Organization-Cognition Fit: Exploring recruitment and selection through Agent -based Modelling

Herath, Gayanga

DOI:
10.21996/0dsd-hh44

Publication date:
2021

Document version:
Final published version

Organization-Cognition Fit

Exploring recruitment and selection through Agent - based Modeling

Gayanga Bandara Herath
PhD Dissertation
August 2021
Department of Language and Communication
University of Southern Denmark

Organization-Cognition Fit

Exploring recruitment and selection through Agent - based Modeling

Gayanga Bandara Herath

Supervisor:

Associate Professor Davide Secchi

Dissertation for the acquirement of the degree of Philosophiae Doctor (PhD)

Department of Language and Communication

Faculty of Humanities

University of Southern Denmark

August 2021

About the author

Gayanga Bandara Herath is a PhD Research Fellow at the University of Southern Denmark's Department of Language and Communication. He is one of the University's youngest research fellows. He also serves as an active member of the Research Centre for Computational and Organizational Cognition (CORG), a research center dedicated to the study of cognitive aspects in and around organizations, with a focus on encouraging a diverse range of approaches and research methodologies, with a special emphasis — but not exclusively — on computational social science and distributed cognition. Moreover, he also serves as the communications and marketing officer for the special interest group on Organizational Behavior for the European Academy of Management which is Europe's largest learned society dedicated to the advancement of the academic discipline of management and organizational studies.

He holds a Bachelor of Engineering (Hons) degree in Computer Networks and Security, as well as knowledge and project experience in the field. He also holds a Master's degree with distinction from the University of Lancaster — a top ten university in the UK — in the fields of IT, management, and organizational change. His current research interests are in Organizational Cognition and Behavior, with a focus on computational simulation, particularly Agent-Based Simulation Modeling (ABM). In addition, he is actively working on projects in the areas of Policy Evaluation, Unforeseen Aspects of Peer Review, Sustainable Consumer Behavior, Human Resource Management (HRM), and Recruitment and Selection (R&S).

Abstract

Over the years the area of human resource management (HRM) and especially the organizational recruitment and selection (R&S) process have had a fair share of research interest. Accordingly, R&S is a vital component of any organization as it operationalizes the process of finding a suitable candidate for an available job position. In so doing the R&S process deals with the entire process that takes place in finding an appropriate candidate where, for example, it includes everything from the identification of the requirements for the potential candidate, to the planning and development of the job position, to making it an attractive job offer and most importantly the operationalization of the selection process to identify the most suitable candidate (the temporal stages of these steps may vary). In light of this, throughout the years scholars have introduced various theories and potential solutions for the facilitation of effective R&S. One such widely used and popularized stream of research is the *Person-Environment fit* (*P-E fit*) paradigm. Essentially, *P-E fit* carries the notion that for an individual to effectively fit in to an environment, there should be a match (referred to as 'fit') between both parties either in terms of a shared ground of understanding or by providing what the other is looking for. In following this underlying premise, researchers have introduced a range of measurements such as *Person-Person fit*, *Person-Organization fit*, *Person-Vocation fit* and many more. All things considered, these measures are operationalized to seek compliance at a particular point of time based on either values, goals, vocational aspirations, career opportunities, or job requirements.

In spite of these efforts, research on these measurements have shown that they tend to be insufficient in effectively representing fit between a person and an environment. This insufficiency can be traced back to the fundamental operationalization of fit, where they are reliant on fitting certain units, processes, or structures at a given point in time, hence rendering them to function as static measures. In so doing, this PhD study attempts to address these issues that are present in currently

operationalized fit measures used in organizations. By this means, this study instigates that a possible solution to overcome these issues would be to operationalize an approach that accounts the dynamic nature of organizational life, which is inherently rooted in an unavoidable social oriented cognitive temperament. As an approach to further inquire the bounds of this proposition, the study follows a distributed cognitive perspective to understand the distributed nature of operating in an organizational environment. As such, the ability in which it provides to understand highly complex dynamic situations that adapts based on aspects such as the environment, other social beings, tools, temporality and spatial positioning; deemed this approach a perfect fit for its inquiry.

Given the study's cognitive orientation along with the need for an approach that can capture the bounds of dynamic organizational life, this study attempted to transcend the static dimensions employed in current fit measures. In so doing, the human tendency referred to as 'docility'—which originated from Herbert Simon's work and was later adapted in relation to distributed cognition—is considered as an effective measurement that has the potential to map the social organization (referred to as *organizational cognition* in this study) of individuals in a social environment. Accordingly, this study utilized the essence of distributed cognition and the tendency 'docility' to operationalize an approach that can capture the bounds of social organization in a social oriented work environment. Hence, given its organizational and cognition-oriented context and operationalization, this approach was referred to as *Organization-Cognition fit* (*O-C fit*) in this study.

Subsequently, in order to test the bounds of the proposed *O-C fit* approach, the study expressed the importance of utilizing an epistemic tool that has the potential to explore the boundaries of a highly complexed theoretical proposition (i.e. due to overwhelming interactional qualities of social environments such as organizations). In this manner, the utility of Agent-based simulation modeling (ABM) was particularly promising, given the distinctive advantages it provided over other more conventional research methods in exploring highly complex multifaceted and adaptive systems.

In essence, ABM is a particular approach to computational simulation modeling which is generally centered around observing behavioral outcomes that stem from the simulation of autonomous agents that interact in relation to its environment and other agents.

Accordingly, an Agent-based simulation model was developed from the ground up to encompass the dynamics of R&S in relation to social team learning and problem solving. The ABM model featured two primary components, namely, (a) a recruitment and selection component to operationalize the proposed *O-C fit* approach, and (b) a team problem solving component to comparatively analyze the influence of *O-C fit* on team problem solving and collaborative team performance in general. Through the course of this study the above-mentioned ABM model was expanded to include two facets of *O-C fit*, thus providing the study to explore the utility of two variants of *O-C fit*, namely the *supplementary O-C fit* and the *complementary O-C fit*. Where the former represents seeking similarity or in other words congruence in *organizational cognition*, while the latter represents seeking change in the form of complementing/providing what one party is missing, thus attempting to change the existing level of *organizational cognition*.

The ABM model developed in this study produced simulated data based on the theoretical bounds that were modelled to explore the utility of *O-C fit* in relation to team problem solving. By this means, the analysis of the resultant simulated data was used as the premise to explore and unravel the utility of *O-C fit* with regards to other various factors that either contribute or contravene effective problem solving. Interestingly, this exploration indicated a number of very noteworthy and resourceful insights into the utility and the viability of the proposed *O-C fit* approach in relation to attaining effective problem solving and optimum performance. Most importantly, the findings from the overall study indicated that it is simply not sufficient to only factor in the competencies one holds, but rather the ability in which one can make use of their competencies in a social environment is key to effective problem-solving success. As such the study shows that docility plays a crucial role in facilitating the effective use of competencies, thus allowing individuals to head in the direction of attaining optimum potential. In turn, indicating an effective balance between competence and docility is needed to attain greater problem-solving performance. In this manner, the study also shows that even though docility has a promising influence on problem-solving, yet it cannot be understood and utilized in a vacuum, but rather the situational conditions that either play into the effective facilitation of docility or on the contrary conditions that impair docility should also be factored in. Thus, highlighting the need to employ the *O-C fit* approach in a strategic manner which plays into its emphasized strengths as presented in this study.

Resumé

I årenes løb har området indenfor *human resource management* (HRM) og især den organisasoriske rekruttering og udvælgelses — *recruitment and selection* (R&S) — proces har haft en rimelig andel forskningsinteresse. Derfor er R&S en vigtig komponent i enhver organisation, da den operationaliserer processen med at finde en passende kandidat, til en ledig stilling. Dermed beskæftiger R&S-processen sig med hele processen, der finder sted i forhold til at finde en passende kandidat, hvor der for eksempel inkluderes alt fra identifikationen af de stillede krav til den potentielle kandidat, til planlægning og udvikling af jobpositionen, for at gøre det til et attraktivt tilbud og vigtigst operationaliseringen af udvælgelsesprocessen for at identificere den bedst egnede kandidat (rækkefølgen af disse trin kan varierer). I lyset af dette har forskere gennem årene introduceret forskellige teorier og mulige løsninger til at faciliterer effektiv R&S. En sådan meget udbredt og populariseret strøm af forskning er *Person-Environment fit* (*P-E fit*). Essentielt handler P-E fit begrebet om, at for at en person effektivt kan passe ind i et miljø, skal der være et match (kaldet 'fit') mellem begge parter, enten med hensyn til en fælles baggrundsforståelse eller ved at udbyde det, som den anden part kigger efter. Ved at følge denne underliggende forudsætning har forskere introduceret en række målinger som Person-Person fit, Person-Organization fit, Person-Vocation fit og mange flere. Alt taget i betragtning, er disse målinger operationelle for at søge efter overensstemmelser på et bestemt tidspunkt baseret på enten værdier, mål, erhvervsmæssige ambitioner, karrieremuligheder eller jobkrav.

På trods af disse bestræbelser har forskning på disse målinger vist, at de har tendens til at være utilstrækkelige for effektivt at repræsentere et match mellem en person og et miljø. Denne utilstrækkelighed kan spores tilbage til den grundlæggende operationalisering af matches, hvor de er afhængige af tilpasningen af bestemte enheder, processer eller strukturer på et givet tidspunkt, hvilket for dem til at fungere som statiske mål. Dermed forsøger denne Ph.d.-afhandling at adressere de

problemer, der er til stede i aktuelle operationelle match-målinger, som anvendes i organisationer. På denne måde medvirker denne afhandling til, at en mulig løsning til at overvinde disse problemer ville være at operationalisere en tilgang, der tager højde for den dynamiske natur i organisationslivet, som fundamentalt er forankret i en uundgåeligt socialt orienteret kognitivt natur. Som en tilgang til yderligere at undersøge grænserne for dette forslag, følger denne afhandling et distribueret kognitivt perspektiv for at forstå den distribuerede natur ved at operere i et organisatorisk miljø. På den måde giver forslaget en evne til at forstå meget komplekse dynamiske situationer, der tilpasser sig baseret på aspekter som miljøet, andre sociale eksistenser, værktøjer, midlertidighed og rumlig positionering: anses denne tilgang som et perfekt match til dets formål.

I betragtning af afhandlingens kognitive orientering sammen med behovet for en tilgang, der kan opfange grænserne for dynamisk organisatorisk liv, forsøgte denne afhandling at overskride de statiske dimensioner, der er anvendt i de nuværende match-målinger. Dermed blev den menneskelige tendens kaldet 'føjelighed' (*docility*) —som stammer fra Herbert Simons arbejde og senere blev tilpasset i forhold til distribueret kognition—betragtet som en effektiv måling, der har potentialet til at kortlægge den sociale organisation (kaldet *organizational cognition* i denne afhandling) af enkeltpersoner i et socialt miljø. Derfor anvendte denne afhandling essensen af distribueret kognition og tendensen 'føjelighed' til at operationalisere en tilgang, der kan fange grænserne for social organisation i et socialt orienteret arbejdsmiljø. Altså, i betragtning af sin organisatoriske og kognitionsorienterede kontekst og operationalisering, blev denne tilgang kaldt *Organization-Cognition fit* (*O-C fit*) i denne afhandling.

For at teste grænserne for den foreslåede *O-C fit* -tilgang udtrykte afhandlingen vigtigheden af at bruge et epistemisk værktøj, der har potentialet til at udforske grænserne for et meget kompleks teoretisk forslag (dvs. på baggrund af overvældende interaktionskvaliteter i sociale miljøer, så som organisationer). På denne måde var anvendeligheden af *Agent-based simulation modeling* (ABM) særligt lovende, i forhold til de karakteristiske fordele, ABM gav til sammenligning med andre mere konventionelle forskningsmetoder for at udforske meget komplekse alsidige og fleksible systemer. I det væsentlige er ABM en partikulær tilgang til computerdreven simuleringsmodellering, hvilket generelt er centreret omkring observering af adfærdsmæssige udfald, der stammer fra simulation af autonome agenter der agerer i relation til deres miljø og andre agenter.

I overensstemmelse med dette, var en Agent-based simulerings model udviklet fra bunden til at omfatte dynamikken i R&S i forhold til social teamlæring og problemløsning. ABM-modellen indeholdt to primære komponenter, nemlig (a) en rekrutterings- og udvælgelseskomponent til at operationalisere den foreslåede *O-C fit* -tilgang, og (b) en gruppeproblemløsningskomponent til sammenlignende analyse af *O-C fit*'s indflydelse på gruppeproblemløsning og samarbejdsgruppers præstation generelt. I løbet af denne afhandling blev den ovennævnte ABM-model udvidet til at omfatte to facetter af *O-C fit*, hvilket giver afhandlingen grund til at undersøge anvendeligheden af to varianter af *O-C fit*, nemlig supplementary *O-C fit* og complementary *O-C fit*. Hvor førstnævnte repræsenterer at søge lighed eller med andre ord kongruens i organizational cognition, mens sidstnævnte repræsenterer at søge ændring i form af at supplere/give det, som en anden part mangler, og således forsøge at ændre det eksisterende niveau af organizational cognition.

ABM-modellen, der er blevet udviklet i denne afhandling, producerede simulerede data, baseret på de teoretiske grænser, der blev modelleret for at undersøge nytten af *O-C fit* i forhold til gruppeproblemløsning. På denne måde blev analysen af de resulterende simulerede data brugt som forudsætning for at undersøge og finde ud af nytten af *O-C fit* med hensyn til andre forskellige faktorer, der enten bidrager til eller strider mod effektiv problemløsning. Interessant nok viste denne undersøgelse en række meget bemærkelsesværdige og ressourcefulde indsigter i nytteværdien og levedygtigheden af den foreslåede *O-C fit* -tilgang i forhold til at opnå effektiv problemløsning og optimal ydeevne. Vigtigst er det, at resultaterne fra den samlede undersøgelse viste, at det simpelthen ikke er tilstrækkeligt kun at indregne de kompetencer, man har, men nærmere hvordan man kan bruge sine kompetencer i et socialt miljø, og det er nøglen til effektiv problemløsning. Dermed viser undersøgelsen, at føjelighed spiller en afgørende rolle i at faciliterer den effektive anvendelse af kompetencer, hvorved enkeltpersoner kan gå i retning af at opnå dets fulde potentiale. Til gengæld er det nødvendigt at indikere en effektiv balance mellem kompetence og føjelighed for at opnå bedre problemløsning. På denne måde viser denne afhandling også, at selvom føjelighed har en lovende indflydelse på problemløsning, kan det alligevel ikke forstås og bruges enestående, men snarere de situationelle forhold, der enten spiller ind i en effektiv facilitering af føjelighed, eller tværtimod, forhold der forringer føjelighed, bør også medregnes. Dette understreger således behovet for at anvende *O-C fit* -tilgang på en strategisk måde der spiller in i dens understregede styrker som bliver præsenteret i denne afhandling.

Acknowledgements

First and foremost, I'd like to express my gratitude to everyone who has contributed to this incredible PhD journey and supported me throughout my time at the University of Southern Denmark. I'd also like to thank Dr. Davide Secchi, my supervisor, for guiding, supervising, and most importantly, providing me with the opportunity to progress and grow as a researcher throughout this research study; without his supervision and guidance, I would have not been able to achieve what I have in this progressive PhD journey.

I'd also like to take this opportunity to express my gratitude to everyone who helped me along the way, from the support staff to my colleagues at SDU Slagelse and Odense, as well as the directors and administrative staff, for providing me with all of the essential direction and assistance. Finally, I'd want to thank all of my friends here, at home, and around the world, as well as my girlfriend, my family and particularly my brother for being such an important part of this incredible adventure. This has been a very constructive and unforgettable learning experience that I will proudly carry with me for the rest of my life. In so doing, I would eternally be grateful to everyone who helped me in this wonderful PhD journey.

TABLE OF CONTENT

List of tables

Chapter 1: Introduction

Ever since the introduction of human resource management (HRM) with the human relations movement in the early twentieth century, a vast body of research and practice initiatives have been introduced throughout the years (Tubey, *et al.*, 2015). This sparked the field of research inquiry that focused on the importance of employees in an organizational landscape. Therefore, it is not surprising as to why a significant deal of research attention has been put on personal selection initiatives in contemporary human resource management (Schmitt, 2007). Coupled with the interest on personal selection initiatives, given that the employees were now considered a more prominent aspect of organizational processes (Tubey, *et al.*, 2015; Searle, 2009), researchers began to investigate on the psychology and wellbeing of employees in the workplace (Cooper and Marshall, 1978; Danna and Griffin, 1999; Warr, 1990).

It is with this increase in research interest in both personnel selection as well as psychology and wellbeing of employees at the workplace that led to the introduction of the currently widely used *Person-Environment fit* (P-E fit) research paradigm to management (Edwards and Billsberry, 2010; Edwards, 2008) and organizational psychology research (Arthur *el al.*, 2006; Vianen, 2000). The underlying assumption behind P-E fit was that there must be a fit (match) between the prospective employee and the work environment that the employee is to be placed in. Throughout the years a variety of measurements that followed this underlying logic were introduced (notably, *Person-Organization fit, Person-Job fit, Person-Group fit, Person-Culture fit* and many more). These measures relied on the fit between factors such as values, beliefs, objectives and aspirations at a given point in time.

Yet with time researchers realized that there were fundamental issues with such measures as they seemed, for instance, to disregard vital components of organizational life such as: the dynamic change that exists in organizational environments (Boon and Biron, 2016; Edwards, 1991; 2008; Drazin and Van de Ven, 1985). For instance, working in an organizational team would imply that one must at times work with other work colleagues and in the process use a variety of organizational resources (e.g. personal and group office spaces, boardrooms, computers, work trips and more) that vary based on a variety of situational conditional changes. This dynamic nature is especially apparent when considering the unavoidable deeply rooted social-driven cognitive nature that exists in change driven organizational environments (Heyes, 2012; Secchi, 2021c; Hutchins, 1995; Herath, 2019b). These changes for example could be differed based on aspects such as social formation (e.g. the specific team members present at work on a given day), physical location (e.g. at the boardroom in front of executives or at the team meeting room) and time driven aspects (e.g. the start of a project or the end when running on a strict deadline). Therefore, it is reasonable to argue that this cognitively driven dynamic nature of organizational life should play a considerable role in personnel selection initiatives such as the P-E fit paradigm.

However, even though such cognitively distributed aspects have been reflected in cognitive sciences (Lant and Shapira, 2000), management science has not reflected such a distributed view of cognition in organizations (Secchi and Adamsen, 2017; See *Chapter 2*). In fact, this is the basis for this PhD study, where the primary objective of this study is to inquire on the possibility of introducing a newer approach to fit that would allow to capture these cognitive driven dynamic aspects that are fundamentally missing in current P-E fit measures. In so doing, this study attempts to investigate the importance of an individual's cognitive ability to maneuver his/herself in a dynamic organizational environment.

On the whole, it is clear that working in such organizational environments could lead to an overwhelming set of situational changes and interactions (Secchi and Cowley, 2021). Therefore, in order to facilitate the investigation of such a cognitively adaptable individual in a dynamic organizational environment, it is crucial that a research method which is capable of handling such complexity is utilized. In light of handling complexity, agent-based simulation modeling has recently had a fair share of interest (Edmonds and Meyer, 2017). As such Secchi (2021a) defines agent-based simulation modeling as "an object-based computational approach to model heterogeneous entities (called agents) that operate in a given dynamic environment and act according to adaptive mechanisms (also called rules)". Therefore, given the explorative requirements of this study, this approach would provide the perfect test bed. This is why agent-based simulation modeling is considered to be an appropriate fit for this PhD study's investigation (Edmonds and Meyer, 2017; See *Chapter 3*).

Accordingly, the remainder of *Chapter 1* will first present a more comprehensive look into what was presented so far. In so doing it will first introduce the cognitive gap in conventional management science and in the process reflect the importance of a cognitively adaptable individual in a dynamic environment such as an organization (in *section 1.1*). This will then be followed by an introduction to the *Person-Environment fit* literature so that the reader is presented with an understanding of how it is operationalized (in *section 1.2*). Then in connection to its operationalization the following section (*section 1.3*) will highlight the shortcomings of the current P-E fit measurements and highlight how a possible solution may lie through the viewpoint of a distributed cognitive perspective (Hutchins, 1995; Perry, 2003; Hollan *et al.*, 2000; Cowley and Vallee-Tourangeau, 2013). Thereafter, given the aforementioned complexity in situational changes and interactions that exist at the root of this study's investigation, an appropriate research method (i.e. agent-based simulation modeling) capable of fulfilling these demands are discussed briefly in *section 1.4* (a more comprehensive look in to the choice of research methods is later presented in *Chapter 3*). Finally, an overview of the entire PhD study is provided so that the reader is acquainted with the structure of how the study is presented in this PhD thesis (in *section 1.5*).

1.1. Area of concern

Since 1980, the number of papers published on organizational cognition has increased in management science, indicating that management scholars are becoming more interested in the topic (Secchi and Adamsen, 2017). Thus, management science has increasingly started to embrace cognition and has experimented with cognition in a multitude of settings (Schneckenberg *et al.*, 2019; Aggarwal, and Woolley, 2019; White *et al.,* 2015; Hodgkinson and Healey, 2008). Yet in general, in contrast to cognitive sciences (Lant and Shapira, 2000), cognition within organizational literature and management science, which is referred to as *organizational cognition* research, has not progressed to include a more heterodox view to the classical computational[1] and interpretive cognition approaches (Secchi and Adamsen, 2017; see *Chapter 2*).

Yet, *organizational cognition* is a term which has been around for quite some time, spanning over few decades (e.g., Ilgen *et al.* 1994; Hodgkinson and Healey 2008). As Secchi and Adamsen (2017) show in their work, there were three waves in the number of papers published on cognition-related topics in top-tier management and organizational studies (MOS) journals between 1980 and 2015. These waves appeared in the early Nineties, around year 2000, and year 2010. Thus, legitimizing the study of cognition in management and organizational studies related topics. However, Secchi and Adamsen (2017) also highlight in their work that the field's focus is yet somewhat unclear.

In spite of this, Walsh (1995) identifies cognition in organizations as a form of knowledge structures[2] which are analyzed at the organizational level, group level and the individual level. Alternatively, a more recent take on cognition in organizations by Hodgkinson and Healey (2008) claims that cognition differs depending on the following approaches: "(a) schema theory and related

[1] In the classical view of cognition, it was assumed that cognitive processes were central to the human mind and that the manipulation of symbols within the mind resulted in cognitive processing, hence, cognition can be viewed as computational in nature (Horst, 1999; Rescorla, 2017; von Neumann, 1958; Von Neumann and Kurzweil, 2012).
[2] According to Walsh (1995, p. 281) a "knowledge structure is a mental template that individuals impose on an information environment to give it form and meaning".

conceptions of mental representations (especially the notion of mental models), (b) behavioral decision theory (especially work on heuristics and biases), (c) attribution theory, (d) social identity theory and related conceptions, and (e) enactment and the related notion of sense making" (2008, p.391). On the contrary, Walsh' s (1995) representation of cognition in organizations is somewhat restrictive in the sense that it limits the domain by overemphasizing the psychology of cognition while overseeing or underemphasizing other aspects. In spite of this, Chemero (2009) argues that Walsh's (1995) viewpoint has an emphasis on a 'representationist' view of cognitive processes and claims that even though this is one way to approach cognition, it is certainly not the only viable way. Which as a result would limit the research scope and domain hence creating a divide between cognitive processing and behavior. Accordingly, in this regard Secchi and Adamsen (2017, p.310) claim that "representationism becomes more restrictive, and less 'distributed', and significantly delimit the domain."

They also raise another extremely important point arguing that it is perfectly rational and understandable why learning "on certainty and describing the field using the status quo" is acceptable, however as a result "it may signal that some opportunities are lost and some semantic elements in the term 'organizational cognition' [are] overlooked" (Secchi and Adamsen, 2017, p.310). Building on this, Secchi and Cowley (2021) argue that highly socialized organizational environments are pivotal in cognitive processing, hence such social aspects should be seen as the core of organizational cognition (OC). Yet, as it seems, the positioning of OC or, in other words, the realm of research it belongs to, has had a fair share of uncertainty.

In this regard, to make better sense of these uncertainties with regards to such theories/perspectives/approaches, Secchi and Adamsen's (2017) conceptual abstract theoretical framework to understand organizational cognition research, could seem promising. Accordingly, Secchi and Adamsen (2017) argue that the current theoretical approaches can be framed into four different categories, thus aiding the discussion surrounding organizational cognition in highlighting some of the important aspects of this research context. Thus, (a) the *additive approach* sees both organization and cognition to be separate but addictive. This approach can also be seen to as the ‘rational’ system in management (Scott, 2003), where cognition is only studied as a part of individual decision making (Scott and Osgood, 1979). (b) The *combination approach* as highlighted by Secchi and Adamsen, (2017) sees both organization and cognition still separate however yet sharing a common space while keeping the domains separate (e.g., Weick 1995). (c) The *intersection approach* considers the crossing between both domains as the only relevant component to organizational cognition, which in turn indicates that something “unique is defined when these two are together” (p. 313)— e.g. Cannon-Bowers and Salas, 2001). (4) The *conditional approach* considers cognition to be an element amongst many others in which can be used to study organizations. It is also the most popular in the sense that it is the most accepted and used approach of OC in Managerial and Organizational Cognition (MOC) studies (e.g. Hodgkinson and Healey, 2008).

Following the evaluation of the above represented four approaches, Secchi and Adamsen (2017) argue that the most sophisticated and advanced approach is the intersection approach where there is an overlap between the two research domains. Hence, claiming that only the intersection approach presents more advanced perspectives (e.g. sensemaking) that strive away from a “rather static and old-fashioned view of cognition where the social and the dynamics of interaction are overlooked”, which all the other approaches are particularly attached to (Secchi and Adamsen, 2017, p.324).

Yet, in spite of following such a “old-fashioned view of cognition” (Secchi and Adamsen, 2017, p.324), classical organizational literature and management science still acknowledge the notion that organizations more generally influence employee thinking patterns and associated social dynamics at work (Gavetti *et al.*, 2012; March 1994). This in turn highlights a counterproductive aspect of the classical approaches, as they acknowledge the presence of social dynamics and interaction, yet they do not make use of a detailed understanding of such social dynamics (i.e. due to their reliance on the classical computational and interpretive view of cognition). This unbalanced conundrum is further heightened by the fact that employers have shifted their focus to seek employees that are more adaptable and compliant with an everchanging and unsettling work environment (Doeze Jager-van Vliet 2019; Aggarwal *et al.*, 2019; Deloitte 2018). For instance, the recent COVID 19 pandemic is a great example, where the existing structures of workplaces and its day-to-day employee behavior had to be completely restructured in most or if not all workplaces in an attempt to adhere to newly imposed governmental restrictions while also encouraging safety precautions such as social distancing. Accordingly, such a need for an adaptable individual which can withstand constant change has in turn inflicted a need to refocus on to the 'adapting' aspect of organizational work. Thus, implying the need to change the focus from the conventional micro and macro perspective driven approaches of cognition in organizations, to the 'meso domain' of social organizing of employees in such adaptive environments (Secchi and Cowley, 2021). This has resulted in a gap in conventional organizational literature, hence enacting a need to update the organizational literature in terms of theoretical developments to represent a more varied use of cognition as seen in contemporary cognitive sciences (Perry, 2003; Hutchins, 1995; Hollan *et al.*, 2000; Norman, 1994).

1.1.1. A starting point to reflect an adaptable individual

Given this need to reflect the adaptable individual in connection to an organizational environment, it is reasonable to suggest that such a shift should begin with the fundamentals of human resource management (HRM) and particularly the recruitment and selection (R&S) process of employees. This is especially the case due to the fact that such organizational environments[3] are formed on the basis of

[3] Which are primarily consistent of employee that collectively organize in a social manner. This process is also referred to as 'social organizing' by some scholars (Secchi and Cowley, 2021).

personnel selection initiatives imposed by the recruitment and selection process of organizations (Breaugh, 2013; Searle, 2009; Barber, 1998; Turban and Greening, 1997), which ultimately could facilitate the inclusion of such adaptive change driven individuals into organizations. Therefore, organizational aspects such as human resource management and particularly the recruitment and selection process of organizations should be considered a starting point to reflect a varied understanding of cognition in relation to fostering adaptive individuals into organizations. In other words, the recruitment and selection process of an organization is a vital component in human resources management (Breaugh, 2013; Searle, 2009), primarily due to the fact that the R&S process not only oversees the entire process from attracting prospective candidates (Barber, 1998; Turban and Greening, 1997) to selecting an appropriate candidate (Searle 2009), but most importantly also describes and formulates what a potential job position would entail and require. Thus, given its capability to allow organizations to effectively recruit candidates that can efficiently coordinate themselves (adapt) in change driven organizational (social-oriented) contexts, in turn, makes the R&S process the perfect point of application.

In this regard, within the research domain of R&S the stream of conventional organizational literature referred to as the *Person-Environment Fit* (P-E fit) paradigm (Edwards, 2008) is the most widely used and popularized R&S branch of literature. The P-E fit paradigm includes a series of measures that are used to find a recruit that is compliant with a specific environment (see the following subheading - sections 1.2 - for a thorough review about the P-E paradigm). Such measures range from, for example, fitting a person with another person (P-P fit), a person with a group (P-G fit), a person with an organization (P-O fit), a person with a role (P-R fit) and many more (see following section 1.2.2). Irrespective of the measure used the underlying concept behind the Person-Environment paradigm has historically been centered around either looking for congruence between certain units (e.g. goals, values) or dissimilarity between them. The latter is referred to as the *complementary* *fit* tradition while the former is referred to as the *supplementary fit* tradition (Muchinsky and Monahan, 1987). Nevertheless, such measures have typically been applied in terms of the congruence or dissimilarity through the measurement of for example goals (Kristof-Brown and Stevens, 2001; Pierro *et al.*, 2015; Witt, 1998), vocational aspirations (Holland 1985; Reeve and Heggestad, 2004; Vogel and Feldman, 2009), career opportunities (Cha *et al.*, 2009; Parasuraman *et al.*, 2000), values (Vogel and Feldman, 2009; Adkins *et al.*, 1996; Hobman *et al.*, 2003; Jehn *et al.*, 1999; Pierro *et al.*, 2015), or job requirements (Kristof-Brown *et al.*, 2005; Lauver and Kristof, 2001). Thus, such measures have overarchingly relied on the consolidation of certain units, processes, and structures at a given point in time to operationalize fit (Drazin and Van de Ven, 1985). Such a static operationalization of fit between various units, processes, and structures such as — e.g., values, goals, opportunities and aspirations — at a certain point in time would in turn indicate that perhaps such P-E fit measures too have been operationalized through a classic micro and macro conception of organizations, as seen in conventional organizational literature. Thus, failing to take into account the fundamental essence of integrating into a socially distributed environment, where dynamic aspects such as adapting/social organizing (Secchi and Cowley, 2021) is fundamental for effective operation within an organizational environment. In this regard, in order to provide the reader with a systematic understanding of how fit is operationalized in the *Person-Environment fit* literature, the following section will highlight different operational sorts of fit found in literature along with some of the currently utilized fit measures.

1.2. Investigating the Person-Environment fit literature

The notion of fitting or matching a set of characteristics between two parties or entities has been a key procedure ever since the dawn of time. For instance, Herbert Spencer in *Principles of Biology* (1896) based on Charles Darwin's book on the *Origin of Species*, uses the phrase ‘Survival of the fittest' to describe what Darwin referred to as 'natural selection'. This was later acknowledged by Darwin and was even used by himself. In a broader sense, it is a claim that for species to survive they have to fit the environment they live in; hence the fit species will remain, while the unfit species die out due to the lack of fit with the environment and the characteristic of the specific species. Yet, one may question if this notion of 'fit' can be applied to an organizational context. The short answer would be yes, as scholars in psychology (Arthur el al., 2006; Vianen, 2000) and management (Edwards, 2008; Edwards and Billsberry, 2010) have considered these aspects to be linked with improvisation at work and organizations more generally. As a result, it is a widely accepted concept in the field of management (Edwards, 1996; 2008). Hence, carrying the notion that 'fit' perhaps is the key element that bridges the gap between various compatible entities (e.g. environment and people, jobs and people, technology and people).

However, research has shown from time and time again, fit is not just a phenomenon that involves matching two entities (based on the various characteristics they embody), but rather a more complex phenomenon (Boon and Biron, 2016; Edwards, 1991; 2008; Drazin and Van de Ven, 1985). This is why it is critical to grasp the concept of fit in a systematic manner, thus prompting the questions: a) What is fit in an organizational context? and b) what operationalizes the key elements of fit? Accordingly, Drazin and Van de Ven (1985, p. 515) assert that the following conceptual approaches of fit surfaced in the formation of contingency theory in regards to organizational performance: 1) Fit as *Selection*, where "fit is the assumed premise underlaying a congruence between context and structure"; 2) fit as *Interaction,* where it is "the interaction of pairs of organizational context-structure factors" and 3) fit as *Systems,* where it is "the internal consistency of multiple contingencies and multiple structural characteristics". In spite of these efforts, research has shown that the above-mentioned approaches are unsuccessful in explaining relationships that exist with organizational performance, and it requires a "more sophisticated approach" (Drazin and Van de Ven, 1985, p. 535; see

Chapter 2). Accordingly, due to the lack of evidence with regards to fit being just a "simple interaction between isolated pairs of unit-context and structure and processes dimensions on performance", the view of mainstream contingency theorists can be seen unjustifiable (Drazin and Van de Ven, 1985, p. 535; see *Chapter 2*). This could in fact assert that, since contingency theory (i.e. which relies on the premise that situational factors may affect the relationship between variables) seem to be insufficient, perhaps it may be more important to study factors that may cope with ("deal with") such situational factors.

Yet, thus far, a large body of research on fit is still focused on the idea of studying specific static aspects that are fitted together to represent fit between, for example, an individual and an organization, individual and a career, individual and a community, and more. However, such studies seem to undermine the fact that fit is a far more complex phenomenon than it may seem (Boon and Biron, 2016; Edwards, 1991; 2008; Drazin and Van de Ven, 1985). This complexity can be seen as an accumulation of various interconnections that collectively explain the phenomenon of 'fit', opposed to simply considering it as an output of a single relationship between two entities. Thus, certain aspects of 'fit' could essentially have higher importance (higher influence) than others. Accordingly, it is fair to argue that perhaps a multitude of fit aspects could transversally interact with each other to ultimately explain the true picture of fit in the real world (Jansen and Kristof-Brown, 2006). Therefore, Jansen and Kristof-Brown (2006) proposed a multidimension model of *Person-Environment* (P-E) *fit* which considers person P-E fit to be an entity that embodies the interactions of other forms of fit (Person-Vocation fit, Person-Job fit, Person-Organization fit, Person-Group fit, Person-Person fit). Accordingly, they developed a model which proclaims that "individual differences, environmental characteristics, and temporal stage moderate the relative influence of PP, PJ, FG, PO, and PV fit on the overall experience of fit" (Jansen and Kristof-Brown, 2006, p. 206). Which in principle should go in the direction of assessing the role of fit in the improvisation of employees at work, thus perhaps resulting in a deeper understanding of P-E fit in practice.

However, Edwards and Billsberry (2010) in their work show that the multidimensional model by Jansen and Kristof-Brown (2006) does not accomplish the goal it strives to attain, thus indicating that the combinatorial approach to fit may not be the most viable solution. In line with these findings, the multidimensional model (Jansen and Kristof-Brown, 2006) only looks into this phenomenon through an individual perspective (individual-level outcomes). Thus, suggesting that even though fit may at times provide positive results for individual outcomes, in turn it could also result in negative outcome for other levels of the environment (e.g., Edwards, 1991; Kristof, 1996). For instance, Ostroff and Rothausen (1997) in their research found that when looking through the group level rather than the person level a far better prediction of certain outcomes could be obtained.

Therefore, it is evident that the phenomenon of fit should be investigated through a foundation which encompasses not only individual aspects but also the social aspects of fit as well. This in essence should be more capable in allowing researchers to systematically study and understand a more precise depiction of fit opposed to just a one-dimensional or even an individual-level outcome driven multidimensional approach (Jansen and Kristof-Brown, 2006). In light of this, as the underlying approach in measuring fit could evidently have a great influence on the fitting itself, it is also equally as important to be pragmatic when endeavoring to define the mechanisms of a ‘fit’ measure. Therefore, the following section will highlight the different sorts of ‘fit’ used in the literature in an attempt to provide the building blocks necessary to guide this study.

1.2.1. Fit sorts breakdown

The literature surrounding ‘fit’ has had a fair share of development with fit been sorted into various categories with respect to how it is measured and how it integrates with the environment (e.g. organization). Therefore, in order to give a better outlook in to these categories, the following sections will describe the most widely accepted sorts of fit that have surfaced throughout the years in the person-environment fit literature.

