven et al., 1998) served as a proxy for intelligence (Jensen, 1998).

Job level. The international standard classification for occupations of 2008 (ISCO-08; International Labour Office, 2012) served as a measure of job level as shown in Table 2.

Salary. Participants were directly asked for their total monthly net income, which we transformed into normalized US dollars per year (World Bank, 2015).

Job satisfaction. Participants were directly asked "How satisfied are you with your current job?" This was rated on a scale ranging from 1 (*extremely dissatisfied*) to 7 (*extremely satisfied*).

Analyses

Tailored assessment suites for each company resulted in a lot of data that were missing largely by design. Missing data ranged from 12% for the group learning subscale of the SF-SLAM, which was assessed in only nine out of 11 companies, up to 54% for job complexity, which was assessed in only six out of 11 companies. To account for data that were missing, we imputed five data sets with categorical (intelligence) and continuous (all other) variables in the MPlus 7.1 software package (Muthén & Muthén, 1998-2014) as proposed by Asparouhov and Muthén (2010). We then tested whether the self-report scale items were affected by common method bias by applying Harman's single-factor test with a threshold of less than 50% variance explained by a single factor. Third, we investigated the factor structure of all multi-item scales (i.e., SF-SLAM, job complexity, innovation-related learning activities, intelligence) by applying a confirmatory factor analysis (CFA) within the structural equation modeling approach (SEM; Bollen, 1989). Fourth, we examined the SF-SLAM's nomological network on the basis of latent correlations. Sample descriptive statistics were calculated with SPSS 21 (Tables 1 and 2) and latent data analyses with the Mplus 7.1 statistical package. To compute our main analyses, the latent measurement model of the SF-SLAM and the latent correlations, we used the robust maximum likelihood estimator (MLR) for continuous and categorical data with five or more categories (Rhemtulla et al., 2012). To compute the latent measurement model of intelligence, which contained categorical indicators with fewer than five categories, we used the robust weighted least squares estimator (WLSMV). The WLSMV and MLR were applied to assess the goodness of fit of all models with the comparative fit index (CFI), the root mean square error of approximation (RMSEA), the standardized root mean square residual (SRMR; only for MLR), and the weighted root mean square residual (WRMR; only for WLSMV) with respect to their recommended cutoff values for performance tests (i.e., intelligence; CFI > .95, RMSEA < .06, see Hu & Bentler, 1999; WRMR < .90, see Yu, 2002) and questionnaires (all others; CFI > .90, see Bentler & Bonett, 1980; RMSEA < .08, see Browne & Cudeck, 1993; SRMR < .08, see Hu & Bentler, 1999).

Results

Tables 2 and 3 show the sample characteristics and descriptive statistics for all variables. The data from the self-reported variables had the potential to suffer from common method bias. Thus, we tested a CFA with a single factor structure across all self-report items. It explained less than 30% of the variance, indicating no support for common method bias. We proceeded with investigating the reliability and factorial validity in RQ1, as well as the nomological network in RQ 2 to 5.

RQ1 (Reliability and Factorial Validity): Does the SF-SLAM measure OL reliably on its five dimensions?

With regard to RQ1, we examined whether the SF-SLAM successfully preserved the original SLAM's strong reliability and factorial validity of five dimensions. As a result, the SF-SLAM revealed good reliability and constrained factorial validity. Reliability was good for the three levels of individual learning (ω_{ind} = .89), group learning (ω_{group} = .91), and organizational learning (ω_{org} = .92), as well as for feed-forward learning (ω_{ff} = .86) and feedback learning (ω_{fb} = .87). Similar to the original 50-item SLAM (Bontis et al., 2002), our data supported a five-dimensional structure of the SF-SLAM with a satisfactory model fit (see Table 4). However, all dimensions, except individual learning, were strongly correlated with each other with ρs between .75 and .95 (all *p*s < .001; Table 5) and several factor loadings were as low as .42 on feed-forward learning, and .38 on feedback learning (see Table 1). Thus, to substantiate the support for a five-dimensional structure, we compared the model fit of the five-dimensional CFA with more parsimonious CFAs. First, we tested a two-dimensional CFA with the individual learning items in the first and all items of the other, highly correlated dimensions in the second factor. This two-factor solution fitted the data significantly worse than the suggested five-factor solution ($\Delta\chi^2$ = 142.338, p < .001, Δdf = 8). An even more parsimonious one-factor solution that did not distinguish between the five dimensions at all also fitted the data significantly worse than the original five-factor solution ($\Delta\chi^2$ = 498.243, p < .001, Δdf = 10). These comparisons supported a five-factor solution for the SF-SLAM, despite the presence of four out of five highly intercorrelated latent factors in our sample (see Figure 1).

RQ2 to 5 (Construct Validity): To what extent is the SF-SLAM related to its network?

To explore the SF-SLAM's nomological network as proposed in RQ2 to RQ5, we first checked all remaining latent variables' measurement models and reliabilities and then examined whether the SF-SLAM revealed the relations that should theoretically exist with innovation-related learning activities (RQ2) and innovative job behavior (staying up-to-date, negotiating, learning from colleagues, handling job complexity; RQ3), and showing higher levels of education and intelligence (RQ4), and individual job performance (RQ5), indicated by job level, salary, and job satisfaction.

First, we tested the model fits and reliabilities of innovation-related learning activities ($\omega = .86$), intelligence ($\omega = .94$), and job complexity ($\omega = .86$). All reliabilities were high. Resulting model fits are depicted in Table 4. Innovation-related learning activities had a just-identified model with significant factor loadings of λs > .74 (all *p*s < .001), thus supporting the assumption of an adequate measurement model and permitting the nomological network analysis. A solution with fixed path coefficients provided a satisfactory fit to the data (Table 4). The intelligence model fitted the data well with the exception of a WRMR value (1.00) slightly above its cutoff (< .90). For the nomological network analysis, we reduced the number of indicators from 31 items to three parcels in order to yield a more parsimonious model. In doing so, we followed the item-to-construct balance recommended by Little, Cunningham, Shahar, and Widaman (2002). The item-to-construct balance resulted in a just-identified model of intelligence with significant and substantial factor loadings on the intelligence factor (λs > .86; with all *p*s < .001).

Next, we examined correlations between the SF-SLAM's individual learning, group learning, organizational learning, feed-forward learning, and feedback learning with the proposed variables from its nomological network. As the α error accumulates when applying multiple significance tests, we set a conservative α-level of .01. All latent correlations are shown in Table 5 and the model fit of the corresponding SEM in Table 4.

With regard to RQ2, which explored the relation between the SF-SLAM and innovation-related learning activities, two of the five OL dimensions in the SF-SLAM were significantly correlated with innovation-related learning activities (individual learning: $\rho = .36$; group learning: $\rho = .20$, *p*s < .001). Despite a very high correlation with group learning ($\rho = .95$, $p < .001$), feed-forward learning occurred distinguishable from group learning due to its insignificant correlation with innovation-related learning activities ($\rho = .18$, $p > .001$)

With regard to RQ3, which explored the relations between the SF-SLAM and innovative job behavior (i.e., staying up-to-date, negotiating, learning from colleagues, and handling job complexity), only some indicators of innovative job behavior were correlated with some dimensions of OL in the SF-SLAM (i.e., staying up-to-date, negotiating, learning from colleagues, but not handling job complexity). Whereas individual learning was significantly correlated with staying up-to-date ($r = .23$, $p < .001$) and negotiating ($r = .17$, $p = .006$), group learning, organizational learning, feed-forward learning, and feedback learning were correlated with learning from colleagues (*r*s = .23 to .34; all *p*s < .001). All correlations between the five OL learning dimensions and job complexity were small and nonsignificant.

With regard to RQ4, which assessed the relations between the SF-SLAM and level of education and intelligence, only individual learning ($r = .16$ $p = .001$) was significantly correlated with level of education. Correlations between the organizational learning dimensions and intelligence were small and nonsignificant.

With regard to RQ5, which assessed the relations between the SF-SLAM and *individual* job performance variables (i.e., job level, salary, and job satisfaction), individual learning ($r = .23$, $p < .001$), group learning ($r = .13$, $p = .003$), and feed-forward learning ($r = .18$, $p < .001$) were significantly correlated with salary. Only individual learning ($r = .13$, $p = .003$) was significantly correlated with job level. Job satisfaction was correlated with all learning dimensions, ranging from $r = .46$ for individual learning to $r = .62$ for feed-forward learning (all *p*s < .001).