Subjective fit

Subjective fit is the individual perception of the environment and how well it fits together (van Loon, Leisink, and Vandenabeele, 2017). Thus, this perspective measures the subjective fit by asking the individual to describe how much they think their characteristics will fit the characteristics of the organization they are applying for (Hoffman and Woehr, 2006). Therefore, once the individuals describe themselves along with their perceptions of the organizational characteristics, the “degree of fit is then calculated by assessing the discrepancy between a respondent’s self-description and that same respondent’s description of the organization” (Hoffman and Woehr, 2006, p. 391). It is apparent that this perspective does not rely on explicitly measuring either the individual or the environmental characteristics (Edwards, 1991), rather in this perspective “respondents are assumed to have a mental representation of the organizational profile and to cognitively examine the congruence between their personal characteristics and their perception of the organizational profile” (Hoffman and Woehr, 2006, p. 391).

Perceived fit

Perceived fit is the perceptions of how well an individual fits an organization, thus fit is determined simply by the perception of fit opposed to assessing if the individual actually has these characteristics (i.e. values and norms or practices) that fit with the relevant organizational characteristics (Chan, 1996; Edwards *et al.*, 2006; Kristof-Brown, Zimmerman, and Johnson, 2005; van Loon *et al.*, 2017). Perceived fit can be either other-perceived or self-perceived, where for example an individual thinks he/she fits the organization well (Chan, 1996). Some scholars, however, criticize this type of fit that relies on direct measures because they tend to confuse the impartial effects of individual and environment variables (Edwards, 1991; Chan, 1996). Accordingly, Perceived fit is measured by asking an individual to describe their self along with their perceptions of the characteristics of the organization (Hoffman and Woehr, 2006). Thereafter, the degree of fit is measured by the "discrepancy between a respondent's self-description and that same respondent's description of the organization" (Hoffman and Woehr, 2006, p. 391).

Furthermore, Edwards *et al.* (2006) with regards to perceived fit proposes three different approaches to studying fit. The first being the 'atomistic approach', where it measures both the perceived person and the environment separately and finally combine them thus attempting to capture P-E fit (Cable and Judge, 1996; Edwards, 1996; Edwards *et al.*, 2006; French, Caplan, and Harrison, 1982). On the contrary the 'molecular approach' derives the perceived discrepancy between the person and environment and then directly assesses it. This approach is argued to be suitable for instance to assess if the person's ability with the job demands are either lesser or greater (Beehr, Walsh, and Taber, 1976; Edwards *et al.*, 2006; Rizzo, House, and Lirtzman, 1970) or to assess if the rewards at work are seen inadequate with the person's needs (Edwards *et al.*, 2006; Lance, Mallard, and Michalos, 1995; Rice, McFarlin, and Bennett, 1989). Finally, the 'molar approach' represents studies that requires the subjects to rate the fit they see between themselves and the subsequent organization (Cable and DeRue, 2002; Edwards *et al.*, 2006; Judge and Cable, 1997; Saks and Ashforth, 1997), in other words such studies directly measure the fit between the person and the environment (Edwards *et al.*, 2006). More importantly, the findings of Edwards *et al.* (2006, p. 822) shows that all three approaches are "not interchangeable and treating them as such will hinder the accumulation of knowledge in P-E fit research". Thus, asserting the notion that all three approaches should be considered theoretically and empirically distinct (Edwards *et al.*, 2006).

Interestingly enough, subjective fit measures are conceptually similar to perceived fit measures as "the degree of fit in both is operationalized as the discrepancy between an individual's self-image and the same individual's perceptions of the organization" (Hoffman and Woehr, 2006, p. 391). The main difference between the two being that subjective fit is measured by "asking respondents how well they fit with their organization using self-report items" while perceived fit is measured by "explicitly ask[ing] respondents to describe both their own characteristics and the organization's characteristics via questionnaires" (Hoffman and Woehr, 2006, p. 391).

Objective fit

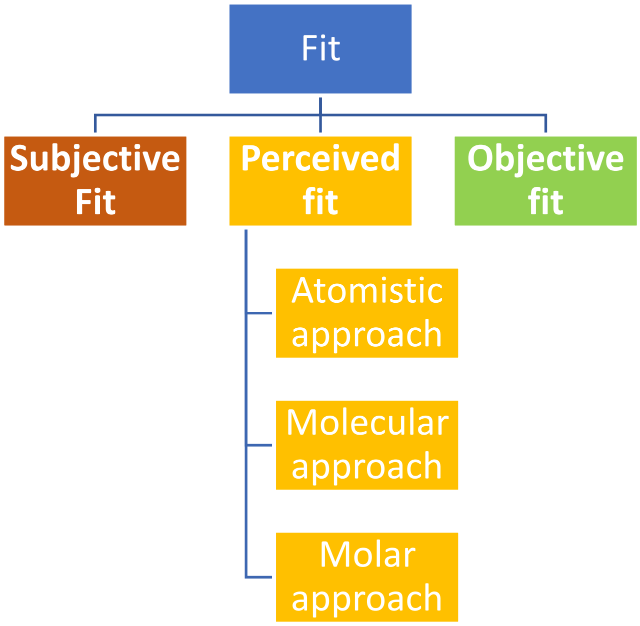
Objective fit or, as some refer to as, 'actual fit', is seen by some researchers as a method to avoid some of the problems associated with direct measures such as perceived fit (Cable and Judge, 1996; Chan, 1996; French, Rogers, and Cobb, 1974; van Loon *et al.*, 2017). This perspective considered fit to be the congruence between the 'objective' elements of the organization and the characteristics of the individual (Chan, 1996). Thus, Chan (1996, p. 198) claims that this perspective of fit is objective in the sense that it "allow[s] verification (e.g., company records) and the assessment of similarity or match between person and organizational characteristics", hence not depending on individualistic perceptions. Moreover, Chan (1996) also points out that the "objectivity" of this perspective simply implies only to the measurement strategy, and it does not suggest that objective fit measures are superior to the measures of perceived fit. Accordingly, subjective fit and perceived fit both differ to objective fit on the premise that objective fit asks not only the individual to describe their own characteristics, but also ask the members of the organization to describe the characteristics of the organization (Chatman, 1989; Hoffman and Woehr, 2006). Hereafter the members' responses are combined into a measure that represents ‘organizational climate’, where “[f]it is then operationalized as the congruence between an individual’s self-description and the aggregate organizational climate” (Hoffman and Woehr, 2006, p. 391).

Interestingly, research has shown that objective fit measures are more strongly correlated to behavioral outcomes when compared to subjective fit (Hoffman and Woehr, 2006). This reaffirms the notion that the method used to measure fit is an important moderator to the outcome of the fit relationship. In addition, objective fit can be seen more amenable to be incorporated into a personnel selection system when compared to perceived and subjective fit measures (Hoffman and Woehr, 2006). This is because objective fit measures only require a respondent to report their personal characteristics[4], thus providing the benefit of not needing the respondents to be familiar with the organizational characteristics (Hoffman and Woehr, 2006). This is also another factor that further differentiates Objective fit from Perceived and Subjective fit measures, as they require the respondent to have familiarity with the organizational value system (Hoffman and Woehr, 2006).

Finally in order to provide the reader with a comprehensive outlook of the underlying sorts of fit in the *person-environment fit* literature, a figure was created (see Figure 1). Accordingly, Figure 1 shows a visual breakdown of fit with respect to the above-mentioned sorts and sub sorts of fit.

[4] which is then compared to the pre-recorded ‘organizational climate’ (Hoffman and Woehr, 2006).

Figure 1: Fit sorts breakdown



Given these insights into the fit sorts breakdown and the operationalization of fit, it is apparent that Objective fit may be seen a more appropriate fit for this study. In particular there are three major reasons for why Objective fit is more appropriate than the other two approaches in regard to this study.

1) It provides the ability to reduce subjectivity (the dependence on individualistic perceptions) by employing a more objective approach on the premise of employing a two-way test with one targeting prospective candidates and the other targeting the organizational members (Chatman, 1989; Hoffman and Woehr, 2006).
2) The stronger correlation it has with behavioral outcomes in comparison to the other approaches (Hoffman and Woehr, 2006), which makes objective fit more suitable because inquiring on behavioral outcomes is at the root of this study's proposition.

3) The ability in which it is easily employable in personnel selection processes when compared to the other approaches, as when using objective fit it is not required that the respondents are familiar with the characteristics of the organization (Hoffman and Woehr, 2006).

1.2.2. Current Fit measures

This sub-section is a showcase of the numerous fit measures that have been implemented over the years in the Person-Environment Fit literature. In so doing, it is intended to provide the reader with a brief understanding of the operationalization of each fit measure found in literature. Table I presents a succinct summary of these measurements. Before examining and breaking down the fit literature, it should also be mentioned that all the measures discussed below relate to an individual fitting into an organizational work environment while the spectrum of measures is much broader (see *Chapter 2* for details).

Table I: Current fit measures

Fit measures	Description
Person-Supervisor fit (Person-Person fit) — **P-S Fit / P-P Fit**	Kristof-Brown *et al.* (2005, p. 287) referred to *Person-Supervisor fit* as "dyadic relationships between individuals and others in their work environments". This measure of fit is also referred to as Person-Person (P-P) fit by some researchers (Jansen and Kristof-Brown, 2006; Ostroff and Zhan, 2012). Primarily, as Kristof-Brown *et al.* (2005) mentioned, this is because of the emphasis some put on the "dyadic relationships" to which it is applied. Historically, it has been used to study the compatibility of, for example, applicants and recruiters (Graves and Powell, 1995), mentors and protégées (Turban and Dougherty, 1994), and between co-workers (Antonioni and Park, 2001). While the most researched variation of this measure falls among supervisors and sub-ordinates (Adkins, Russell, and Werbel, 1994; Kristof-Brown *et al.*, 2005; Van Vianen, 2000).
Person-Group fit — **P-G Fit**	Person-Group fit is concerned with the expertise of both parties as well as the interpersonal compatibility of for example an employee and their immediate work group. (Jansen and Kristof-Brown, 2006; Judge and Ferris, 1992; Kristof-Brown *et al.*, 2005; Kristof, 1996; Vogel and Feldman, 2009; Werbel and Gilliland, 1999). It has mostly been applied along the lines of the compatibility of goals (Kristof-Brown and Stevens, 2001; Pierro *et al.*, 2015; Witt, 1998), values (Adkins, Ravlin, and Meglino, 1996; Hobman, Bordia, and Gallois, 2003; Jehn, Northcraft, and Neale, 1999; Pierro *et al.*, 2015), and personality traits (Barsade, Ward, and Sonnenfeld, 2000; Kristof-Brown *et al.*, 2005; Pierro *et al.*, 2015).
Person-Organization fit —	Kristof (1996, p. 45) referred to Person-Organization fit as the match that arises between an individual and an organization "when: (a) at least one entity provides what the other needs, or (b) they share similar fundamental characteristics, or (c) both". P-O fit carries the rationale that, people want to work in settings that reinforce their own principles and values, and since these are important factors in how people perceive situations and decide acceptable behavior, it assumes that maintaining continuity in those values and principles is critical to effectively adapting to the workplace (Vogel and Feldman, 2009). Conversely, when the values of an individual and

P-O Fit	the organization (or the work environment) are misaligned, it is read as a state of 'misfit' (Brigham, De Castro, and Shepherd, 2007).
Person-Job fit — **P-J Fit**	Person-Job fit can be seen as the compatibility of an individual with his/her work conditions and incentives to carry out the associated job. Hence, P-J fit has an influence on similar behavior outcomes as P-O fit and, perhaps for this reason, together with it, is one of the most researched types of fit (Kristof-Brown *et al.*, 2005; Lauver and Kristof, 2001; Muchinsky and Monahan, 1987; van Loon *et al.*, 2017). Interestingly, even though a large number of studies have suggested P-O fit and P-J fit to mediate the relationship between individual characteristics and work outcomes (Cable and DeRue, 2002; Cable and Judge, 1996; Saks and Ashforth, 1997; van Loon *et al.*, 2017; Vogel and Feldman, 2009), these measures' are considered different as they refer to different environ-mental levels (Boon, den Hartog, Boselie, and Paauwe, 2011; Kristof, 1996; van Loon *et al.*, 2017).
Person-Vocation fit — **P-V Fit**	Person-Vocation fit occurs when an individual's skills, ambitions and desires are aligned with the criteria and attributes of his/her vocational aspirations. (Holland, 1985; Reeve and Heggestad, 2004; Vogel and Feldman, 2009). In other words, it is usually understood as the "congruence of skills and needs at the level of the occupation" (Vogel and Feldman, 2009, p. 70). Accordingly, P-V fit encompasses vocational choice theories (historically based on the work of Parsons, 1909; Super, 1953) which operationalizes the fit between an individual and a compatible career that meets his/her desires (Holland, 1985; Jansen and Kristof-Brown, 2006; Kristof-Brown *et al.*, 2005).
Person-Career fit — **P-Ca Fit**	It can be considered Person-Career fit when an individual's work environment allows him or her to grow his or her career through a variety of opportunities that meet their need for optimum career success (Cha *et al.*, 2009; Parasuraman, Greenhaus, and Linnehan, 2000). Yet, the difference between a career and a vocation is seen by many as a very unclear domain, which ties back to religion and personal beliefs (Cullen, 2011). However, at face value, one can consider a vocation to be all about what an individual believes is his or her life's path based on his or her personal values and personal attributes, while a career is about an industry-related form of path that one might be employed to advance in (Cullen, 2011). In other words, Person-Career fit occurs when the abilities and competencies of an individual can be leveraged through the career opportunities provided by the workplace (Cha *et al.*, 2009; Parasuraman *et al.*, 2000). Accordingly, some refer to such needs as 'career orientations', which are defined as "a type of work-related values reflected in individual preferences regarding various job types, performance standards, and forms of recognition in the context of work careers" (Gerpott, Domsch, and Keller, 1988, p. 441).
Person-Culture fit — **P-Cu Fit**	The fit between an individual and the culture of the organization and/or the community in which he or she serves is referred to as Person-Culture fit (Elfenbein and O'Reilly, 2007; Hua and Liu, 2017; Kincaid, Yum, and Woelfel, 1983; Kristof, 1996; Woelfel and Fink, 1980; Zhu, Liu, and Fink, 2016). In an organizational/workplace environment, culture is defined by O'Reilly and Chatman (1996, p. 160) as having "shared values (that define what is important) and norms that define appropriate attitudes and behaviors for organizational members (how to feel and behave)".
Person-Role fit — **P-R Fit**	The resemblance between an individual's personal characteristics and the characteristics and related features of the ability with which he or she is employed for, is used to determine Person-Role fit (DeRue and Morgeson, 2007). Interestingly, even though some may argue this type of fit to be similar to P-J fit (Edwards, 1991), P-R fit considers 'roles' to be more focused on one's responsibilities in a team environment (DeRue and Morgeson, 2007; Ilgen, 1994). Thus, DeRue and Morgeson (2007, p. 1242) differentiates the two as follows, "the term job focuses on the established or formal task elements of work" while the term 'role' includes "both established task elements and the emergent task elements that are specified by social sources such as teams".
See *Chapter 2* or Herath, G. (2021). A missing link: a distributed cognitive perspective on fit. International Journal of Organization Theory and Behavior. https://doi.org/10.1108/IJOTB-09-2020-0168 — for more information.	

1.3. In search of a solution

In light of the above explained measurements, researchers have argued that they operate as static measurements, due to their operationalization on the premise of fitting certain units, processes, or structures at a given point in time (Edwards, 2008; Boon and Biron, 2016). Thus, this operationalization undermines the unsettling and rapidly evolving nature of organizations (Suddaby, and Foster, 2017; Boon and Biron, 2016), hence asserting the need for measures that can transcend these static dimensions of fit (Drazin and Van de Ven, 1985; Boon and Biron, 2016; see *Chapter 2*). Given this structural constraint imposed on current fit measures, it is not too surprising as to why such measures have been (a) underperforming as they are unable to effectively explain employee and organizational performance (Edwards, 2008, 1991; Kristof-Brown *et al.*, 2005; Greguras and Diefendorff, 2009; see *Chapter 2*), and (b) have been ineffective when combined with other fit measures (Edwards and Billsberry, 2010). As a consequence, it is clear that these problems have arisen as a result of the inherent expectations and rationale of fit in organizations. Although these measures seem to be beneficial in principle, they often fall short in practice, particularly when considering their static nature of fit (Drazin and Van de Ven, 1985; Boon and Biron, 2016; see *Chapter 2*).

Accordingly, this is where the need for varied and heterodox views to the classical computational and interpretive cognition approaches is clearly apparent, as there is an evident need to reform certain traditional management approaches such as *P-E fit* which is especially nested in environment driven situational dynamics of organizational life. For instance, the work from Winsor (2001, p. 6) which analyzed “a group of six engineering students working as summer interns in the engineering center of a large manufacturer of agricultural equipment” (which she calls “AgriCorp” in order to provide anonymity), provides an important example to explicate the dynamic evolving nature of organizational landscapes and the importance of cognitive attunement. She points out that “[i]n organizations in which knowledge is unstable, newcomers and experienced workers alike must remain attuned to a shifting environment" (Winsor, 2001, p. 26). And highlights that for both regular employees as well as the interns, "cognition at AgriCorp is distributed across different people who are able to supplement and support one another's work" (Winsor, 2001, p. 14).

With this consideration in mind, it is clear the attunement of social-interactions and the desire to learn alongside others or without others are both aspects that, in one way or another, make use of an unavoidable social driven cognitive nature (Heyes, 2012; Secchi, 2021c; Hutchins, 1995; Herath, 2019b). Thus, some researchers refer to this need for more accurate, practical resources and solutions to reform certain traditional approaches, as the 'social gap' in recruitment and selection interventions (Searle 2009). In so doing, this highlights the importance of needing measures that can structurally correspond to the socially driven cognitive nature of organizations. And in turn allowing to perhaps inquire on aspects that attempt to transcend the currently operationalized static structural aspects (i.e. units, processes, and structures) found in conventional organizational literature (i.e. P-E fit).

In line with this, the act of moving from one situation to another is embodied as change in an organizational and management science context (Suddaby, and Foster, 2017; Vogel *et al.*, 2020). Thus, each situation based on various micro bodily aspects as well as macro structural aspects can produce a unique collection of situational characteristics (Perry *et al.*, 2003). For example, the previously mentioned research on "AgriCorp" by Winsor (2001) again provides important insights into such situational bound aspects of working in organizations. In so doing she highlights that, at different times in the integration process of newcomers at "AgriCorp", they "seem to learn from their mentors, their hands-on contact with the organization's objects, and their playing around with tools available to them"; and in the process "function in an environment where no one seems to know everything and where unsettled knowledge is not always a bad thing" (Winsor, 2001, p. 26). Similarly other research has also indicated findings alike (Herman, 1973; Peters and O'Connor, 1980; Ferguson and Cheek, 2011).

As a result, it is clear that this cross-situational movement across varying inputs (e.g. mentors, organizational resources and tools) is fundamentally divided by geographical assets and altering time scales (Hollan *et al.,* 2000; Cowley and Vallée-Tourangeau, 2013; Perry *et al.*, 2003). Thus, these varying situations can either initiate or halt certain situational cognitive processes, hence facilitating change. Therefore, it is of importance to inquire if there is a 'fit' between an organizational environment and its workers' cognitive processes that are distributed across varying situations. The idea here is that such a cognitive-oriented fit approach that is based on aspects of time and space, would in turn allow to capture a dynamic understanding of how an individual would maneuver oneself in such a change driven environment, and in the process transcend conventional static approaches. In turn this would also allow to gain a better understanding of what are the certain micro (e.g. personality traits, behavior patterns, skills) and macro (e.g. organizational rules, power structures, resources) aspects that might have an influence on either facilitating or hindering organizational performance (e.g. team problem solving performance) in relation to recruitment and selection (R&S). In line with this, for instance if such an R&S approach is able to effectively integrate an individual into a pre-existing social environment (e.g. team), then such an operationalization of fit on the premise of a more nuanced understanding of team composition (Mathieu *et al.*, 2013a; Mathieu *et al.*, 2013b; Devine and Philips, 2001) and team cohesion trajectories (Acton *et al.*, 2019; Bell and Outland, 2017; Bell, 2007), may in turn have an impact on employee turnover and retention (Sheridan, 1992; Mainiero, 1993; Holtom *et al.*, 2008; Mitchell *et al.*, 2001) in the long term.

Therefore, given the importance of inquiring and systematically understanding the dynamic and adaptive nature of what is at the core of assessing 'fit' between a potential worker and an existing dynamic environment (i.e. organization), the distributed (e-)cognition (DEC) perspective (see *Chapter 2*) is considered in this PhD project to be highly suited for its investigation. In its essence, when compared to the classical computational and interpretive view of cognition — i.e., cognition being centered around one's mind, which is assumed to function in a computational nature (Horst, 1999; Rescorla, 2017; von Neumann, 1958; Von Neumann and Kurzweil, 2012) — the distributed (e-) cognition (DEC) perspective holds on to the idea that cognition is not just within oneself but rather it is spread from within to the world around us (Hutchins, 1995; Perry, 2003; Hollan *et al.*, 2000; Cowley and Vallee-Tourangeau, 2013). In so doing, it highlights five important normative aspects of cognition — i.e., *Embedded, Enacted, Embodied, Ecological* and *Extended* (Cowley and Vallée-Tourangeau, 2017; Herath, 2019b; Secchi and Cowley, 2021 — see article 1 in *Chapter 2*. As such, this perspective has proven to be most useful when applied to complex dynamic scenarios requiring adaptation to the environment — e.g., directing a ship to a port (Hutchins, 1995), other individuals — e.g., problem solving in a team environment (Bardone and Secchi, 2017), and surrounding resources — e.g., the use of artificial arms (Clark, 2003). As a result of these considerations, this study demonstrates the utility of a distributed cognitive (DEC) viewpoint to study complex phenomena that is rooted in a cognitively driven environment such as an organization for example. In so doing, DEC serves as the study's underlying cognitive architecture (see *Chapter 2* for a more comprehensive explanation).

Coupled with the aforementioned shift in employers need for more adaptable employees (Doeze Jager-van Vliet 2019; Aggarwal *et al.*, 2019; Deloitte 2018), in recent times, adaptability-driven corporate management methods (e.g. agile project management) have also had a rise due to the flexibility and change prone fundamentals they provide (Duguay, Landry and Pasin, 1997; Purvis, Gosling and Naim, 2014; Coleman, 2017; Herath, 2019b). As a result, it is evident that such a plastic/flexible environment is present to some extent in all organizations (Herath, 2019a). For example, even in a rare case of an organization that is highly structured and inflexible, a global pandemic such as COVID 19 would systematically restructure the working of its employees and ultimately influence the organization as a whole. Thus, in this domain, the primary focus lies especially on attaining individual cognitive plasticity/adaptability with an organizational environment, and also in understanding organizational characteristics that either favor or hinder individual cognitive plasticity/adaptability (Herath, 2019b). Given its climate and the associated stream of literature (of this study), the attaining of individual cognitive plasticity/adaptability with an environment is referred to as '*organization-cognition fit*' (O-C fit) in this study. Thus, in other words it can perhaps be considered *O-C fit* when the characteristics related (referred to as the level of *organizational cognition* in this study, see *Chapter 4* and *5*) to a match (fit) resonate with the distributed cognitive attributes of an environment. Therefore, also being consistent with Simon (1993, p.156) as he articulates based on the modern evolutionary theory of fitness that, "One can speak of the fitness of an individual or the average fitness of a group to which the individual belongs".

In regard to this, Secchi (2011) explains the aforementioned concept of fitness through the consumption of an individual's openness to the social side of human relation — i.e. docility (Secchi and Bardone, 2009). He argues that an individual who is more open to his/her social side of human relation will fit in to the social environment far better than an individual who doesn't consider the social side of human relation. In line with this conception, this study attempts to operationalize an approach that essentially re-establishes the utility of docility for the purpose of being used as a proxy of *O-C fit* (see *Chapter 4* and *5*), thus attempting to capture the adaptability of an individual when an organization is plastic/flexible. In other words, such an operationalization of *O-C fit* would imply how well an individual fits in to a more plastic/flexible environment. In so doing such an approach would attempt to transcend conventional static aspects of fit by instead relying on aspects such as — docility (see *Chapters 4* & *5*) — that represents an individual's adaptability to a dynamic social environment.

Thus, if seeking congruence (see *Chapter 4*), then the more favorably aligned an individual is to the existing plastic/flexible environment (by using docility as a proxy to map congruence) the higher *the O-C fit* of that individual would be (organizational situational characteristics that lead to favor individual cognitive plasticity/adaptability), on the contrary the less favorably aligned an individual is to the existing plastic/flexible environment the lower the *O-C fit* of that individual would be (organizational situational characteristics that lead to hinder individual cognitive plasticity/adaptability). In contrast to seeking congruence, if the goal is to seek improvement, then one can also operationalize *O-C fit* (this time by using docility as a proxy to map transformation) to seek improvement through change, as done in *Chapter 5*. In doing so, *O-C fit* would then capture the existing level of *organizational cognition* in the plastic/flexible environment through the use of docility as a proxy and then seek an individual with a level of *organizational cognition* that attempts to improve the existing level (see *Chapter 5*). All things considered, regardless of how *O-C fit* is operationalized (either to seek congruence in *Chapter 4* or to seek improvement in *Chapter 5*), it is evident that the research area of focus in this study is highly interconnected with both organizational behavior as well as cognition, hence falling into the research domain of Organizational Cognition.

1.4. The need for an appropriate research method

Given all that is discussed above, it is evident that organizations are fundamentally complex in nature due to the institutional complexity and the resultant organizational responses, as well as the distributed social cognitive interactional structures that inform behavior in organizations (Rybakov, 2001; Greenwood *et al.*, 2011; Wood and Bandura, 1989). As such, the exploration of organizational cognition may lead to an overwhelming set of interactional complexity (Secchi and Cowley, 2021). This in turn asserts the need for a research method that can facilitate such a study of complex systems. One such method that has had a recent increase in recognition among social scientists with regards to the study of complex systems, is agent-based simulation modeling (Edmonds and Meyer, 2017; see *Chapter 3*). This is due to its capacity to simulate complex situations where understanding the process and effects of a phenomena is critical, as well as the maneuverability it offers over other techniques (Gilbert, 2008; Secchi 2021a) — see *Chapter 3* for a more detailed explanation. Thus, this method provides the research tools to effectively explore and unwind the web of interconnected interactions that take place when social beings traverse and improvise in a highly complex organizational system. As a result, this study utilizes agent-based simulation modeling (ABM) as the research method to explore the theoretical bounds of the propositions brought forward in this study.

In so doing, this study demonstrates that the present approaches used in conventional 'fit' research (either alone or in combination) does not grasp the inevitable essence of cognition. As a result, the study highlights a newer approach to assess fit — *organization-cognition (O-C) fit* — which differs from conventional fit measurements in the sense that it is constructed to provide a dynamic understanding of recruitment and the subsequent effect it has on the environment over time. Yet, it should be understood that even though *O-C fit* is differently operationalized to current P-E fit measurements, it still subscribes to the underlying logic of current fit measures. All things considered, *O-C fit* follows the essence of the DEC perspective through human attributes such as docility (see *Chapters 4* and *5*) to gain a more nuanced understanding of an individual fitting into an organizational environment, thus attempting to provide a more sophisticated perspective of fit. By this means, in this study an agent-based simulation model is constructed from the ground up to essentially test the bounds of the proposed *organization-cognition (O-C) fit* approach. In so doing two different operationalizations of *O-C fit* (i.e. *supplementary fit* and *complementary fit*) are simulated and examined in this study. Where the former indicates an attempt to seek similarity to the existing level of organizational cognition (see *Chapter 4*), while the latter represents an attempt to change the existing level of organizational cognition (see *Chapter 5*). Thus, this process is intended to perhaps provide a more sophisticated understanding of which situations can be considered either enabling or hindering the performance of employees at work, and also to understand what such a dynamic adaptation (through

O-C fit) would offer organizations in return. Hence the primary objective of this study is to essentially investigate the feasibility of utilizing *O-C fit* in organizations.

This would, on the one hand, enable us to better understand how *O-C fit* may be employed, and on the other, explore its potential for operationalization in practice, to achieve the best recruiting outcomes. As a result, it would contribute to the body of literature on human resources management (HRM), and recruitment and selection (R&S) by potentially considering *O-C fit* as a feasible option, and more crucially, a strategy that strives to address critical features that have been overlooked in traditional *Person-Environment fit* (P-E fit) assessments. Thus, in turn attempting to enrich and provide practical implications not only for R&S research but also wider human resource management, distributed cognition and organizational behavior research.

1.5. Overview of the study conducted

This dissertation is written as an anthology where it compromises of a collection of research articles. Accordingly, this dissertation includes 3 research articles. First and foremost, chapter 1 will first introduce the topic area at hand along with the research subject and the objectives of the study. Once the overview of the study along with the associated theory is highlighted, from *Chapter 2* the central part of this dissertation will commence.

Accordingly, *Chapter 2* (consisting of Article 1) titled ‘A missing link: a distributed cognitive perspective on fit’, talks about moving the focus from the entities being fitted, to the substance that is the by-product of these entities. It provides a framework to understand the fit literature and also provides two research streams that could perhaps go in the direction of avoiding the current problems with fit measures. Namely, stream 1: combining existing fit measures in relation to the distributed cognition framework, while also indicating that this approach has been attempted before (Jansen and

Kristof-Brown, 2006) and has shown to underperform (Edwards and Billsberry, 2010). Stream 2: creating a new measure that focuses more on the underlying process that takes place when two entities interact. Finally, in order to provide the reader with a visual outlook of how each of the currently existing fit measurements would be categorized according to the proposed framework in *Chapter 2*, a figure is provided in Appendix - A.

In light of the propositions brought forward in *Chapter 2*, due to prior studies indicating insufficiency with research stream 1 as highlighted in *Chapter 2*, the remainder of the dissertation focuses on the research stream 2 as it can be considered to be the most fruitful approach from the two. Moreover, in order to add depth and clarity to the study's focus area, the dissertation also further narrows its focus to the social aspect of cognition. On the one hand this is done due to the fact that the social aspect is the most universal aspect that is proposed in *Chapter 2*, as most organizations feature some form of a social environment. On the other hand, this is also because the social aspect is one-of or if-not the most vital part when managing an organizational work environment, which is inherently social and complex in nature (Wang *et al.*, 2019; Rauter *et al.*, 2018; Wageman *et al.*, 2012; Sinclair, 1992).

As a result, it is clear that, given the complexity of the social cognitive interactions under investigation, it is best to analyze such a complex concept in a systematic manner, which is why, as discussed in this study, the distributed cognition perspective also known as systemic cognition (Cowley and Vallée-Tourangeau, 2017; Hutchins 1995; Herath, 2019b; Secchi and Cowley, 2021), would be an excellent alternative. Hence, the research that is conducted on this PhD study is done with respect to a distributed cognitive perspective, in order to understand the interactions and the phenomenon that takes place with regards to the cognitive adaptability of individuals when organizations are more uncertain/plastic/flexible. Thus, the research area of interest is on the cognitive adaptability of individuals in a certain type of environment (i.e. changing/plastic/flexible) and to understand the process and what it leads to. Therefore, as this inquiry involves a highly complex dynamic nature with regards to how individuals interact and function in such an organizational environment, it is highly important to utilize an approach that is capable of handling such a vast web of interactions (Edmonds and Meyer, 2017). Hence, this study considers Agent-based modeling (ABM) to be an approach that is highly suitable for this inquiry (see *Chapters 3*, *4* and *5*).

In this regard, the following chapter (*Chapter 3*) illustrates the primary research method utilized in this study. Accordingly, this study uses Agent-based simulation modeling (ABM) to investigate the viability of the proposed proposition. In other words, ABM is used as a catalyst to understand the compounds of the proposed proposition. Therefore, this chapter first provides a description on the epistemology of using models in research and how simulation models such as ABM can be used as an epistemic tool to explore such complex topics, such as the topic at hand. This is then followed by a description of *Agent-based simulation modeling* and the unique benefits and theoretical explorative ability it provides. Finally, *Chapter 3* also highlights how this study made use of an ABM driven research methodology.

Consequently, *Chapter 4* presents the second research article featured in this dissertation, which is titled '*Cognitive Fit in Recruitment and group Dynamics*'. This chapter follows the research stream 2 (as deliberated in *Chapter 2*), where it investigates the viability of such an approach on the basis of a *distributed cognition* perspective (Cowley and Vallée-Tourangeau 2013; Hutchins 1995) and the attitude of *docility* (Secchi and Bardone 2009; Secchi, 2021b; Secchi, 2007). Where *docility* is considered a suitable human attitude that is capable of determining the underlying cognitive processes that take place in a highly social environment such as an organizational team. In so doing, this chapter refers to this approach as *Organizational-Cognition* (*O-C*) *fit* and examines this theory by utilizing an Agent-based simulation model (ABM) to investigate the viability of such an approach. Accordingly, the simulation investigates the viability of opting to hire a recruit that shares a similar cognitive orientation (*organizational cognition*) to the currently existing orientation of an organizational team. Hence following a *Supplementary fit* tradition to *fit* as highlighted in the *Person-Environment fit* literature (see Appendix-C in section 7.3). *Chapter 4* is also complemented with its very own appendix which provides a detailed look into the workings of the model (see Appendix-B in section 7.2), through the use of a protocol referred to as the ODD protocol (Grimm *et al.*, 2020). The ODD protocol is used by ABM modelers to describe and structure ABM models to effectively highlight its features and procedures. Finally, Appendix-B (which complements *Chapter 4*) also describes the calibration process that was conducted to identify the most suitable parameter values to use for the simulation on the *O-C fit* ABM model.

Thereafter the reader is presented with the third research article titled 'Supplementary fit or Complementary fit in relation to O-C fit' in *Chapter 5*. This chapter further investigates the utility of *O-C fit* and follows a similar underlying concept of *Organizational-Cognition* as in *Chapter 4*. However, this *chapter* differentiates itself from *Chapter 4* by shifting its focus to investigate the viability of *Organizational-Cognition fit* when wanting to change the currently existing team dynamic (opposed to seeking congruence). Hence following a *Complementary fit* tradition to *fit* as highlighted in the *Person- Environment fit* literature. In so doing, *Chapter 5* also highlights that *O-C fit* due to its focus on the *social organizing* and the dynamics of social interactions, differs from the traditional use of cognition in management research which is predominantly based on the micro and macro perspective of organizations. Finally, *Chapter 5* also has an accompanying appendix (see Appendix-C in section 7.3), where it contains a written description to provide the reader with a more thorough understanding of the *supplementary fit* literature in relation to the *complementary fit* tradition discussed in *Chapter 5*.

Lastly, *Chapter 6* connects all three *articles* in a manner where it attempts to provide; a) a conclusive notion of what was learned from this study, and b) highlight what must be done to further enrich this inquiry on attaining improved social organizing in organizations. In this regard, *Chapter 6* also attempts to provide the reader with an idea of what is to be expected in the future with regards to broadening the depth of the current focus. Thus, further contributing to not only the body of literature on the *Person-Environment fit* paradigm and the *Distributed Cognition* perspective, but also to the proposed approach of *Organizational-Cognition fit* (*O-C fit*) itself.

1.6. References

Acton, B., Braun, M. and Foti, R. (2019), "Built for unity: assessing the impact of team composition on team cohesion trajectories", *Journal of Business and Psychology*, Vol. 35 No. 6, pp. 751-766.

Adkins, C., Ravlin, E., & Meglino, B. (1996). Value Congruence between Co-Workers and its Relationship to Work Outcomes. Group & Organization Management, Vol. 21 No. 4, pp. 439-460.

Adkins, C., Russell, C., and Werbel, J. (1994). Judgments of fit in the selection process: The role of work value congruence. *Personnel Psychology*, Vol. 47 No. 3, pp. 605–623.

Aggarwal, I. and Woolley, A. (2019), "Team Creativity, Cognition, and Cognitive Style Diversity", *Management Science*, Vol. 65 No. 4, pp. 1586-1599.

Antonioni, D., and Park, H. (2001). The effects of personality similarity on peer ratings of con-textual work behaviors. *Personnel Psychology*, Vol. 54, pp. 331–360.

Arthur, W., Bell, S., Villado, A. and Doverspike, D. (2006), The use of person-organization fit in employment decision making: An assessment of its criterion-related validity, *Journal of Applied Psychology*, Vol. 91 No. 4, pp. 786-801.

Barber, A. (1998). *Recruiting employees*. Thousand Oaks: Sage.

Bardone, E. and Secchi, D. (2017), "Inquisitiveness: distributing rational thinking", *Team Performance Management: An International Journal*, Vol. 23 No. 1/2, pp. 66-81.

Barsade, S., Ward, A., Turner, J., & Sonnenfeld, J. (2000). To Your Heart's Content: A Model of Affective Diversity in Top Management Teams. *Administrative Science Quarterly*, Vol. *45* No. 4, p. 802.

Beehr, T. A., Walsh, J. T., & Taber, T. D. (1976). Relationships of stress to individually and organizationally valued states: Higher-order needs as a moderator. *Applied Psychology*, Vol. 61, pp. 41–47.