Discussion

The current study investigated the psychometric properties and construct validity of the SF-SLAM. We contributed to the research on OL by shortening the useful, reliable, and valid but lengthy SLAM into the resulting SF-SLAM, applying the SF-SLAM for the first time at the level of the individual in an employee sample across a range of occupations, and validating the SF-SLAM along five research questions, RQ1 to RQ5. The findings allowed us to draw research and practice implications on how to use and develop the SF-SLAM in organizations.

The SF-SLAM is reliable and five-dimensional (RQ1)

In this employee sample, we were able to widely replicate the reliability and factorial validity of previous research at the level of the firm, which, on the basis of manager samples, suggested a latent measurement structure of five moderately to highly associated learning dimensions (Bontis et al., 2002; Real et al., 2006). However, in the employee sample used in the current study, the SF-SLAM's factorial validity was restricted due to partly very high associations between all learning dimensions, except individual learning, whereas the manager sample used by Bontis and colleagues (2002) showed very high associations between only feed-forward and feedback learning. That is, tested at the individual level in the current study, the SF-SLAM distinguished individual learning best from all other dimensions. However, comparing the one-, two-, and five-dimensional models resulted in support for a five-dimensional model that corresponded with OL theory and the original SLAM's measurement structure at the level of the firm (Bontis et al., 2002; Crossan et al., 1999). Eventually, the five dimensions could be distinguished from each other on the basis of their differential relations with variables of their nomological network.

The SF-SLAM is related to its nomological network (RQ2 to 5)

Results on the SF-SLAM's nomological network revealed empirical relations that differed across the five learning dimensions. That is, only individual learning was associated with staying up-to-date, negotiating, educational level, and job level and was more strongly correlated with innovation-related learning activities and salary than any other learning dimensions were. All of the other learning dimensions were associated with learning from colleagues and showed only few differential relations. Surprisingly, none of the learning dimensions were associated with intelligence or job complexity, thus suggesting that how individuals score on the SF-SLAM has little to do with how complex their jobs are or how they score on an intelligence test. This was unexpected, as human intelligence enables learning to get the job done, stay knowledgeable, and generate new knowledge, especially in complex positions that demand more learning than simpler ones (Gottfredson, 2002; Ng et al., 2005; Schmidt & Hunter, 2004). We expected intelligence and complexity to increase with increasing OL activities in the SF-SLAM, which should require more learning, and thus more intelligent employees, the more complex the job gets. However, intelligence and complexity were not related with each other in the current study. This negative finding might also be due to different assessment methods of intelligence on the one hand, and complexity and the SF-SLAM on the other hand (i.e. intelligence is a performance test and the others are self-reports). That is, a performance based approach to OL activities, or vice versa self-reported intelligence might yield different results (Paulhus, 1998). Finally, all learning dimensions were associated with job satisfaction, thus replicating findings from previous research (Bontis et al., 2002).

The overall pattern of results suggests that individual learning plays the largest role in work-related learning and success (e.g., staying up-to-date, job level, and salary). Group learning (e.g., to build a shared understanding) also matters, specifically in applying new ideas to real life, learning from colleagues, increasing salary, and being satisfied with work.

Organizational, feed-forward and feedback learning play a role in engaging with and learning from colleagues, and being satisfied with work. Specifically, enabling organizational structures (i.e., high organizational learning), knowledge sharing (i.e., high feed-forward learning), and strategic guidance (i.e., high feedback learning) matter in order to learn from each other and being more satisfied as an employee. This finding supports the importance of explorative (i.e., feed-forward) and exploitative (i.e., feedback) learning found in previous studies (e.g., Fang & Chen, 2016; Messeni Petruzzelli, Albino, Carbonara, & Rotolo, 2010). Moreover, feed-forward learning ties to salary, which could mean that sharing new knowledge with colleagues and managers translates (eventually) into increased salary.

Taken together, the five dimensions of OL activities were found in the SF-SLAM for the first time at the individual level in a heterogeneous employee sample. However, at this level, individual learning was distinguished best. In support of this pattern, individual learning revealed largely consistent associations with constructs that were conceptually close to OL activities with the exceptions of intelligence and job complexity. The constructs in the network of the SF-SLAM were constructs on the individual level, which might explain, why individual learning held the most and strongest relationships (see also limitations).

Research Implications: The Pursuit of Exploration and Exploitation

The original SLAM served as an indicator of ambidexterity as it took the interplay between explorative and exploitative activities at the individual level, the group level, and the organizational level into account. Ambidexterity relates to the simultaneous pursuit of explorative and exploitative activities (Cao et al., 2009). A growing camp in the literature of OL and strategic renewal argued that explorative and exploitative activities might be mutually enhancing despite their fundamentally different learning logics to learn new ways while concurrently exploiting established ways of working (Gupta et al., 2006). With its high intercorrelations between OL activities on different levels, the SF-SLAM supports this picture of simultaneously pursued, if not mutually enhancing OL activities. The SF-SLAM indicated the close interrelatedness of OL activities of individuals, groups, and organizations, and activities between these levels. This pattern of results supports previous research (Groysberg & Lee, 2009; Raisch et al., 2009) that suggested strong learning efforts of groups and organizations might empower individuals to be innovative and grow with their work. Conversely, strong learning efforts of individuals might have a positive effect on groups and organizations. However, as the current and previous studies (e.g., Groysberg & Lee, 2009) employed cross-sectional data, such interpretations require adequate future research to not only better understand how ambidexterity — as perceived from the employee — develops over time, but also how ambidexterity in the SF-SLAM ties up to learning mechanisms that make firms agile.

Practical Implications: Selecting Appropriate Learning Mechanisms

To some extent, the SF-SLAM for employees might serve managers as a diagnostic tool to monitor, direct, and improve their current OL efforts. That is, with the OL activity levels of the SF-SLAM at hand and constrains due to their high intercorrelations in mind, managers can monitor, whether their planned learning mechanisms of setting goals, communicating vision and urgency, building task forces, and establishing programs promote OL on and between the intended level (i.e., individuals, groups, and organization). For example, if the strategic intent was to develop a new product, the managers would ideally set into place learning mechanism that cultivate OL in groups in order to enhance innovation (Lumpkin & Dess, 1996); whether a set up to encourage OL in groups led to, for example, shared understandings of issues and more productive meetings, would be reflected in high group level scores in the SF-SLAM. Vice versa, if the intent was to improve an established businesses, the managers would ideally push their employees to attend expert trainings to become more efficient in what they already do and thereby to stay ahead of their competitors (e.g., Atuahene-Gima, Slater, & Olson, 2005); whether this intent was met by reality and led to employees, who, for example, stay up to date, have high energy levels, feel pride in their work, and break out of traditional mindsets, would be reflected in high individual level scores in the SF-SLAM. In sum, within constrains of closely related dimensions, managers can evaluate with their employees' view at hand, whether learning takes place, gets stuck, or crosses levels, where it should according to their strategy and environment, and see how new ideas enter the organization via feed-forward learning, or how established ideas reach the company floor via feedback learning (Bontis et al., 2002).

Strengths, Limitations, and Future Research

We shortened the SLAM into a more feasible SF-SLAM, explained how we shortened it, and examined the SF-SLAM's psychometric properties and construct validity. Previous studies have also shortened the SLAM, but such studies did not specify how exactly the SLAM was shortened, nor did these previous studies investigate the construct validity of the shorter version with respect to the SLAM's nomological network (Real et al. 2014; Vargas et al., 2014; Wong, 2011). Using an employee sample across different industries and occupations, we were able to investigate OL activities from the perspective of the employee.

When interpreting the results, a few limitations and prospects for future research need to be taken into account. First, the data was cross-sectional and did not include constructs on an organizational level, such as business performance. Cross-sectional data limits inferences about causalities, and a lack of organizational constructs limits the interpretation of construct validity as OL measured with the SF-SLAM is a construct on three levels, whereas its nomological network, which we tested in this study, included only individual-level constructs. Variables that are measured on an organizational level that are conceptually related to OL are the type of leadership, organizational culture, organizational citizenship behavior, and organizational-level measures for OL developed in the management literature such as learning orientation. Second, future research could also compare employee samples with manager samples in order to, for example, compare the manager's view with the employee's view. Third, we disregarded a potential multi-level structure in our data of individuals clustered in organizations. However, the low number of 11 companies did not allow multilevel analyses to address cluster effects (Hox, 2010). A replication study with more companies could investigate, whether companies have an effect on the OL structure and relationships in the SF-SLAM. Finally, future research should address contingencies between learning mechanisms that bring about OL, strategic intent and environments that determine OL, and OL activities in the SF-SLAM, and how these contingencies impact organizational success. That is, the next relevant research questions to ask are, to what extent learning mechanisms empirically predict OL activities in the SF-SLAM and to what extent OL activities in the SF-SLAM that are contingent with strategy and environment predicts success of the organization.

Conclusions

Shortened by half and applied to employees, the SF-SLAM largely preserved the psychometric properties of the original SLAM at the level of the individual with only a few restrictions and revealed some associations with its nomological network. In the SF-SLAM, individual learning is the only one of the five subscales of OL activities that demonstrated construct validity. Despite a superior five-dimensional structure, only individual learning revealed strong discriminant validity in the SF-SLAM and was consistently associated with higher innovation-related learning activities, more innovative job behavior, and higher education, job level, and salary. The finding that four of its five dimensions highly correlate might contribute to an understanding of ambidexterity to be a function of closely interrelated OL activities of and between the levels of an organization. The empirical relations to its nomological network suggest that the SF-SLAM has potential to help managers to promote the OL they intended and evaluate the OL they got in return. To conclude, the SF-SLAM is short, reliable, and valid for examining individual learning, whereas future research is needed to take effects over time into consideration in order to further validate and understand the role of individual, group, organizational, feed-forward, and feedback learning for successful strategic renewal in the eye of the employee.

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Figures

Figure 1

Figure 1. Five-dimensional measurement model for the SF-SLAM. Factor loadings and latent correlations from the current study are shown. i1-i5 = Items 1-5 for individual learning; g1-g5 = Items 1-5 for group learning; o1-o5 = Items 1-5 for organizational learning; f1-f5 = Items

1-5 for forward learning; b1-b5 = Items 1-5 for backward learning. All factor loadings were significant at the $p < .001$ level and all correlations at the $p < .01$ level.

THE SHORT FORM STRATEGIC LEARNING ASSESSMENT MAP

Table 1

SF-SLAM Item Selection with Factor Loadings from the Current Study and from Bontis and Colleagues (2002)

Dimension	SLAM question	λ (current study)	SE (current study)	λ (Bontis et al., 2002)
Individual SF-SLAM	I feel confident in my work	.62	.06	.75
	I feel a sense of pride in my work	.79	.04	.81
	I have a high level of energy at work	.77	.04	.78
	I am able to grow through my work	.76	.04	.77
	I am able to break out of traditional mindsets to see things in new and different ways	.59	.07	.74
Group SF-SLAM	In meetings, we seek to understand everyone's point of view	.77	.03	.77
	We have effective conflict resolution when working in groups	.76	.03	.75
	We have the right people involved in addressing issues in groups	.73	.04	.78
	Different points of view are encouraged in our group work	.77	.03	.82
	We are prepared to rethink group decisions when presented with new information	.71	.05	.79
Organizational SF-SLAM	The organizational structure supports our strategic direction	.79	.04	.83
	The organizational structure allows us to work effectively	.82	.03	.82
	Our operational procedures allow us to work	.78	.03	.75

THE SHORT FORM STRATEGIC LEARNING ASSESSMENT MAP

	efficiently			
	We have a realistic yet challenging vision for the organization	.80	.04	.76
	We have an organizational culture characterized by a high degree of trust	.73	.05	.76
Feed-Forward SF-SLAM	Lessons learned by my group are actively shared with others	.71	.04	.74
	We propose innovative solutions to organization-wide issues	.55	.06	.79
	Recommendations by my group are adopted by the organization	.83	.04	.83
	Results of the group are used to improve products, services and processes	.48	.06	.84
	I have input into the organization's strategy	.42	.07	.80
Feedback SF-SLAM	Company goals are communicated throughout the organization	.60	.05	.73
	Company files and databases provide the necessary information to do our work	.78	.04	.71
	Training is readily available when it is needed to improve knowledge and skills	.76	.04	.69
	Cross-training, job rotation and special assignments are used to develop a more flexible workforce	.78	.03	.63
	Group decisions are supported by individuals	.38	.05	.73

Note. SF-SLAM items used in the present study. All λs in the current study were significant at the $p < .001$ level.

λ = factor loading; SE = standard error.

Table 2

Sample Characteristics

Industry	%	Educational level [a]	%	Job level [b]	%
IT	16.7	Primary	.7	Lower level [c]	11.0
Engineering	56.0	Lower secondary	28	Clerical	24.8
Entrepreneurs	2.5	Upper secondary	3.7	Technician	13.5
Health Care	9.4	Post secondary, Nontertiary	19.5	Professional	8.7
Agriculture	15.1	Bachelors or equivalent	13.5	Manager	36.0
		Masters or equivalent	30.0		
		Doctorate or equivalent	4.6		
Missing	.02		0		6.0

Note. $N = 434$.

[a] For educational level, an adjusted version of the international standard classification for education (ISCED) was used. [b] For job level, an adjusted version of the international standard classification for occupations of 2008 (ISCO-08) was used. [c] Lower level jobs included service and sales workers, skilled agricultural workers, craft and related trades workers, plant and machine operators and assemblers, and elementary occupations.

Table 3

Descriptive Statistics for All Variables

Variable	N	Minimum	Maximum	*M*	*SD*
Individual SF-SLAM	316	1	7	5.92	.78
Group SF-SLAM	385	1	7	5.43	.93
Organizational SF-SLAM	280	1	7	5.29	1.14
Feed-Forward SF-SLAM	278	1	7	5.17	1.20
Feedback SF-SLAM	269	1	7	5.26	1.03
Innovation Learning Activity	326	1	5	3.72	.75
Job Complexity	158	1.5	5	4.05	.74
Staying Up-to-date	323	1	5	2.95	1.07
Negotiating	323	1	5	3.12	1.5
Learning from colleagues	434	1	5	3.41	1.1
Intelligence	234	340	800	554.83	103.68
Salary (in US dollars per year)	255	9,113.88	174,683.52	42,180.16	2,385.44
Job Satisfaction	225	1	5	3.91	.84

Note. *M* = Mean and *SD* = Standard Deviation. SLAM items ranged from 1 (*I fully disagree*) to 7 (*I fully agree*). Innovation Learning Activity is represented as the mean of three items whose ratings ranged from 1 (*Not at all*) to 7 (*To a very high extent*). Job Complexity, Negotiating, Staying Up-to-date, and Learning from colleagues are comprised of ratings that ranged from 1 (*never*) to 5 (*every day*). The mean and SD of Intelligence in the current sample (*N* = 434) are presented in standardized scores that were also based on the total sample (*N* = 1,126, with *M* = 500 and *SD* = 100; LLLight´in´Europe, 2015a, 2015b, 2015c). The mean and *SD* of Salary are in normalized US dollars per year. Job Satisfaction was rated from 1 (*Extremely dissatisfied*) to 5 (*Extremely satisfied*).

Table 4

Goodness of Fit Indices for all Models, Including One-, Three-, and Five-Factor Solutions for the SLAM, Solutions for Intelligence, and Job Complexity, as well as the Latent Correlation and Regression Models

Model	$\chi 2$	*df*	*p*	CFI	RMSEA	SRMR (WRMR)[a]
1. SF-SLAM - 1-dimensional	1985.124	275	<.001	.761	.084	.103
1. SF-SLAM - 2-dimensional	696.725	273	<.001	.878	.060	.075
3. SF-SLAM 5-dimensional	500.085	265	<.001	.931	.046	.064
3. Innovation Learning Activity[b]	3.726	1	.054	.988	.090	.075
4. Job Complexity	5.824	8	.667	1.00	.000	.022
5. Intelligence[c]	541.476	377	<.001	.960	.029	1.00
6. Latent correlations	1427.237	797	<.001	.900	.043	.077

Note. SLAM - 1-dimensional = one-factor solution of the SLAM scale; SLAM 5-dimensional = five-factor solution; df = degrees of freedom. CFI = comparative fit index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual; WRMR = weighted root mean square residual.