Bell, S. T. (2007). Deep-level composition variables as predictors of team performance: A meta-analysis. *Journal of Applied Psychology*, 92, 595–615.

Bell, S. T., & Outland, N. (2017). Team composition over time. In *Team Dynamics Over Time* (Vol. 18, pp. 3–27). UK: Emerald publishing limited.

Boon, C. and Biron, M. (2016), "Temporal issues in person–organization fit, person–job fit and turnover: The role of leader–member exchange", *Human Relations*, Vol. 69 No. 12, pp. 2177-2200.

Boon, C., den Hartog, D. N., Boselie, P., and Paauwe, J. (2011). The relationship between perceptions of HR practices and employee outcomes: Examining the role of person-organisation and person-job fit. *The International Journal of Human Resource Management*, Vol. 22, pp. 138-162.

Breaugh, J. (2013). Employee Recruitment. *Annual Review Of Psychology*, Vol. 64 No. 1, pp. 389-416.

Brigham, K., De Castro, J., & Shepherd, D. (2007). A Person-Organization Fit Model of Owner-Managers' Cognitive Style and Organizational Demands. *Entrepreneurship Theory And Practice*, Vol. *31* No. 1, pp. 29-51.

Cable, D. M., & Judge, T. A. (1996). Person--Organization Fit, Job Choice Decisions, and Organizational Entry. *Organizational Behavior & Human Decision Processes*, Vol. 67 No. 3, pp. 294-311.

Cable, D., & DeRue, D. (2002). The convergent and discriminant validity of subjective fit perceptions. *Journal Of Applied Psychology*, Vol. 87 No. 5, pp. 875-884.

Cannon-Bowers, J. A., & Salas, E. (2001). Reflections on shared cognition. *Journal of Organizational Behavior*, Vol. 22, pp. 195–202.

Cha, J., Kim, Y. and Kim, T. (2009), "Person-career fit and employee outcomes among research and development professionals", *Human Relations*, Vol. 62 No. 12, pp. 1857-1886.

Chan, D. (1996). Cognitive Misfit of Problem-Solving Style at Work: A Facet of Person-Organization Fit. *Organizational Behavior And Human Decision Processes*, Vol. *68* No. 3, pp. 194-207.

Chatman, J. A. (1989). Improving Interactional Organizational Research: A Model of Person-Organization Fit. *Academy of Management Review*, Vol. 14 No. 3, pp. 333-349.

Chemero, A. (2009). *Radical embodied cognitive science*. Cambridge, MA, US: MIT Press.

Clark, A. (2003), *Natural-born cyborgs*, Oxford University Press, Oxford.

Coleman, A. (2017), "Flexible and agile management at the heart of project success - Raconteur", *Raconteur*, available at: https://www.raconteur.net/flexible-and-agile-management-at-the-heart-of-project-success/ (accessed 6 August 2021).

Cooper, C. L., & Marshall, J. (1978). *Understanding Executive Stress*. London: Macmillan.

Cowley, S. and Vallee-Tourangeau, F. (2013), *Cognition Beyond the Brain*, Springer London, London.

Cullen, J. (2011), "Differentiating between Vocations and Careers", *SSRN Electronic Journal*, doi:10.2139/ssrn.1943566.

Danna, K., & Griffin, R.W. (1999). Health and well-being in the workplace: A review and synthesis of the literature. *Journal of management*, Vol. 25 No. 3, pp. 357-384.

Deloitte. (2018). The Adaptable Organization: Harnessing a networked enterprise of human resilience. pp. 2-22. Retrieved from https://www2.deloitte.com/content/dam/Deloitte/global/Documents/HumanCapital/adaptableorganization.pdf.

DeRue, D. and Morgeson, F. (2007), "Stability and change in person-team and person-role fit over time: The effects of growth satisfaction, performance, and general self-efficacy.", *Journal of Applied Psychology*, Vol. 92 No. 5, pp. 1242-1253

Devine, D. J., Philips, J. L. (2001). Do smarter teams do better—A meta-analysis of cognitive ability and team performance. *Small Group Research*, 32: 507-532.

Doeze Jager-van Vliet, S., Born, M., & van der Molen, H. (2019). “Using a portfolio-based process to develop agility among employees”. *Human Resource Development Quarterly*, Vol. 30 No. 1, pp. 39-60.

Drazin, R. and de Ven, A. (1985), "Alternative Forms of Fit in Contingency Theory", *Administrative Science Quarterly*, Vol. 30 No. 4, p. 514.

Duguay, C., Landry, S. and Pasin, F. (1997). From mass production to flexible/agile production. International Journal of Operations & Production Management, 17(12), pp.1183-1195.

Edmonds, B. & Meyer, R., Eds. (2017). *Simulating Social Complexity. A Handbook*. Heidelberg: Springer, second edition.

Edwards, J. (1991), "Person-job fit: A conceptual integration, literature review, and methodological critique", in Cooper, C. and Robertson, I.,*International review of industrial and organizational psychology*, Wiley, New York, pp. 283-357.

Edwards, J. (2008), "Person–Environment Fit in Organizations: An Assessment of Theoretical Progress", *The Academy of Management Annals*, Vol. 2 No. 1, pp. 167-230.

Edwards, J. and Billsberry, J. (2010), "Testing a Multidimensional Theory of Person-Environment Fit", *Journal of Managerial Issues*, Vol. 22 No. 4, pp. 476-493.

Edwards, J. R. (1996). An Examination of Competing Versions of the Person-Environment Fit Approach to Stress. *The Academy of Management Journal*, Vol. 39 No. 2, pp. 292-339.

Edwards, J. R., Cabe, D. M., Williamson, I. O., Lambert, L. S., & Shipp, A. J. (2006). The Phenomenology of Fit: Linking the Person and Environment to the Subjective Experience of Person-Environment Fit. *Journal of Applied Psychology*, Vol. 91 No. 4, pp. 802-827.

Elfenbein, H. and O'Reilly, C. (2007), "Fitting In: The Effects of Relational Demography and Person-Culture Fit on Group Process and Performance", *Group & Organization Management*, Vol. 32 No. 1, pp. 109-142.

Ferguson, T. and Cheek, R. (2011), "How Important Are Situational Constraints in Understanding Job Satisfaction?", *International Journal of Business and Social Science*, Vol. 2 No. 22.

French, J. R. P., Caplan, R. D., & Harrison, R. V. (1982). The mechanisms of job stress and strain. *Journal of Psychosomatic Research*, Vol. 27 No. 4, pp. 332-333.

French, J. R. P., Rogers, W., & Cobb, S. (1974). Adjustment as person–environment fit. In G. V. Coelho, D. A. Hamburg, & J. E. Adams (Eds.), *Coping and adaptation*. New York: Basic Books.

Gavetti, G., Greve, H., Levinthal, D. and Ocasio, W. (2012), "The Behavioral Theory of the Firm: Assessment and Prospects", *Academy of Management Annals*, Vol. 6 No. 1, pp. 1-40.

Gerpott, T., Domsch, M. and Keller, R. (1988), "Career orientations in different countries and companies: An empirical investigation of West German, British and US industrial R&D professionals", *Journal of Management Studies*, Vol. 25 No. 5, pp. 439-462.

Gilbert, G. (2008). *Agent-based models*. Los Angeles: Sage Publications.

Graves, L., and Powell, G. (1995). The effect of sex similarity on recruiters' evaluations of actual applicants: A test of the similarity–attraction paradigm. *Personnel Psychology*, Vol. 48, pp. 85–98.

Greenwood, R., Raynard, M., Kodeih, F., Micelotta, E., & Lounsbury, M. (2011). Institutional Complexity and Organizational Responses. Academy Of Management Annals, Vol. 5 No. 1, pp. 317-371.

Greguras, G. and Diefendorff, J. (2009), "Different fits satisfy different needs: Linking person-environment fit to employee commitment and performance using self-determination theory.", *Journal of Applied Psychology*, Vol. 94 No. 2, pp. 465-477.

Herath, D. (2019a). Structural Disorganization. In D. Herath, *Business Plasticity Through Disorganization*. Emerald Publishing Limited.

Herath, G. (2019b). "Studying the Cognitive Elements of Disorganization". In D. Herath, *Business Plasticity Through Disorganization*, Howard House: Emerald Group Publishing, pp. 113-116.

Herman, J. (1973), "Are situational contingencies limiting job attitude—job performance relationships?", *Organizational Behavior and Human Performance*, Vol. 10 No. 2, pp. 208-224.

Heyes, C. (2012). New thinking: the evolution of human cognition. *Philosophical Transactions Of The Royal Society B: Biological Sciences*, Vol. *367* No. 1599, pp. 2091-2096.

Hobman, E., Bordia, P., & Gallois, C. (2003). Consequences of Feeling Dissimilar from Others in a Work Team. *Journal Of Business And Psychology*, Vol. *17* No. 3, pp. 301-325.

Hodgkinson, G. P., & Healey, M. P. (2008). Cognition in organizations. Annual Review of Sociology, Vol 59, 387–417.

Hoffman, B. J., & Woehr, D. J. (2006). A quantitative review of the relationship between person–organization fit and behavioral outcomes. *Journal of Vocational Behavior*, Vol. 68 No. 3, pp. 389-399.

Hollan, J., Hutchins, E. and Kirsh, D. (2000), "Distributed cognition", *ACM Transactions on Computer-Human Interaction*, Vol. 7 No. 2, pp. 174-196.

Holland, J. (1985), *Making vocational choices: A theory of vocational personalities and work environ-ments*, Prentice Hall, Englewood Cliffs, NJ.

Holtom, B., Mitchell, T., Lee, T. and Eberly, M. (2008), "Turnover and Retention Research: A Glance at the Past, a Closer Review of the Present, and a Venture into the Future", *Academy of Management Annals*, Vol. 2 No. 1, pp. 231-274.

Horst, S. (1999). Symbols and Computation A Critique of the Computational Theory of Mind. *Minds and Machines*, Vol. 9, pp. 347–381.

Hua, Y. and Liu, A. (2017), "An investigation of person-culture fit and person-task fit on ICT adoption in the Hong Kong construction industry", *Architectural Engineering and Design Management*, Vol. 13 No. 6, pp. 423-438.

Hutchins, E. (1995), *Cognition in the wild*, MIT Press, Cambridge, Mass.

Ilgen, D. (1994). Jobs and roles: Accepting and coping with the changing structure of or-ganizations. In M. Rumsey, C. Walker & J. Harris, *Personnel se-lection and classification* (pp. 13-22). Hillsdale, NJ: Erlbaum.

Jansen, K. and Kristof-Brown, A. (2006), "Toward a Multidimensional Theory of Person-Environment Fit", *Journal of Managerial Issues*, Vol. 18 No. 2, pp. 193-212.

Jehn, K., Northcraft, G., & Neale, M. (1999). Why Differences Make a Difference: A Field Study of Diversity, Conflict, and Performance in Workgroups. *Administrative Science Quarterly*, Vol. *44* No. 4, p. 741.

Judge, T. A., & Cable, D. M. (1997). Applicant personality, organizational culture, and organization attraction. *Personnel Psychology*, Vol. 50, pp. 359–394.

Judge, T., & Ferris, G. (1992). The Elusive Criterion of Fit in Human Resources Staffing Decisions. *Human Resource Planning*, Vol. *4*, pp. 47-67.

Kincaid, D. L., Yum, J. O., and Woelfel, J. (1983). The cultural convergence of Korean im-migrants in Hawaii: An empirical test of a mathematical theory. *Quality and Quantity*, Vol. 18, pp. 59–78.

Kristof, A. (1996), "Person-organization fit: an integrative review of its conceptualizations, measurement, and implications", *Personnel Psychology*, Vol. 49 No. 1, pp. 1-49.

Kristof-Brown, A., & Stevens, C. (2001). Goal congruence in project teams: Does the fit between members' personal mastery and performance goals matter?. *Journal Of Applied Psychology*, Vol. *86* No. 6, pp. 1083-1095.

Kristof-brown, A., Zimmerman, R. and Johnson, E. (2005), "Consequences of individuals' fit at work: a meta-analysis of person-job, person-organization, person-group, and person-supervisor fit", *Personnel Psychology*, Vol. 58 No. 2, pp. 281-342.

Kristof-brown, A., Zimmerman, R. and Johnson, E. (2005), "Consequences of individuals' fit at work: a meta-analysis of person-job, person-organization, person-group, and person-supervisor fit", *Personnel Psychology*, Vol. 58 No. 2, pp. 281-342.

Lance, C. E., Mallard, A. G., & Michalos, A. C. (1995). Tests of the causal directions of global-life facet satisfaction relationships. *Social Indicators Research*, Vol. 34, pp. 69–92.

Lant, T. and Shapira, Z. (2000), *Organizational cognition*, Psychology Press.

Lauver, K. and Kristof-Brown, A. (2001), "Distinguishing between Employees' Perceptions of Person–Job and Person–Organization Fit", *Journal of Vocational Behavior*, Vol. 59 No. 3, pp. 454-470.

Mainiero, L. (1993), "Is your corporate culture costing you?", *Academy of Management Perspectives*, Vol. 7 No. 4, pp. 84-85.

March, J. (1994), *A primer on decision making*, Free Press, New York.

Mathieu, J. E., Tannenbaum, S. I., Donsbach, J. S., Alliger, G. M. (2013a). Achieving optimal team composition for success. In Salas, E. (Ed.), *Developing and enhancing high-performance teams: Evidence-based practices and advice* (pp. 520-551). San Francisco: Jossey-Bass.

Mathieu, J., Tannenbaum, S., Donsbach, J. and Alliger, G. (2013b), "A Review and Integration of Team Composition Models", *Journal of Management*, Vol. 40 No. 1, pp. 130-160.

Mitchell, T., Holtom, B. and Lee, T. (2001), "How to keep your best employees: Developing an effective retention policy", *Academy of Management Perspectives*, Vol. 15 No. 4, pp. 96-108.

Muchinsky, P. M., & Monahan, C. J. (1987). What is person-environment congruence? Sup-plementary versus complementary models of fit. Journal of Vocational Behavior, Vol. 31 No. 3, pp. 268-277.

Norman, D. A. (1994). *Things that make us smart*. Boston, MA, USA: Addison-Wesley Longman Publishing Co., Inc.

O'Reilly, C. and Chatman, J. (1996), "Culture as social control: Corporations, cults, and commitment", in Staw, B. and Cummings, L.,*Research in organizational behavior*, JAI, Greenwich, CT, pp. pp. 157-200.

Ostroff, C. and Zhan, Y. (2012), *Person–Environment Fit in the Selection Process*, Oxford Handbooks Online.

Ostroff, C., & Rothausen, T. J. (1997). The moderating effect of tenure in person - environment fit: A field study in educational organizations. *Journal of Occupational and Organizational Psychology*, Vol. 70 No. 2, p. 173.

Parasuraman, S., Greenhaus, J. and Linnehan, F. (2000), "Time, person-career fit, and the boundaryless career", in Cooper, C. and Rousseau, D.,*Trends in organizational behavior*, Wiley, Chichester, pp. 63–78.

Parsons, F. (1909). *Choosing a vocation*. Boston: Houghton-Mifflin.

Perry, M. J. (2003). Distributed cognition. In J. M. Carroll (Ed.), *HCI Models, Theories, and Frameworks: Toward a Multidisciplinary Science* (pp. 212–223). San Francisco, CA, USA: Morgan Kauffman Publishers.

Peters, L. and O'Connor, E. (1980), "Situational Constraints and Work Outcomes: The Influences of a Frequently Overlooked Construct", *The Academy of Management Review*, Vol. 5 No. 3, p. 391.

Pierro, A., Sheveland, A., Livi, S. and Kruglanski, A. (2015), "Person-group fit on the need for cognitive closure as a predictor of job performance, and the mediating role of group identification.", *Group Dynamics*, Vol. 19 No. 2, pp. 77-90.

Purvis, L., Gosling, J. and Naim, M. (2014). The development of a lean, agile and leagile supply network taxonomy based on differing types of flexibility. International Journal of Production Economics, 151, pp.100-111.

Rauter, S., Weiss, M., & Hoegl, M. (2018). Team learning from setbacks: A study in the context of start-up teams. *Journal Of Organizational Behavior*, Vol. *39* No. 6, pp. 783-795.

Reeve, C. and Heggestad, E. (2004), "Differential relations between general cognitive ability and interest-vocation fit", *Journal of Occupational and Organizational Psychology*, Vol. 77 No. 3, pp. 385-402.

Rescorla, M. (2017). The Computational Theory of Mind. In E. N. Zalta (Ed.), *The Stanford Encyclopedia of Philosophy* (Spring Ed.). Retrieved from https://plato.stanford.edu/archives/spr2017/entries/computational-mind/

Rice, R. W., McFarlin, D. B., & Bennett, D. E. (1989). Standards of comparison and job satisfaction. *Journal of Applied Psychology*, Vol. 74, pp. 591–598.

Rizzo, J. R., House, R. J., & Lirtzman, S. I. (1970). Role Conflict and Ambiguity in Complex Organizations. *Administrative Science Quarterly*, Vol. 15 No. 2, pp. 150-163.

Rybakov, L. (2001). Environment and Complexity of Organizations. Emergence, Vol. 3 No. 4, pp. 83-94.

Saks, A. M., & Ashforth, B. E. (1997). A longitudinal investigation of the relationships between job information sources, applicant perceptions of fit, and work outcomes. *Personnel Psychology*, Vol. 50, pp. 395–426.

Schmitt, N. (2007), "The Value of Personnel Selection: Reflections on Some Remarkable Claims", *Academy of Management Perspectives*, Vol. 21 No. 3, pp. 19-23.

Schneckenberg, D., Velamuri, V. and Comberg, C. (2019), "The Design Logic of New Business Models: Unveiling Cognitive Foundations of Managerial Reasoning", *European Management Review*, Vol. 16 No. 2, pp. 427-447.

Scott, W. A., Osgood, D. W., & Peterson, C. (1979). *Cognitive structure: Theory and measurement of individual differences*. Washington: Winston & Sons.

Scott, W. R. (2003). *Organizations. Rational, natural, and open systems* (5th ed.). Englewood Cliffs, NJ: Prentice-Hall.

Searle, R. (2009). Recruitment and selection. In D. Collings & G. Wood, *Human Resource Management: a Critical Approach* (pp. 151-168). London: Routledge.

Secchi, D. (2011), *Extendable Rationality,* Springer, New York.

Secchi, D. (2021a). *How Do I Develop an Agent-Based Model?*, Edward Elgar Publishing. Dissertation companions.

Secchi, D. (2021c), "Cognitive attunement in the face of organizational plasticity", *Evidence-based HRM*, Vol. 9 No. 2, pp. 192-208.

Secchi, D. and Adamsen, B. (2017), "Organizational cognition: A critical perspective on the theory in use", in Cowley, S. and Vallee-Tourangeau, F.,*Cognition Beyond the Brain*, Springer, Heidelberg, pp. 305-331.

Secchi, D. and Bardone, E. (2009), "Super-docility in organizations: an evolutionary model", *International Journal of Organization Theory & Behavior,* Vol. 12 No. 3, pp. 339-379.

Secchi, D., & Cowley, S. J. (2021). Cognition in Organisations: What it Is and how it Works. *European Management Review,* Vol. 18 No. 2, pp. 79-92.

Secchi, D., (2007). A Theory of Docile Society: The Role of Altruism in Human Behavior. *Journal Of Academy Of Business And Economics*, Vol. 7 No. 2, pp. 146-160.

Secchi, D., (2021b). *Computational Organizational Cognition. A study on thinking and action in organizations*. Emerald.

Sheridan, J. (1992), "Organizational Culture and Employee Retention", *Academy of Management Journal*, Vol. 35 No. 5, pp. 1036-1056.

Simon, H. (1993), "Altruism and Economics", *The American Economic Review*, Vol. 83 No. 02, pp. 156–161.

Sinclair, A. 1992. The Tyranny of a Team Ideology. *Organization Studies*, Vol. *13* No. 4, pp. 611-626.

Spencer, H. (1896). The principles of biology (Vol. 2). D. Appleton.

Suddaby, R., & Foster, W. (2017). History and Organizational Change. Journal Of Management, Vol. 43 No. 1, pp. 19-38.

Super, D. (1953). A theory of vocational development. *American Psychologist*, Vol. 8, pp. 185–190.

Tubey, R., Rotich, K.J., & Kurgat, A. (2015). History, Evolution and Development of Human Resource Management: A Contemporary Perspective. *European Journal of Business and Management*, Vol 7, pp.139-148.

Turban, D. and Dougherty, T. (1994), "Role of Protégé Personality in Receipt of Mentoring and Career Success", *Academy of Management Journal*, Vol. 37 No. 3, pp. 688-702.

Turban, D., & Greening, D. 1997. Corporate social performance and organizational attractiveness to prospective employees. *Academy Of Management Journal*, 40(3), 658-672.

Van Loon, N., Vandenabeele, W., & Leisink, P. (2017). Clarifying the Relationship Between Public Service Motivation and In-Role and Extra-Role Behaviors: The Relative Contributions of Person-Job and Person-Organization Fit. *The American Review Of Public Administration*, Vol. *47* No. 6, pp. 699-713.

Van Loon, N., Vandenabeele, W., & Leisink, P. (2017). Clarifying the Relationship Between Public Service Motivation and In-Role and Extra-Role Behaviors: The Relative Contributions of Person-Job and Person-Organization Fit. *The American Review Of Public Administration*, Vol. *47* No. 6, pp. 699-713.

Vianen, A. (2000), Person–organization fit: The match between newcomers' and recruiters' preferences for organizational cultures, *Personnel Psychology*, Vol. 53 No. 1, pp. 113-149.

Vogel, D., Jording, M., Kupke, C. and Vogeley, K. (2020), "The Temporality of Situated Cognition", *Frontiers in Psychology*, Vol. 11.

Vogel, R. and Feldman, D. (2009), "Integrating the levels of person-environment fit: The roles of vocational fit and group fit", *Journal of Vocational Behavior,* Vol. 75 No. 1, pp. 68-81.

Von Neumann, J. (1958). *The Computer and the Brain*. New Haven and London: Yale University Press.

Von Neumann, J. and Kurzweil, R. (2012), *The computer & the brain*, Yale University Press, New Haven, Conn.

Wageman, R., Gardner, H., & Mortensen, M. (2012). The changing ecology of teams: New directions for teams research. *Journal Of Organizational Behavior*, Vol. *33* No. 3, pp. 301-315.

Walsh, J. P. (1995). Managerial and organizational cognition: Notes from a trip down memory lane. *Organization Science*, Vol. 6 No. 3, pp. 280–321.

Wang, J., Cheng, G., Chen, T., & Leung, K. (2019). Team creativity/innovation in culturally diverse teams: A meta-analysis. *Journal Of Organizational Behavior,* Vol. *40* No. 6, pp. 693-708.

Warr, P. (1990). The measurement of well-being and other aspects of mental health. *Journal of Occupational Psychology*, Vol. 63, pp. 193-210.

Weick, K. E. (1995). *Sensemaking in organizations* (1st ed.). Thousand Oaks, CA: Sage.

Werbel, J., & Gilliland, S. (1999). Person-environment fit in the selection process. In G. Ferris, *Research in personnel and human resource management* (pp. 209-243). Stamford, CT: JAI Press.

White, L., Pothos, E. and Busemeyer, J. (2015), "Insights from quantum cognitive models for organizational decision making", *Journal of Applied Research in Memory and Cognition*, Vol. 4 No. 3, pp. 229-238.

Winsor, D. (2001), "Learning to Do Knowledge Work in Systems of Distributed Cognition", *Journal of Business and Technical Communication*, Vol. 15 No. 1, pp. 5-28.

Witt, L. (1998). Enhancing organizational goal congruence: A solution to organizational politics. *Journal Of Applied Psychology*, Vol. *83* No. 4, pp. 666-674.

Woelfel, J., and Fink, E. L. (1980). *The measurement of communication processes: Galileo theory and method*. New York, NY: Academic Press.

Wood, R., & Bandura, A. (1989). Social Cognitive Theory of Organizational Management. Academy Of Management Review, Vol. 14 No. 3, pp. 361-384.

Zhu, L., Liu, M. and Fink, E. (2016), "The Role of Person-Culture Fit in Chinese Students' Cultural Adjustment in the United States: A Galileo Mental Model Approach", *Human Communication Research*, Vol. 42 No. 3, pp. 485-505.

Chapter 2: A missing link: a distributed cognitive perspective on fit[5]

Article 1

Title	A missing link: a distributed cognitive perspective on fit
Authors	Gayanga Bandara Herath
Research output	Journal article
Status	Published - https://doi.org/10.1108/IJOTB-09-2020-0168
About Journal / Book	The International Journal of Organization Theory & Behavior
Note	This article was first accepted and presented at the European Academy of Management in (EURAM) 2019. Then was later improved and submitted to 'The International Journal of Organization Theory & Behavior', which has now been accepted and published.

[5] This article is published in the International Journal of Organization Theory and Behavior, it can be assessed through this link- https://doi.org/10.1108/IJOTB-09-2020-0168

Abstract

Purpose: This article presents a cognitive framework to study dynamic/adaptive aspects of a collection of popular fit measures used in organization research, in an attempt to highlight what there is to be gained.

Design/methodology/approach: This paper uses a *distributed e-cognition* (DEC) framework to examine the current organizational literature of fit measures.

Findings: This paper highlights that most measures have a rather narrow focus and do not address dynamic/adaptive aspects in complex social systems (e.g., organizations). To both provide a way to integrate fit measures and to cover the cognition gap in this literature, this article highlights the need for a more sophisticated measure.

Originality: This paper provides a novel approach to examining organizational fit literature through a distributed (e)-cognitive framework.

Keywords: Complexity, Organizational change, Distributed cognition, Person–environment fit, Adaption, Organizational cognition

2.1. Introduction

Scholars have worked with cognition in numerous ways, for example by integrating it with — or, sometimes, by simply juxtaposing it to — more longstanding traditional concepts in organizational behavior (e.g., Hodgkinson and Healey, 2008; Schneckenberg *et al.*, 2019). This has been the case with the work on, for example, teams (e.g., Healey *et al.*, 2015; Aggarwal, and Woolley, 2019), and organizational decision making e.g., (White *et al.*, 2015). As recently discussed in a critical literature review (Secchi and Adamsen, 2017), the number of papers published on organizational cognition has increased overall since 1980, witnessing a growing interest in the topic among management scholars. This, however, has not been matched by a deeper and more varied use of cognition, especially as far as theoretical developments are concerned (Secchi and Adamsen, 2017). While cognitive science has moved to include views that are heterodox to the classic computational and interpretive approaches (see, Lant and Shapira, 2000), the organizational literature has not reflected these updates — with limited but noticeable exceptions (e.g., Michel, 2007; Heavey and Simsek, 2017; Secchi and Cowley, 2021).

Yet, there seems to be a general belief that organized work (and organizations, more broadly) affect the way people think and/or rationalize quite substantially (Gavetti *et al.*, 2012; March 1994). This notion further compounds the predicament that organizational change greatly affects the improvisation of employees at work (Suddaby, and Foster, 2017). As a result, in recent times employers have shifted their focus, from the need to fit specific units between an individual and an environment, to the need to fit (find) employees that are less vulnerable and more adaptive to such unsettling environments (Doeze Jager-van Vliet, 2019; Deloitte, 2018). This shift in focus has created a gap in literature, thus undermining the utility of current organizational 'fit' measures, due to their focus on the relationship between static dimensions (units) that are inadequate to tackle the dynamic nature of unsettling change (Boon and Biron, 2016).

In essence, change in an organizational context exemplifies moving from one situation to another (Vogel *et al.*, 2020), hence each situation may yield a different set of situational characteristics (Perry *et al.*, 2003). Thus, it is evident that this transversal movement across situations divide through spatial resources (i.e. social entities like people and even physical instruments) and varying time scales (Hollan *et al.*, 2000; Cowley and Vallée-Tourangeau, 2013; Perry *et al.*, 2003). Therefore, to transcend the conventional dimensions of organizational 'fit' measures, the focus on adaption requires a more nuanced understanding on temporality and spatial positioning. Accordingly, it is not too far-fetched to assume that it may be crucial to ask the question on whether there is an overall 'fit' between the organization and its members' distributed cognitive processes (i.e. in relation to time and space). The idea is that organizational situations are scattered-across time and space, and in the process, they enable and/or disable specific cognitive processes — when one executes a task, alone or in groups, for example. For this reason, on the one hand there may be much to gain from a better understanding of (a) which conditions categorize as enabling or disabling, (b) whether there is dynamic adaptation, and most importantly (c) explore which perspective could contribute to the understanding of (a) and (b). On the other hand, the literature on organizational 'fit' quite substantially seem to overlook the need for dimensions that can facilitate adaption through fluid integration of cognition that is distributed through space and time (distributed cognition).

The organizational 'fit' literature deals with measures that utilize value congruence between a prospective applicant and a specific environment such as for example organizations or teams (Edwards, 2008; Jansen and Kristof-Brown, 2006; Vogel and Feldman, 2009). However, the currently existing 'fit' measures seem to (a) be insufficient when used as explanatory variables of organizational performance (Edwards, 2008, 1991) and (b) as mentioned before, they render inadequate to tackle the unsettling change in organizations (Boon and Biron, 2016). Therefore, it is argued that studies on organizational 'fit' require a fairly dynamic approach due to the need to inquire on the mutual interconnectivity of two or more units that cut-across space and time. Hence, this paper addresses that there is a need to both explore what alternative approaches may bring to the fore for organizational 'fit' research and to understand where they could be employed more satisfactorily. In doing so, it is argued in this paper that an alternative approach should reflect the distributed nature of organizational work by encompassing space (i.e. external social/non-social resources) and temporality. This notion contends that such an inclusion would allow to find a candidate that is more adaptable to an unsettling environment, hence would integrate relatively easily and plausibly lead to better performance and employee-turnover. Thus, this paper is intended to perhaps provide answers to the above-mentioned drawbacks associated with organizational fit measures and possibly provide a catalyst for future research to build upon.

Given the complex and adaptive nature of what is required from an alternative approach, this paper considers the distributed (e-)cognition (DEC) perspective to be highly suitable for its inquiry. The DEC perspective has been most effective when applied to complex dynamic situations where adaptation to the environment, other people, and tools is key (complex-dynamic and adaptive-systems). This includes, for example, navigating a ship into a port (Hutchins, 1995), team problem solving (Bardone and Secchi, 2017), and employing artificial arms (Clark, 2003). Hence, due to its ability to study the interactions between humans and their surrounding environment in relation to spatial positioning and temporality, DEC is particularly suited to study organizations which are inherently complex-dynamic and adaptive-systems. Thus, this paper uses an advanced version of distributed (e-) cognition (DEC) to frame research in a specific area of management and organizations.

Accordingly, DEC started with the work of Varela *et al.* (1991), Hutchins (1995) and Clark and Chalmers (1998), in which they pointed, respectively, at the *embodied*, *ecological* and at the *extended* characteristics of cognition. In short, Hutchins refers to the systemic (better: *ecological*) effects that the environment has on cognitive processes while Clark and Chalmers highlight the tightly coupled ties that are formed between internal (the brain) and external (especially artefacts) cognitive resources such that they *extend* cognition. Varela *et al.* (1991) instead point at the obvious connection that any cognitive process has with the "hardware" and explore the means through which it happens. This is, in other words, the physiological elements of the human body that affect, shape and is affected by — it is *embodied* in — the cognitive process. These initial three aspects were further developed by the same authors and by a plethora of others, who also added more to the first three 'e' (see, for example, Cowley and Vallée-Tourangeau, 2017). Following this perspective, some claim that the situational elements (the here-and-now) of any cognitive process also shall be factored in, and refer to them as *embeddedness* (Wheeler, 2005). Others have indicated that some cognition appears in the "doings", hence interpreting behavior as a key feature of these processes. In some shape or form, this has been reflected in the work on sensemaking (Weick, 1993), and it has been labelled "through doing" or *enaction* (Magnani, 2007; Secchi and Bardone, 2009: Secchi and Cowley, 2021). Accordingly, the DEC perspective has delivered significant advancements in our understanding of cognition in relation to space and time (Cowley and Vallée-Tourangeau, 2017; Herath, 2019; Secchi and Cowley, 2021).

In light of this, in the following pages, the paper defines a DEC-framework and explains how it was adapted to the study of fit mechanisms. Then an overview of the literature is presented to understand what is there to be taken from a more DEC-oriented understanding of the processes in place and finally two future research streams are outlined with the hope of moving research forward in this area.

2.2. A framework for the study of organizational fit mechanisms

The literature surrounding fit in organizations involves a great number of variants (Jansen and Kristof-Brown, 2006; Kristof-Brown *et al.*, 2005). In this regard, Person-environment (P-E) fit is considered to be the congruence between an individual and his/her work-environment (Edwards, 2008;

Jansen and Kristof-Brown, 2006; Vogel and Feldman, 2009). Moreover, some consider P-E fit to be a combination of Person-Vocation (P-V) fit, Person-Job (P-J) fit, Person-Organization (P-O) fit, Person-Group (P-G) fit and Person-Person (P-P) fit (Jansen and Kristof-Brown, 2006). Interestingly, Drazin and Van de Ven (1985) state that three conceptual approaches to fit emerged in the development of contingency theory with respect to organizational performance and defined them as: (1) *selection* where fit is the "assumed premise underlaying a congruence between context and structure"; (2) *interaction*, where "fit is the interaction of pairs of organizational context- structure factors"; and (3) *systems*, where "fit is the internal consistency of multiple contingencies and multiple structural characteristics" (Drazin and Van de Ven, 1985, p.515). In relation to this classification, empirical research (Edwards, 2008, 1991) has shown that these approaches fail when used as explanatory variables of organizational performance so that, authors conclude, a "more sophisticated approach" that is different to currently employed dimensions of fit is needed (Drazin and Van de Ven, 1985, p. 535). This asserts a 'more sophisticated approach' should not consider fit to simply be the congruence between specific dimensions of units, processes, and structures (Drazin and Van de Ven, 1985), but rather go beyond such dimensions. Accordingly, fit measures are particularly operationalized as static measures, where it is assumed that at a given point in time certain units (e.g., goals, values, personality-traits, expectations, requirements) can be matched to fit an individual into an environment. However, this disregards the constant change in organizations and its individuals (Suddaby, and Foster, 2017), hence such measures are not designed to accommodate the dynamic elements that are typical of a social set of relations (Boon and Biron, 2016). In other words, such measures operationalize on the congruence of units that do not withstand through time and space; therefore, they seem to lack dimensions of temporality and spatial positioning. These issues have remained in the interest of scholars and have been shown in classifications even more than twenty years later (Edwards, 2008; Boon and Biron, 2016).

This article starts from this need for a 'more sophisticated' framework which can be thought of as an attempt to more effectively tackle with each variant of fit by also considering the constant changes in organizations. And the article claims that a DEC approach would go in that direction thus enabling future research to consider other dimensions that could perhaps go beyond specific static dimensions of units, processes, and structures. In this regard, the current literature focuses more on the entities that are being 'fit' rather than on the underlying processes which take place when individuals interact with and/or integrate into an environment (Cools *et al.,* 2009; Kirton and McCarthy, 1988). And this is where a 'cognitive ecology' (Hutchins, 2014), under the frame of DEC (Secchi and Cowley, 2018; Secchi and Cowley, 2021) could support the quest for a 'more sophisticated' perspective.

2.3. Building a framework through the elements of distributed e-cognition

As conveyed by Secchi and Cowley (2018), DEC asserts that cognitive activities materialize when "linking bodies, central nervous systems and experience as people engage with social, linguistic and material phenomena" (par. 2.5). In other words, DEC exemplifies the interactions that emerge in accordance with the surrounding social, technological, and organizational entities. Thus, cognitive activities are considered to be built on how people learn to leverage alliances and resultant interactions, to find socioculturally suitable ways of behaving (Secchi and Cowley, 2018). In line with this, each one of the elements of the DEC was taken and a framework that can be applied to the literature on 'fit' was outlined.

First, one could consider the role of artefacts (Clark and Chalmers, 1998; Rogers and Ellis, 1994; Aoki, 2020). As Magnani explains, artefacts can be seen and understood as cognitive *mediators* (Magnani, 2001, 2007; Magnani, 2018). This emphasizes that people create external artefacts (e.g. physical/non-physical) with specific positions and duties that have a strong effect on their life in different ways, which ultimately affect their ability to understand the world or more simply put ‘to know’ their surroundings (Magnani, 2007). Interestingly, with respect to cognition in the workplace, Rogers and Ellis (1994) also accord with this notion as they considered cognition to encompass the relationships which constitutes an assortment of people and artefacts. As a result, fitting in an environment shall consider the role that the various artefacts may bring in the process. Hence, the inclusion of *artefacts* (see Figure 2) is a first step in attempting to classify the literature on fit.