[a] WRMR only for intelligence; [b] Solution with fixed path coefficients in order to yield a model fit; [c] Unparceled solution.

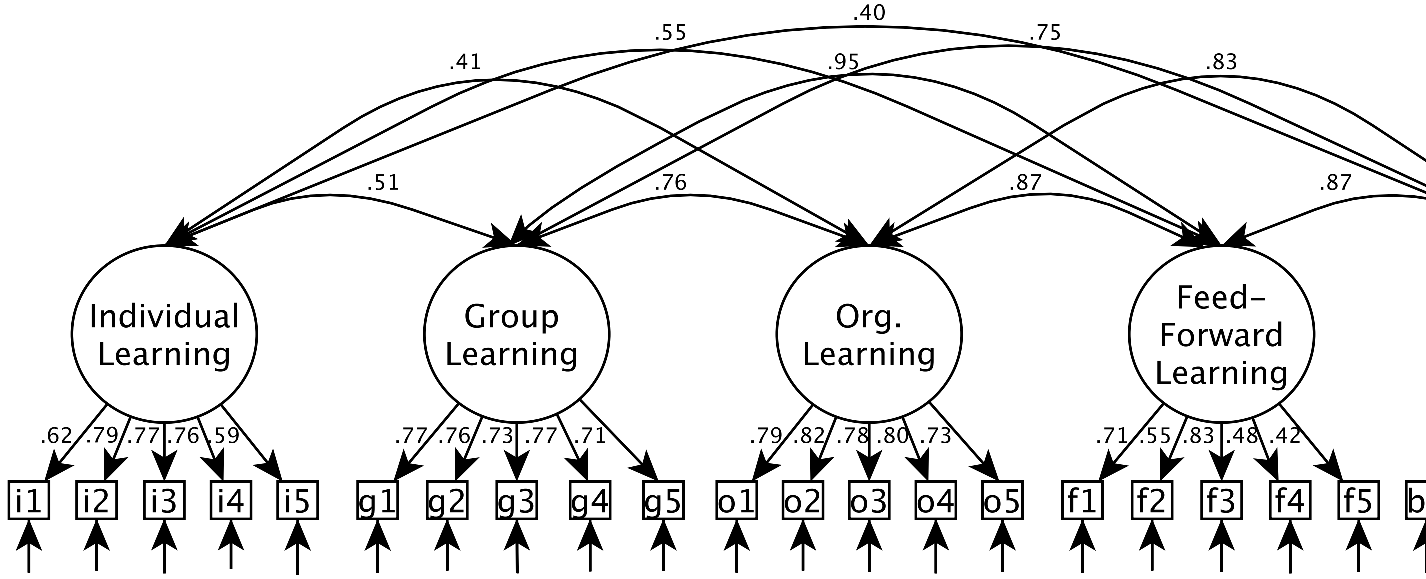
THE SHORT FORM STRATEGIC LEARNING ASSESSMENT MAP

Table 5

SEM-Based Latent Correlations between Measures and their Reliabilities (on the diagonal)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) Individual SF-SLAM	(.89)														
(2) Group SF-SLAM	.51*	(.91)													
(3) Organizational SF-SLAM	.41*	.76*	(.92)												
(4) Feed-Forward SF-SLAM	.55*	.95*	.87*	(.86)											
(5) Feedback SF-SLAM	.40*	.75*	.83*	.87*	(.87)										
(6) Innovation Learning Activity	.33*	.20*	.04	.18	.15	(.86)									
(7) Job Complexity	.09	-.03	-.10	.03	.04	.41*	(.86)								
(8) Staying Up-to-date	.23*	.08	.03	.12	.07	.41*	.54*								
(9) Negotiating	.17*	.04	.06	.11	.07	.28*	.46*	.38*							
(10) Learning from colleagues	.03	.34*	.24*	.33*	.28*	.18	.24*	.11	.03						
(11) Educational Level	.16*	.09	-.02	.06	.01	.27*	.30*	.25*	.22*	-.14					
(12) Intelligence	.00	.02	.01	.03	.01	.11	-.03	.06	.05	.07	.51*	(.94)			
(13) Job Level	.13*	.05	-.05	-.10	.04	.20*	.32*	.28*	.29*	-.14	.78*	.33*			
(14) Salary (US Dollars per year)	.23*	.13*	.00	.18*	.12	.24*	.21	.25*	.33*	-.03	.45*	.23*	.61*		
(15) Job Satisfaction	.46*	.46*	.59*	.62*	.52*	.07	-.16	-.06	-.03	.17	.09	.14	.10	.11*	

Note. N = 434. Model-based latent correlations are reported below the diagonal. If applicable, also McDonald's ω_H is reported in parentheses as a measure of reliability on the diagonal; Job Complexity = latent variable involving six complexity items (see Method); Educational Level = international standard classification for education (ISCED); Job Level = international standard classification for occupations of 2008 (ISCO-08 [inverse scoring]); Salary = total yearly net income normalized by applying the purchasing power parity conversion factor (World Bank, 2015). One-tailed p-value: $^*p < .01$ (because of the potential inflation of the α-level due to multiple comparisons).



.40
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Individual Learning
Group Learning
Org. Learning
Feed-Forward Learning
.62 .79 .77 .76 .59
.77 .76 .73 .77 .71
.79 .82 .78 .80 .73
.71 .55 .83 .48 .42
i1 i2 i3 i4 i5
g1 g2 g3 g4 g5
o1 o2 o3 o4 o5
f1 f2 f3 f4 f5

Changes in Manuscript ID JKM-11-2016-0494 entitled
"How Employees Perceive Organizational Learning: Construct Validation of the 25-Item Short Form of the Strategic Learning Assessment Map (SF-SLAM)"
(which we submitted to the Journal of Knowledge Management)

We would like to thank the reviewers and the editor for suggesting some revisions on the basis of their valuable input, guidance, and remarks. We are delighted about the encouraging review, the chance to resubmit a substantiated manuscript, and the reviewers' notes on positive features of our work, especially in terms of Research Questions (Reviewer 1), Method (Reviewer 2), Sample (Reviewer 1), and presentation of results (Reviewer 1). However, in full awareness of the substantial issues that occurred across the manuscript, we used the past month to craft a **revised manuscript largely involving a theoretical framework, the manuscript structure, the presentation of results, and implications for research and practice** that were based on the reviews and editorial comments, and that we will outline and explain in detail in a point-by-point reply in this letter.

We took all of the comments of the Editor and Reviewer into consideration, and we believe that this revision addresses all of your concerns. We describe in detail the issues that were raised and our responses below.

Reviewer: 1
Comments to the Author
6. Quality of Communication: "*The paper is well written. The language is clear and the standard of English is good.*

Regarding the structure of the paper this can be improved a little bit:

- The first section of the paper has not any title. Better to untitle it. Maybe the title could be: "Background". Since here the conceptual and methodological background of the tested questionnaire is presented.

- The second section is untitled "The present study". Here the research questions of the study are presented. Therefore, it would be better to untitle this section "Research questions". This is more direct and clear. "

We want to thank the Reviewer for the guidance, how to achieve a more direct and clear mode of presentation and implemented the suggestions together with those of Reviewer 2 in the text: The paper begins with a half-page introduction and entitles the theory part "**Theoretical Framework**" with the subsections "**OL can be more explorative or exploitative**" (p. 3), and "**OL in the Strategic Learning Assessment Map (SLAM)**" (p. 4). We renamed the "Present Study" into "Research Questions" and structured the section, the Results and the Discussion accordingly.

We believe that we have improved the quality of communication by far and hope to convince the reviewer of the result.

Reviewer: 2
Comments to the Author

1. Originality: "*The paper is an interesting piece as it focuses a relevant topic, i.e. organisational learning and its measures. Some major weaknesses should be fixed before suggesting publication.*"

We acknowledge that our paper carried some major weaknesses and identified them according to this review in a necessary restructuring of the first part (see point 2), an improvable theoretical framework with an extended view on relevant paradigms from the current literature (see point 2; e.g., learning mechanism, Cirella, Canterino, Guerci, & Shani, 2016), the presentation and explanation of results (see point 4), and a more in depth discussion with point-by-point interpretations of the findings, the role of each dimension, and implications for research and practice (see point 5).

2. Relationship to Literature: "*I would suggest to completely re-structure the first part of the paper, in particular creating separate sections, i.e. an introduction, an overview of relevant literature and then a hypotheses development section.*

For building and reinforcing an introduction and an overview of literature, I would engage more with the literature, using and combining different perspective and points of view that, overall, emphasise the relevance of the topic.
For example, the recent debate about organisational learning mechanisms that could be included in this overview (three recent pieces, for example, are Cirella et al. 2016; Fang and Chen, 2016; Coghlan et al. 2016).
In general, I would make sure to use (more) recent literature and also some articles from JKM in order to position the paper in a broader context and discussion.

For the section including hypotheses, I would clearly and explicitly state and mark the hypotheses."

We thank the reviewer for the suggestion of (a) a new structure and we agree that it was necessary to engage more with (b) the literature. First of all, we developed sections and subsections from the beginning to the end of the manuscript that, for example, carry on the presentation of research questions to the presentation of their results and finally, to their point-by-point discussion (see our reply to Reviewer 1 and reply Reviewer 2, point 5 for details). In particular, we (a) explicated and marked the research questions on page 11 (ff.):

"In summary, we investigated in a large employee sample the validity of the SF-SLAM in five RQs, namely:

RQ1: Does the SF-SLAM for employees measure OL reliably on five dimensions of individual learning, group learning, organizational learning, feed-forward learning, and feedback learning?

RQ2: To what extent is the SF-SLAM for employees related to their innovation-related learning activities?

RQ3: To what extent is the SF-SLAM for employees related to their innovative job behavior, such as staying up-to-date, negotiating, learning from colleagues, and handling job complexity?

RQ4: To what extent is the SF-SLAM for employees related to their level of intelligence and education?

RQ5: To what extent is the SF-SLAM for employees related to their job performance in terms of job level, salary, and job satisfaction?"

On (b), the reviewer's literature recommendations were a helpful starting point to update the manuscript and emphasize the relevance of the topic, and led to a broader and more in-depth discussion. To begin with, we mention the founding work of Crossan et al. (1999) on page 2:

"OL in the SLAM describes a set of learning activities on multiple organizational levels. First, individuals intuit and interpret knowledge that is shared in groups and later integrated and institutionalized in systems, structures, or routines (Bontis et al., 2002; Crossan, Lane, & White, 1999). The SLAM was a direct operationalization of the seminal work of Crossan et al. (1999), who delineated OL in their 4I framework, which has been received extensively in theoretical and empirical work (Berson, Da'as, & Waldman, 2015; Crossan et al., 2011; Lloria & Moreno-Luzon, 2014; Real Leal, & Roldán, 2006; Real, Roldán, & Leal, 2014; Vargas & Lloria, 2014). "

Further on page 2 (ff.), we introduce the new structure and the extended **Theoretical Framework** in response to Reviewer 2, before we narrow the paper down to organizational learning (OL) activities based on the founding work of Crossan et al. (1999) mentioned above, and as assessed in the SF-SLAM**:**

"**Theoretical Framework**

The OL activities in the SLAM represent drivers of strategic renewal and long-term organizational success with multiple dimensions of and between individuals, groups, and their organization (Crossan et al., 1999). Recently, researchers largely explained how organizational strategy and environment determine the direction of OL activities (Fang & Chen, 2016) and how different learning mechanisms encourage organizational members to gather and apply OL activities for the creation of new knowledge (Cirella, Canterino, Guerci, & Shani, 2016; Chou & Wang, 2003; Coghlan, Shani, & Roth, 2016). Strategy can determine innovation or consolidation and the environment can determine change or stability of the business (Fang & Chen, 2016). Learning mechanisms can be planned symbols, as for example, promoting a sense of urgency and setting overall organizational goals (Mitki, Shani, & Stjernberg, 2008), structures, as for example, task forces, quality teams, and open workspace layouts (Coughlan, 2012), as well as procedures, such as regular learning meetings, and programs to capture and apply new knowledge and skills (Pedler, 2011). Learning mechanisms, organizational strategy, and business environment are core concepts that contribute different perspectives on OL activities as assessed in the SLAM.

OL activities can be explorative or exploitative. Concerning strategy, Fang and Chen (2016) found evidence in their multiple case study that a strategy for developing new products or entering into new markets will cultivate explorative OL activities in groups to innovate, whereas a strategy for defending established businesses, centralized authority, and cost control will promote exploitative OL activities of individuals to stay ahead of their market competitors (e.g., Atuahene-Gima, Slater, & Olson, 2005). Moreover, rapidly changing business environments require explorative OL activities to bring in new knowledge to the organization in order to innovate and stay agile, whereas stable environments call for exploitative OL activities to improve, specialize, be profitable, and fulfill aspired benchmarks (Armstrong & Foley, 2003; Chao & Kavadias, 2008). Inspiring visions are a major learning mechanism to focus employees on exploration or exploitation (Berson et al., 2015).

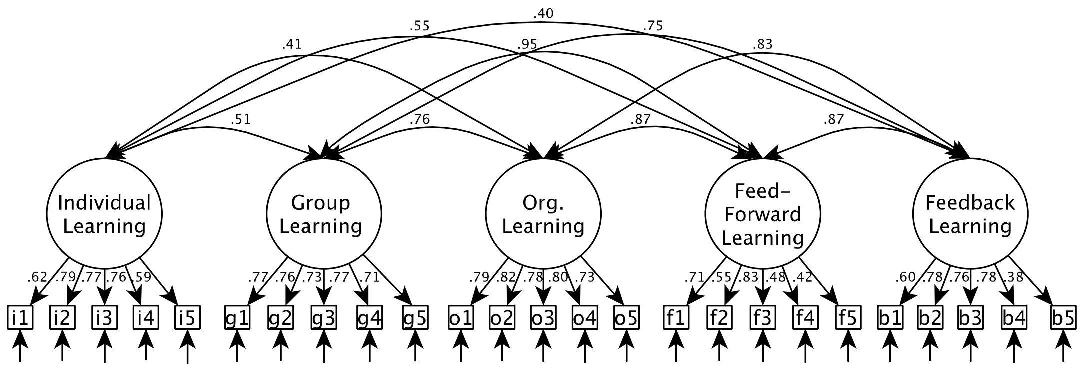
Hence, depending on learning mechanism, strategy, and environment, OL activities can be more explorative or more exploitative in nature (Berson et al., 2015; Crossan et al., 1999; March, 1991; Wong & Huang, 2011)."

On (b) later, in the discussion, we also refer to literature that was published in JKM (Messeni Petruzzelli, Albino, Carbonara, & Rotolo, 2010; p. 20 ff.):

"This finding supports the importance of explorative and exploitative learning found in previous studies (e.g., Fang & Chen, 2016; Messeni Petruzzelli, Albino, Carbonara, & Rotolo, 2010)."

4. Results: "*Results could be explained better. The last figure (CFA) should be redesigned.*"

We acknowledge that our original explanations of results could be improved in many ways and that our factor model (Figure 1) should be redesigned. To improve, we more clearly presented the findings to research question (RQ) 1, aligned the presentation of results with the research questions and simplified Figure 1 by removing the error terms for the sake of clarity and by improving the Figure description:



"*Figure 1*. Five-dimensional measurement model for the SF-SLAM. Factor loadings and latent correlations from the current study are shown. i1-i5 = Items 1-5 for individual learning; g1-g5 = Items 1-5 for group learning; o1-o5 = Items 1-5 for organizational learning; f1-f5 = Items 1-5 for forward learning; b1-b5 = Items 1-5 for backward learning. All factor loadings were significant at the p < .001 level and all correlations at the p < .01 level."

On page 16 (ff.), we structure the findings according to our RQs and particularly improved the presentation of RQ1 (Reliability and Factorial Validity):

"(…) We proceeded with investigating the reliability and factorial validity in RQ1, as well as the nomological network in RQ 2 to 5.