Another stream of DEC research considers interactions with other individuals key to the study of emergent cognitive processes (Hollan *et al.*, 2000; Secchi, 2011; Herath, 2019; Secchi and Cowley 2021). In line with this, Hollan *et al.* (2000) highlights that research from various fields all take a stance to consider the cognitive elements/properties of sociocultural individuals. He contends that, since the knowledge-flow within a community is primarily defined by the social organization in combination with the structures of action, social organization itself can be considered a type of cognitive architecture. Likewise, Secchi (2011) argues the “social” plays a vital part in cognition since our rationality benefits from the interconnected relationship between decision-making and social networks. As a result, the interactions with other individuals (i.e. the social channels; see also Simon, 1993) are seen as a crucial part of fitting in an environment. Back to the classification, the inclusion of the *social* element (Figure 2) allows to offer a more complete perspective (Hollan *et al.*, 2000; Secchi, 2011).

The fit literature involves interactions between individuals and various social environments (Jansen and Kristof-Brown, 2006; Kristof-Brown *et al.*, 2005). It also includes interactions between an individual and abstract and/or artificial elements such as jobs, roles, cultures, organizations, careers, vocations or even technologies (DeRue and Morgeson, 2007; Jansen and Kristof-Brown, 2006). From this angle, it seems that the DEC distinction between social resources and artefacts can be used to map this literature. This would allow to more effectively differentiate the ‘fit’ literature to identify areas in which cognition can be found. Some of the artefacts have a clear social nature (e.g., roles, cultures), but the idea of the framework is to make a distinction between human interactions on the one side, and material/immaterial resources on the other. From this perspective, the word "social" is here used *strictu sensu* as it only refers to a relation between two or more human beings. So, for instance, when the focus is on a human-to-human interaction (e.g., in a work-group, with a supervisor), it is classified as a *social* form of fit (upper part of the crossing between 'individual' and 'social' in Figure 2). Whereas, for instance, when the focus is on a human-to-material/immaterial interaction (e.g., job, role, culture or with a technology), then it is an *artifactual* form of fit (lower part of overlap between 'individual' and 'artefacts' in Figure 2).

To provide with an example, briefly reflect on how 'fit' works through the framework when considering an individual and specific technology (e.g., a software application or a specific device; Lee *et al.*, 2007; Tate *et al.*, 2015). Technology is a tangible and material artefact that is qualitatively different from the abstract types of artefacts mentioned above. For this reason, and with the purpose of limiting confusion, the proposed framework differentiates between intangible/immaterial and tangible/material artefacts (the split in 'artefacts' in Figure 2). In other words, the latter types of artefacts are considered differently than for example a job or a role.

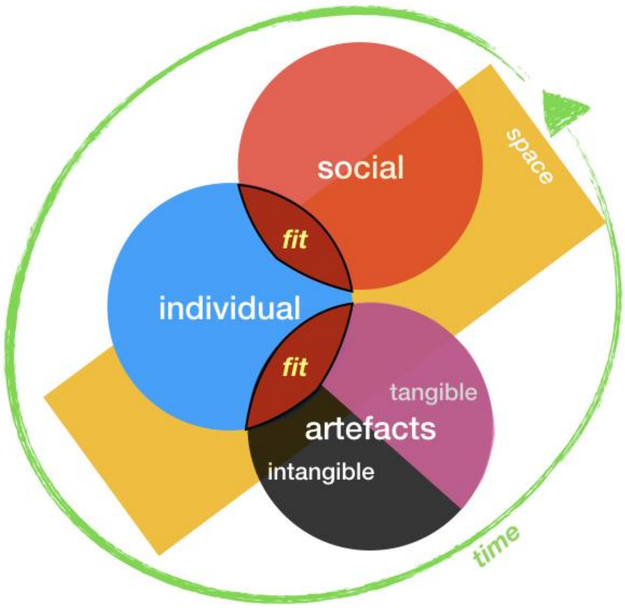
2.4. Two essential additions: time and space

Still drawing on DEC, Figure 2 also shows that there are two other variables that may have an influence on fit. The first is *time*. It is apparent that products from previous events could alter the essence of subsequent events (Hollan *et al.*, 2000; Vogel *et al.*, 2020) and, as a result, Cowley and Vallée-Tourangeau (2013) claim that such cognitive processes tend to be distributed-across time. In relation to this some argue that on the one hand in certain contexts the recurrence of certain activities is irregular due to the continuously evolving nature of the problem space (Perry, 2013). One the other hand based on the availability of knowledge, intellectual and physical resources; identical activities may take place over drastically different time scales (Perry, 2013). Hence, situation awareness can be a vital part when adapting into an environment. In this respect, research has shown that organizations achieve different fit through time due to the dynamic nature of organizational requirements and milestones (Hinings and Greenwood, 1988; Miller, 1992). For instance, sometimes organizations prefer to maintain fit internally, and other times they seek external fit (Miller, 1992). Therefore, researchers now assert that studying a single dimension of fit without taking into account *time* and context is no longer sufficient to effectively understand fit (Jansen and Kristof-Brown, 2006).

The second variable appearing in Figure 2 is *spatial positioning* (space). The DEC perspective considers the environment in which people interact as a cognitive *space* which extends the internal cognition (mind/brain) to its surrounding external environment (Cowley and Vallée-Tourangeau, 2013; Perry *et al.*, 2003; Newcombe, 2018). It asserts that humans logically process information by leveraging external-resources found in an environment. These external-resources are also seen as a shared medium in which other people in the same environment could leverage, thus enabling co-ordination and collaboration. As a result, Perry *et al.* (2003) argue that coordination does not just exist socially, but it is extended to-and-within "real" spaces which carry their own meaning and, in turn, provide constrains that enable the interpretation of certain forms of use. Therefore, in cognitive science, *space* is considered as a support to the cognitive functions that are used to formalize a sense of community with regards to social organizing (Perry *et al.*, 2003). From this angle, the notion of *space* can easily be understood as influencing fit. In fact, Kirton and McCarthy (1988) state that organizations may push people to work in a certain way irrespective to their preference. In other circumstances, the dynamic of *space* may also be applied when organizations have to adapt according to their external environments (Miller, 1992).

Accordingly, in line with the outlined framework, each element of DEC was summarized into a visual diagram of the above explained components, as shown in Figure 2— where fit is identified by overlap between the (a) individual and the social, and (b) individual and the tangible and intangible artefactual. Meanwhile space cuts-across the fit area to represent the cognitive space, which embraces the internal and the surrounding external environment. While time circles around these components to signify the dynamic nature of fit.

Figure 2: A DEC framework to classify the literature.



2.5. Applying the DEC-framework to the study of 'fit'

This section will be broken in to two subsections. Firstly, literature with regards to work-environment related fit measures will be categorized according to the proposed DEC-framework (In Table II). Then the variables of time and space will be factored in (In Table III).

2.6.Categorization of fit measures

The aim of this subsection is to identify how each fit measure can be categorized according to the rationalities of the DEC-framework. In a nutshell, the proposed DEC-framework makes a distinction between human interactions (*social*) and the material/immaterial resources (*artifactual*). As to make the classification clearer, the *artifactual* category is further differentiated into (a) *Intangible artifactual* (intangible/immaterial resources) and (b) *Tangible artifactual* (tangible/material resources). Table II, is an attempt in this direction. It presents all the fit mechanisms as they are classified across the three (i.e. *social*, *intangible artefactual* and *tangible artefactual*) categories, through the aid of the DEC-framework as discussed before.

The first column to the left of Table II, reports the different variants of fit measures analyzed through the DEC-Framework. There are 10 different measures highlighted in this analysis. Out of the 10 measures highlighted, the first 8 of them are mainstream person environment fit (P-E fit) measures. The remaining two measures are not traditionally found in P-E fit literature, but are fit measures that are related to, and, associated with work-environments. The second column provides a definition for each of the fit variants, to provide the reader with a basic understanding of what the measures entail. The third column on Table II, highlights the reasoning behind the classification of each fit measure. The final classification is then reported in the fourth column. Finally, the fifth column presents the references related to each of the respective fit measures.

Table II: A descriptive illustration of how each fit measure is categorized.

Note: Person-Vocation (P-V) fit, Person-Job (P-J) fit, Person-Organization (P-O) fit, Person-Group (P-G) fit, Person-Person (P-P) fit, Person-Career (P-Ca) fit, Person-Culture (P-Cu) fit, Person-Role (P-R) fit, Person-Technology (P-Tech) fit, Cognitive fit (Cog).

Fit type	Definition	Entities of Congruence	Category	References
P-G	P-G fit focuses on the skills between both parties and the interpersonal compatibility that exists between the individual and their immediate work group.	**Individual → ← Single member or whole group** Here the comparison is between two or more human entities. Therefore, it is a human interaction, which is evidently social.	**Social**	Kristof-Brown *et al.*, 2005; Vogel and Feldman, 2009
P-S	P-S fit is essentially a “dyadic relationships between individuals and others in their work environments” (Kristof-Brown *et al.*, 2005, p. 287).	**Individual → ← Specific person** Similar to P-G fit, the entities that interact here are social in the sense that they are human entities.	**Social**	Jansen and Kristof-Brown, 2006; Ostroff and Zhan, 2012

P-O	P-O fit is the "compatibility between people and organizations that occurs when: (a) at least one entity provides what the other needs, or (b) they share similar fundamental characteristics, or (c) both" (Kristof, 1996 p.4-5).	**Individual → ← Organizational values** Deals with values which are abstract and are a construction of human interaction that is structured through time. This highlights their intangible nature and the impossibility to locate them on a single individual in the organization.	**Intangible Artefacts**	Westerman and Cyr, 2004; O'Reilly *et al.*, 1991; Kristof, 1996
P-J	Vogel and Feldman (2009) claim that P-J fit is the "individuals' congruence with the requirements of their job and the inducements provided to perform it" (p. 69).	**Individual → ← Requirements of a job** Social elements inherent to a job are extremely apparent, but the stress has been traditionally on the idealized aspects that allow to identify a job, rather than a definition of social skills and interactions that are necessary to perform this job.	**Intangible Artefacts**	Kristof-Brown *et al.*, 2005; Lauver and Kristof, 2001
P-V	An individual's abilities and interests matched with the requirements and the characteristics of their aspirations is the domain of P-V fit.	**Individual → ← Vocational aspirations** This depicts the vocation as either the characteristics needed to define an occupation or to vocation as aspirations towards it, hence intangible.	**Intangible Artefacts**	Holland, 1985; Reeve and Heggestad, 2004; Vogel and Feldman, 2009
P-Ca	This particular type of fit occurs when the work-environment of an individual can develop his/her career through various opportunities that satisfy their need for optimal career success.	**Individual → ← Career orientation** Some refer to such needs as 'career orientations', which are defined as "a type of work-related values reflected in individual preferences regarding various job types" (Gerpott, Domsch, and Keller, 1988, p. 441). Hence, intangible.	**Intangible Artefacts**	Cha, Kim, and Kim, 2009; Parasuraman, Greenhaus, and Linnehan, 2000
P-Cu	P-Cu fit is the congruence between an individual and the culture of the organization and/or the group they work in.	**Individual → ← Constructed culture** Even though, culture is inherently socially construed, here, only the "construction" part of the above is highlighted and that resonates with the nature of an artefact.	**Intangible Artefacts**	Elfenbein and O'Reilly, 2007; Hua and Liu, 2017; Zhu, Liu, and Fink, 2016
P-R	This type of fit is measured by the similarity between an individual's personal characteristics and the characteristics and associated features of the capacity in which he/she is hired for.	**Individual → ← What a Role entails** Perhaps, given the nature of what a role entails (e.g., manual labor), one may see P-R fit as dealing more with tangible artefacts. However, it is intended as compatibility with the perception of what a 'role' entails.	**Intangible Artefacts**	DeRue and Morgeson, 2007
P-Tech	*P-Tech fit*, is when the capabilities and expertise/practice with the type of technology available to fulfil the task at hand, are matched with the individual.	**Individual → ← Specific technology** By classifying P-Tech fit as tangible artefactual, it is intended to focus on the "doings", i.e. on its applied nature.	**Tangible Artefacts**	Suryani and Sumiyana, 2014; Caldwell and O'Reilly, 1990
Cog	Cog fit is observed when the mental representation of a problem solver matches the problem-solving element (e.g. table or graph)	**Individual → ← Cognitive representation** Cognitive fit within its literature, is always considered as a visual representation (e.g., graphs and tables found in word processing), hence tangible in nature.	**Tangible Artefacts**	Umanath and Vessey, 1994; Vessey, 1991; Vessey and Galletta, 1991.

When looking at Table II, one could see that there are two variants that operate under the *social* category: (a) *person-group* and (b) *person-supervisor* fit. One may argue that, since the inner qualities or characteristics (goals, values and personal interests) are being measured between both parties, *person-group* and *person-supervisor* fit may not be rightly considered a 'social' form of fit. However, it is considered 'social' in the narrow sense mentioned before, specifically because it focuses on the way an individual is compatible with a single person or with a group. In other words, the study of a social relation is the key here.

The following six measures operationalize on the premise of comparing elements that are both abstract perceived constructs and, as such, related to and/or a product of a working environment. *Person-organization* fit, and *person-culture* fit both share in one way or another, a construction of human interaction that is structured through time. The attention here is placed on the “construction”, thus highlighting the intangible nature of these measures. Instead, *Person-job* and *person-role* measures are intangible in the sense that, they are what allows to identify what a perceived role or idealized job entails. In essence, such ideals and perceptions are traditionally considered intangible. Whereas, *person-vocation* fit and *person-career* fit both represent the characteristics necessary to define what they are and more importantly it signifies the aspirational value one associates with certain jobs/occupations. In other words, these characteristics and aspirational values both focus on defining or comprehending the essence of a certain job or an occupation, which is evidently intangible in nature.

Interestingly, when looking at the body of work-environment related literature surrounding the comparison and matching of material artefacts, two types of fit measures emerge: *Task-Technology fit*, and *Person-Task fit*. The first is “the usability degree of the information technology that helps individuals to accomplish their tasks” (Suryani and Sumiyana, 2014, p. 102. The second type, *Person-Task fit*, is the congruence between requirements of a task and the capabilities of an individual (Caldwell and O’Reilly, 1990). As elaborated, it is evident that both types share the entity ‘task’. While *Task-Technology fit* does not involve any individual since it studies the compatibility between the description of a task and the characteristics of a technology, *Person-Task fit* is back to a more traditional type of fit. It is fair to assume that most tasks require the use of technology to be performed, hence this paper claims that *Person-Task fit* should include (more or less explicitly) aspects of *Task-*

Technology fit. This is why the two can be broadly categorized, namely *P-Tech fit*, where capabilities and expertise/practice with the type of technology available in order to fulfil the task at hand are matched with the individual. The combination of the two types of fit is even more apparent when one considers “computer-aided working environments” (Hua and Liu, 2017, p. 426). Thus, P-Tech fit is classified as tangible artefactual due to its applied nature.

Fit mechanisms involving technology and its related tasks are somewhat overlooked by the fit literature in management and organizational research. It is within a more technical literature (e.g., information systems, human-computer interaction) that a fit measure referred to as ‘cognitive-fit’ appears (Vessey, 1991, 2015). This type of fit is strictly used in studies on information processing with the intentions of obtaining better processing performance. Due to the association with ‘task’ it can be argued that P-Tech fit may somewhat be related to this interpretation of ‘cognitive-fit’. However, it is apparent that the latter has a stronger attention to cognition as information processing whereas *P-Tech* emphasizes task performance through the use of technology. One could be factored as a component of the other, but not vice-versa (at least, according to the literature). *Cognitive-fit* involves a problem representation, and this is, within the domain of *cognitive-fit* literature, always considered as a visual representation (e.g., graphs, figures, charts, and tables found in word processing) and hence tangible in nature (Vessey, 1991). Therefore, it is fair that this variant of fit is considered a direct comparison between an individual and a tangible artefact.

2.7. Factoring in time and space

The DEC-framework presented earlier includes the two categories of *space* and *time*. These two are entering transversally into the domains of fit, such that it is difficult to determine when time and space affect the various measures classified in the previous section. Table III, is an attempt in this direction. In so doing, it takes an analytical approach to DEC as a classification tool for fit measures. The aim of Table III, — and, as already stated in the introduction, of the paper overall — is that of indicating the ways in which cognition could be used to explain fit dynamics in organizations.

Table III, takes the five principal components of DEC (i.e. *embedded*, *enacted*, *embodied*, *ecological*, and *extended*) and organizes them according to *time* and *space*. While most of these cognition-related components would be susceptible to both (Cowley and Vallée-Tourangeau, 2013; Perry *et al.*, 2003; Vogel *et al.*, 2020), the one dimension that seems prominent within that component was chosen. In some respects, this approach follows a similar underlying notion to Vogel *et al.* (2020) where it embraces that the focus should be on the dynamic continuous aspects of moving from one situation to another. However, at the same time it takes a different approach to Vogel *et al.* (2020), by identifying the more prominent dimension (i.e. *time* or *space*) per each DEC component. The intention here is to provide a framework which can be used to isolate and capture the DEC components per dimension that are more prominently covered by each fit measure, thus providing the grounds to more effectively map what each measure is missing or is in lack of. Considering this new categorization, it would be worth mentioning the five components of DEC. The first two, *embedded* and *enacted* cognition, refer respectively to the centrality of the situational context in which cognition happens and to the behavior that is usually associated with the process (Secchi and Cowley, 2018). These two are usually connected to dynamic aspects. Think, for example, of an employee performing a task. The surroundings usually represent a nested set of values, norms, and routines that are part of the team or of the organization. The action of performing the task is never instantaneous, but requires time and, by definition, this time depends on the type of task (Cowley and Vallée-Tourangeau, 2013; Hollan *et al.*, 2000; Vogel *et al.*, 2020). For these reasons, *embedded* and *enacted* cognition are simplified and defined more time-bound.

The three remaining components of DEC — *embodied*, *ecological*, and *extended* —are connected to the *space* dimension. *Embodied* cognition highlights the importance of the self, mostly related to bodily perceptions (Varela *et al.*, 1991; Secchi and Cowley, 2018). As such, it is fairly obvious that the locus in which cognition happens is identified with the body and it is crucial to its understanding. The systemic or *ecological* component needs a spatial dimension to be understood (Hutchins, 1995; 2014; Secchi and Cowley, 2018), since the interacting parts of the cognitive system do not exist in a vacuum. Finally, *extending* cognition to the various resources located outside of the human brain, immediately points at a place in space (Secchi and Cowley, 2018; Perry *et al.*, 2003). The physical act of an employee performing a task requires an understanding of the coordination between one's behavior and, for example, the technology with which one interacts. Where the task is performed matters in terms of the use of physical and mental abilities, and the various internal-external interactions.

The first column on the left of Table III, reports the three categories used to classify the fit literature: (a) social, (b) intangible artefacts, (c) tangible artefacts. Using an approach similar to the one used above in regard to space and time, Table III, is populated with fit measures. By looking at the literature, aspects of fit measures that would approximate one or more components of DEC was then isolated. Moreover, one or more words were written to remind the reason why that fit measure stands where it does. In performing this classification exercise, a reconfiguration of the literature is provided, by giving raise to ways of looking differently into existing approaches of fit.

Table III: An illustration of how each fit measure could be seen through DEC

	Time		**Space**		
	Embedded	**Enacted**	**Embodied**	**Ecological**	**Extended**
Social	P-G **goals, values, personality**	P-G **behavior**	-	P-G **social-environment**	-
	P-S **situation-bound**	P-S **behavior, work-ethic**	-	-	-

Intangible Artfacts	P-O **situation**	-	-	P-O **work-environment, organizational characteristics**	-
	P-J **situation**	P-J **work-ethic**	-	-	-
	-	-	P-V **interests**	P-V **work-environment, opportunities**	-
	-	-	P-Ca **abilities, competencies**	P-Ca **work-environment, opportunities**	-
	-	P-Cu **behavior, routines**	P-Cu **shared values, interests**	P-Cu **context, awareness**	-
	P-R **situation**	P-R **behavior, work-ethic**	-	-	-
Tangible Artefacts	-	P-Tech **skills in action**	-	-	P-Tech **tools, technology**
	-	Cog **expertise, experience**	-	-	Cog **tools, problem-representation**

Note: Person-Vocation (P-V) fit, Person-Job (P-J) fit, Person-Organization (P-O) fit, Person-Group (P-G) fit, Person-Person (P-P) fit, Person-Career (P-Ca) fit, Person-Culture (P-Cu) fit, Person-Role (P-R) fit, Person-Technology (P-Tech) fit, Cognitive fit (Cog).

When inspected through space and time, *Person-Group* and *Person-Supervisor fit* can be considered together. They are both related to time through the *embedded* and *enacted* components, while *Person-Group fit* also connects to the *ecological*. They are *enacted* in the sense that the behavior between supervisor/group members and another individual may be considered through compatibility of behavior (Kristof-Brown *et al.*, 2005) that specify cognitive processes (Secchi, 2011). They are also *embedded* because the comparison of individual characteristics between parties (Kristof-Brown *et al.*, 2005) defines situational conditions that enable compatibility (Cowley, 2015). *Person-Group fit* is also seen as *ecological* due to its sensitivity to its local social-environment (i.e. the group) that works as a synergy allowing people to have a shared interpretation of working relationships

(Hutchins, 1995).

When looking at P-O fit, it can be seen that it can be made to relate to the *embedded* and *ecological* components. Due to its focus on, mostly, values (Vogel and Feldman, 2009; Kristof, 1996), it depends on both situational conditions that allow these values to take a form and apply and to a broader ecological/systemic (or macro) setting from where organizational values come from (Hutchins, 2014).

Person-Job and *Person-Role fit* can be considered together (Edwards, 1991) because they both deal with practical issues at work (i.e. jobs and roles), and with the conditions through which these can be interpreted. The first aspect implies that cognizing about a role or a job requires putting them into practice (*enacted* cognition), that is behaving in that job or role (Vogel and Feldman, 2009; DeRue and Morgeson, 2007). The other aspect implies the common understanding — usually set in a wider context — of what a job or a role entails and that is *embedded* in a given situation, defined through the relationships of a working environment (Vogel and Feldman, 2009; DeRue and Morgeson, 2007).

According to the literature vocation and career are two concepts that are hard to distinguish (Cullen, 2011). It should not come at a surprise when they appear to be analyzed through the same components, namely *embodied* and *ecological* cognition. The latter classification is perhaps easier to grasp, because both vocations and roles are designed to fit into the larger scheme of an organization (DeRue and Morgeson, 2007; Holland, 1985). In other words, they are bound by opportunities and reach that are possible within the structure of a given organization. The former points at the perception element of a career or a vocation (Cullen, 2011; Parasuraman *et al.,* 2000; Holland, 1985), to highlight that ecological/systemic constraints are filtered personally, and made to work through one's personal attitudes, feelings, rationalizations, and preferences. This brings the self back at the center stage (Secchi and Cowley, 2018).

When considering culture (*Person-Culture fit*) it can be reasoned in a way similar to what was already mentioned above for the *ecological* and the *embodied* components. On the one hand, organizational culture is defined at a broader level, with the stratified contribution of the many participants of the life of an organization (O'Reilly and Chatman, 1996; Schein, 1985). On the other hand, how this broad view is understood and perceived by individual members of the community is also crucial. There is an additional point here, that is essential to any living culture: *enaction*. No possible interpretation and understanding of a culture is possible if one does not act on it and contributes to its daily dynamics, eventually altering it (Hutchins, 2014).

The only two measures that map on the *extended* component are those related to the performance of a task, i.e. *P-Tech* and *Cognitive fit*. The reason is obvious, since both technology and any task need external-resources to be performed and, without these external-tools, there is no reasoning about the task (Clark, 2003). Also, and very clearly through the literature on these type of fit (Suryani and Sumiyana, 2014; Caldwell and O'Reilly, 1990; Vessey, 1991), the emphasis is on performing a task, hence on cognizing "through doing" (*enacted* component; Magnani, 2007).

2.8. Discussion: The need for a more-sophisticated fit mechanism

In spite of the many attempts, on several occasions and over the years scholars have shown that P-E fit measures hardly capture the complex dynamic nature of organizational life (Edwards, 2008; Drazin and Van de Ven, 1985). In this regard, Boon and Biron (2016 pp. 2178-2179) claim that researchers argue "measuring fit at one particular moment provides an inaccurate understanding of how individuals and environments mesh in the long run" and that "PE fit should be viewed as a process". Given that DEC is an approach to cognition that is particularly suited to study complex-dynamic and adaptive processes. The rather ambitious goal of this paper has been that of using a cognitive lens to classify the fit literature in an attempt to understand how a DEC perspective could contribute.

In introducing a DEC perspective, its main components were highlighted— i.e. the ‘e’ elements — and indicated that they make particular attention to the *space* and *time* dimensions (Cowley and Vallée-Tourangeau, 2013; Perry *et al.,* 2003; Vogel et al., 2020). In other words, DEC was presented and used as a tool to define complex-dynamic and adaptive elements. Figure 2 and Table III are two different ways to represent these aspects. Figure 2 is a graphical representation of three categories — *individual, social,* and *artefactual* — that identify fit by overlap. Concurrently, in an attempt to represent an indispensable element, space cuts-across these fit areas and time circles around them. Table III presents a more articulated view on the same topic. And it is this last one that provides the most useful information. In fact, from its reading, it is immediately apparent that none of the measures covers all the areas. Some cut-across time and space-related components, but none have a comprehensive take. To achieve a more comprehensive outlook on fit between a person and one or more aspects of organizational life, two potential streams for research are proposed based on the DEC-framework.

2.9. Research-stream 1: A combinatorial approach

One research-stream would be that of combining existing measures of fit to cover most (if not all) of the components in the DEC-framework. This would mean that, for example, a manager interested in exploring whether a new member of the team has an acceptable fit, would be looking at combining several measures. The manager may start with an attempt to understand how much convergence the new team member has with software, or technology in general, that are used in the team, hence covering the *extended* cognitive part with P-Tech. At the same time, such measure of fit would also cover some aspects related to the skills necessary to *use* that technology, hence covering parts of what is labelled *enacted* cognition. She/he could then assess *Person-Career fit* (or *Person-Vocation fit*), allowing the evaluation to extend itself to aspiration levels to explore possible conflicts with the position offered and overlaps with aspirations of other team members. This takes care of the *embodied*, due to the feelings usually associated with aspired states, and of the *ecological*, because it requires coordination with a wider understanding of the team dynamics. A third measure could be *Person-Group fit*, adding other aspects of the already covered *enacted* cognition, by enquiring about the compatibility between the newcomer and the other members of the team. The manager would still miss the *embedded* component, and that could be added by more situation-oriented measures, such as *Person-Job*/*Person-Role fit* or *Person-Supervisor fit*.

These ones above are not the only combinations available to one who is considering fit measures together. Also, the advantage of the ones selected above is that it also covers — quite transversally — all three categories, i.e. the *social* and the two *artefactual*. Thus, the following research questions may provide future research the means to inquire on *research stream 1* — (a) what is the impact of covering all three categories, on organizational outcomes? (b) does such a DEC driven combinatorial approach deliver the desired affect when integrating an individual into an environment? and (c) what are the most effective strategies to deploy *research-* stream *1*.

In regard to the research questions above, researchers attempting to study *research-stream 1* should contemplate the following overarching hurdles. (1) Firstly, combinations are limited such that some constructs may be used more while others may be almost completely neglected. This is a problem that has surfaced the literature before, in that some have signaled that there is overlap among some of these constructs (e.g., Edwards and Billsberry, 2010; Edwards, 2008). Hence, the approach above may lead to redundant measurements. (2) Another, perhaps more serious, problem is that this approach — i.e. combining fit measures together (Jansen and Kristof-Brown, 2006) — has been attempted before, and it has not performed well (Edwards and Billsberry, 2010). Yet in comparison to prior combinatorial approaches (Jansen and Kristof-Brown, 2006), *research-stream 1* provides a platform to combine measures in a less redundant manner while covering all aspects of the DEC-framework. (3) Finally, a fatal problem is that none of these measures — with the limited exception of *cognition-fit* (Vessey, 1991, 2015) — have been designed to cover DEC-oriented cognitive aspects. In fact, most of the cognitive references are indirect, at best (Pierro *et al.,* 2015; Cools *et al.,* 2009). And yet, most of the relationships that these measures aim at capturing have a very strong cognitive backing. Whether it is the perception of a relation (social resources), evaluation of skills (actions and doings), use of technology (expertise, learning), or assessment of values, beliefs, and career aspirations (second order thinking), the cognitive element seems rather obvious (Secchi and Cowley, 2018).

2.10. Research-stream 2: Developing a new measure

A way to overcome the limitations of *research-stream 1* would be that of creating a new measure based on DEC such that it would focus more prominently on the dynamic space-and-time bound social aspects without neglecting the artefactual ones. By tackling with all the DEC-components, this new measure would especially focus on the traversing situational-interactions between the artefactual and the social. Hence attempting to solve the aforementioned gap in literature by addressing (a) the temporal and situational issues of current measures raised by Boon and Biron (2016). And (b) perhaps head in the direction towards resolving the issues of inadequacy with current measures i.e., regarding organizational and employee performance (Edwards, 2008, 1991). To emphasize these aspects, this measure may be called *Organization-Cognition (O-C) fit* and both integrate existing fit measures and provide new insights on overlooked aspects by building on the components of the proposed framework (Table III).

In designing this measure based on the more socially oriented DEC literature (Secchi, 2011; Secchi and Adamsen, 2017), researchers attempting *research-stream 2* would need to incorporate three core features. (a) Focus on adaptation. As shown above, cognition is an adaptive process in which loosely or tightly coupled units interact (Clark, 2003; Clark and Chalmers, 1998). Any attempt to study cognition in organizations should tackle with dynamic adaptation of units (e.g., teams, individuals, departments) that work together towards one or more goals. Another feature would be captured by (b) understanding that cognition is a study of interactivity (Cowley and Vallée-Tourangeau, 2017), hence it requires that O-C fit has a very fluid way of defining it, depending on the situation to which it is applied. In other words, this means that there is no O-C fit if nodes of a network are considered individually and irrespective of the surrounding environment and the presence of a temporal dimension. Finally, in order to fully define a measure of complex dynamic adaptive units, (c) one shall lean on tools to study these types of systems. One such tools is a combination of either qualitative/quantitative studies with advanced computational simulation, for example, agent-based modeling (Edmonds and Meyers, 2017). Some have already started to show how DEC combines with such an advanced technique (e.g., Secchi and Cowley, 2018; Secchi and Cowley 2021; Herath and Secchi, 2021), although applications using empirical data are somehow lacking. O-C fit may bridge this gap.

Thus, future research exploring *research-stream 2* should investigate and question if capturing the cognitive-oriented dynamic aspects, provide practitioners a more reliable measure to effectively find an individual that is less vulnerable and more adaptable to the dynamic nature of organizations. It is argued here that due to this approach's focus on individuals with dynamic adaptability, this in principle should allow individuals to integrate into an environment relatively easily (Doeze Jager-van Vliet 2019; Deloitte 2018). In return this may foster employees that are more productive and perpetually satisfied (i.e. adjust and remain engaged/fulfilled) at work, thus plausibly leading to better performance at work and ultimately lower employee-turnover. This implies that a misfit in O-C fit may result in employees that are easily affected and more vulnerable to changes, thus potentially resulting in the inverse outcomes. It is these questions that researchers should seek to explore, thus as mentioned above research endeavors combining qualitative/quantitative methods with advanced computational-simulation may seem fruitful.

Finally, given the above, it is argued here that future research on O-C fit and fit more generally should consider studying the adaptive-interactions between cognitive mechanisms, processes, and logics of two organizational entities (e.g., individual and team) that are dynamically coupled through working relationships which are scattered-across space-and-time. Thus, exceeding the classical micro (physiological) and macro (structural-organizational aspects) perspective of organizations, by putting emphasis on the adaptive-interactions of socially organizing (cognizing) at work (Secchi and Cowley 2021; Herath and Secchi, 2021).

2.11. Concluding remarks

The paper has introduced a *distributed e-cognition* approach using the five components of the DEC and detailed how more specific aspects of cognition (i.e. temporality, spatial-positioning and social/non-social external-resources) could be factored in the various fit measures. In so doing, it has highlighted that these current mechanisms (taken singularly or in combination) do not satisfy the need for cognition. Thus, the paper suggests that there are two possible research streams for future research and conclude that perhaps a new measure of *organization-cognition fit* that matches each of the DEC components and designed to integrate existing measures, may provide a more sophisticated view of fit.

2.12. References

Aggarwal, I. and Woolley, A. (2019), "Team Creativity, Cognition, and Cognitive Style Diversity", *Management Science*, Vol. 65 No. 4, pp. 1586-1599.

Aoki, K. (2020), "The Roles of Material Artifacts in Managing the Learning–Performance Paradox: The Kaizen Case", *Academy of Management Journal*, Vol. 63 No. 4, pp. 1266-1299.

Bardone, E. and Secchi, D. (2017), "Inquisitiveness: distributing rational thinking", *Team Performance Management: An International Journal*, Vol. 23 No. 1/2, pp. 66-81.

Boon, C. and Biron, M. (2016), "Temporal issues in person–organization fit, person–job fit and turnover: The role of leader–member exchange", *Human Relations*, Vol. 69 No. 12, pp. 2177-2200.

Caldwell, D. and O'Reilly, C. (1990), "Measuring person-job fit with a profile-comparison process.", *Journal of Applied Psychology*, Vol. 75 No. 6, pp. 648-657.

Cha, J., Kim, Y. and Kim, T. (2009), "Person-career fit and employee outcomes among research and development professionals", *Human Relations*, Vol. 62 No. 12, pp. 1857-1886.

Clark, A. (2003), *Natural-born cyborgs*, Oxford University Press, Oxford.

Clark, A. and Chalmers, D. (1998), "The Extended Mind", *Analysis*, Vol. 58 No. 1, pp. 7-19.

Cools, E., Van den Broeck, H. and Bouckenooghe, D. (2009), "Cognitive styles and person–environment fit: Investigating the consequences of cognitive (mis)fit", *European Journal of Work and Organizational Psychology*, Vol. 18 No. 2, pp. 167-198.

Cowley, S. (2015), "How peer-review constrains cognition: on the frontline in the knowledge sector", *Frontiers in Psychology*, Vol. 6, doi:10.3389/fpsyg.2015.01706.

Cowley, S. and Vallee-Tourangeau, F. (2013), *Cognition Beyond the Brain*, Springer London, London.

Cowley, S. and Vallée-Tourangeau, F. (2017), Cognition Beyond the Brain, Springer International Publishing, Cham, 2nded.

Cullen, J. (2011), "Differentiating between Vocations and Careers", *SSRN Electronic Journal*, doi:10.2139/ssrn.1943566.

Deloitte. (2018). “The Adaptable Organization: Harnessing a networked enterprise of human resilience”. pp. 2-22. Retrieved from https://www2.deloitte.com/content/dam/Deloitte/global/Documents/HumanCapital/adaptable-organization.pdf.

DeRue, D. and Morgeson, F. (2007), "Stability and change in person-team and person-role fit over time: The effects of growth satisfaction, performance, and general self-efficacy.", *Journal of Applied Psychology*, Vol. 92 No. 5, pp. 1242-1253.

Doeze Jager-van Vliet, S., Born, M., & van der Molen, H. (2019). “Using a portfolio-based process to develop agility among employees”. *Human Resource Development Quarterly*, Vol. 30 No. 1, pp. 39-60.

Drazin, R. and de Ven, A. (1985), "Alternative Forms of Fit in Contingency Theory", *Administrative Science Quarterly*, Vol. 30 No. 4, p. 514.

Edmonds, B. and Meyer, R. (2017), *Simulating Social Complexity*, Springer, Heidelberg, 2nded.

Edwards, J. (1991), "Person-job fit: A conceptual integration, literature review, and methodological critique", in Cooper, C. and Robertson, I.,*International review of industrial and organizational psychology*, Wiley, New York, pp. 283-357.

Edwards, J. (2008), "Person–Environment Fit in Organizations: An Assessment of Theoretical Progress", *The Academy of Management Annals*, Vol. 2 No. 1, pp. 167-230.

Edwards, J. and Billsberry, J. (2010), "Testing a Multidimensional Theory of Person-Environment Fit", *Journal of Managerial Issues*, Vol. 22 No. 4, pp. 476-493.

Elfenbein, H. and O'Reilly, C. (2007), "Fitting In: The Effects of Relational Demography and Person-Culture Fit on Group Process and Performance", *Group & Organization Management*, Vol. 32 No. 1, pp. 109-142.

Gavetti, G., Greve, H., Levinthal, D. and Ocasio, W. (2012), "The Behavioral Theory of the Firm: Assessment and Prospects", *Academy of Management Annals*, Vol. 6 No. 1, pp. 1-40.

Gerpott, T., Domsch, M. and Keller, R. (1988), "CAREER ORIENTATIONS IN DIFFERENT COUNTRI-Career orientations in different countries and companies: An empirical investigation of West German, British and US industrial R&D professionals", *Journal of Management Studies*, Vol. 25 No. 5, pp. 439-462.