RQ1 (Reliability and Factorial Validity): Does the SF-SLAM measure OL reliably on its five dimensions?

(…) Similar to the original 50-item SLAM (Bontis et al., 2002), our data supported a five-dimensional structure of the SF-SLAM with a satisfactory model fit (see Table 4). However, all dimensions, except individual learning, were strongly correlated with each other with ρs between .75 and .95 (all ps < .001; Table 5) and several factor loadings were as low as .42 on feed-forward learning, and .38 on feedback learning (see Table 1). Thus, to substantiate the support for a five-dimensional structure, we compared the model fit of the five-dimensional CFA with more parsimonious CFAs. First, we tested a two-dimensional CFA with the individual learning items in the first and all items of the other, highly correlated dimensions in the second factor. This two-factor solution fit the data significantly worse than the suggested five-factor solution ($\Delta\chi^2 = 142.338$, $p < .001$, $\Delta df = 8$). An even more parsimonious one-factor solution that did not distinguish between the five dimensions at all also fitted the data significantly worse than the original five-factor solution ($\Delta \chi 2 = 498.243$, $p < .001$, $\Delta df = 10$). These comparisons supported a five-factor solution for the SF-SLAM, despite the presence of four out of five highly intercorrelated latent factors in our sample (see Figure 1).

RQ2 to 5 (Construct Validity): To what extent is the SF-SLAM related to its network?

(…)"

5. Implications for research, practice and/or society: "*Discussion should really go more in-depth. The hypotheses should be discussed more carefully and the role of each one of the 5 dimensions should be underlined more extensively.*
The role of the 5 dimensions, taken together, is discussed, but I would like to read more about the role of each one of them. Clear and more extensive implications for research and practice should be developed (with separate sections or sub-sections)."

The reviewer is right that the previous manuscript's discussion neither sufficiently addressed the conceptual side of the five SF-SLAM dimensions, nor presented enough implications for research and practice. These previous shortcomings were due to two reasons. First, our concentration on the psychometric properties and empirical validity was clearly at the expense of conceptual depth. Second, a picture of both constrained factorial validity and constrained validity on the basis of the SF-SLAMs nomological network limited the interpretability for each learning dimension and demanded us to formulate implications for research and practice with caution. – The correlations between the five OL dimensions were high or very high, except for individual learning and the SF-SLAM showed only few differential relations with variables from its nomological network.

However, as an immediate response to the Reviewer and for the sake of a deeper discussion, we added a paragraph that explicates the roles of each dimension (see p. 21):

"The overall pattern of results suggests that individual learning plays the largest role in work-related learning and success (e.g., staying up-to-date, job level, and salary). Group learning (e.g., to build a shared understanding) also matters, specifically in applying new ideas to real life, learning from colleagues, increasing salary, and being satisfied with work. Organizational, feed-forward and feedback learning play a role in engaging with and learning from colleagues, and being satisfied with work. Specifically, enabling organizational structures (i.e., high organizational learning), knowledge sharing (i.e., high feed-forward learning), and strategic guidance (i.e., high feedback learning) matter in order to learn from each other and being more satisfied as an employee. This finding supports the importance of explorative (i.e., feed-forward) and exploitative (i.e., feedback) learning found in previous studies (e.g., Fang & Chen, 2016; Messeni Petruzzelli, Albino, Carbonara, & Rotolo, 2010). Moreover, feed-forward learning ties to salary, which could mean that sharing new knowledge with colleagues and managers translates into increased salary."

Next, for the same reason, we shed a new light on the part of results that were unexpected (i.e. the lack of correlation between scores in the SF-SLAM and intelligence and complexity) on page 20:

"Surprisingly, none of the learning dimensions were associated with intelligence or job complexity, thus suggesting that how individuals score on the SF-SLAM has little to do with how complex their jobs are or how they score on an intelligence test. This was unexpected, as human intelligence enables learning to get the job done, stay knowledgeable, and generate new knowledge, especially in complex positions that demand more learning than simpler ones (Gottfredson, 2002; Ng et al., 2005; Schmidt & Hunter, 2004). We expected intelligence and complexity to increase with increasing OL activities in the SF-SLAM, which should require more learning, and thus more intelligent employees, the more complex the job gets. However, intelligence and complexity were not related with each other in the current study. This negative finding might also be due to different assessment methods of intelligence on the one hand, and complexity and the SF-SLAM on the other hand (i.e. intelligence is a performance test and the others are self-reports). That is, a performance based approach to OL activities, or vice versa self-reported intelligence might yield different results (Paulhus, 1998)."

Moreover for the sake of a deeper discussion, we advise the reader now why the individual level results are stronger than the other results on page 21:

"The constructs in the network of the SF-SLAM were constructs on the individual level, which might explain, why individual learning held the most and strongest relationships (see limitations)."

Further, for the sake of clarity, we gave more structure to the discussion along our five Research Questions with subheading. (see p. 19 onwards):

"The SF-SLAM is reliable and five-dimensional (RQ1)
(…)
The SF-SLAM is related to its nomological network (RQ2 to 5)
(…)"

Next, we drew and extended research and practice implications from our findings that shed a light on each dimension from page 22 onwards:

"**Research Implications: The Pursuit of Exploration and Exploitation**

(…)However, as the current and previous studies (e.g., Groysberg & Lee, 2009) employed cross-sectional data, such interpretations require adequate future research to not only better understand how ambidexterity — as perceived from the employee — develops over time, but also how ambidexterity in the SF-SLAM ties up to learning mechanisms that make firms agile.

Practical Implications: Selecting Appropriate Learning Mechanisms

To some extent, the SF-SLAM for employees might serve managers as a diagnostic tool to monitor, direct, and improve their current OL efforts. That is, with the OL activity levels of the SF-SLAM at hand and constrains due to their high intercorrelations in mind, managers can monitor, whether their planned learning mechanisms of setting goals, communicating vision and urgency, building task forces, and establishing programs promote OL on and between the intended level (i.e., individuals, groups, and organization). For example, if the strategic intent was to develop a new product, the managers would ideally set into place learning mechanism that cultivate OL in groups in order to enhance innovation (Lumpkin & Dess, 1996); whether a set up to encourage OL in groups led to, for example, shared understandings of issues and more productive meetings, would be reflected in high group level scores in the SF-SLAM. Vice versa, if the intent was to improve an established businesses, the managers would ideally push their employees to attend expert trainings to become more efficient in what they already do and thereby to stay ahead of their competitors (e.g., Atuahene-Gima, Slater, & Olson, 2005); whether this intent was met by reality and led to employees, who, for example, stay up to date, have high energy levels, feel pride in their work, and break out of traditional mindsets, would be reflected in high individual level scores in the SF-SLAM. In sum, within constrains of closely related dimensions, managers can evaluate with their employees' view at hand, whether learning takes place, gets stuck, or crosses levels, where it should according to their strategy and environment, and see how new ideas enter the organization via feed-forward learning, or how established ideas reach the company floor via feedback learning (Bontis et al., 2002)."

In sum, the discussion picked up the Theoretical Framework of OL to draw the implications above, and encouraged future research on multilevel structures and the interplay of learning mechanisms, strategic intent, and organizational environment with OL activities in the SF-SLAM (see p. 23 ff.):

"Third, we disregarded a potential multi-level structure in our data of individuals clustered in organizations. However, the low number of 11 companies did not allow multilevel analyses to address cluster effects (Hox, 2010). A replication study with more companies could investigate, whether companies have an effect on the OL structure and relationships in the SF-SLAM. Finally, future research should address contingencies between learning mechanisms that bring about OL, strategic intent and environments that determine OL, and OL activities in the SF-SLAM, and how these contingencies impact organizational success. That is, the next relevant research questions to ask are, to what extent learning mechanisms empirically predict OL activities in the SF-SLAM and to what extent OL activities in the SF-SLAM that are contingent with strategy and environment predicts success of the organization."

Summary

The initial set of reviews of this paper provided a great deal of help in laying out what we believe to be a clear contribution of this paper to OL research, namely the validated SF-SLAM as a diagnostic tool to monitor, direct, and improve OL efforts in alignment with strategy and context (see p. 21 ff.). We hope that the revised paper makes our Research Questions clearer, easier to follow, and does so in a way that respects the value of not wasting journal pages. If we had not been convinced that the paper had clear and practical implications, we would not have resubmitted it to the Journal of Knowledge Management, and we hope that we have now made a good argument for publishing this paper.

We are hopefully looking forward to your decision!

The Team of Authors

6

General Discussion

6. Discussion

The aim of this thesis was to validate CPS and OL as relevant constructs in the changing nature of work on the basis of comprehensive assessments along three research questions in four corresponding papers. The three research questions translated into original research on CPS at work, CPS in entrepreneurship, and OL in strategic renewal. This research is relevant to understand the roots of occupational and organizational success in the 21st century and clear the way for future research on the interplay of different sources of success. The four corresponding Papers 1, 2, 3, and 4 are the core of this thesis and showed that (1) CPS incrementally predicted occupational success above GMA and education, (2) CPS incrementally predicted activities in the early stages of entrepreneurship, and (3) OL was distinct on different levels of an organization, but with constraints, and associated with indicators and outcomes of a learning organization, but with constraints.

6.1 Implications

6.1.1 CPS

CPS appears to play at least to a certain extent a unique role for success in the workplace (Paper 2) and in the early stages of entrepreneurship (Paper 3) with implications for theory and practice. As presented in Paper 2, linkages of CPS to markers of success could neither be explained as an artifact of the relations between GMA and job success nor between the level of education and job success. On the contrary, parts of CPS appeared to be (1) distinct from GMA and education and (2) relatively important to explain success with up to 8% of incrementally explained variance in the outcomes. That is, CPS contributes higher-order thinking skills to receive higher pay, hold higher level jobs, and deal with complexity and its higher-order thinking skills are aspects of complex cognition that GMA and education do not capture.

As receiving higher pay and holding complex, higher level jobs indicate occupational gravitation to success and reveal successful personnel selection, CPS has the potential to extend theory of occupational gravitation (e.g., Gottfredson, 1986) and practice of personnel selection with higher order thinking skills that neither theory nor practice have yet incorporated. That is, the question of whether individuals sort themselves (or get sorted) in more or less complex and well-paying jobs might not be determined entirely by GMA and education, but possibly also by CPS.

Paper 3 found that CPS predicted a facette of opportunity identification in fictional tasks beyond several relevant control variables. This is first empirical evidence that CPS matters—at least to some extent—in early entrepreneurial activities. Specifically, CPS contributes the higher order thinking skills knowledge acquisition and knowledge application to theory of entrepreneurial cognition. That is, individuals with high levels of CPS might be better than others in exploring, simplifying, and controlling complex tasks involved in identifying concrete opportunities. If solving complex problems is part of what entrepreneurs do in their early venture activities, CPS could possibly enrich the entrepreneurial classroom by emphasizing knowledge acquisition and knowledge application in start-up training practices.

6.1.2 OL

The validity of OL in the SF-SLAM appears to be limited if addressed to employees, instead of managers only. Paper 4 reported good reliability of the SF-SLAM, but constrained factorial validity for the five learning dimensions on three levels that reflect the ambidexterity issue in OL in the SF-SLAM and only few relations with other indicators of a learning organization that reflect limited construct validity of the SF-SLAM. At the moment, the SF-SLAM for employees is short, reliable, and only valid for examining individual learning. However, the perspective of employees on aspects of the ambidexterity issue in OL undeniably matters in the changing nature of work. Thus, whether an application of the SF-SLAM in on all organizational levels from the point of view of employees is warranted requires future research.

6.2 Limitations and future research

Some noteworthy limitations calling for future research remain regarding the construct validity of CPS and OL.

6.2.1 Limitations and future research regarding CPS

First, the choice of measures and samples in Paper 1, Paper 2 and Paper 3 may limit the generalizability of the findings reported.

CPS was solely assessed with MicroDYN and MicroFIN, which comprise multiple short CPS tasks of varying difficulties and semantics for the sake of reliability and internal validity on a level that single long tasks of CPS do not provide (Greiff, Fischer, et al., 2014; Greiff, Stadler, Sonnleitner, Wolff, & Martin, 2015). However, single long CPS tasks, such as the Tailorshop (Funke, 2003), simulate complex problems that due to their length of task and wealth of detail are potentially closer to the actual workplace than MicroDYN and MicroFIN tasks (Funke, Fischer, & Holt, 2017). These qualities serve the external validity of the measure and task acceptance of the participants, which in turn multiple short CPS tasks are short of (Greiff et al., 2015). If the psychometric properties were acceptable, a single task measure of CPS would therefore generally improve the validity of CPS in situations, where external validity and acceptance play a key role, such as at the workplace. However, single task measures of CPS are psychometrically not there, yet (Greiff, Stadler, Sonnleitner, Wolff, & Martin, 2017). In order to adjust multiple short CPS tasks, such as MicroDYN and MicroFIN, to the demands of workplace assessments, future research should focus on a sensible trade-off between external and internal validity by attempting to integrate the advantages of multiple short and single long CPS tasks for the sake of both good psychometric properties and real-world task resemblance.

On the side of relevant controls for the prediction of success, GMA was either not at all (Paper 3), or only narrowly assessed (Paper 1 + 2) in this thesis. This might be problematic, as GMA plays a role in entrepreneurial cognition and different aggregate measures of GMA might alter the results. Paper 1 and Paper 2 used a figural reasoning test that is widely accepted as a valid measure of the fluid intelligence side of GMA with consistently high loadings on one aggregate GMA factor (Jensen, 1998). However, hierarchical conceptions of GMA, such as Carroll's (1993) three-stratum model of cognitive ability, include not only fluid intelligence, but also crystallized intelligence, working memory, visual perception, auditory perception, memory retrieval ability, and cognitive speed. As CPS presumably involves most of these faculties, aggregating more cognitive tests than figural reasoning for testing an increment of CPS for success might alter the results leading to different conclusions regarding the predictive validity of CPS in the context of work.

However, figural reasoning as a GMA measure complies with previous research in the domain of education (for an overview, see Stadler, Becker, Gödker, et al., 2015) and appears to be a rigorous test of the increments of CPS, as reasoning is the very component of GMA that is at its core (Lohman & Lakin, 2009) and most closely related to CPS. Conceptually, CPS tasks and reasoning tasks both require going beyond the information that is given by elaborating and using appropriate strategies (Babcock, 2002). But while some aspects of CPS, such as drawing inferences from information, might depend on reasoning (Lohman & Lakin, 2009), other aspects at the core of CPS are separable from reasoning, such as the dynamic interactions necessary in CPS for acquiring previously unknown information as well as applying this knowledge using subsequent, interdependent steps (Raven, 2000). Empirically, reasoning tasks had the same meta-analytical correlations with CPS as broad GMA measures (Stadler, Becker, Gödker, Leutner, & Greiff, 2015) and reasoning tasks were the only tasks of broad GMA tests that showed significant positive relationships with CPS (Kretzschmar, Neubert, Wüstenberg, & Greiff, 2016). That is, if GMA explains CPS, then it should be its reasoning parts. Consequently, whether a broader GMA measure had altered the correlation against our argumentation here remains a contention that is subject to speculation. At least, this contention was already rejected in the domain of education (Kretzschmar et al, 2016; Stadler, Becker, Gödker, et al., 2015) and is an interesting starting point for future research that could compare the effects of different operationalizations of GMA and CPS in the world of work.

On the side of relevant outcomes of success, Paper 2 misses the supervisor's rating of employee job performance as the most common measure of success on the job (Murphy, 2008). Although subjective job performance ratings are widely regarded a poor method for measuring success, it is very common and very different from objective methods, such as salary, job level and complexity in Paper 2. The inclusion of job performance ratings in future research on CPS at work would therefore enhance the generalizability allowing comparisons of the predictive power in studies that commonly used ratings and possibly also leading to different conclusions regarding the predictive power of CPS.