Healey, M., Vuori, T. and Hodgkinson, G. (2015), "When Teams Agree While Disagreeing: Reflexion and Reflection in Shared Cognition", *Academy of Management Review*, Vol. 40 No. 3, pp. 399-422.

Heavey, C. and Simsek, Z. (2017), "Distributed Cognition in Top Management Teams and Organizational Ambidexterity", *Journal of Management*, Vol. 43 No. 3, pp. 919-945.

Herath, G. (2019). “Studying the Cognitive Elements of Disorganization”. In D. Herath, *Business Plasticity Through Disorganization*, Howard House: Emerald Group Publishing, pp. 113-116.

Herath, G., & Secchi, D. (2021). “Supplementary or complementary fit in organization-cognition fit”. In D. Secchi, R. Gahrn-Andersen, & S. J. Cowley (Eds.), *Organizational Cognition: The Theory of Social Organizing* Routledge.

Hinings, C. and Greenwood, R. (1988), *The dynamics of strategic change*, Basil Blaclswell, Oxford.

Hodgkinson, G. and Healey, M. (2008), "Cognition in Organizations", *Annual Review of Psychology*, Vol. 59 No. 1, pp. 387-417.

Hollan, J., Hutchins, E. and Kirsh, D. (2000), "Distributed cognition", *ACM Transactions on Computer-Human Interaction*, Vol. 7 No. 2, pp. 174-196.

Holland, J. (1985), *Making vocational choices: A theory of vocational personalities and work environ-ments*, Prentice Hall, Englewood Cliffs, NJ.

Hua, Y. and Liu, A. (2017), "An investigation of person-culture fit and person-task fit on ICT adoption in the Hong Kong construction industry", *Architectural Engineering and Design Management*, Vol. 13 No. 6, pp. 423-438.

Hutchins, E. (1995), *Cognition in the wild*, MIT Press, Cambridge, Mass.

Hutchins, E. (2014), "The cultural ecosystem of human cognition", *Philosophical Psychology*, Vol. 27 No. 1, pp. 34-49.

Jansen, K. and Kristof-Brown, A. (2006), "Toward a Multidimensional Theory of Person-Environment Fit", *Journal of Managerial Issues*, Vol. 18 No. 2, pp. 193-212.

Kirton, M. and McCarthy, R. (1988), "Cognitive climate and organizations", *Journal of Occupational Psychology*, Vol. 61 No. 2, pp. 175-184.

Kristof, A. (1996), "Person-organization fit: an integrative review of its conceptualizations, measurement, and implications", *Personnel Psychology*, Vol. 49 No. 1, pp. 1-49.

Kristof-brown, A., Zimmerman, R. and Johnson, E. (2005), "Consequences of individuals' fit at work: a meta-analysis of person-job, person-organization, person-group, and person-supervisor fit", *Personnel Psychology*, Vol. 58 No. 2, pp. 281-342.

Lant, T. and Shapira, Z. (2000), *Organizational cognition*, Psychology Press.

Lauver, K. and Kristof-Brown, A. (2001), "Distinguishing between Employees' Perceptions of Person–Job and Person–Organization Fit", *Journal of Vocational Behavior*, Vol. 59 No. 3, pp. 454-470.

Lee, C., Cheng, H. and Cheng, H. (2007), "An empirical study of mobile commerce in insurance industry: Task–technology fit and individual differences", *Decision Support Systems*, Vol. 43 No. 1, pp. 95-110.

Magnani, L. (2001), *Abduction, reason, and science*, Kluwer Academic/Plenum, New York.

Magnani, L. (2007), "Animal abduction. From mindless organisms to artifactual mediators", in Magnani, L. and Li, P.,*Model-Based Reasoning in Science, Technology, and Medicine*, Springer, pp. 3--37.

Magnani, L. (2007), *Morality in a technological world*, Cambridge University Press.

Magnani, L. (2018), "Ritual Artifacts as Symbolic Habits", *Open Information Science*, Vol. 2 No. 1, pp. 147-155.

March, J. (1994), *A primer on decision making*, Free Press, New York.

Michel, A. (2007), "A Distributed Cognition Perspective on Newcomers' Change Processes: The Management of Cognitive Uncertainty in Two Investment Banks", *Administrative Science Quarterly*, Vol. 52 No. 4, pp. 507-557.

Miller, D. (1992), "Environmental Fit Versus Internal Fit", *Organization Science*, Vol. 3 No. 2, pp. 159-178.

Newcombe, N. (2018), "Three Kinds of Spatial Cognition", in Wixted, J.,*Stevens' Handbook of Experimental Psychology and Cognitive Neuroscience*, John Wiley & Sons, Hoboken, pp. 521–552.

O’Reilly, C. and Chatman, J. (1996), "Culture as social control: Corporations, cults, and commitment", in Staw, B. and Cummings, L.,*Research in organizational behavior*, JAI, Greenwich, CT, pp. pp. 157-200.

O'Reilly, C., Chatman, J. and Caldwell, D. (1991), "People and organizational culture: a profile comparison approach to assessing person-organization fit", *Academy of Management Journal*, Vol. 34 No. 3, pp. 487-516.

Ostroff, C. and Zhan, Y. (2012), *Person–Environment Fit in the Selection Process*, Oxford Handbooks Online.

Parasuraman, S., Greenhaus, J. and Linnehan, F. (2000), "Time, person-career fit, and the boundaryless career", in Cooper, C. and Rousseau, D.,*Trends in organizational behavior*, Wiley, Chichester, pp. 63–78.

Perry, M. (2013), "Socially Distributed Cognition in Loosely Coupled Systems", in Cowley, S. and Vallee-Tourangeau, F.,*Cognition Beyond the Brain*, Springer, London, pp. 147-169.

Perry, M., O'Hara, K., Spinelli, G. and Sharpe, B. (2003), "The role of space in socially distributed cognition: some issues for cognitive engineering", in *Annual Meeting of the Cognitive Science Society*, available at: https://escholarship.org/uc/item/9b38c1j5.

Pierro, A., Sheveland, A., Livi, S. and Kruglanski, A. (2015), "Person-group fit on the need for cognitive closure as a predictor of job performance, and the mediating role of group identification.", *Group Dynamics*, Vol. 19 No. 2, pp. 77-90.

Reeve, C. and Heggestad, E. (2004), "Differential relations between general cognitive ability and interest-vocation fit", *Journal of Occupational and Organizational Psychology*, Vol. 77 No. 3, pp. 385-402.

Rogers, Y. and Ellis, J. (1994), "Distributed cognition: an alternative framework for analysing and explaining collaborative working", *Journal of Information Technology*, Vol. 9 No. 2, pp. 119-128.

Schein, E. (1985), *Organizational Culture and Leadership*, Jossey-Bass, San Francisco, CA.

Schneckenberg, D., Velamuri, V. and Comberg, C. (2019), "The Design Logic of New Business Models: Unveiling Cognitive Foundations of Managerial Reasoning", *European Management Review*, Vol. 16 No. 2, pp. 427-447.

Secchi, D. (2011), *Extendable Rationality*, Springer, New York.

Secchi, D. and Adamsen, B. (2017), "Organizational cognition: A critical perspective on the theory in use", in Cowley, S. and Vallee-Tourangeau, F.,*Cognition Beyond the Brain*, Springer, Heidelberg, pp. 305-331.

Secchi, D. and Bardone, E. (2009), "Super-docility in organizations: an evolutionary model", *International Journal of Organization Theory & Behavior*, Vol. 12 No. 3, pp. 339-379.

Secchi, D. and Cowley, S. (2018), "Modeling Organizational Cognition: The Case of Impact Factor", *Journal of Artificial Societies and Social Simulation*, Vol. 21 No. 1.

Secchi, D., & Cowley, S. J. (2021). Cognition in Organisations: What it Is and how it Works. *Euro-pean Management Review*, Vol. 18 No. 2, pp. 79-92.

Simon, H. (1993), "Altruism and Economics", *The American Economic Review*, Vol. 83 No. 02, pp. 156–161.

Suddaby, R., & Foster, W. (2017). History and Organizational Change. Journal Of Management, Vol. 43 No. 1, pp. 19-38.

Suryani, W. and Sumiyana, S. (2014), "Task-technology fit and person-job fit: a beauty contest to improve the success of information systems", *Journal of Indonesian Economy and Business*, Vol. 29 No. 2.

Tate, M., Evermann, J. and Gable, G. (2015), "An integrated framework for theories of individual attitudes toward technology", *Information & Management*, Vol. 52 No. 6, pp. 710-727.

Umanath, N. and Vessey, I. (1994), "Multiattribute Data Presentation and Human Judgment: A Cognitive Fit Perspective", *Decision Sciences*, Vol. 25 No. 5-6, pp. 795-824.

Varela, F., Thompson, E. and Rosch, E. (1991), *The embodied mind: Cognitive science and human experience*, MIT Press, Cambridge, MA.

Vessey, I. (1991), "Cognitive Fit: A Theory-Based Analysis of the Graphs Versus Tables Literature", *Decision Sciences*, Vol. 22 No. 2, pp. 219-240.

Vessey, I. (2015), "The Theory of Cognitive Fit: One Aspect of a General Theory of Problem Solving?", in Zhang, P. and Galletta, D.,*Human-computer interaction and management information systems*, Taylor and Francis, New York, pp. 141 - 183.

Vessey, I. and Galletta, D. (1991), "Cognitive Fit: An Empirical Study of Information Acquisition", *Information Systems Research*, Vol. 2 No. 1, pp. 63-84.

Vogel, D., Jording, M., Kupke, C. and Vogeley, K. (2020), "The Temporality of Situated Cognition", *Frontiers in Psychology*, Vol. 11.

Vogel, R. and Feldman, D. (2009), "Integrating the levels of person-environment fit: The roles of vocational fit and group fit", *Journal of Vocational Behavior,* Vol. 75 No. 1, pp. 68-81.

Weick, K. (1993), "The Collapse of Sensemaking in Organizations: The Mann Gulch Disaster", *Administrative Science Quarterly*, Vol. 38 No. 4, pp. 628-652.

Westerman, J. and Cyr, L. (2004), "An Integrative Analysis of Person-Organization Fit Theories", *International Journal of Selection and Assessment*, Vol. 12 No. 3, pp. 252-261.

Wheeler, M. (2005), *Reconstructing the cognitive world*, MIT press, Cambridge, Mass.

White, L., Pothos, E. and Busemeyer, J. (2015), "Insights from quantum cognitive models for organizational decision making", *Journal of Applied Research in Memory and Cognition*, Vol. 4 No. 3, pp. 229-238.

Zhu, L., Liu, M. and Fink, E. (2016), "The Role of Person-Culture Fit in Chinese Students' Cultural Adjustment in the United States: A Galileo Mental Model Approach", *Human Communication Research*, Vol. 42 No. 3, pp. 485-505.

Chapter 3: Methods

The aim of this chapter is to give the reader an understanding of the methods used in this research project and, more importantly, to highlight the reasons why such methods were chosen over others. Accordingly, in order to systematically explain the choice of method, firstly this chapter will provide insights into the underlying essence of the topic at hand so that the reader can gain a better sense of what type of approach would be suitable for this inquiry. Then the chapter will provide an introduction to simulation modeling to acquaint the reader with the underlying assumptions of the chosen method and its utility. This will be followed by a description of the chosen research approach — agent-based modeling (ABM) — and will provide the reader with a deeper understanding of what the chosen approach constitutes and what unique attributes it offers over other available options. Finally, the two concluding sections will describe the tools utilized to facilitate the operations of the chosen method, and then provide insights into the operationalization of the research method in relation to the study's needs. On the whole, this chapter will provide the reasons why and how the chosen research methodology was used to inform this PhD study.

3.1. In search for an appropriate research methodology

As indicated in the previous chapters (*Chapter 1* and *2*), the aim of this study is to not only test the utility of a distributed cognition inspired approach to fit, but also to explore the underlying processes and consequences of such an approach. In so doing, it should be acknowledged that due to organizational landscapes' reliance on macro structural components (e.g. organizational rules and processes, allocated resources), as well as micro bodily components (e.g. human tendencies, skills); complex distributed social cognitive interactions are enacted in organizational environments (Rybakov, 2001; Greenwood *et al.*, 2011; Wood and Bandura, 1989). In other words, environmental institutional pressures and its resulting organizational reactions coupled with social interactional aspects of employees (Rybakov, 2001; Greenwood *et al.*, 2011; Wood and Bandura, 1989), produce a constant flux of intraorganizational behavioral dynamics. As a result, an organization's functionality (i.e. fueled by its structural constraints and social dynamics) can inherently be classified as a complex social system (Secchi, 2021b; Rybakov, 2001; Greenwood *et al.*, 2011). In light of this, as represented below, Secchi (2021b) provides a very insightful description of what entails in a complex social system such as an organization.

> "A complex social system is characterized by heterogeneous, interdependent, interacting, and mutually-influencing elements (parts), such that the system's dynamics is subject to change under uncertainty. The loose dependence on initial conditions and mostly non-linear causal relations are constantly self-organised to allow adaptation to the environment and survival" (Secchi, 2021b, p. 39).

In line with the above description of complexity that exists in organizations, this study's attempt to test the utility of using a distributed cognition inspired approach to fit, can only be assessed in relation to the resultant effect it has on the existing organizational landscape (environment). Therefore, to test its viability, on the one hand the study must allow to reflect how such an approach may impact the currently existing organizational environment (e.g. how it would impact the behavior of other employees and, in turn, their performance). On the other hand, the research methodology should also allow to compare and contrast the proposed approach in relation to, for example, other approaches or simply not having an approach. In facilitating these requirements of the study, it will not only allow the study to measure the effect of the proposed approach, but also provide a better understanding of which approaches are more suitable given various situational conditions (imposed by varying organizational rules and selection related specifications). Given these requirements of the study, it is evident that a research method that can facilitate the study of complex social systems is required.

In line with this need for a research method that can explore the complex underlying processes and consequences of such an approach, in recent years, there has been a gradual increase in interest for simulation modeling-oriented approaches in different fields of research (Fioretti, 2013; Edmonds *et al.* 2019; Grimm, 2006; Boero and Squazzoni, 2005). More importantly, as Gilbert (2008) points out, this rise can be attributed to the enhanced operational capability in grasping the process of complex phenomena as opposed to more traditional/other approaches. Considering the theoretical underpinnings of this study (i.e. distributed cognitive viewpoint to study complex social interactions), it is evident that certain simulation-modeling approaches (e.g. agent-based simulation modeling) would be more capable in effectively grasping the complex socio-cognitive phenomena that is associated with this study. As a result, in the following section, an overview of simulation modeling would be provided to provide the reader with a better understanding of why such a research method is considered appropriate for this study.

3.2. Overview of simulation modeling

Before attempting to comprehend the utility of simulation modeling, one must first reflect on the usage and the fundamental reasons why and how models are used in research. As Secchi (2021b) points out in his work, the term "model" is not an uncommon term in scientific research, but rather has long been used as a scientific tool to convey and highlight key knowledge (Gelfert, 2017; Magnani *et al.*, 1999). In this regard Secchi (2021b) also highlights that models are widely used in scientific research to either exemplify a scientific theory (French, 2010), or as part of a series of models that collectively reflect scientific theory (Gelfert, 2017), or as an epistemic tool/instrument to explore a phenomenon (Knuuttila, 2011).

Given this longstanding and wide use of models in scientific research, it is not too startling as to why over twenty types of models have been classified throughout the years (Secchi, 2021b). Yet given the research interest of this project and more importantly the aforementioned complexity it involves (i.e. complex social and intraorganizational interactions), it is highly important to utilize a research method capable of representing such a complex theoretical exploration. In addition, as explained in the previous section, the requirements of (a) needing to capture the cause and effect of the proposed approach on the currently existing social bound organizational environment, (2) need to compare and contrast the utility of other approaches in relation to organizational outputs, and (3) the need to understand the impact of various other factors (e.g. macro organizational aspects and micro bodily aspects) on the whole R&S process; would imply the need for a sophisticated type of model that can both provide research flexibility and most importantly provide the ability to handle research complexity.

In line with this need for a more capable type of model to represent and handle complex knowledge, computer simulation models (e.g. various operationalizations of agent-based models) have increasingly become more common in a variety of research fields (Meyer *et al.*, 2009; Harrison *et al.*, 2007; Carley, 2002; Edmonds and Meyer, 2017; Carley, 1999; Leik and Meeker, 1995; Hanneman *et al.*, 1995). For example, in recent years, organization science, a branch of social science, has begun to recognize the importance of such methods (Harrison *et al.*, 2007; Fioretti, 2013; Carley, 2002; Secchi, 2015; Secchi and Neumann, 2016). Nevertheless, computer simulations have long been considered as a legitimate approach to the study of organizations (e.g. March, 1965; Cohen and Cyert, 1965; Carley, 2002). For instance, this is even more apparent given the fact that "simulation models that reproduce agent interactions are primarily not a tool for handling data, but rather a means to help scientists explore research questions by highlighting the implications of the hypotheses that they make" (Fioretti, 2013, p.228). Thus, simulation modeling can be considered as an effective approach to explore the bounds of a theory in a systematic manner (Harrison *et al.*, 2007; Edmonds and Meyer, 2017; Fioretti, 2013; Carley, 1999). This can also be attributed as a reason to why such models within the domain of simulation informed social sciences are widely used to compose conceptual experiments on intricate interactions between social actors which would be too sophisticated to be done by most other approaches (Fioretti, 2013; Edmonds and Meyer, 2017; Carley, 2002).

Accordingly, in the last few decades researchers from a wide variety of backgrounds such as computer science, sociology, anthropology, geography, engineering, physics, philosophy, biology and economics have demonstrated a great interest in simulation modeling oriented approaches (Edmonds and Meyer, 2013). In this regard, one specific computational simulation technique, referred to as "agent-based modeling", has recently been acknowledged as a particularly promising technique for organizational behavior research (Gómez-Cruz *et al.*, 2017; Secchi, and Neumann, 2016; Fioretti, 2013).

3.3. Agent Based Modeling

Typically, when confronted with complexity, conventional analytical approaches are usually deemed infeasible, whereas natural language approaches are deemed insufficient for describing intricate cause and effect relationships (Edmonds and Meyer, 2013). It is with these kinds of complexity that agent-based simulation models are especially useful, particularly as the human mind is not capable of dealing with such a vast web of interactions as it is not reliable due to extreme intricacy and tediousness (Edmonds and Meyer, 2013 pp.3-13). This is why agent-based modeling is mostly suited for complex topics where understanding the process and the consequences of a phenomenon is important (Gilbert, 2008; Secchi, 2021b). In fact, ABM was initially developed in an attempt to represent heterogeneous autonomous agents that function as distributed units (Hassan *et al.*, 2010), therefore it is evident that complexity is at the root of agent-based modeling. This is why ABM is generally considered to be suitable when dealing with topics that involve several moving parts and hence considered complex (Secchi, 2021b).

Yet, one may question what advantage or added benefits does agent-based modeling provide over more traditional approaches. When compared to variable-based (VB) or system-based (SB) approaches, ABM allows for the modeling of individual heterogeneity, the explicit representation of agents' decisions/rules, and the placement of agents in a geographical or other type of conceptual spaces such as ‘problem space’ for example (Gilbert, 2008). In addition, as Secchi (2021b) points out when compared to other simulation approaches, ABM provides more configurable flexibility in the sense that it provides a more ‘active’ stance opposed to for example NK models (Gavetti, 2005), while also providing the ability to illustrate a more varied sense of agency (Richardson, 2011). Moreover, in comparison to System Dynamics (SD), which is the other most widely used approach to study complexity, ABM employs a disaggregated bottom-up approach as opposed to SD's aggregated top-down approach (Rahmandad, and Sterman, 2008). Thus, given the context of this study (i.e. behavioral aspects of individuals and collaborative coordination), the heterogeneity and flexibility in which the interactions of individuals and networks can be modelled allows ABM to be more suitable over SD as far as the explorative purpose of this study is concerned (Rahmandad, and Sterman, 2008; Marshall *et al.*, 2015; Meyers, 2011). In this regard, in order to truly understand what an agent-based model is and how it functions, one must first understand the primary components of an ABM model. Therefore, in the following three essential components of an agent-based simulation model— (a) *agent*, (b) *environment* and (c) *essence of time* — are discussed.

The Agents

As the name suggests, ‘agents’ are one of the main components of agent-based models and the creation of agents play a vital role in the planning and development process of ABM. As per Gilbert

(2008), there are primary features of an agent, such as autonomy (no global control on what an agent does), social ability (the ability to interact with other agents), reactivity (the capacity to react appropriately to stimulus from its environment), and proactivity (has a goal or goals that it pursues on its own initiative). As a result, the agents must have a set of behavioral rules, a working memory, a rule interpreter, an input procedure, and an output process (Gilbert, 2008). These components in turn are used to interpret the state of their surroundings, accept and communicate signals from other agents, and proactively choose actions to execute based on their current state. Therefore, when developing and ABM model the agents are usually at the center stage, and can take a variety of forms (e.g. people, buildings, tasks) depending on the research topic at hand. For example, in relation to the study conducted in this PhD, there are three different types of agents operating and represented in one ABM model, namely (a) team members (employees/employed), (b) applicants (job seekers/unemployed) and (c) problems (tasks that are to be solved by the employees).

The Environment

In tandem with the agents another component that plays a crucial role in an agent-based model is the environment in which the agents operate. The environment here can also take a variety of forms (e.g. organization or organizations, problem space, Europe, schools), yet generally they either represent a conceptual environment in which the research topic at hand operates or it can also take into account an actual geographical space (Secchi, 2021b; Gilbert, 2008). Regardless, the underlying premise of an environment in agent-based modeling is that agents usually operate under the confines of their respective environment. For instance, in relation to the study conducted in the PhD dissertation, the environment of the associated ABM model represents an organizational landscape in which the employees solve task in teams while also seeking to hire a new recruit. In this manner, in an ABM model the environment can be designed with a great degree of flexibility, where for example it could either be designed to provide inputs to agents or it could be designed in a manner where it does not (Gilbert, 2008). Therefore, the environment similar to the agents in an ABM, can too be created in a multitude of ways, thus further accentuating the varied utility of ABM in research.

The essence of Time

Another vital element of agent-based modeling is time (temporality). As Secchi (2021b) argues, time is an essential component especially for ABM because complex systems (for which ABM is considered a viable approach) and their dynamics are centrally time dependent. In other words, complexity is generally in relation to changing components that adapt and evolve over time (Secchi, 2021b). In this regard, due to ABM models at times simulating large timescales and also due to the fact that most stochastic ABM models are simulated a multitude of times; time in ABM models usually do not operate in real-world time (Secchi, 2021b; Gilbert, 2008). For this reason, ABM models usually use a different unit to represent time, where for example in the most widely used ABM development toolkit (referred to as *NetLogo*) time is represented as a 'tick' (Wilensky, 1999). Here a 'tick' can be represented by a timescale the modeler deems appropriate based on the simulation study at hand.

In light of using a simulation-bound unit to represent time in agent-based models, Gilbert (2008) argues that there are three primary issues surrounding time that should be considered by a modeler in the development process. (1) *Synchronicity*: the order in which agents perform interaction (e.g. send and receive messages from other agents), (2) *Event-driven simulation*: to identify if (a) the model needs to allow each agent a chance to perform a certain interaction in each time unit or (b) if no interactions are to be done (by certain agents) in a particular time unit then to decide if it can be skipped till the next eventful interaction (i.e. jumping from one eventful interaction to another), and (3) *Calibration of time*: mapping the simulation-bound time units to a realistic representation of time that is appropriately simulated based upon the research topic at hand (Gilbert, 2008).

3.3.1. Operationalizing agent-based simulation models

ABM generally allows to represent behavior in a natural way with multiple scales of analysis, emergence of structures at the macro or social level from individual action, and also offers more varied forms of adaptation and learning when compared to other approaches (Gilbert, 2008). However, as the case with all simulation techniques, ABM too needs to be complete, consistent and unambiguous if it is to be effectively executed (Gilbert, 2008; Secchi, 2021b). Hence, it is crucial and highly important that the characteristics of the agents as well as the environment are well understood and researched beforehand to obtain the most accurate simulation outcome (Edmonds *et al.*, 2019; Grimm *et al.*, 2020; Grimm *et al.*, 2017; Secchi, 2021b). Accordingly, as the literature on ABM suggest (Gilbert, 2008; Secchi, 2021b), creating an agent-based simulation model is not a simple task and it requires (a) proper preparation, (b) ABM development skills, and (c) adequate computational power to develop and test a reliable ABM model.

In so doing, when considering ABM as a research method, generally there are two epistemological distinctions that can be made based on the aim of the research endeavors (Edmonds, 2005). On the one hand, as hinted before, an agent-based model could be utilized as an epistemic model in the form of a conceptual representation to either illustrate or test the bounds of a specific theory. For instance, the agent-based garbage can model by Fioretti and Lomi (2008) is an ideal example of how an ABM model can be used to explore a theoretical proposition. On the other hand, an agent-based model can also be used to assess and further inform empirical data, thus following a data driven approach (e.g. Edmonds and Moss, 2005; Dean *et al.*, 2000; Sajjad *et al.*, 2016). These distinctions have methodological implications on the entire research study, for example when using a data driven approach a portion of the effort has to be utilized in preparing (e.g. data collection plan), executing and collecting data so that it can be used to for instance to validate an ABM model. On the contrary, an ABM model that is both theoretically driven and designed to accommodate and assist empirical data-driven explorations can also be developed (e.g. Lorscheid and Meyer, 2021; Secchi and Herath, 2019). Thus, such an approach would in turn not only allow to test the theoretical bounds of a concept but also allow to further validate the theoretical proposition through empirical data (Secchi, 2021b).

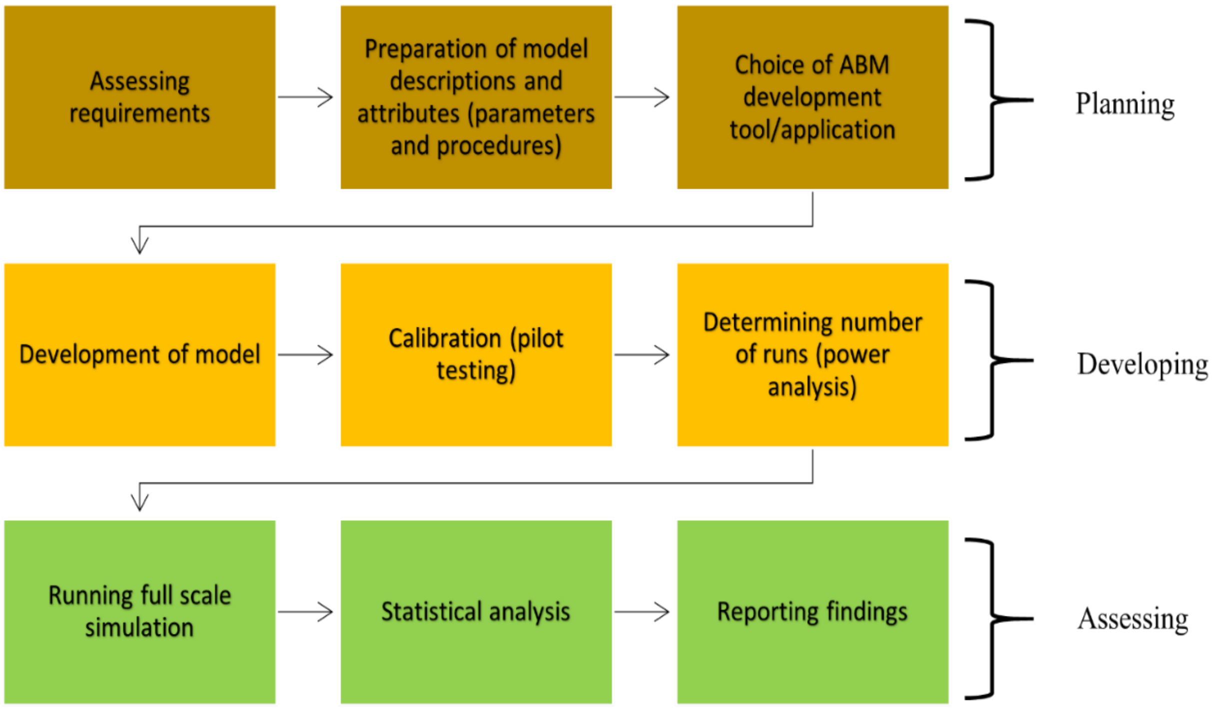
Regardless of the above distinctions, an agent-based model will usually generate simulated data, which is then analyzed through statistical analysis. Thus, the generation of the simulated data is usually conducted on the premise of testing the effects of various parameter configurations on various other aspects of the developed model (Gilbert, 2008; Secchi, 2021b). As a result, this in turn allows the modeler/researcher to assess and examine research findings. Therefore, before generating the simulated data, usually a modeler will go back and forth till an accurate representation of the model dynamics is represented by the model. Then usually prior to running the full-scale simulation, once the model is appropriately developed, the model will then also be pilot tested by running a calibration process (Edmonds and Meyer, 2017; Secchi, 2021b).

This process is conducted to identify suitable parameter configurations, as at times various combinations may potentially produce different results (Edmonds and Meyer, 2017). The calibration process is usually done by conducting a sensitivity analysis (SA). This process tests a range of values for each parameter and either (a) assists the modeler to evaluate as to which values for each parameter provides a sensible representation of model behavior, or (b) outlines the robustness of the parameters used, or (c) assist in quantifying the parameter-based outcome variability of the model (Ten Broeke *et al.*, 2016). Accordingly, as per Ten Broeke *et al.* (2016) there are few options available to perform a SA on model parameters, namely, One-factor-at-a-time (OFAT), Regression-based SA, and the Sobol approach. Each of these methods have their own strengths and weaknesses — e.g. OFAT is effective for examining patterns and model robustness, yet it cannot quantify outcome variability based on parameters, while Sobol' is only capable of quantifying the outcome variability based on parameters. Given these differences, Ten Broeke *et al.* (2016) argue that they should be considered based on the aims and the specified purpose of why a SA is considered with regards to an ABM driven study. Yet, when observing the utility of the above three methods (Ten Broeke *et al.*, 2016), the Regression-based SA seems to be the more universal approach amongst the three as it (if good model fit exists) seems to be operational for the aims of examining (a) model patterns, (b) model robustness, and (c) the quantification of outcome variability based on parameters.

Once an appropriate SA method (calibration process) is conducted then finally a modeler/researcher should decide how many times each parameter configuration should be run in the final simulation. For this reason, some researchers (Secchi and Seri, 2017; Seri and Secchi, 2017) assert that statistical power analysis would be appropriate to effectively identify the number of runs required for the simulation based on the scale of the model. Accordingly, power analysis allows to identify the required number of simulation runs (the number of times a simulation is performed per each configuration of parameters) needed to appropriately represent the scale of an ABM model. As Secchi and Seri (2017, p.98) state in their work, "[t] he power of a statistical test is the probability that it correctly rejects a false null hypothesis, namely one minus β". Thus, they argue that most studies tend to be underpowered due to researchers not performing power analysis as they simply just rely on the sample size to account for errors (Secchi and Seri, 2017). Such an underpowered study could in turn indicate other issue such as (a) defective design, (b) testing the effect of unrelated parameters, and (c) the use of an unsatisfactory number of runs. In converse, Secchi and Seri (2017) express the view that having an overpowered study would also not be sensible as it may result in (a) modelers to detect impacts that are so little that they aren't worth taking into account, (b) researchers may be unable to discern between greater and less relevant effects, and (c) may induce unnecessary financial costs due to needless resources and time wasted. All things considered, it is evident that conducting power analysis would only head in the direction of effectively increasing the accuracy of results produced by an ABM model. Therefore, it is fair-minded to argue that conducting power analysis may very well be considered a necessary step when developing an agent-based simulation model. Finally, once all the above steps are completed, the ABM model can then be run to generate the simulated data for the full-scale study.

In order to provide the reader with a visual outlook of how an ABM model may be developed (as per the methodological literature covered in this section), I have created a step-by step process flow for the development process of an ABM as shown in Figure 3 below. Accordingly, Figure 3 is segmented into 3 stages — (a) the *planning* stage, (b) the *developing* stage, and (c) the *assessing* stage — that collectively represent the entire process of utilizing an agent-based model in research.

Figure 3: Steps to develop an ABM



In view of these critical structural considerations that must be made prior to and throughout the development of an agent-based simulation model, it is critical that these, as well as all other development decisions and model functionality, are documented so that it may be replicated by others if necessary. For this reason, ABM modelers within the field of ecology were first to take a keen interest in systematically recording the functional specifications of agent-based models by using a protocol referred to as the ODD protocol (Grimm *et al.*, 2006). Fortunately, recently this protocol has been remapped to also be compatible for social science research (Grimm *et al.*, 2020). Accordingly, the ODD protocol is a standard used by agent-based simulation modelers to describe and structure their models and its related features and procedures. In so doing, it follows a threefold structure — Overview, Design and Details — which collectively are designed to systematically explain the workings of a model and its associated model behavior (Grimm *et al.*, 2017).

Moreover, in addition to documenting and describing an ABM model, one must also pay great attention to the development process of an agent-based model. Therefore, it is essential that an appropriate application program (toolkit) is utilized for the effective development of an agent-based model.

3.4. Insights into the software program used

The application tool used to develop an ABM model plays a crucial role in effectively making use of a simulation model to appropriately inform a research study (Gilbert, 2008; Secchi, 2021b). In connection with this, the software program used to develop an ABM model has a direct impact on the skills required to develop such a simulation model. Given the requirements of what is needed from an ABM in relation to the requirements of this study, the selection of software program was not too perplexing. Simply due to the fact that the most widely used software program to model ABM's — *NetLogo* (Wilensky, 1999) — is adequately sufficient to fulfil the scope of this study (Thiele *et al.*, 2012; Gilbert, 2008). This wide use can also be attributed to *NetLogo's* relatively user-friendly software structure and the accompanying programming language used for modeling (Secchi, 2021b). Thus, the programming language used in *NetLogo* is a variant of the language Logo, which is known for its simplicity and user-friendly expressions (Secchi, 2021b). As such, it provides the modeler with the added benefit of learning the relevant language to a great extent in a reasonable amount of time when compared to other more complex programming languages such as Object-C, Python and Java, used in other ABM development toolkits such as *Swarm*, *Repast* and *Mason* (Gilbert, 2008).

In addition, due to its vast userbase with regards to agent-based modeling, *NetLogo* driven ABM also has an extensive library of supporting material and related training programs around the world. For example, I attended an agent-based simulation model development summer school for social scientists, which was managed by Flaminio Squazzoni (Editor of Journal of Artificial Societies and Social Simulation- JASSS[6]). Furthermore, when compared to other ABM development toolkits such as *Swarm*, *Repast* and *Mason*, *Netlogo* provides a more user friendly and intuitive functionality for graphical user interface development (Gilbert, 2008). Similarly, the user-friendliness of *NetLogo* is even more apparent given its superior ease of installation when compared to other applications (Gilbert, 2008). All things considered, given its extensive support material, ease of installation, intuitive functionality for graphical user interface development and, most importantly, ease of programming language and reduced learning curve, *NetLogo* was the most appropriate choice for ABM development.

In regard to the manner in which the software is structured, it features three primary user tabs namely the *interface* tab, the *code* tab and the *info* tab. The interface tab consists of a graphical world and also provide the ability to easily choose from a variety of drag and drop objects such as buttons, sliders, switches, choosers, plots, activity monitors and more. These objects would then be connected to the code, which is written in the *code* tab. This is where the programming is performed and the workings of the ABM is modelled, and then is subsequently visualized on the *interface* tab as per the

[6] Is one of the leading academic journals in the field of ABM.

graphical requirements and intentions of the modeler. Finally, the *info* tab is used to describe the model and its associated features along with how to use the model. This is especially useful when the model is to be used by others that are not so familiar with its workings. Lastly, in order to add perspective to the utility of this software program, snapshots of the above-mentioned tabs (i.e. *interface* tab, *code* tab and *info* tab) are represented in Figures 4, 5 and 6.