This leads over to limitations regarding any claims of causality in the prediction of success by CPS, or gravitation to jobs commensurate with the level of CPS. The cross-sectional research design in this thesis does not allow for temporal predictions of success by CPS (or any other predictor) or conclusions about causality and gravitation. The results in Paper 2 are merely consistent, but not confirmative with theories that assign a causal role to CPS in the gravitation to success in jobs that are commensurate with the level of CPS (e.g., Murphy, 1989); that is, the current results support the idea that people with high CPS skills tend to choose or get chosen for jobs that require high CPS skills, but also vice versa. That is, our results are consistent with a growing body of research suggesting that complex jobs stimulate and facilitate cognitive skills and abilities up until old age (Marquie et al., 2010; Schooler, Mulatu, & Oates, 1999; Smart et al., 2014). However, our results can neither test nor distinguish these causalities and reciprocities. There will be considerable payoff in further research to collect longitudinal data that allow to track movement in the job market over time (cf. Wilk et al., 1995) in relation to CPS levels, and to more fully test causal and reciprocal relationships between CPS and well-paying, high level, and complex jobs.

Finally, this thesis did not exploit the process data in the prediction of occupational success. As this thesis merely concentrated on the final task performance in

CPS, there might be room to improve the predictive validity of CPS with process data that is automatically stored in log files on the server of any computer-based assessment. Process data informs in depth, how individuals behave in CPS tasks, and some of these behaviors have predictive power. Very recently, Greiff, Niepel, Scherer, and Martin (2016) showed that the strategy to explore a CPS task and the time spent on a task predict CPS performance. That is, individuals perform best, if they observe, how a problem evolves without their interference, explore the problem step-by-step by varying only one variable at a time (VOTAT strategy, Chen & Klahr, 1999; Wüstenberg, Stadler, Hautamäki, & Greiff, 2014), and neither spend too little, nor too much time on the task (Greiff et al, 2016). It is likely that these behaviors also play a role in complex problems at the workplace and should therefore be considered as predictors in future research. For example, handling a new control desk in a power plant requires an engineer to observe, strategize, and spend adequate time to fulfill this task among many other duties. Future research could already look at the log files in the data set of this thesis and reanalyze the predictive validity of CPS at the workplace with the use of process data.

6.2.2 Limitations and future research regarding OL

In Paper 4, I investigated learning activities that indicate OL in the eyes of the employee and received a sound measurement and meaningful connections to other variables, but solely on the individual level. Sources to improve the measurement of OL and connections to its nomological network include the choice of the employees being assessed and the network constructs being measured.

The employees that were assessed worked across a range of occupations and job levels resulting into a heterogeneous sample. As to perceive learning activities of groups, of the organization, and between individuals, groups and organizations might depend of the job position and job level, the heterogeneous sample in Paper 4 might have compromised the psychometric soundness of the SF-SLAM on these levels (see results of Paper 4, section 1.4.3). For example, an agricultural worker in a low-level position might work less in teams and be less inclined in matters of the organization than an IT professional who advises the executive board of a large pharmaceutical company. Such differences might lead to less distinguished views of a worker than of a professional, or manager on learning activities of groups, of the organization, and between individuals, groups and organizations. Hence, heterogeneous samples might make it difficult for the researcher to discriminate learning activities on these levels in the SF-SLAM, if they are not controlled for occupations and job levels. This could mean that the SF-SLAM is only valid in specific subgroups of high-ranked employees, who see what is going on in their organization. As constructs should be valid in populations (i.e., employees), and not only in subgroups (i.e., professionals, managers), the SF-SLAM might suffer further loss of construct validity than the current study can determine. Future research could therefore attempt to assess larger samples for different job level and occupational group in order to understand the SF-SLAM and even compare employee samples with each other, as well as with manager samples, how and how well they perceive OL in their organization.

Paper 4 measured constructs of the OL network that solely indicated a learning organization on an individual level, such as staying up-to-date, negotiating, educational level, and innovation-related learning activities, omitting constructs on an organizational level, such as business performance. This narrow choice of constructs limited the interpretability of the construct validity since the SF-SLAM measured a construct on three levels, whereas the nomological network in Paper 4 solely included constructs on one level (of the individual). Future research should include constructs that are measured on an organizational level and that are conceptually related to OL in general and the ambidexterity issue in specific, such as the type of leadership, organizational culture, organizational citizenship behavior, and organizational-level measures of organizational learning developed in the management literature, as for example learning orientation.

6.2.3 Joint Future Research on CPS and OL

Furthermore, the individual level constructs in Paper 4 did not comprise skills that make the individual successful in dealing with complex tasks, as they are typical for a changing nature of work (Autor et al., 2003; Brynjolfsson & McAfee, 2016; Levy & Murnane, 2005). CPS is such a skill as Paper 2 and 2 and previous research in the domain of work (e.g., Danner et al., 2011; Mainert et al., 2015) and education (e.g., Sonnleitner et al., 2013; Stadler et al., 2015) imply. If employees have the skills to find new sequences of actions to carry out their daily activities or to tackle new situations, they are considered complex problem solvers (Neubert, Mainert, et al., 2015). This concept implies a repertoire of nonroutine responses to nonroutine problems, through which employees adapt to new circumstances, moving away from fixed patterns of action (see section 1.2). Thus, employees with high CPS scores should be receptive to change and comprehend how to take advantage of it, thus helping the company achieve and sustain its success in times of change.

As staying atop in times of change is the ultimate goal of OL (Crossan, Lane, & White, 1999; March, 1991), CPS opens an avenue for future research to address a possible interplay between CPS and OL as sources of success of the individual and the organization. That is, as much as high-ranked, well-payed jobs are implicated with success on the job, they are implicated with success of the whole organization (Judge et al., 1999). Accordingly, skills that are associated with high-ranked, well-payed jobs are likely to be the same ones that make individuals successful in their job, and help organizations to be successful in their endeavors. In this case, organizations that rely on their OL activities as a source of sustained success in changing markets are likely better off selecting individuals high in CPS, who can solve complex problems that come along the way in technological and organizational change.

Jaster (2016) found first and preliminary support for such relations. In his unpublished work on the basis of N = 433 German employees from the dataset of this thesis Jaster (2016) was able to show a small yet significant correlation between OL and CPS. This supports that some relation exists between the level of an organization's engagement in OL and its employees' skill levels to solve complex problems. CPS has been shown to predict academic achievement and occupational success beyond GMA (e.g., Greiff, Wüstenberg et al., 2013; Paper 2) and has been argued to facilitate human capital in 21st workplaces (Neubert, Mainert et al., 2015; section 1.2). It would be interesting to see, whether CPS and OL influence each other as factors of success and which direction of influence predominates: Do companies that employ effective OL further employees' CPS and individual success? Or do employees with high CPS levels facilitate organizational success?

6.3 Conclusions

This thesis presented original assessment research on CPS at work, CPS in entrepreneurship, and OL in strategic renewal in order to better understand the roots of occupational and organizational success in the 21st century. Paper 2 and Paper 3 of this thesis showed that CPS was comprehensively and reliably measured with MicroDYN and MicroFIN, that CPS carried parts that were empirically distinct from related constructs, such as intelligence and education, and that CPS predicted relevant outcomes. To conclude, CPS on the basis of MicroDYN and MicroFIN appears in this thesis valid and critical for occupational success. This finding potentially informs gravitational theory and makes CPS a future candidate for personnel selection in times of accelerating technology and organizational change, where personnel that solves complex problems becomes irreplaceable for organizations to succeed. Paper 4 revealed a comprehensive and reliable measurement of OL in the SF-SLAM, but individual learning in the SF-SLAM is the only one of the five subscales that demonstrated construct validity. To conclude, OL in the SF-SLAM is short, reliable, but only valid for individual learning in a range of personnel. However, their view on OL undeniably matters, when organizations need to strategically nenew in order to succeed in the changing nature of work.

Taken together, CPS and OL contribute to a comprehensive picture of complex cognition and learning at the workplace, spanning from the individual to the whole of an organization. Whether CPS of the individual and OL of an organization are mutually reinforcing, is currently merely speculation and topic of future research that first has to further validate OL on all levels, before it can investigate their interplay on solid grounds. However, a relationship between CPS and OL occurs theoretically plausible, as skills that make individuals successful in their job are likely to be the same ones that help organizations to be successful in their endeavors. Together, CPS and OL might have potential to address the gap between the type of employee required and the employees who are selected into organizations that face change. If employees high in CPS are those who are receptive to change and comprehend how to take advantage of it in their careers and if organizations realize this potential as a source for their own sustained business success, the changing nature of work possibly creates an increasing set of employment opportunities for individuals who manage to develop these skills.

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