Figure 4: NetLogo user 'Interface' Tab

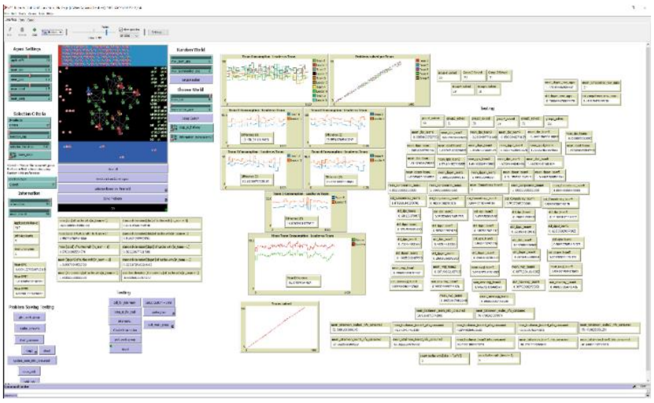


Figure 5: NetLogo user 'Code' Tab

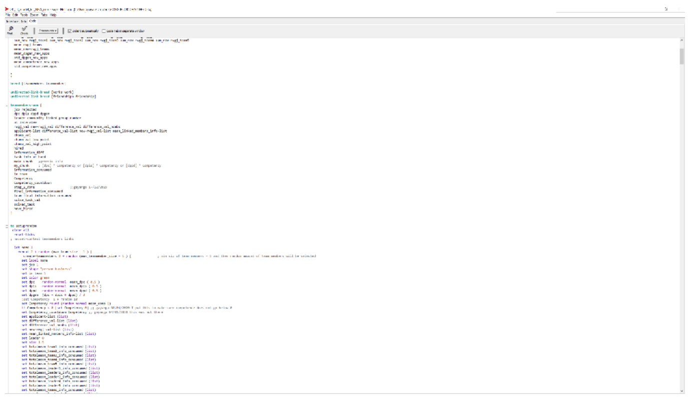
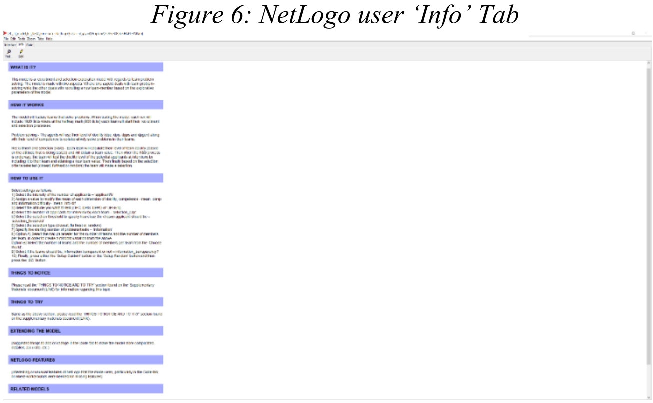


Figure 6: NetLogo user 'Info' Tab



3.5. Making use of Agent-based modeling

Along with the underlying purpose of this study, it can be categorized as a theoretical exposition of a complex social system (Edmonds *et al.*, 2019). As a result, an agent-based modeling approach was considered to be the most suitable epistemic instrument for this study. In so doing, as the prior sections suggested, adequate time had to be dedicated to the development process of the model. Then in order to gain a substantial understanding of agent based modeling and social simulation, I referred to a series of instructional and explanative oriented agent-based modeling related books (notable examples: Gilbert, 2008; Edmonds and Meyer, 2017; Secchi, 2021b; Secchi, and Neumann, 2016; Squazzoni, 2012) and research articles (notable examples: Edmonds *et al.*, 2019; Secchi, 2015; Fioretti, 2013; Edmonds and Moss, 2005; Gómez-Cruz *et al.*, 2017; Grimm *et al.*,2006 ;2017; 2020; Ten Broeke *et al.*, 2016; Secchi and Seri, 2017), while also inspecting a variety of ABM models that associate with either organizations, cognition, employment and team dynamics research to inform my development process (notable examples: Secchi, 2021a; Fioretti and Lomi, 2008; Secchi and Cowley, 2018; Ekmekci, and Casey, 2011; Neves *et al.*, 2019). Once the relevant knowledge was acquired in regard to agent-based modeling, I then decided along with my supervisor that, given the above-mentioned advantages of *NetLogo* (i.e. extensive support material, easy installation, intuitive GUI development, simpler programming language and reduced learning curve), it was the most sensible software program (toolkit) for the development of an agent-based model in this study. I then learned the *NetLogo* language along with the relevant programming concepts and design patters currently used in *NetLogo* driven agent-based modeling research. In addition, I also attended a summer school dedicated to learning agent-based modeling for social science researchers. Here, I significantly improved my understanding of ABM development and associated programming ability.

Subsequently, it was time to put the learned knowledge on constructing ABM models into action by starting to develop the ABM model for the study (*O-C fit* model). At this stage I was confident about the development process and had already made a mind map of how it should be developed. In so doing, in connection with *Overview* stage of the ODD protocol (Grimm *et al.*, 2020), I structured and described how the model would pan out and how it was intended to operate. Then, as I built the ABM model, I continued with the subsequent phases of the ODD protocol, namely the *Design* and *Details* sections, in order to influence my development and design thinking, as well as to incorporate reproducibility to the ABM model. In doing so I followed a similar sequence as the previously provided process flow in Figure 3, and successfully developed an effective ABM model (through a typical programming process of debugging, conducting numerous tests and evaluations) and continued with the calibration process via a Sensitivity Analysis (Ten Broeke *et al.*, 2016).

The choice of an appropriate method for the SA was based primarily on the aim and purpose for why a SA would be considered useful in line with the purpose of the model. Accordingly, the primary purpose and aim of using a SA in regard to the *O-C fit* model was to test its robustness and especially also to identify influential parameters with regards to the outcome variable (problems solved). In line with this, given that Ten Broeke *et al.* (2016, para. 6.3) argues that the "regression-based sensitivity analysis might prove useful in selecting influential parameters for further analysis based on the sensitivity indices or regression coefficients", and since such "descriptive relationships give insight into the robustness and can account for interaction effects", this method seemed promising. In addition, the rationale for selecting 'regression-based SA' was further justified given that the other methods — Sobol' and OFAT (Ten Broeke *et al.*, 2016) — did not solely satisfy both of the above mentioned aims of the *O-C fit* model — i.e. (a) inquire on robustness and (b) inquire on parameter induced outcome variability — (Ten Broeke *et al.*, 2016). As a result, since the 'regression-based SA' method provided the means to satisfy both of the above mentioned aims of the *O-C fit* model, it was deemed an appropriate method to satisfy the selection process of identifying appropriate parameters and associated values for the *O-C fit* model. Subsequently following the SA, I conducted a power analysis (Secchi and Seri, 2017; Seri and Secchi, 2017) to determine the number of runs required (the relevant numbers are presented in *Chapter 4* – see section 4.11).

Finally, once all the model related tests and required parameter values were settled and decided, the final full-scale simulation was run. It should also be acknowledged that, for both the pilot study as well as the full-scale simulation, the high performing computing unit (HPC) *Abacus 2.0*

(Danish supercomputer) and available at the University of Southern Denmark in Odense was used. The primary reason for using a supercomputer to run the simulation was simply due to the fact that it provided unparalleled computing power with regards to significantly reduce the time required to run the simulations. This in turn aided in significantly improving the speed of execution in NetLogo which is generally considered to be slower than other ABM development toolkits such as *Repast* and *Mason* (Gilbert, 2008).

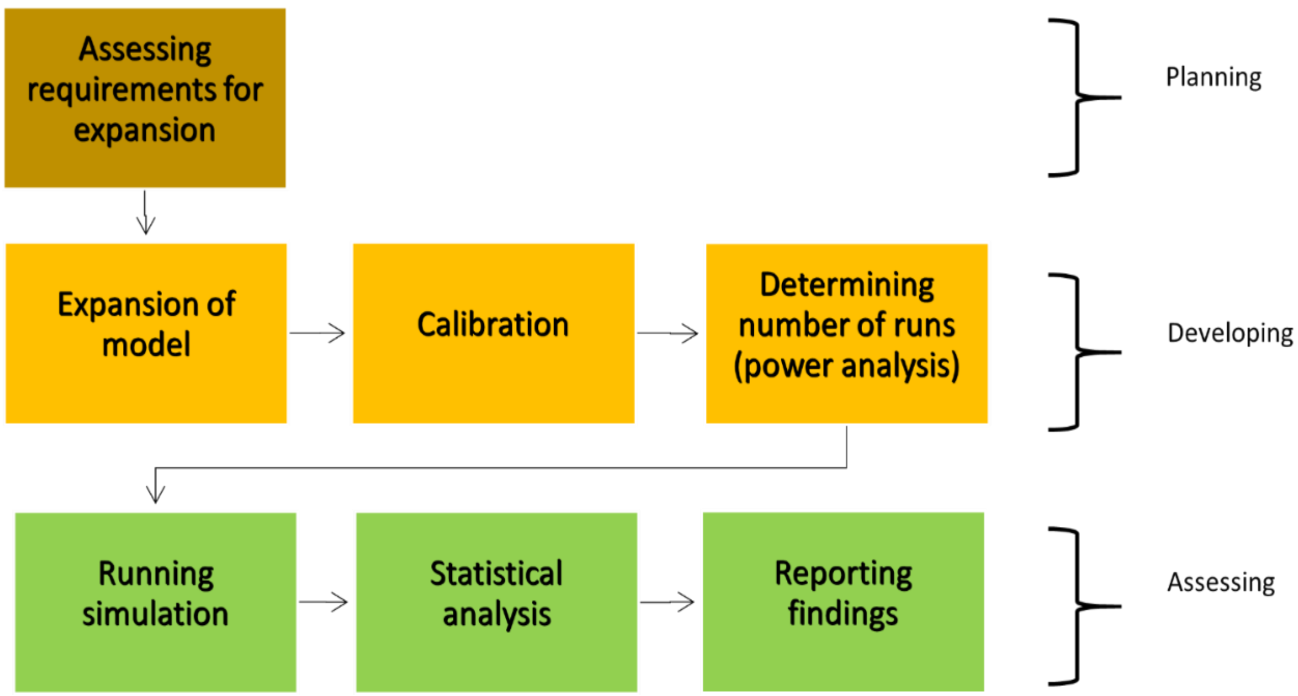
Eventually, once the simulation data was generated, it was downloaded from the supercomputer, and was then ready to be statistically analyzed. The data was then loaded on to R-studio which was subsequently used to conduct statistical analysis and then later reported in Article 2 of this anthological PhD dissertation (see *Chapter 4*). The reason why R-studio was chosen over other statistical analysis programs was due to the added flexibility it offered when compared to other programs such as SPSS, as well as the numerous libraries that R supports, which ultimately made it a highly versatile option for statistical analysis. Once Article 2 in *Chapter 4* was concluded, the initial plan for the subsequent chapter (Article 3) was to conduct an empirical validation of the *O-C fit* model presented in *Chapter 4*. Accordingly, in collaboration with a jobcentre in Slagelse, Denmark, a data collection procedure had already been devised. However, this data collecting plan was abruptly disrupted due to the sudden advent of COVID 19 and its impact and accompanying restrictions, therefore the focus of Article 3 (*Chapter 5*) was shifted to what is currently provided in this PhD dissertation.

Considering these unforeseen circumstances, I was directed by my department head to perhaps further pursue into a theoretical expansion of my proposed concept, as data collection was not feasible given the national restrictions imposed in Denmark. As a result, my supervisor and I decided that even though this was a roadblock to our initial plan, a theoretical expansion on the premise of further exploring the utility and the viability of the proposed approach (*O-C fit* approach) would be a fruitful addition to our understanding of *O-C fit*. In so doing, upon further consideration of the *O-C* *fit* approach and its viability in relation to the P-E fit literature, it was evident that the O-C fit approach in Chapter 4 was focused around effective cognitive integration on the premise of finding a shared ground between the recruit and the environment. Thus, when looking through the conventional lens of the P-E fit paradigm, such a similarity seeking operationalization of fit followed a *supplementary fit* tradition to fit (see *Chapter 5* and its associated *Appendix B* for a thorough explanation). This similarity seeking dynamic in turn meant that in general it would be more suitable for an environment that was performing satisfactorily. As a result, this in turn meant that it would not be a suitable choice for an environment that is performing unsatisfactorily. This meant that such an environment would typically attempt to change the currently existing dynamic, hence looking to improve its performance. By this means, through the lens of the P-E fit paradigm an employer would generally seek for *complementary fit* (see *Chapter 5* for a thorough explanation), thus seeking to complement the existing environment hence possibly allowing it to improve its performance. Given that, at this stage, *O-C fit* was only operationalized on the premise of seeking congruence (in *Chapter 4*), it was sensible for *Chapter 5* to seek the utility of *O-C fit* when an environment sought to improve a poorly performing social environment. As a result, given that this study used an ABM driven research methodology to explore the theoretical bounds of *O-C fit* (*Chapter 4*), it only made sense that a similar research methodology was used to explore the bounds of *O-C fit* when seeking improvement through the complementary fit tradition (in *Chapter 5*).

However, since an effective ABM model was already developed and since it was developed with the possibility of being expanded to test the utility of other approaches, the development process for *Chapter 5* was to essentially expand the model developed for *Chapter 4*. Accordingly, the *complementary fit* approach to *O-C fit* was included into the model code and its associated ABM graphical user interface (*O-C-fit 2.0* model). In this regard, once the model was updated, the calibration process (Ten Broeke *et al.*, 2016) was conducted. However, this time around, the calibration process was far more straightforward, as majority of the model had already been calibrated previously (for *Chapter 4*). Following the calibration process, similar to what was done in *Chapter 4*, a power analysis (Secchi and Seri, 2017; Seri and Secchi, 2017) was conducted to identify the number of runs required for the updated *O-C-fit 2.0* model. Finally, the newly expanded *O-C-fit 2.0* model was run, and the resultant simulated data was generated and statistically analyzed by using R-studio. The results and related findings were then reported in *Chapter 5*.

Moreover, in order to provide the reader with a visual outlook of how the existing ABM model in *Chapter 4* was expanded for *Chapter 5*, a step-by-step methodological process flow is shown in Figure 7. This figure follows a similar visual structure to Figure 3 (methodological process flow for *Chapter 4*), where it is segmented in to three stages: the *planning* stage, *developing* stage and the *assessing* stage.

Figure 7: Steps used in expansion of the O-C fit 2.0 ABM model



Now that the methodological process of the research study along with the research method (i.e. agent-based modeling) and the associated research tools are introduced, the following chapter will present the second research article included in this dissertation. Accordingly, the subsequent chapter will utilize an agent-based modeling approach to examine the viability of an R&S approach which attempts to facilitate fluid socially oriented cognitive integration.

3.6. References

Boero, Riccardo and Squazzoni, Flaminio (2005). 'Does Empirical Embeddedness Matter? Methodological Issues on Agent-Based Models for Analytical Social Science'. *Journal of Artificial Societies and Social Simulation*, Vol. 8 no. 4, p. 6.

Carley, K. (1999), "On generating hypotheses using computer simulations", *Systems Engineering*, Vol. 2 No. 2, pp. 69-77.

Carley, K. (2002), "Computational organizational science and organizational engineering", *Simulation Modelling Practice and Theory*, Vol. 10 No. 5-7, pp. 253-269.

Cohen, K. J., & Cyert, R. M. (1965). *Simulation of organizational behavior*. In J. G. March (Ed.), Handbook of organizations (pp. 305-334). Chicago, IL: Rand McNally.

Dean, J., Gumerman, G., Epstein, J., Axtell, R., Swedlund, A., Parker, M. and McCarroll, S. (2000), "Understanding Anasazi culture change through agent-based modeling", in Kohler, T. and Gumerman, G., *Dynamics in human and primate societies: Agent-based modeling of social and spatial processes*, 179– 205, New York, p. Oxford University Press.

Edmonds, B. (2005) Simulation and Complexity - how they can relate. In Feldmann, V. and Mühlfeld, K. (eds.) *Virtual Worlds of Precision - computer-based simulations in the sciences and social sciences*. Pages 5-365. Lit Verlag.

Edmonds, B. and Meyer, R. (2013). Simulating Social Complexity. Berlin, Heidelberg: Springer Berlin Heidelberg, pp.3-13.

Edmonds, B. and Meyer, R. (2017), Simulating Social Complexity, Springer, Heidelberg, 2nded.

Edmonds, B. and Moss, S. (2005), "From KISS to KIDS–an 'anti-simplistic' modeling approach", in Davidsson, P., Logan, B. and Takadama, K., *Multi-Agent and Multi-Agent-Based Simulation*, Springer, Heidelberg, pp. 130–144.

Edmonds, B., Le Page, C., Bithell, M., Chattoe-Brown, E., Grimm, V., & Meyer, R. et al. (2019). Different Modelling Purposes. *Journal Of Artificial Societies And Social Simulation*, Vol. *22* No. 3.

Ekmekci, O. and Casey, A. (2011), "Computer simulation exploring organizational identification for contingent workers", *Team Performance Management*, Vol. 17 No. 5/6, pp. 279-298.

Fioretti, G. (2013). Agent-Based Simulation Models in Organization Science. *Organizational Research Methods*, Vol. *16* No. 2, pp. 227-242.

Fioretti, G. and Lomi, A. (2008), "An Agent-Based Representation of the Garbage Can Model of Organizational Choice", Journal of Artificial Societies and Social Simulation, Vol. 11 No. 1, available at: (accessed 18 July 2021).

French, S. (2010). Keeping quiet on the ontology of models. Synthese, Vol. 172 No. 2, pp. 231–249.

Gavetti, G. (2005). Cognition and hierarchy: Rethinking the microfoundations of capabilities' development. *Organization Science*, Vol. 16 No. 6, pp. 599–617.

Gelfert, A. (2017). The ontology of models. In L. Magnani & T. Bertolotti (Eds.), *Springer handbook of model-based science*, Springer Handbooks book series (SHB) (pp. 5–23). Springer.

Gilbert, G. (2008). Agent-based models. Los Angeles: Sage Publications.

Gómez-Cruz, N., Loaiza Saa, I., & Ortega Hurtado, F. (2017). Agent-based simulation in management and organizational studies: a survey. *European Journal Of Management And Business Economics*, Vol. *26* No. 3, pp. 313-328.

Greenwood, R., Raynard, M., Kodeih, F., Micelotta, E., & Lounsbury, M. (2011). Institutional Complexity and Organizational Responses. Academy Of Management Annals, Vol. 5 No. 1, pp. 317-371.

Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J. and Goss-Custard, J. et al. (2006), "A standard protocol for describing individual-based and agent-based models", Ecological Modelling, Vol. 198 No. 1-2, pp. 115-126.

Grimm, V., Polhill, G., and Touza, J. (2017). Documenting social simulation models: The ODD protocol as a standard. In Edmonds, B. and Meyer, R., editors, *Simulating Social Complexity: A Handbook*, pages 349–365. Springer, Cham.

Grimm, V., Railsback, S. F., Vincenot, C. E., Berger, U., Gallagher, C., DeAngelis, D. L., Edmonds, B., Ge, J., Giske, J., Groeneveld, J., et al. (2020). The odd protocol for describing agent-based and other simulation models: A second update to improve clarity, replication, and structural realism. *Journal of Artificial Societies and Social Simulation*, 23(2).

Hanneman, R., Collins, R. and Mordt, G. (1995), "Discovering Theory Dynamics by Computer Simulation: Experiments on State Legitimacy and Imperialist Capitalism", *Sociological Methodology*, Vol. 25, p. 1.

Harrison, J., Lin, Z., Carroll, G. and Carley, K. (2007), "Simulation modeling in organizational and management research", *Academy of Management Review*, Vol. 32 No. 4, pp. 1229-1245.

Hassan, S., Antunes, L., & Gilbert, N. (2010). Going back home social simulation and artificial intelligence. *Computational and Mathematical Organization Theory*, Vol. 16 No. 4, pp. 325–328.

Hassan, S., Antunes, L., & Gilbert, N. (2010). Going back home social simulation and artificial intelligence. *Computational and Mathematical Organization Theory*, Vol. 16 No. 4, pp. 325–328.

Knuuttila, T. (2011). Modelling and representing: An artefactual approach to model-based representation. *Studies in History and Philosophy of Science Part A*, Vol. 42 No. 2, pp. 262–271.

Leik, R. and Meeker, B. (1995), "Computer Simulation for Exploring Theories: Models of Interpersonal Cooperation and Competition", *Sociological Perspectives*, Vol. 38 No. 4, pp. 463-482.

Lorscheid, I. and Meyer, M. (2021), "Toward a better understanding of team decision processes: combining laboratory experiments with agent-based modeling", *Journal of Business Economics*.

Magnani, L., Nersessian, N. J., & Thagard, P. (1999). *Model-Based Reasoning in Scientific Discovery*. New York: Kluwer Academic/Plenum Publishers.

March, J. G. (1965). *Handbook of organizations*. Chicago, IL: Rand McNally

Marshall, D., Burgos-Liz, L., IJzerman, M., Osgood, N., Padula, W., & Higashi, M. et al. (2015). Applying Dynamic Simulation Modeling Methods in Health Care Delivery Research—The SIMULATE Checklist: Report of the ISPOR Simulation Modeling Emerging Good Practices Task Force. *Value In Health*, Vol. 18 No. 1, pp. 5-16.

Meyer, M., Lorscheid, I. and Troitzsch, K.G. (2009), “The development of social simulation as reflected in the first ten years of JASSS: a citation and co-citation analysis”, *Journal of Artificial Societies and Social Simulation*, Vol. 12 No. 4, p. 12.

Meyers, R. (2011). *Complex systems in finance and econometrics*. New York: Springer.

Neves, F., Campos, P. and Silva, S. (2019), "Innovation and Employment: An Agent-Based Approach", *Journal of Artificial Societies and Social Simulation*, Vol. 22 No. 1.

Rahmandad, H., & Sterman, J. (2008). Heterogeneity and Network Structure in the Dynamics of Diffusion: Comparing Agent-Based and Differential Equation Models. *Management Science*, Vol. 54 No. 5, pp.998-1014.

Richardson, G. P. (2011). Reflections on the foundations of system dynamics. System Dynamics Review, Vol. 27 No. 3, pp. 219–243.

Rybakov, L. (2001). Environment and Complexity of Organizations. Emergence, Vol. 3 No. 4, pp. 83-94.

Sajjad, M., Singh, K., Paik, E. and Ahn, C. (2016), "A Data-Driven Approach for Agent-Based Modeling: Simulating the Dynamics of Family Formation", *Journal of Artificial Societies and Social Simulation*, Vol. 19 No. 1.

Secchi, D. & Seri, R. 2017. Controlling for 'false negatives' in agent-based models: A review of power analysis in organizational research. *Computational and Mathematical Organization Theory*, 23(1), 94–121.

Secchi, D. (2015). A case for agent-based models in organizational behavior and team research. *Team Performance Management*, 21(1/2), 37–50.

Secchi, D. (2021a), "Cognitive attunement in the face of organizational plasticity", *Evidence-based HRM*, Vol. 9 No. 2, pp. 192-208.

Secchi, D. (2021b). *How Do I Develop an Agent-Based Model?*, Edward Elgar Publishing. Dissertation companions.

Secchi, D. and Cowley, S. (2018), "Modeling Organizational Cognition: The Case of Impact Factor", *Journal of Artificial Societies and Social Simulation*, Vol. 21 No. 1.

Secchi, D. and Herath, G. (2019), "Parallel society: Myth or reality? A question for policy makers", *Journal of Simulation*, Vol. 15 No. 1-2, pp. 148-158.

Secchi, D. and Neumann, M. (2016), *Agent-based simulation of organizational behavior*, Springer, Cham.

Seri, R. & Secchi, D. 2017. How many times should one run a computational simulation? In B. Edmonds & R. Meyer (Eds.), *Simulating Social Complexity. A Handbook* (pp. 229–251). Heidelberg: Springer, 2nd edition.

Squazzoni, F. (2012), *Agent-based computational sociology*, Wiley, Chichester.

Ten Broeke, G., van Voorn, G., & Ligtenberg, A. (2016). Which Sensitivity Analysis Method Should I Use for My Agent-Based Model? *Journal of Artificial Societies And Social Simulation*, Vol. *19* No. 1.

Thiele, J. C., Kurth, W., & Grimm, V. (2012). Agent-based modelling: Tools for linking NetLogo and R. *Journal of Artificial Societies and Social Simulation*, Vol. 15 No. 3, p. 8.

Wilensky, U. (1999). *NetLogo. Evanston*, IL: Center for connected learning and computer-based modeling, Northwestern University.

Wood, R., & Bandura, A. (1989). Social Cognitive Theory of Organizational Management. Academy Of Management Review, Vol. 14 No. 3, pp. 361-384.

Chapter 4: Cognitive Fit in Recruitment and group Dynamics[7]

Article 2

Title	Cognitive Fit in Recruitment and group Dynamics
Authors	Gayanga Bandara Herath & Davide Secchi
Research output	Full Conference paper and future Journal article
Status	Accepted
About Journal / Book	Accepted and presented at the Academy of Management (AOM) 2021 and the European Academy of Management (EURAM) 2021. Also planned to be submitted to the Journal of Management Studies.
Note	This article was accepted for both AOM 2021 and EURAM 2021 and received very good feedback. As a result, my supervisor and I (co-author) plan to eventually submit this paper to a leading management journal based on the positive feedback the article received (*Journal of Management Studies)*.

[7] This full article was accepted and presented for Academy of Management (AOM) 2021 and European Academy of Management (EURAM) 2021. Based on the positive feedback that was received from both AOM and ERUAM, my supervisor and I have decided to submit it to a leading management journal.

The contents of *Chapter 4* (pp. 106-148) have been removed due to possible copyright issues, and the full version of the PhD thesis, including this chapter, can be located at the library in a printed version.

Chapter 5: Supplementary fit or Complementary fit in relation to O-C fit[15]

Article 3

Title	Supplementary fit or Complementary fit in relation to O-C fit
Authors	Gayanga Bandara Herath & Davide Secchi
Research output	Book Chapter
Status	Accepted
About Journal / Book	Organizational Cognition: The Theory of Social Organizing, published by Routledge, and Edited by Davide Secchi, Rasmus Gahrn-Andersen & Stephen Cowley.
Note	This chapter was presented to the editors and was accepted as a chapter for the above-mentioned book. The updated O-*C-fit 2.0* model for *Chapter 5* is available through this Link – https://drive.google.com/file/d/1rM1ltsex3QvrsfkdvW-crr4vYRzfudgB/view?usp=sharing

[15] This article was presented to the editors and was accepted as a chapter for the book titled 'Organizational Cognition: The Theory of Social Organizing', published by Routledge, and Edited by Davide Secchi, Rasmus Gahrn-Andersen & Stephen Cowley.

The contents of *Chapter 5* (pp. 150-188) have been removed due to possible copyright issues, and the full version of the PhD thesis, including this chapter, can be located at the library in a printed version.

Chapter 6: Implications and conclusions

This chapter will present a conclusive interpretation of the study conducted in this PhD thesis. In so doing, it will first highlight a summary of the main results with regards to the three research articles presented in this PhD thesis. This will then be followed by a section that underlines insights with regards to the operationalization of the proposed *O-C fit* approach, and subsequently highlight its contributions to literature in the following section. The two final sections will describe some of the limitations of the study and then discuss future work in an attempt to both provide an indication of the drawbacks associated with the study as well as the possible future steps for the *O-C fit* approach.

6.1. Summary of the main results

This study started from the need to transition the current measures found in the Person-Environment fit paradigm, due to structural issues that prevent them from effectively capturing the dynamic nature of organizational life. Thus, through the lens of a distributed e-cognition perspective this study attempted to seek and transcend beyond conventional *P-E fit* measures. In so doing, the essence of the current fit measures found in literature was identified. The literature also showed that current fit measures (a) tend to fall short when taken as explanatory variables of employee performance (Edwards 2008; Edwards 1991; Kristof-Brown *et al.*, 2005; Greguras and Diefendorff, 2009), (b) are inadequate when used in combination with other fit measures (Edwards and Billsberry, 2010), (c) function as static measures that fail to take in to account the dynamic constantly evolving nature of organizations (Boon and Biron, 2016). This study (particularly *article 1* in *Chapter 2*) determined that such issues stem from the inability of current measures to account especially the deeply rooted rudiments of — situational social interactions, temporality and spatial positioning — all of which constitute an individual's ability to maneuver oneself in an organizational environment. By this means, this PhD study intended to operationalize an approach that attempts to address the drawbacks associated with current organizational fit measures.

Accordingly, a new approach to fit was introduced in this study, namely *Organization-Cognition fit* (*O-C fit*). This approach was based on the fact that attuning to team dynamics and the capacity to learn in social contexts (e.g. organizational team environment) are all tasks that need a socially oriented cognitive disposition (Heyes 2012; Secchi 2011; Hutchins 1995; Herath, 2019b). This is why the newly proposed approach utilized a distributed cognitive perspective with a particular emphasis on the social aspects of distributed cognition and was designed to provide a more sophisticated view of fit. The *O-C fit* approach carried an underlying need to act as a dynamic measure that can capture how employees cognitively socially organize in an environment, hence avoiding the aforementioned fundamental issues of current fit measures. Given this need, due to its ability to effectively represent an individual's tendency to both gather and provide various forms of information in a social setting, the study utilized a human trait referred to as *docility* (Secchi and Bardone, 2009). By doing so the practicality of docility was re-introduced in this study (theoretically) for the purpose of being used as a proxy to capture social organizing and one's attunement to team dynamics and in the process allowing to effectively be used as a dynamic approach that is capable of facilitating fluid socially oriented cognitive integration.

In order to test the theoretical bounds of the proposed *O-C fit* approach, an agent-based simulation model was then developed (*O-C fit model*). The model featured not only a component to operationalize *O-C fit* in the form of a R&S approach, but also featured multiple teams working with one another to solve problems in a collaborative team learning environment. In so doing, Article 2 (in *Chapter 4*), attempted to test the bounds of the *Organization-Cognition fit* approach by testing the above-mentioned *O-C fit model*. *Chapter 4* proposed that, given the ability of *docility* to facilitate one's sensitivity to team dynamics as it is tightly linked to *social organizing*, it has the potential to be utilized as a dimension to identify an individual who organizes their social connections in a similar way to a potential team. To put in other words, by doing so one can look for a recruit that "fits" within a team's social structure. Thus, in *Chapter 4* the potential of the *O-C fit* approach was explored on the bounds of its capabilities to find a candidate that shares a similar level of *organizational cognition*. Hence, through the lens of the *P-E fit* literature, this similarity seeking process can be considered as following the *supplementary fit* tradition to fit (Cable and Edwards, 2004; Kristof-Brown *et al.*, 2005; Vogel and Feldman, 2009; Wingreen and Blanton, 2007; Muchinsky and Monahan, 1987).

The results from the above model simulation (from *Chapter 4*), showed that the increase of a potential recruit's level of docility and level of competence increased the chances of attaining better problem-solving performance. Yet, the simulation also showed that extreme levels of these (e.g. extremely high docility or competence) had a negative effect, thus reducing performance. Given this dynamic, the simulation indicated that the *O-C fit* approach is slightly more viable due to its similarity seeking properties, hence avoiding extreme values. On the one hand, due to its similarity seeking nature it manages to avoid extreme levels of *docility*. On the other hand, as a result of this, it improves better utilization of *competence*, hence allowing the *O-C fit* approach to attain better problem-solving performance (opposed to not using *O-C fit*). Apart from the above-mentioned distinct differences between utilizing *O-C fit* and not using *O-C fit*, the simulation disclosed other valuable insights into numerous aspects that may affect the R&S process.

Interestingly, the simulation indicated that the transparency in which information flow in an organizational team has a great impact on attaining improved performance. Where an organization's information flow should be transparent in order to attain the highest number of problems solved. This suggested that promoting information and knowledge transparency (Che *et al.*, 2019) and decreasing power hierarchies (Pfeffer, 1992) may actually allow teams to thrive in their job performance. As a result, these findings are consistent with the work of others that demonstrate the benefit of a more flexible and transparent work environment (Herath *et al.*, 2017; Herath, 2019a; Herath, 2019b; Fioretti and Lomi 2008a; Fioretti and Lomi 2008b). The simulation also suggested that having larger teams and having a greater number of potential jobseekers (applicants looking for a certain job), both tend to improve the chances of getting better problem-solving performance. Moreover, the findings from *Chapter 4* also showed that having a stringent selection criterion (threshold) in terms of *organizational cognition* similarity may be detrimental to achieving improved performance, as it tends to spend more time searching for the suitable candidate. Thus, when employing a *supplementary fit* tradition in the form of *O-C fit*, to attain the highest number of problems solved, a relaxed selection criterion (threshold) may be a better solution, in order to have a perfect balance of congruence and procedural swiftness. In addition, the simulation also revealed the more apparent findings that harder problems do in fact have a detrimental impact on problem solving performance, and that having a larger selection pool increases the swiftness with which a suitable candidate may be found, thereby enhancing problem-solving performance.

The article presented in *Chapter 4* also indicated valuable strategic insight into the utilization of the *O-C fit* approach (as far as the supplementary fit tradition is concerned). Accordingly, the simulation results showed that in certain instances there is a level of risk involved in leveraging certain aspects based on various structural constrains (e.g. information transparency, number of team members, selection threshold). For instance, when dealing with a highly docile recruit and when using a relaxed threshold in larger teams has a risk factor, as it either performs exceptionally or below average. In this case, on the one hand, it means that sometimes more team members could actually result in a classic case of ‘too many cooks spoil the broth’ (Groysberg *et al.* 2010), where for instance they end up over interacting hence delaying the process, but at other times, they may work effectively based on their capabilities. On the other hand, a relaxed threshold could at times end up spending more time to find a recruit therefore delaying the process, but at other times, for instance when a team is already highly docile, this may inflict the need for a stricter threshold to attain optimal performance (assuming that an ample supply of eligible candidates are available). Nevertheless, interestingly enough, the findings from *Chapter 4* show that, despite the small difference, *O-C fit* managed to produce somewhat improved performance in such risky difficult scenarios. Considering the above, these findings indicate that perhaps optimizing each parameter towards its strengths in relation to the *O-C fit* (*supplementary fit*) approach would enable a team to facilitate an environment that fosters improved problem solving; thus, making these insights on *O-C fit* more meaningful when combined with other parameters that positively contribute to this process.

Therefore, as a conclusive assertion from the findings of *Chapter 4*, provided two overarching findings. (1) The utilization of the *O-C fit* approach (*supplementary fit* tradition) may not be a one-size-fits-all kind of solution, but rather it is dependent on situational conditions. (2) Given that *O-C fit* (*supplementary fit* tradition) is used strategically with respect to the possible risks and rewards, it may in fact be considered a viable approach to facilitate fluid socially oriented cognitive integration.

Given the findings from *Chapter 4*, it was apparent that *O-C fit* has the potential to aid conventional R&S processes. Therefore, the third article in *Chapter 5* was intended to further investigate the utility of *O-C fit* and in the process add to our understanding of *O-C fit*. In so doing, *Chapter 5* highlighted that the *O-C fit* approach differs from traditional approaches in that it restructures the conceptualization of cognition used in traditional management, which is dominated by a traditional micro and macro view of organizations (Secchi and Adamsen, 2017). Thus, *Chapter 5* took in to account that organizational outcomes are actively worked on and achieved through *social organizing* (Secchi and Cowley, 2021), hence shedding light on the importance of utilizing *social organizing* to study the meso domain that operates between the classical micro and macro domains (Secchi and Cowley, 2021; Secchi *et al.*, 2021; see *Chapters 1* & *2*).

In doing so, *Chapter 5* emphasized that, at the time of writing, *O-C fit* had only been conceptualized and tested on the basis of the aforementioned *supplementary fit* tradition (*Chapter 4*). As a result, the utility of *O-C fit* had only been explored when a recruiter is seeking for congruence between the team and a potential recruit. Thus *Chapter 5* highlighted that this conception would be most suitable for an environment that is functioning satisfactorily due to its similarity seeking nature. Hence, it did not present a solution to a recruiter who is attempting to fill a void in an environment (e.g., seeking improvement in a poorly performing team). Thus *Chapter 5* took a step in that direction, where it was intended to test the bounds of *O-C fit* with regards to improving the social organizing (meso domain) of a team.

Therefore, the purpose of this chapter was to leverage *docility* by employing a *complementary fit* tradition (Muchinsky and Monahan, 1987; Cable and Edwards, 2004; Guan *et al.*, 2011; Wingreen and Blanton, 2007; Edwards *et al.*, 2006) to *O-C fit*, in which the present social environment will be complemented with a recruit attempting to improve *social organizing*. As a result, this article evaluated how a *complementary fit* tradition to *O-C fit* would contribute to our understanding of its application, and therefore, whether it could be deemed a viable option for R&S in general.

Accordingly, *Chapter 5* followed a similar underlying concept to the operationalization of *Organizational-Cognition fit* in *Chapter 4*, yet it was different in the sense that it focused on the viability of *O-C fit* when seeking change (e.g. improve a poorly performing team), opposed to seeking congruence. In so doing, the original *O-C fit* model was modified to include the *complementary fit* tradition (referred to as the *O-C-fit 2.0 model*). The results of the simulated data from *Chapter 5* indicated that generally the *complementary fit* tradition of the *O-C fit* approach outperformed the other two approaches (i.e. *Supplementary fit* in *Chapter 4* and not using O-C fit) marginally. Interestingly, the results also showed that the variables (1) a new recruits' *docility* and (2) a new recruits' *competence*, (3) a new recruits' *standard deviation of competence*, (4) *problem difficulty*, (5) *team size*, and the (6) *complementary O-C fit* approach itself; all had a statistically significant influence on problem-solving performance even though the beta coefficients were relatively low. Considering this, one could argue that when aiming to achieve the best possible outcome particularly in today's highly competitive business landscapes (Biedenbach and Söderholm 2008; Herath, 2019b), such effects even though relatively low, become more relevant especially when combined with other parameters that positively contribute towards achieving optimal results.

In line with this, further investigation revealed that there were three significant aspects — i.e., having a higher level of *docility* in a new recruit, having a larger *team size*, and having a higher level of *competence* in a new recruit — that all contributed favorably to the effectiveness of *complementary O-C fit* approaches ability to improve a team's problem-solving performance. Most notably, the results suggested that when utilizing the *complimentary O-C fit* approach, having a recruit with a good mix of *competence* and *docility* is critical. For example, the best results were obtained when both *competence* and *docility* were reasonably strong, though one can sometimes compensate for the lack of the other. Considering this, *Chapter 5* also indicated an insightful dynamic, that a recruit's *docility* tends to play a larger part in defining the limits for providing the necessary compensation/balance to enhance a team, thus suggesting that *competence* has a relative co-dependence on *docility* to attain optimal performance.

Chapter 5 also presented findings with regards to when not to use the *complementary fit* tradition to *O-C fit*. Thus, the findings showed that there are two factors that have a negative impact on the utility of *the complementary O-C fit* approach: (a) harder problems have a negative impact on problem-solving performance, and (b) an increase in the distribution of a new hire's *competence* has a negative impact on the two *O-C fit* approaches due to an increase in the potential to achieve extreme results. Importantly, the findings also indicated that when using the *complementary fit* tradition to *O-C fit*, especially in unfavorable conditions (i.e. increase in the distribution of a new recruit’s *competence* combined with a *smaller team* and *harder problems*), it is critical to ensure that the recruit has an adequate level of *competence* to complement and take advantage of the recruit's *docile* nature; in order to achieve the best results.

6.2. What have we learned in relation to the operationalization of O-C fit?

Given the exploration of the *complementary fit* and *supplementary fit* approaches to *O-C fit* in *Chapters 4* and *5*, it is important to understand the benefits of employing *complimentary* or *supplementary fit* in relation to when one is more appropriate/suitable than the other. For this reason, this section will highlight some of the overarching findings of the entire study and will put the two approaches (i.e. *complementary fit* and *supplementary fit*) to *O-C fit* in to perspective with regards to their utility.

As a starting point, it should be acknowledged that *O-C fit* is not intended to be a sole solution to the issues present in *Person-Environment fit* measures within organizations. Rather it is intended to be an approach that would essentially make up for the missing socially-oriented cognitive dynamics of an individual fitting in to a work environment (*Chapter 2*). Therefore, it is more sensible not to recommend the use of *O-C fit* in isolation, but rather to be used in tandem with the other measures. Perhaps, the classification framework presented in *Chapter 2* (Article 1) can be used as a catalyst to better understand the operationalization of fit with regards to (a) the entities being fitted — i.e., social and artefactual, (b) the influence of time and space, and (c) the utility of existing fit measures in relation to the characteristics of distributed cognition. Thus, given the gap that *O-C fit* attempts to fill, it may be sensible to reevaluate the combinatorial approach as attempted before[27] (Jansen and Kristof-Brown, 2006), yet this time by using a more varied understanding of fit (i.e. using the framework presented in *Chapter 2*) and by also including the *O-C fit* approach (as used in *Chapters 4* and *5*). In so doing, it is argued that perhaps these inclusions may go in the direction of alleviating some of the issues that prevented the prior attempts of a combinatorial approach to assessing fit (see *Chapter 2*; Edwards and Billsberry, 2010).

By this means, this study presented two different operationalizations to *O-C fit* (i.e. *complementary fit* and *supplementary fit*), therefore it is important to understand the implications of these findings on the use of one or the other and in the process perhaps gain a better understanding of when one should be used over the other. For this reason, the underlying utility of each approach to *O-C fit* should be considered vital in informing practice. Accordingly, the *supplementary fit* operationalization of *O-C fit*, on the one hand, was intended to facilitate fluid social oriented cognitive integration (see *Chapter 4*). On the other hand, when looking from the eyes of a practitioner or an employer, it could be seen most appropriate when wanting to expand a team that is functioning satisfactorily, hence enabling the need to facilitate a similar environment to which existed prior to recruitment. Therefore, in an exemplary scenario where an employer needs to expand a satisfactorily performing team (e.g. due to increased demands), an employer may opt to find a shared ground between the existing members and the recruit. In such a scenario, the *supplementary fit* tradition to *O-C fit* is more likely to provide a shared level of *organizational cognition* when compared to the *complementary fit* tradition to *O-C fit* and not accounting for *O-C fit* in general. Therefore, one can consider the similarity seeking properties of the *supplementary fit* tradition to *O-C fit* as an advantage of its operationalization

[27]Jansen and Kristof-Brown (2006) suggested a multidimensional model of P-E fit where P-E fit was presented as an embodiment of the interactions of P-V fit, P-J fit, P-O fit, P-G fit, and P-P fit. Yet, Edwards and Billsberry (2010) demonstrated in their study that this model fails to achieve the aim it seeks, indicating that the combinatory approach to fit may be more complex than it seems.

when wanting to obtain fluid integration on the premise of a shared level of *organizational cognition*. Yet as the findings from *Chapter 4* suggested, this may not be a 'plug and play' kind of situation.

This is especially evident, on the one hand, when considering aspects such as the existing level of team docility (*organizational cognition*) and competence. For instance, operationalizing *O-C fit* to follow the *supplementary fit* tradition would most likely be a viable approach when dealing with a team that is already highly docile in nature. This is due to its underlying assumption of wanting to seek similarity on the premise of congruence. In turn it means that this approach would not be a viable approach when dealing with a lower level of team docility. However, in such a scenario where the existing team has a lower level of docility, yet the goal is to still maintain a shared level of *organizational cognition*, then it would be more sensible for HRM practitioners to perhaps consider utilizing a relaxed threshold to seek a slight improvement in docility while still maintaining a shared ground.

On the other hand, as the findings from *Chapter 4* also show there is risk associated with certain combinations of other aspects such as: employing a less strict threshold in a larger team when the docility of the recruit is high. This implies that even though the findings from *Chapter 4* showed *O-C fit* (*supplementary fit*) to have a very slight edge over not having *O-C fit* in such a scenario, striving to attain a best possible outcome may not always be a simple task. Rather other structural aspects such as — information transparency (e.g. could digress the effective utilization of docility and competence in a social environment), the number of team members (e.g. could over complicate the team collaboration process due to increased inputs), the number of job seekers (e.g. low numbers could indicate more time spent seeking for an appropriate candidate) and the number of applicants called in for interviews (e.g. could increase the efficiency in finding an appropriate recruit) — should be factored in to the decision making process of HRM practitioners. This in turn indicates that *O-C fit* (*supplementary fit*) is simply not possible to just be implemented without the consideration of other factors that might have an impact on the ‘fitting’ process. Therefore, its weaknesses and strengths should be factored in relation to other aspects (e.g. selection formalities and goals, team formation, and other structural elements of team dynamics and R&S) that either contribute or hinder its utility.

On the contrary to seeking congruence if the goal of an employer is to change the currently existing dynamic of a team with the hopes of improving its performance, then given the findings from *Chapter 5* the *complementary fit* tradition to *O-C fit* is generally a better approach when compared to the *supplementary fit* tradition and also not using *O-C fit*. This is due to the positive-change seeking operationalization of the *complementary fit* tradition to *O-C fit*, hence providing the advantage of facilitating improvement, as its sole purpose is to capture the currently existing dynamic and complement it with an individual that is capable of improving the existing dynamic. Therefore, in a scenario where a team is performing poorly, an employer (or HRM practitioners) can consider employing the *complementary fit* tradition of *O-C fit* to identify a potential candidate that would go in the direction of possibly improving the current team dynamics.

Interestingly the findings from *Chapter 5* also show that due to the relationship that exists between docility and competence, HRM practitioners can attempt to leverage the research insights presented in *Chapter 5* to attain better problem-solving performance. Accordingly, *Chapter 5* presented three valuable aspects of this relationship that would allow to improve team performance. Firstly, it showed that a fine balance of both docility and competence is needed to attain improved problem-solving performance. Secondly, in connection to this balance required, the study also showed that docility held a more prominent role as competence seemed to be comparatively co-dependent on docility. This indicates that HRM practitioners should indeed be more concerned with how employees work with one another in a social setting and should strive to facilitate improved collaboration in such an environment. Thirdly, the study (in *Chapter 5*) also showed that there is a compensation effect that exists between docility and competence. Again, the study showed the prominence of docility in this relationship as it indicated that docility tends to provide a better compensation effect when compared to competence compensating for docility. Considering these insights, practitioners should clearly be able to see why utilizing the *O-C fit* (*complementary fit*) approach to attract candidates that feature a higher level of docility would be beneficial. In other words, practitioners should aim to utilize an approach such as *O-C fit* (*complementary fit*) to aid in the improvement of team problem-solving performance. For instance, HRM practitioners could perhaps consider spending less on finding a candidate that features an exceled level of competence, instead focus more on a candidate that has a sufficient level of competence accompanied with an elevated level of docility. Alternatively, in a scenario where there is a shortage of prospective candidates that feature a relatively elevated level of docility, then practitioners could aim to spend more resources finding a candidate that has a relatively higher level of competence.

As a final note on the operationalization of the *complementary fit* tradition, similar to the comments regarding the utility of the *supplementary fit* tradition to *O-C fit*, the *complementary fit* tradition to *O-C fit* should also be used in relation to its strengths and weaknesses, because fitting a person into a dynamic environment, as discussed in this study, is a complex task that can be influenced by a variety of factors that can either elevate or hinder the utility of the approach used (see *Chapter 5*). Ultimately this would also imply that the organizational structure in which employees operate hold a great deal of weight in facilitating team performance. This in turn coupled with aspects such as information transparency indicate that perhaps propositions such as seeking organizational plasticity through disorganization (Herath *et al.*, 2017; Herath, 2019a) may head in a promising direction that would allow to facilitate a more flexible environment. This in the process could allow R&S propositions such as *O-C fit* the ability to be leveraged to its strengths while avoiding its weaknesses.

6.3. Contributions to literature

The findings from the three articles in *Chapter 2*, *Chapter 4* and *Chapter 5* not only offered practical implications for HRM practitioners, but in the process also provided theoretical support for Secchi and Bardone's (2009) assertion that the strategic utilization of social resources is altered by one's level of *docility*. These findings also in general support the underlying proposition of this study that research on *Person-Environment fit* should attempt to transcend conventional approaches by moving the focus from static units, processes, or structures at a particular moment in time (Edwards, 2008; Boon and Biron, 2016), to proxies such as *docility* that can apprehend the capacity of an individual to handle dynamic situations. In so doing, this study highlights the importance of an individual's capability to facilitate bidirectional information sharing (i.e. *docility*) to effectively contribute to the *social organizing* of a social environment.

Although one must keep in mind that despite the fact that the findings from the overall study indicated that *docility* is important in promoting the use of social resources and *social organizing*, it can be challenging at times (see *Chapter 4*). In turn indicating that when utilizing the essence of the meso domain to understand the complexity of social organizing, one must not solely depend on *docility*, but also on the consideration of other factors that either support or dismantle the capacity of *docility* in facilitating the effective use of distributed social resources. Thus, being consistent with the work of Herath (2019b), Hutchins (1995), Cowley and Vallée-Tourangeau (2017), in showing that in an ever expanding and competitive advantage seeking world, it is simply not enough to have the necessary skills and competencies, rather the capacity to make use of distributed cognitive resources is especially important.

In turn, these insights provide researchers with an effective approach to measure and capture the complexity of social dynamics in a social environment, and also demonstrate the benefits of utilizing the *social organizing* within the so called 'meso domain' (Secchi and

Cowley, 2021; Secchi *et al.*, 2021) to reimagine the conventional thinking behind management and organizational research. In so doing, through the lens of a distributed cognitive perspective, this study formulated a R&S approach — *Organization-Cognition fit* — in an attempt to contribute and enrich our understanding of identifying a suitable candidate for a highly complex dynamic environment such as an organizational team. Therefore, on the one hand, this study contributes to the *P-E fit* literature by introducing a R&S approach that can be either configured to satisfactorily improve (change) the current dynamic of an organizational team environment (*Chapter 5*) or seek congruence on the premise of facilitating fluid socially oriented cognitive integration (*Chapter 4*). On the other hand, it offers R&S professionals a tool to help them increase their likelihood of acquiring better performance. This study therefore (a) offers not only important insight into two operationalizations of *O-C fit* (i.e. *Supplementary O-C fit* and *Complementary O-C fit*) and their respective goals and performance, but in the process also (b) emphasize the utility of characteristics such as 'docility' and 'social organization' that are alien to present *P-E fit* and R&S measures.

Interestingly, in facilitating these research operations this study also indicated the importance of pre-assessing vital factors such as: (a) finding an appropriate research method and (b) comprehending the complex multifaceted nature of organizational team environments — that must be taken into consideration when attempting to investigate complex socio-cognitive phenomena such as social organizing in the meso domain of organizational processes (Secchi and Cowley, 2021; Secchi *et al.*, 2021). This is especially evident given the findings form this study which show that there are a variety of dynamic elements (e.g. social dynamics, organizational configurations and objectives, team composition and individual human aspects) that collectively contribute in the facilitation of effective team performance.

When considering other factors that may also play a role as far as organizational teams are concerned, the overall findings from this study also touch upon the research conducted on cognitive diversity (Mannix and Neale, 2005; Hong and Page, 2001; Phillips and Loyd, 2006; Mello and Rentsch, 2015; Aggarwal and Woolley, 2018; Aggarwal *et al.*, 2019). Essentially 'cognitive diversity' or as some call it 'team cognitive diversity', follows the notion that having a more heterogeneous cognitive input available to a team would ensure that the team is better equipped for example to effectively solve work tasks (Hong and Page, 2001; Phillips and Loyd, 2006; Woolley *et al.*, 2008; Mello and Rentsch, 2015; Aggarwal and Woolley, 2018; Aggarwal *et al.*, 2019). As such, Aggarwal *et al.* (2019, p. 2) argues that the "benefits of diversity stem from the cognitive inputs it can make available to teams; by influencing the activities of thinking, knowing, and processing information, the team's cognitive inputs are likely to provide it with the essential building blocks to process information that is directly applicable to the tasks they encounter". In this regard, the aforementioned findings from this study, and especially *Chapter 5*, provide interesting insights into the utility of promoting diversity within a team with the purpose of improving team problem solving performance. However, the results from *Chapter 5*, only partially confirm this notion as the advantage of facilitating diversity (through *complementary fit* of *organizational cognition*) only provides a marginal improvement in performance when held on its own. This is to an extent in line with the findings of Homberg and Hong (2013) where they showed that when considering top management teams, the sole effect of diversity did not show a significant influence. Yet as indicated in *Chapters 4* and 5 given certain situational conditions and procedural choices (e.g. based on structural elements such as team formation, selection formalities, pre-existing team composition and R&S objectives) diversity may be strategically utilized to attain better organizational performance.

In line with such facets of team composition, the findings from this study on the one hand, can also perhaps emphasize the importance of studying aspects such as 'collective intelligence' in teams (Woolley *et al.*, 2010; Woolley *et al.*, 2015; Lorscheid and Meyer, 2021). In other words, it may illuminate the benefits of examining a team's ability to integrate and adapt all of its resources and procedures, which could allow for consistent performance across a variety of problem-solving settings that are constantly evolving and demanding in the process (Aggarwal *et al.*, 2019). The work conducted in this study also show a link to the work conducted by Lorscheid and Meyer (2021) on team decision processes and aspects of team collective intelligence, especially as far as —(a) highlighting the importance of socio-cognitive processes in team settings and (b) utilizing agent-based simulation modeling as an effective research method to explore intra team cognitive activity— is concerned. On the other hand, the findings from this study also confirms the notion posed by Weick and Roberts (1993) that cognition is a collective pattern of connections that collectively represent social composition (e.g. in a team), thus in turn shedding light on the utility of using a distributed cognitive perspective for the study of team collaboration and associated team dynamics (Hutchins, 1995; Perry, 2003; Hollan *et al.*, 2000; Cowley and Vallee-Tourangeau, 2013; Herath, 2019b; and *Chapter 2*).

As such, all things considered, this PhD study contributes to the body of literature surrounding and within the intersections of *Person-Environment fit*, Human Resource Management (HRM), Team Dynamics, Occupational Psychology, Distributed-Cognition, Agent-based modeling (ABM) and most prominently literature on Organizational Cognition.

6.4. Limitations of the study

It should be noted that this research study has a few limitations with regards to the design of the agent-based simulation model. To begin with, the research was created for problem-solving oriented teams[28], therefore the implications and conclusions would not be appropriate for non-

[28] Even though not a limitation, it is worth noting that, since the proposed approach works with team dynamics rather than more static characteristics, it is more likely for a new recruit to affect the currently existing dynamic more evidently in a smaller team than in a larger one.

problem-solving oriented team situations (e.g. academic lecturers/professors employed at university departments who are not generally assessed based on their direct problem solving performance but rather on other outputs such as quality of research and teaching).

In addition, with regards to *Chapter 5*, the study only explores the *complementary fit* tradition to the *O-C fit* approach on the basis of the *demands–abilities fit* variant, hence not accounting the *needs-supplies fit* variant (Edwards *et al.*, 2006; Wingreen and Blanton, 2007; Kristof-Brown *et al.*, 2005). This in turn only accounts *complementary fit* from the perspective of an employer which seeks to fulfil the objectives of an organization/team (i.e. *demands–abilities fit*), while not accounting to fulfil the desires of an applicant (i.e. *needs-supplies fit*). Therefore, this can also be considered a limitation of the study, as it only provides an employer-oriented approach to *complementary fit*.

On a final note, one could also argue that since the simulation was built on the assumption that both *O-C fit* approaches had sufficient resources to continue their search until a suitable candidate was discovered (e.g., a profession for which there are a large number of applicants), it may be viewed as a limitation of the study. Particularly as it does not account for circumstances in which a recruit must be chosen from a pool of eligible applicants (e.g. a profession for which there are a scarce number of applicants or simply a team with limited resources, perhaps in a small-to-medium enterprise).

6.5. A way forward

Given the breadth of theory discussed and tested in this PhD study, it is crucial that as a way to move things forward, the validity of these propositions is explored by validating the *O-C fit* ABM model with empirical data. In so doing, research is intended to be carried on according to the plan that was in action prior to the disruption caused by COVID 19 (hence forcing the data collection to be excluded from the PhD study due to national restrictions). Accordingly, such a validation of the *O-C fit* model via empirical data would aid in the improvement of its informativeness (Secchi, 2021). In so doing, model behavior may be mapped onto empirical data (perhaps through data collection from ‘Jobcentre Slagelse’, as previously envisioned prior to COVID 19) in assisting the modeler to determining which parameter values either reproduce the data trend the best or which parameter values are verified by the data trend (Secchi, 2021; David *et al.*, 2017). All in all, a validation procedure such as this would help to reduce the gap between the desired pattern and the model output (Secchi, 2021), hence perhaps attempting to further explore the viability of the *O-C fit* approach.

Subsequent to an empirical validation of the *O-C fit* approach, a promising avenue for future research would then be to perhaps conduct a longitudinal research study that explores the potential long-term effects of employing such an approach. In this regard, an interesting stream of research would be to explore the effect of *O-C fit* with regards to employee retention and turnover (Sheridan, 1992; Mainiero, 1993; Holtom *et al.*, 2008; Mitchell *et al.*, 2001). It would be fruitful to explore how the different operationalizations (i.e. *complementary fit* and *supplementary fit* traditions) may affect the retention and turnover of employees in the long run. For instance, one aspect of this research could be structured to test the effect of a *supplementary fit* tradition to *O-C fit* (which attempts to facilitate social-oriented fluid integration) and its long term impact on employee retention and turnover, while the other aspect could perhaps explore the potential long term impact in facilitating cognitive diversity (Mannix and Neale, 2005; Hong and Page, 2001; Phillips and Loyd, 2006; Mello and Rentsch, 2015; Aggarwal and Woolley, 2018; Aggarwal *et al.*, 2019) of *organizational cognition* through a *complimentary fit* tradition to *O-C fit*. Thus, seeking to explore how such approaches might facilitate their respective purposes in the long run. Such a direction would then provide us with a more comprehensive understanding of how these approaches can be more effectively utilized based on the requirements of recruitment and selection goals. In so doing, this would perhaps provide the opportunity to offer strategic suggestions in connection with the literature on for example team composition (Mathieu *et al.*, 2013a; Mathieu *et al.*, 2013b; Devine and Philips, 2001), team cohesion trajectories (Acton *et al.*, 2019; Bell and Outland, 2017; Bell, 2007) and environment-based team creation — e.g., innovation driven creative problem-solving environments (Somech and Drach-Zahavy, 2011).

In addition to the above-mentioned research trajectories for the *O-C fit* approach, another interesting aspect that could further add to our understanding of its utility would be to operationalize the effect of tangible situational artefacts, and in turn explore its impact on social behavior and problem solving. Hence, in the process expanding the *Organization-cognition fit* approach to account for the fit between, for example, an individual or perhaps a team and a certain tangible artefactual element such as technology/machinery. This would in turn for instance allow us to explore the socio-technical impact of technology on human behavior and social dynamics.

Subsequently, in relation to the previously mentioned limitations of the *O-C fit* model, a way to move things forward would be to expand the model to fulfil these limitations and as a result improve its functionality and utility. Firstly, the current *O-C fit* model can be extended to include different formations of team collaborations, for example, expanding the model to include inter-team collaboration (between teams) could be an interesting avenue. Secondly, in order to complete the entire spectrum of the *complementary fit* tradition to *O-C fit*, the model can also be expanded to include the operationalization of the *needs-supplies fit* variant (Edwards *et al.*, 2006; Wingreen and Blanton, 2007; Kristof-Brown *et al.*, 2005), where the requirements of an applicant would be fulfilled by the team specific attributes. This would in turn allow us to explore how the *O-C fit* approach can be used to aid decision making with regards to selecting appropriate careers/vocations that fit an individual's intrinsic aspirations. As a final extension, the model can also be expanded to feature the ability to select the most suitable recruit from a given pool of applicants to replicate R&S scenarios where either a particular profession has a scarce number of potential candidates, or a scenario were the resources for R&S is limited.

As a final take away, it is believed that the above-mentioned future work in the form of model validation through empirical data, the exploration of longitudinal effects, the inclusion of tangible artefacts to assess resultant human behavior and the inclusion of the above discussed extensions would go in the direction of (a) enabling us to expand our understanding of *O-C fit* and (b) would in turn yield a variety of promising research avenues for future research.

6.6. References

Acton, B., Braun, M. and Foti, R. (2019), "Built for unity: assessing the impact of team composition on team cohesion trajectories", *Journal of Business and Psychology*, Vol. 35 No. 6, pp. 751-766.

Aggarwal, I. and Woolley, A. (2018), "Team Creativity, Cognition, and Cognitive Style Diversity", *Management Science*, Vol. 65 No. 4, pp. 1586-1599.

Aggarwal, I., Woolley, A., Chabris, C. and Malone, T. (2019), "The Impact of Cognitive Style Diversity on Implicit Learning in Teams", *Frontiers in Psychology*, Vol. 10.

Bell, S. T. (2007). Deep-level composition variables as predictors of team performance: A meta-analysis. *Journal of Applied Psychology*, 92, 595–615.

Bell, S. T., & Outland, N. (2017). Team composition over time. In *Team Dynamics Over Time* (Vol. 18, pp. 3–27). UK: Emerald publishing limited.

Biedenbach, T., & Söderholm, A. (2008). The Challenge of Organizing Change in Hypercompetitive Industries: A Literature Review. *Journal Of Change Management*, Vol. *8* No. 2, pp. 123-145.

Boon, C. and Biron, M. (2016), "Temporal issues in person–organization fit, person–job fit and turnover: The role of leader–member exchange", *Human Relations*, Vol. 69 No. 12, pp. 2177-2200.

Cable, D., & Edwards, J. (2004). Complementary and Supplementary Fit: A Theoretical and Empirical Integration. *Journal Of Applied Psychology*, Vol. *89* No. 5, pp. 822-834.

Che, T., Wu, Z., Wang, Y., & Yang, R. (2019). Impacts of knowledge sourcing on employee innovation: the moderating effect of information transparency. *Journal Of Knowledge Management*, Vol. 23 No. 2, pp. 221-239.

Cowley, S. and Vallee-Tourangeau, F. (2013), *Cognition Beyond the Brain*, Springer London, London.

Cowley, S. and Vallée-Tourangeau, F. (2017), *Cognition Beyond the Brain*, Springer International Publishing, Cham, 2nded.

David, N., Fachada, N., & Rosa, A. C. (2017). Verifying and validating simulations. In B. Edmonds & R. Meyer (Eds.), *Simulating Social Complexity* (pp. 173–204). Springer.

Devine, D. J., Philips, J. L. (2001). Do smarter teams do better—A meta-analysis of cognitive ability and team performance. *Small Group Research*, 32: 507-532.

Edwards, J. (1991), "Person-job fit: A conceptual integration, literature review, and methodological cri-tique", in Cooper, C. and Robertson, I.,*International review of industrial and organizational psychology*, Wiley, New York, pp. 283-357.

Edwards, J. (2008), "Person–Environment Fit in Organizations: An Assessment of Theoretical Progress", *The Academy of Management Annals*, Vol. 2 No. 1, pp. 167-230.

Edwards, J. and Billsberry, J. (2010), "Testing a Multidimensional Theory of Person-Environment Fit", *Journal of Managerial Issues*, Vol. 22 No. 4, pp. 476-493.

Edwards, J. R., Cabe, D. M., Williamson, I. O., Lambert, L. S., & Shipp, A. J. (2006). The Phenomenology of Fit: Linking the Person and Environment to the Subjective Experience of Person-Environment Fit. *Journal of Applied Psychology*, Vol. 91 No. 4, pp. 802-827.

Fioretti, G., & Lomi, A. (2008a). An Agent-Based Representation of the Garbage Can Model of Organizational Choice. *Journal Of Artificial Societies And Social Simulation*, Vol. 11 No. 1, p. 1.

Fioretti, G., & Lomi, A. (2008b). The garbage can model of organizational choice: An agent-based reconstruction. *Simulation Modelling Practice And Theory*, Vol. 16 No. 2, pp. 192-217.

Greguras, G. and Diefendorff, J. (2009), "Different fits satisfy different needs: Linking per-son-environment fit to employee commitment and performance using self-determination theo-ry.", *Journal of Applied Psychology*, Vol. 94 No. 2, pp. 465-477.

Groysberg, B., Polzer, J., & Elfenbein, H. (2010). Too Many Cooks Spoil the Broth: How High-Status Individuals Decrease Group Effectiveness. *Organization Science*, Vol. *22* No. 3.

Guan, Y., Deng, H., Risavy, S. D., Bond, M. H., & Li, F. (2011). Supplementary Fit, Complementary Fit, and Work-Related Outcomes: The Role of Self-Construal. *Applied Psychology: An International Review*, Vol. 60 No. 2, pp. 286-310.

Herath, D. (2019a), *Business plasticity through disorganization*, Emerald Group Publishing, Howard House.

Herath, D., Costello, J., & Homberg, F. (2017). Team problem solving and motivation under disorganization – an agent-based modeling approach. *Team Performance Management: An International Journal*, Vol. 23 No. 1/2, pp. 46-65.

Herath, G. (2019b). “Studying the Cognitive Elements of Disorganization”. In D. Herath, *Business Plasticity Through Disorganization*, Howard House: Emerald Group Publishing, pp. 113-116.

Heyes, C. (2012). New thinking: the evolution of human cognition. *Philosophical Transactions Of The Royal Society B: Biological Sciences*, Vol. *367* No. 1599, pp. 2091-2096.

Hollan, J., Hutchins, E. and Kirsh, D. (2000), "Distributed cognition", *ACM Transactions on Computer-Human Interaction*, Vol. 7 No. 2, pp. 174-196.

Holtom, B., Mitchell, T., Lee, T. and Eberly, M. (2008), "Turnover and Retention Research: A Glance at the Past, a Closer Review of the Present, and a Venture into the Future", *Academy of Management Annals*, Vol. 2 No. 1, pp. 231-274.

Homberg, F. and Bui, H. (2013), "Top Management Team Diversity", *Group & Organization Management*, Vol. 38 No. 4, pp. 455-479.

Hong, L. and Page, S. (2001), "Problem Solving by Heterogeneous Agents", *Journal of Economic Theory*, Vol. 97 No. 1, pp. 123-163.

Hutchins, E. (1995), *Cognition in the wild*, MIT Press, Cambridge, Mass.

Jansen, K. and Kristof-Brown, A. (2006), "Toward a Multidimensional Theory of Person-Environment Fit", *Journal of Managerial Issues*, Vol. 18 No. 2, pp. 193-212.

Kristof-brown, A., Zimmerman, R. and Johnson, E. (2005), "Consequences of individuals' fit at work: a meta-analysis of person-job, person-organization, person-group, and person-supervisor fit", *Personnel Psychology*, Vol. 58 No. 2, pp. 281-342.

Lorscheid, I. and Meyer, M. (2021), "Toward a better understanding of team decision processes: combining laboratory experiments with agent-based modeling", *Journal of Business Economics*.

Mainiero, L. (1993), "Is your corporate culture costing you?", *Academy of Management Perspectives*, Vol. 7 No. 4, pp. 84-85.

Mannix, E. and Neale, M. (2005), "What Differences Make a Difference?", *Psychological Science in the Public Interest*, Vol. 6 No. 2, pp. 31-55.

Mathieu, J. E., Tannenbaum, S. I., Donsbach, J. S., Alliger, G. M. (2013a). Achieving optimal team composition for success. In Salas, E. (Ed.), *Developing and enhancing high-performance teams: Evidence-based practices and advice* (pp. 520-551). San Francisco: Jossey-Bass.

Mathieu, J., Tannenbaum, S., Donsbach, J. and Alliger, G. (2013b), "A Review and Integration of Team Composition Models", *Journal of Management*, Vol. 40 No. 1, pp. 130-160.

Mello, A. and Rentsch, J. (2015), "Cognitive Diversity in Teams", *Small Group Research*, Vol. 46 No. 6, pp. 623-658.

Mitchell, T., Holtom, B. and Lee, T. (2001), "How to keep your best employees: Developing an effective retention policy", *Academy of Management Perspectives*, Vol. 15 No. 4, pp. 96-108.

Muchinsky, P. M., & Monahan, C. J. (1987). What is person-environment congruence? Sup-plementary versus complementary models of fit. Journal of Vocational Behavior, Vol. 31 No. 3, pp. 268-277.

Perry, M., O'Hara, K., Spinelli, G. and Sharpe, B. (2003), "The role of space in socially distributed cognition: some issues for cognitive engineering", in *Annual Meeting of the Cognitive Science Society*, available at: https://escholarship.org/uc/item/9b38c1j5.

Pfeffer, J. (1992). *Managing with power: politics and influence in organizations*. Boston, Mass: Harvard Business School Press.

Phillips, K. and Loyd, D. (2006), "When surface and deep-level diversity collide: The effects on dissenting group members", *Organizational Behavior and Human Decision Processes*, Vol. 99 No. 2, pp. 143-160.

Secchi, D. (2011), *Extendable Rationality*, Springer, New York.

Secchi, D. (2021). *How Do I Develop an Agent-Based Model?,* Edward Elgar Publishing. Dissertation companions.

Secchi, D. and Adamsen, B. (2017), "Organizational cognition: A critical perspective on the theory in use", in Cowley, S. and Vallee-Tourangeau, F.,*Cognition Beyond the Brain*, Springer, Heidelberg, pp. 305-331.

Secchi, D. and Bardone, E. (2009), "Super-docility in organizations: an evolutionary model", *International Journal of Organization Theory & Behavior,* Vol. 12 No. 3, pp. 339-379.

Secchi, D., & Cowley, S. J. (2021). Cognition in Organisations: What it Is and how it Works. *European Management Review*, Vol. 18 No. 2, pp. 79-92.

Secchi, D., Gahrn-Andersen, R., & Cowley, S. (2021). Organizational Cognition: The Theory of Social Organizing. Routledge.

Sheridan, J. (1992), "Organizational Culture and Employee Retention", *Academy of Management Journal*, Vol. 35 No. 5, pp. 1036-1056.

Somech, A. and Drach-Zahavy, A. (2011), "Translating Team Creativity to Innovation Implementation", *Journal of Management*, Vol. 39 No. 3, pp. 684-708.

Vogel, R. and Feldman, D. (2009), "Integrating the levels of person-environment fit: The roles of vocational fit and group fit", *Journal of Vocational Behavior*, Vol. 75 No. 1, pp. 68-81.

Weick, K. and Roberts, K. (1993), "Collective Mind in Organizations: Heedful Interrelating on Flight Decks", *Administrative Science Quarterly*, Vol. 38 No. 3, p. 357.

Wingreen, S. and Blanton, J. (2007), A social cognitive interpretation of person-organization fitting: The maintenance and development of professional technical competency, *Human Resource Management*, Vol. 46 No. 4, pp. 631-650.

Woolley, A., Aggarwal, I. and Malone, T. (2015), "Collective Intelligence and Group Performance", *Current Directions in Psychological Science*, Vol. 24 No. 6, pp. 420-424.

Woolley, A., Chabris, C., Pentland, A., Hashmi, N. and Malone, T. (2010), "Evidence for a Collective Intelligence Factor in the Performance of Human Groups", *Science*, Vol. 330 No. 6004, pp. 686-688.

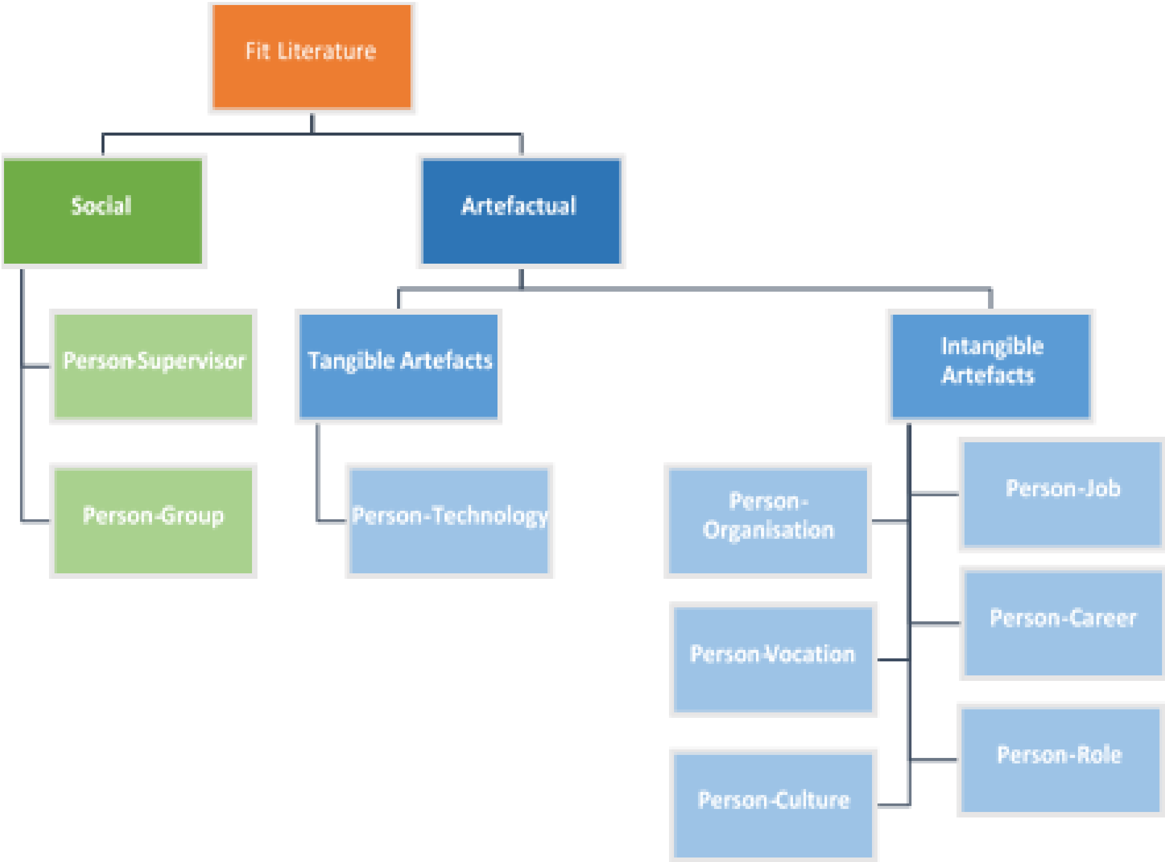
Woolley, A., Gerbasi, M., Chabris, C., Kosslyn, S. and Hackman, J. (2008), "Bringing in the Experts", *Small Group Research*, Vol. 39 No. 3, pp. 352-371.

Appendix

7.1. Appendix – A

Figure 20 shows a visual outlook of how each measure discussed in the paper is broke down according to the proposed DEC oriented framework.

Figure 20: Breakdown of fit measurements used in work environments.



7.2. Appendix – B

7.2.1. The Odd Protocol

The ODD protocol is a standard used by agent-based simulation modelers to describe and structure their models and its related features and procedures. The ODD protocol was first made to accompany ecological models, however in recent times it has been updated to suit social science related models (Grimm *et al.*, 2020). The ODD protocol uses a threefold structure — Overview, Design and Details — which together are designed to systematically explain the model and its behavior (Grimm *et al.*, 2017).

Overview

The following subsections will present the reader with the purpose of this study in relation to the model, then the associated agents and environment will be outlined and finally the process overview of the model will be described.

Purpose and pattern

The general purpose of the O-C Fit model can be labelled as a theoretical exposition (Edmonds *et al.* 2019). Accordingly, the objective of this model is to explore how to hire a new candidate into an already existing team problem solving environment (i.e. work team) and to observe if the proposed theory provides any benefit/decrement to team problem solving. This is done with respect to matching or as we call it fitting and individual based on their attitudes towards docility and their level of competence. The basic idea is that the level of docility in individuals determines how willing they are to extend to their surrounding external environment, which in this case is their associated team members. Additionally, this level of individual docility is further compounded with their unique level of competence to characterize the fact that individuals who are highly docile may not always extend to their surrounding resources to their fullest, simply due to their unique limits of skill and ability. In the associated chapter (*Chapter 4)* we have further explained why we chose docility and its associated preconditions i.e. sense of community (*dpc*), shared team standards (*dpis*), attitudes towards a shared public domain (*dppd*) and overall docility (*dpgen*). The main focus of this model is to explore if looking for a shared pattern of interactions (based on docility) is something that is advisable. We call this *Organizational cognition fit* (*O-C fit*).

Moreover, we are also interested to explore how the dynamics of a team may alter following a recruitment process with particular interest on team problem solving. Therefore, the model essentially features two aspects: a team problem solving aspect and a recruitment and selection (R&S) aspect. The primary purpose of this study is to explore if such an approach can be used to aid organizations to make a successful hiring.

Entities, state variables, and scales

In this model there are 3 types of agents i.e. *applicants*, *team members* and *problems*. The model was designed in a way where the above mentioned three types of agents share the same breed, which is referred to as *teammembers* in the model code. These three types of agents are distinguished based on their different state variable ("attribute") values. On the one hand, the two agent types — *applicants* and *team members* — share similar attributes, however they are distinguished based on their employment status. On the other hand, the agent type *problems* use only one non graphical attribute, i.e. the difficulty of the problem. Keep in mind that since the agent type *problems* is modeled as the same breed in the model code, *problems* also contain the same variables as the other two types of agents (i.e. *applicants* and *team members*), but these values are assigned 0 as they are not of any use to *problems* (and vice versa for the other types of agents, to distinguish one another).

Applicant characteristics

Applicants are agents that are seeking for jobs (job seekers). Once they get a job interview, they will then take part in the recruitment and selection (R&S) process and if chosen they will join their respective work teams and if not will be segmented out to a pool of unfit applicants. Applicants are distributed randomly on the section of the model environment dedicated for the job seekers market.

Team member characteristics

Team members are agents that are a part of a work team. Each team also features a team member that functions as the team leader and has a unique role in the problem-solving process (explained in the coming sections). Team members are made in the setup of the model where the number of teams and the number of team members in the model can be selected. Moreover, if an applicant gets hired then that agent is also considered a team member. Both of the above-mentioned types of agents (i.e. *applicants* and *team members*) are assigned similar attributes as shown below, with the only non-graphical exception being – their employment status (hired or not):

- **Sense of community (DPC) -** Is the agents mean attitude towards the sense of community. It is distributed as follows, ~ N (*mean_dpc*, 0.5) where *mean_dpc* = the number chosen from the *mean_dpc* slider (on the Netlogo interface) ranging from 1 to 3 (with an increment of 0.5) and the 0.5 in the above equation is the standard deviation.
- **Shared standards (DPIS) -** Is the agents mean attitude towards a shared standard of team-based cultural milieu. It is distributed as follows, ~ N (*mean_dpis*, 0.5), where *mean_dpis* = the number chosen from the *mean_dpis* slider (on the Netlogo interface) ranging from 1 to 2 (with an increment of 0.5) and the 0.5 in the above equation is the

standard deviation.

- **Public domain (DPPD) -** Is the agents mean attitude towards the belief of a shared domain. It is distributed as follows, ~ N (*mean_dppd,* 0.5), where *mean_dppd* = the number chosen from the *mean_dppd* slider (on the Netlogo interface) ranging from 1 to 2 (with an increment of 0.5) and the 0.5 in the above equation is the standard deviation.

- **General attitude towards docility (DPGEN)** – This attribute represents the overall attitude of docility or in other words the general attitude of docility. This is a function of dpc, dpis and dppd, where dpgen = (dpc+ dpis + dppd) / 3.

- **Competence -** Is the level of competence (i.e. skills and ability) that is attributed to each agent. It is distributed as follows, ~ N (*mean_comp,* 1), where *mean_comp* = the number chosen from the *mean_comp* slider (on the Netlogo interface) ranging from 2 to 8 (with an increment of 1) and the 1 in the above equation is the standard deviation. Then the distributed values are rounded off, to eliminate decimal points. Moreover, if any value is lower than 0 it will be reassigned to 0.

Problem characteristics

Problems are quite self-explanatory, where these are the work tasks that the team members have to solve as a group. In the model code, *problems* are referred to as information, as it is conceptualized in the model that problems are solved based on a level of information processing, so when the information is understood and processed it is considered completed. *Problems* are distributed on the model environment based on what was chosen at the setup of the model. Moreover, new problems will regenerate when existing problems are solved.

Accordingly, each agent-problem is assigned the following attribute,

- **Difficulty of problem** - Is the difficulty of the *problems*. It is distributed as follows, ~ N (*mean_info-dif,* 1), where *mean_info-dif* = the number chosen from the *mean_info-dif* slider (on the Netlogo interface) ranging from 100 to 120 (with an increment of 10) and 1 in the above equation is the standard deviation. Similar to competence, the distributed values are rounded off, to get rid of decimal points. Moreover, also note that the difficulty of *problems* is distributed from 90 to 119, which mean that if any values go below or above these values (90 <= *mean_info-dif* <= 119) they will be reassigned to their respective margins.

Other setup conditions

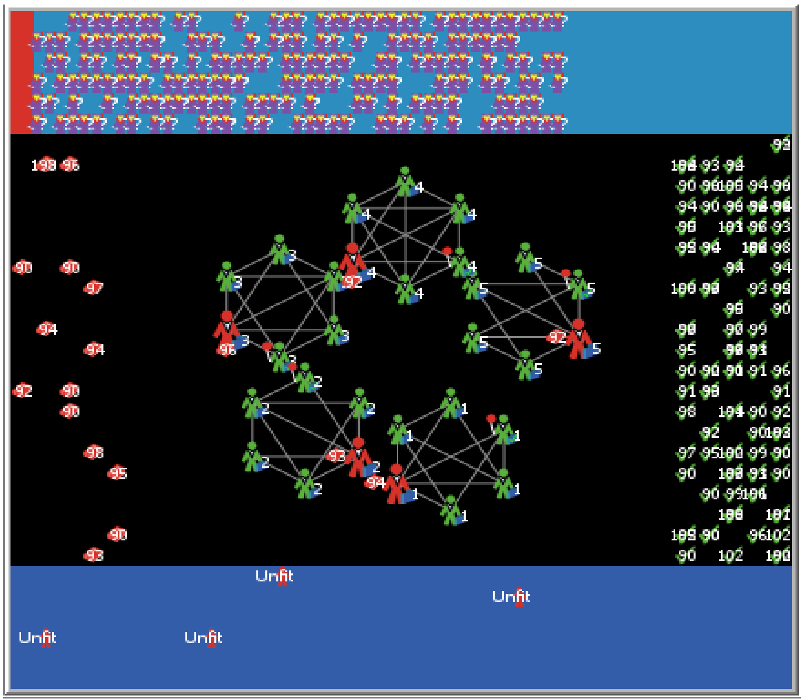
The variables briefly presented below are conditions that need to me specified/selected prior to the start of the model.

- **Number of applicants** – Is the number of jobs seeking *applicants*. It is in relation to the number for all team members regardless of their respective teams, where the number of *applicants* = the number of all *team members* * the number chosen by the *applicant%* slider (ranging from 1 to 20).
- **Number of team members** - The number of *team members* for each team is chosen by the *teammember_size* slider (ranging from 5 to 15, with an increment of 5).
- **Number of teams** - The number of teams is chosen by the team_size slider (ranging from 1 to 5, with an increment of 1).
- **Number of starting problems** - The number of *problems* (referred to as *information* in the model code) can be chosen from the *information* slider (ranging from 5 to 30, with an increment of 5).

- **Docility condition selector (attitude of docility for selection)** - This variable represents which variation from dpc, dpis, dppd and dpgen is selected to be used for the selection process. The desired choice can be selected on the *DP-Selector* chooser.
- **Selection approach** - This parameter is used to select which approach should be used to select the recruits (closest = O-C fit (supplementary fit, hence seeking similarity), random = non-O-C-fit). The desired choice can be selected on the *selection_type* chooser.
- **The selection cap** - Is the number of *applicants* that will be called in for the selection process for each team, in other words it determines the *applicants* considered for the selection pool. The selection cap can be chosen from the slider *selection_cap* (ranging from 2 to 10, with an increment of 1).
- **The selection threshold** – Is the threshold used to indicate how close the new group value with the new recruit should be, in comparison to the existing group value (i.e. 0.01 = 1%, 0.05 = 5% and 0.1 = 10%). The selection threshold can be chosen from the slider *selection_threshold* (ranging from 0.01 to 1, with an increment of 0.01).
- **Information transparency** - This variable determines the type of information transparency in the teams. If set to 'on' all available problem information is presented to the *team members*, and if set to 'off' only portion of the information is passed on to the team (e.g. access controlled information). In the setup of the model either 'on' or 'off' should be selected on the *information_transparency?* switch.

Space and temporal scales

Figure 21: Model environment



The model is designed in a way which shows the observer both aspects in a single environment. The team problem solving aspect in the simulation is as follow. On the very left of the Observer in Netlogo (Wilensky, 1999) are the *problems* (problem space), while on the very right of the Observer are the completed *problems* (solved space). When the simulation is performed, each team will be randomly assigned one of the available *problems*. Then the teams will go through several procedures and collectively solve the problem at hand. Once a team completes an assigned problem then it will be passed on to the right of the black rectangle in the Observer environment to indicate that it is solved. As soon as a team has completed a problem, they will be assigned another one and the same team problem solving process will continue. The environment also re-introduces new *problems* once some are solved and this process also continues till the simulation ends.

The procedures of the recruitment aspect can be visually identified if the environment is observed from the top to bottom. The lighter blue rectangle shown on the top of the environment in the Observer mimics the applicant market (applicants seeking for jobs), which also features waves of new applicants that emerge from time to time. The idea here is to mimic real-world dynamics in the sense that they represent applicants who are at a different stage of their job seeking process. In turn this represents that some applicants have more time to find a job than others. This is simulated in the model by randomly locating applicants within this light blue rectangle and by moving them to their left at a slow pace and once they approach the red line on the far left, they are no longer considered as looking for jobs. The single team member on each team with a red balloon represents the newly hired recruit ('Fit'), while the red agents in the darker blue rectangle at the bottom of the environment represent the applicants who were called in for the selection process but didn't get selected, hence label 'Unfit' (located in the 'Unfit' space).

Regarding the temporality of the model, we decided to observe how the model would perform in one years' time. Therefore, the model was designed to assume one tick in Netlogo (Wilensky, 1999) as one hour, meaning that one work week would add up to 40 hours, and that one work year would sum up to 1920 hours or ticks in relation to Netlogo.

Process overview and scheduling

Since the goal of the model is to uncover the utility of the proposed selection approach (O-C fit), the model had to first record how the teams functioned without the new recruit, in order to compare and contrast what the new recruit provided to their respective teams. Therefore, the above 1920 work hours (one work year/1920 Netlogo ticks) were segmented into two parts, where it was assumed that roughly halfway into the model around the 960 work hours mark (Netlogo ticks) is when the new recruit is selected.

The model as previously explained has two aspects and they are interdependent. The team members will solve problems with the help of their work colleagues (indicated through work-links) in their respective teams. Once the R&S process finishes the teams will each have a new recruit, on the one hand this will change the dynamic of the team and will also affect the team problem solving efficiency. On the other hand, the R&S process is also highly dependent on the current attitudes of the existing team members. Thus, explaining the interdependency mentioned above.

Team problem solving

The agents as mentioned before use their attitudes of docility in relation with their level of competence to work with other work colleagues. This is done in a number of steps, where firstly the leaders of a team will extract/learn information from the problem at hand. This process is dependent on the leader's unique attributes and is done by breaking the learned information into two different components, first being the information that is handed to the leader with regards to the task where no added learning is required to comprehend (referred to as *main_chunk* in the model code), the second component signifies the understanding and formalizing ability of the leader to prepare the problem (referred to as *my_chunk* in the model code), which is dependent on the leaders docility and competence. This process is outlined below.

Note: *random_float* reports a random floating-point number greater than or equal to 0 but strictly less than 0.15 in this case.

Leader [

main_chunk = (0.7 + random_float 0.15) OF the difficulty of the problem

my_chunk = dpc of self · competence of self

Final learned amount = main_chunk + my_chunk

]

Thereafter, if information transparency is '*on*' the team members will also do the same as the leader, but if it is '*off*' then the team members will learn information from what the leader has already learned, as shown below.

If information transparency is set to ‘on’,

Team member [

main_chunk = (0.7 + random_float 0.15) OF the difficulty of the problem

my_chunk = dpc of self · competence of self

Final learned amount = main_chunk +my_chunk

]

If information transparency is set to ‘off’,

Team member [

main_chunk = (0.7 + random_float 0.15) OF the final learned amount of leader

my_chunk = dpc of self · competence of self

Final learned amount= main_chunk +my_chunk

]

Then once this step is done the team members will look for potential other work colleagues that have learned more than them self and will also check if these colleagues also meet the other conditions as explained below.

Condition 1: A member should not have a low attitude of docility, where the members attitude of docility should be higher than the models assigned mean attitude of docility minus (–) the standard deviation (which is set to 0.5 in this case). The rational is that these members are not docile enough to attain information from others to solve and understand the problem.

Condition 2: A member looking to work and attain information from others should have direct work links to other members of the team, for them to seek information.

Condition 3: At least one of the directly connect work linked member should have more information (learned more) with regards to the problem.

Condition 4: Finally, if all the above conditions are met then the member can work with other members but is only allowed to interact (work) with them a unique number of times. This number is determined by the competence of the member.

Once this is done, and if such a colleague is found then the team member will work with this colleague based on its (self) competence and docility. Docility here is used to determine how much a member can learn (extract information from others), while competence is used as the number of times a member can work with another colleague (e.g. if competence is 4 then the member can work 4 times with another colleague as long as the aforementioned conditions are still met).

It should also be mentioned that the problem solving in this model is based on the idea that solving a problem is essentially learning as much information as possible, where the difficulty of the problem is considered as the required information learned level needed to finish the problem. Therefore, the goal of the *team members* is to attain the highest possible level of information learned as they can.

Finally, after all the members have finished working with one another they will pass on what they have done to their leader and the leader will use this work to finalize and complete the problem at hand. This is done by the leader attaining the mean average of its team's final amount of information learned. Then the leader will finalize the problem by completing the remainder of the required information learned level needed. Here the leader will try to reach the value which is assigned to the difficulty of the problem at hand (e.g. if the difficulty of the problem at hand is 105 and if the final team information learned is 95, then the remainder is what the leader will finalize). The idea is that the leader will check up on everything and finalize the problem and this time here is considered as the processing time for finalizing the problem. This is achieved in the model by implementing a count-up function, where in regard to the above example, it will count up from 95 till 105. This assures that a team that has attained a higher average level of information learned will require less processing time (as they should).

Recruitment & selection (R&S)

The recruitment and selection process as mentioned before is set to start at the halfway mark of the total Netlogo number of ticks assigned to each model run, in other words it starts when the Netlogo ticks reaches 960. Firstly, each team leader will call in the chosen applicants for the interview process. The number of applicants called in depends on the *selection_cap* slider, where the number selected on the above slider will represent the number of applicants considered for the R&S process for each team. Importantly, when the model is initially set up each team will calculate the *rWG* (agreement statistic used for aggregation and justification, see footnote 29) for their respective teams. The *rWG* agreement statistic is used to obtain the aggregated attitudes of docility (i.e. dpc, dpis & dppd) and the general attitude of docility (dpgen) for each team.

Accordingly, once the potential applicants are brought in for the interviews, each potential applicant's attitudes of docility will be obtained and combined with their respective team and a *new-rWG* will be generated for each potential applicant. This means that each interviewed applicant will have their own unique *new-rWG* value in relation to their respective teams. Once this is done with all the potential applicants for each of their respective teams, on the one hand if the *selection_type* chooser is set to 'Closest', then from the interviewed applicants the applicants that are within selection threshold will be identified. Thereafter from these identified applicants the applicant with the lowest absolute integer value of the difference will be selected (most *supplementary fit* candidate). The lowest values signify the applicant that provides the closest match (*new-rWG*) to the previous *rWG* of the team[30]. The above selected applicant will then be considered hired to its respective team. The above elaborated 'Closest' approach

---

[29] James, L., Demaree, R., & Wolf, G. (1984). Estimating within-group interrater reliability with and without response bias. Journal Of Applied Psychology, 69(1), 85-98.

[30] In the case of seeking *complementary fit* as operationalized in *Chapter 5*, then the *new-rWG* with the highest aggregate value will be selected to identify the recruit that provides the most improvement (opposed to seeking similarity as seen in *Chapter 4*). In the *O-C-fit 2.0* model this improvement seeking process (for *Chapter 5*) will take place if the selection_type chooser is set to 'Furthest_Improve'.

signifies that the O-C-fit approach (as discussed in *Chapter 4*) was used in the R&S process.

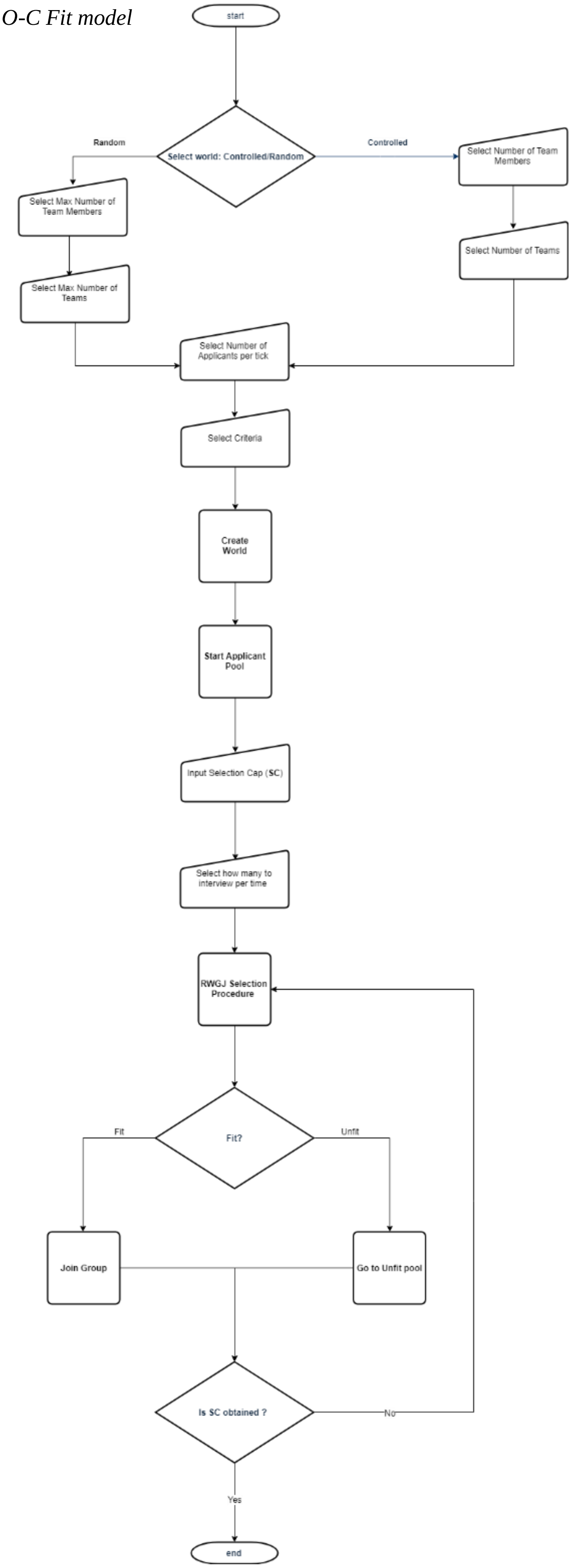
On the other hand, if the *selection_type* chooser is set to ‘Random’, then 1 random applicant from the interviewed applicants will be selected and hired on to its respective team. This in turn means that the O-C fit approach was not considered in the R&S process. The above-mentioned selection approaches are represented below in pseudo-code.

```
Leaders [
    IF 'selection_type' is set to 'Closest'
        THEN [
            applicants that are within the threshold will be selected
                FROM the applicants that are within threshold
                  [
                    the lowest absolute integer value of the difference will be selected
                  ]
                ]
    IF 'selection_type' is set to 'Random'
        THEN [
                 1 random potential applicant will be selected
                ]
          ]
```

To give the reader a better understanding of how the model works, a flowchart of the model is provided in the following page (see Figure 22).

========================
See next page for Figure 22
========================

Figure 22: Flow chart for the O-C Fit model



Design Concepts

Emergence

This model produces results that represent the number of problems solved in relation to its different model options/ behavior approaches. Therefore, these results are an emergent property that is a result of the dynamics imposed by the agents and their behavior with the model's various options and behavior approaches. Thus, it is difficult to pinpoint the exact proportion to which each agent and behavior contributes exactly. However, statistically examining the different emergent property based on the different approaches of agent behavior and various model options is possible and is used as the premise to which the analysis of this study is conducted.

Moreover, in this model it is hard to distinguish model results that are imposed by the model itself as the model is designed in a way that is affected and relative to the other components of the model. Hence, each change in a model parameter will have an effect to the model results in some way which makes it difficult to consider the model results as relatively imposed by the model rules. The rational for such a design is that organizations and its embedded organizational behavior is a complex adaptive system that is interconnected to all its associated components in one way or another (Edmonds and Meyer, 2017).

Adaption

The O-C fit model as explained before, adapts team *rWG* values based on the objective of the selection approach. The process of obtaining *new-rWG*s of each applicant and finding the applicant that is the closest and also within the selection threshold can be considered as adaptation to a certain extent. This process of interviewing and obtaining new-*rWG*s of applicants is done till an applicant with a *new-rWG* is found that is within the assigned selection threshold. If multiple agents that satisfy these conditions are found, then as explained before the one with the lowest difference is selected to attain the most congruent new-rWG to the initial rWG. On the one hand the process of being selected and moved into the team (based on the above) can also be seen as adaption. On the other hand, the process of being rejected (classified unfit) and moved to the unfit zone can too be seen as adaption.

Learning and problems solving in this model is also designed as an adaptive mechanism, where based on the previously mentioned conditions, if they are met the team members will learn from one another (work/interact) and in the process increase their percentage of the current problem solved/information learned (e.g. from 65% to maybe 73%). This behavior can be regarded as direct object seeking where the team members constantly look to see if the related conditions are met so that they can interact and learn from other viable team members. The direct object seeking is done till an equilibrium is met where the team members cannot fulfil the associated conditions.

Objectives

a) The objective of the *team members* and the team as a whole is to attain the highest number of information learned with regards to solving the current problem at hand. This objective measure is driven by the docility and the competence of the *team members* in connection with the associated conditions as pointed out before. This objective measure is calculated by the increase of the value for the information learned variable, where the team goal is to attain the highest possible value for the information learned variable (towards its max value). This required max value is seen as the objective measure for each problem and this objective measure (max value) is the difficulty of the problem at hand (the unique difficulty value for each problem). The rationale for this is that a more difficult problem will need more time to solve.

b) The objective of the R&S process is to hire the closest fit potential applicant from the pool of interviewed *applicants* as long as the new hire is within the threshold set in the model. This objective is driven by the attitudes of docility of the *team members* in connection with the *rWG* agreement statistic and the attitudes of docility of the job *applicants* chosen for the interviews. The rationale for this is that the attitudes of each team member will coincide with their associated *team members* which in turn will represent the team's combined attitudes of docility. This objective measure is calculated based on the *rWG* and *new-rWG* agreement statistic as shown below.

Within-group docility level (*rWG*) : $$\frac{\left(y\left(1-\frac{var(x)}{4}\right)\right)}{y\left(1-\frac{var(x)}{4}\right)+\left(\frac{var(x)}{4}\right)}$$

Where, based on Secchi (2011) and Secchi and Bardone (2009) y represents the dimensions of docility, accordingly y = 4 (for dpc), 2 (for dpis), 3 (for dppd) and 9 (for dpgen). In addition, var(x) = variance of the dimension of docility in team.

New within-group docility level (*new-rWG*) : $$\frac{\left(y\left(1-\frac{var(z)}{4}\right)\right)}{y\left(1-\frac{var(z)}{4}\right)+\left(\frac{var(z)}{4}\right)}$$

Where, again based on Secchi (2011) and Secchi and Bardone (2009) y represents the dimensions of docility, accordingly y = 4 (for dpc), 2 (for dpis), 3 (for dppd) and 9 (for dpgen). In addition, $var(z)$ = new variance of the dimension of docility in team (with new recruit).

Learning

This model does not include any learning apart from the *team members* ability to learn from one another to solve the current team problem at hand.

Prediction

This model does not feature any direct forms of prediction. However, one could say that the model includes some form of implicit prediction where the model assumes that the selection approach will have some effect on the problem solving of the teams.

Sensing

The sensing in the model is explained more thoroughly in the previous section. In brief there is sensing used in this model in the problem-solving component. In the model the leaders will first sense the difficulty of the problem (variable name: *information_diff*) at hand and then will extract information from the problem based on their own levels of docility and competence. As explained before this model has implemented a problem-solving mechanism based on information learned, where the goal is to extract as much information from the problem as possible (based on the competence and docility of each individual member, including the leaders) and to reach the value associated with the difficulty of the problem. Given the above, in other words the leader first senses the difficulty of the problem at hand and keeps that in mind (saved to variable *information_diff*) and then the leader senses the problem yet again in order to understand and formalize the problem at hand. This is done by the leader sensing a certain portion of the problem (saved in variable *main_chunk*) and then it is combined with the unique sensing of the problem which is based on the leader's competence and docility (saved in variable *my_chunk*). Then these two components will be combined and saved in the variable *information_consumed*. This process is done to add uncertainty into the sensing mechanism.

Then the team members will start sensing from the leader. This process is conditioned by the *information_transparency?* switch in the model, where if the switch is set to 'on' then the same sensing process done by the leader will be done by the team members. Here the team members will extract from the variable *information_diff* of the leader. However, if the switch is set to 'off' then the team members will do the same sensing process as the leader but will sense from the variable *information_consumed* of the leader instead of the variable *information_diff*.

Moreover, there is also sensing implemented when the team members work with one another. As explained before, there are four conditions that should be met for the team members to work with other team members to solve the problem at hand. As a result, the team members keep constantly sensing to see if these conditions are met so that they can work with other team members that fulfil these conditions.

Condition 1: the sensing is done to check if the level of docility is higher than the mean – standard deviation of docility to make sure that agents with very low levels of docility cannot work with other members. Variables used - *dpc*.

Condition 2: the sensing here is to check if the agents (i.e. *team members*) that want to work with other agents (i.e. other *team members*) have work links established with other *team members*.

Conditions 3: the sensing here is to check if the member who wants to work with other members have other connected members that have more information learned than itself. Variables used - *information_consumed* of linked team members, *information_consumed* of the member wanting to work with others.

Condition 4: here the sensing is to check how many times one could work with other members who fulfil the conditions. The sensing for this condition is based on the *competence* of the team member who wants to work with other members, where the team member can work with others only a limited number of times, which is based on their own competence (e.g. if competence is 4 for this agent, then the agent can work with other members who fulfil the conditions only 4 times).

Interaction

The O-C fit model features the following forms of interactions as listed below.

a) Interaction between *applicants* called in for interviews and the team leaders. Here the *applicants* will be called in for interviews by the team leaders. This interaction can be classified a direct form of interaction.

b) Interestingly, the above interaction is followed by a mediated interaction by the associated teams in which the *applicants* are interviewed for. This is because the R&S process involves the comparison of an agreement statistic between the existing team and the existing team combined with the potential applicant. Therefore, it can be classified a mediated interaction.

c) The team leaders interact with the *problems* to be solved, at the beginning and the end of the problem-solving process. Firstly, the leader will be assigned a problem and will interact with the problem to learn about it. Secondly the leader will finalize the problem in order to consider it finished, this interaction is further affected as explained in the next point.

d) Teams interact with the interactions between the *problems* at hand and the team leaders, this can be classified as a mediated interaction because the team problem-solving process indirectly affects how a leader interacts with a problem at hand. In other word the problem-solving done as a team affects how much formalizing and processing is required by the leader to consider the problem at hand finished.

e) The interaction between the team leaders and the individual *team members* can also be seen as a direct interaction between the two parties. This is when each team member extracts problem information from the leader before attempting to work with other *team members*.

f) Regarding the above, another interaction is among the *team members* themselves, where they share and exchange information in order to finish the problem at hand. This is a case in which there is a combination of both direct interaction and mediated interactions. The direct interaction is when a team member exchanges information with another team member.

g) The above-mentioned mediated interaction is in regard to the previously elaborated conditions that should be met for the team members to be able to work with one another. Here the conditional status of other *team members* mediates the direct interactions between the team members.

Stochasticity

The O-C fit model features a handful of pseudorandom numbers to introduce stochasticity to the model. These random components are characterized below:

- The locations of the agents are segmented to their respective areas in the model. However, these agents appear on random locations within the allocated respective areas. Therefor these random locations can be considered stochastic.
- The model also features several distributions as specified below, to create variability between the agents.
    - Sense of community (DPC)
    - Shared standards (DPIS)
    - Public domain (DPPD)
    - Competence
    - Problem difficulty
- The interactions where the team members work with one another can also be considered stochastic to a certain extent, as it is not predictable due to the constant change in the conditional status of each agent, which in turns determines if they can work with other members or not.

Collectives

The O-C fit model as explained before feature three variations of agents i.e., *applicants*, *team members* (including the leaders), *problems*. However, these are not necessarily considered as collectives but rather 3 different types of agents.

In regard to collectives, there are two different collectives that can be identified in the model. Firstly, the *applicants* that are chosen for the interviews can be recognized as a collective because they are viewed by the leaders as their own pool of potential applicants. These collectives can be further categorized as emerging collectives as they are randomly chosen by the leaders of the teams. Accordingly, their individual characteristics (i.e. attitudes of docility) have an impact on the selection process where an applicant is ultimately chosen. In other words, these agents "are affected by the characteristics of the aggregations"[31], therefore these agents can be considered as collectives for their respective teams (Grimm *et al.*, 2020).

Secondly within the context of problem solving, the *team members* themselves can be considered as collectives because they affect and get affected by one another within their respective teams. Each of these teams are considered their own social group with their own human networks that affect one another. Moreover, these collectives can be considered as explicitly represented collectives because they are setup based on the model setup inputs given by the researcher, where each team is segregated based on their state variable *label*.

Observation

There is no empirical data collected for this topic area as this is the first of its kind in regard to the tested theory of O-C fit. Therefore, the model results cannot be compared with other empirical observations yet. Accordingly, this comparison is extremely interesting and is considered as future work with regards to this study.

In regard to what model outputs were observed, the key outputs from the model used for the analysis is highlighted below.

- Number of problems solved. This allows us to compare and contrast how the approaces used in this study affected these numbers.
- In order to get an understanding of how and what the various values for specific variables were when the above-mentioned problems solved output was achieved, the mean dpc, mean dpis, mean dppd, mean dpgen and mean competence of teams were also recorded.
- The number of hired applicants and unfit applicants that were rejected by the teams were also counted. This was done to make sure that the model performed as it was expected to perform

[31] Supplementary file S1 to: Grimm, V. et al. (2020) 'The ODD Protocol for Describing Agent-Based and Other Simulation Models: A Second Update to Improve Clarity, Replication, and Structural Realism' Journal of Artificial Societies and Social Simulation 23 (2) 7: http://jasss.soc.surrey.ac.uk/23/2/7.html [10.18564/jasss.4259]

in terms of the model dynamics and to consider/not-consider certain results that might have had errors/issues (when using statistical analysis).

- Finally, the mean and standard deviation of the dpgen attitudes and the mean and standard deviation of the competence of the newly hired applicants were also recorded and observed to have a clear picture of the attributes of these newly hired applicants.

Details

Initialization

At the beginning of the model setup or in other words before running the simulation, the model parameter settings shown below should be assigned. These represent the settings that can be controlled to customize the bounds of the agent-based simulation model. *keep in mind the steps represented below are copied from the 'HOW TO USE IT' section in the NetLogo 'info' tab for the model file '*OC_fit_model_full.nlogo'*.

Select settings as follows,

1) Select the intensity of the number of applicants – '*applicant%*'

2) Assign a value to modify the mean of each dimension of docility (*mean_dpc*, *mean_dpis, mean_dppd*). Then assign the competence - *mean_comp* and information difficulty - *mean_info-dif*.

3) Select the attitude you want to test (*DPC, DPIS, DPPD* or *DPGEN*).

4) Select the number of applicants for interview, for each team - '*selection_cap*'.

5) Select the selection threshold to specify how close the chosen applicant should be – '*selection_threshold*'

6) Select the selection type (*Closest*, *Furthest* or *Random*)

7) Specify the starting number of *problems*– '*information*'

8) Option A) Select the max parameter for the number of teams and the number of members per team, in order to create a random variation from the above.

Option B) Select the number of teams and the number of members per team from the ‘Choose World’.

9) Select if the teams should be, information transparent or not – ‘*information_transparency?’*

10) Finally, press either the ‘*Setup Custom*’ button or the ‘*Setup Random*’ button and then press the ‘*GO*’ button.

Input data

Other than the basic rationalities for when to start the R&S process and how to create the job seeker market (see previous sections), this model does not use any input data, as the model serves purely as a theoretical exploration. In light of this, the rationalities for why and how the values represented in the model were parametrized and rendered through computational means is provided below.

Rationalities behind parametrization

- *Docility* – Docility was model based on the preconditional rudiments which are deemed to be in place for docility to have an effect (Secchi 2011; Secchi and Bardone 2009). Therefore, the general docility (DPGEN) of an individual was factored in as a function of the preconditions (i.e. *Sense of community*, *Shared standards*, *Public domain*) as mentioned in *Chapter 4*. Accordingly, the model was parameterized in a manner where the mean of the distribution of docility can be maneuvered so that the effect of having a generally high level of docility in a population of agents can be compared to when dealing with a population that features a generally low level of docility. The idea here was that this would provide with a better representation of how the proposed approach may function in relation to different population differences in docility.

- *Competence* - This parameter was modeled to exemplify competence based on the need to represent a differentiation on increased values and lower values while making sure that every individual had at least some level of competence (even though very low at times). The idea was to theoretically assess what impact a higher level of competence would have when compared to a lower level of competence.

- *Difficulty of problem* - Similar to the conceptualization of competence, the difficulty of problems too was model in order to assess what effect variability (spectrum of values ranging from low to high) would have on other aspects of the model. In so doing, it was also made sure that there is always some form of difficulty (very low at least) associated with a problem so that its effect was taken into consideration in regard to the problem-solving component of the model.

- *Number of team members* - The number of team members was developed in the model in a flexible manner where it allows to set a variety of values. Yet the values that were used for the simulation was chosen on the premise of identifying what effect the proposed approach would have on a smaller team when compared to a larger one. For this reason, it was made sure that the values used for the sensitivity analysis (of the model) was at least twice the size of the previous values, so that there is a distinguishable difference between the team member sizes.

- *Number of teams* – The number of teams in the simulation was developed again in a manner that could be adjusted. Yet since the simulation was meant to be run a several number of times the number of teams used didn't make a significant difference in the process. For this reason, the number was decided as 5 teams so that there was still enough variability between the teams per each run of the simulation.

- *Number of applicants* - Similar to the previous rationalities for assessing the variability of parameters in relation to its effect on the proposed R&S approach, the number of applicants was too modelled in a way where the difference between a low number of applicants can be assessed in relation to a higher number of applicants. In so doing, the values used for the sensitivity analysis (SA) was based on assessing what an increase of value could do to the model dynamics.

- *Number of starting problems* - The number of starting problems used for the SA was again chosen based on the need to seek variability so that its impact on other parts of the model dynamics could be assessed. In so doing, a smaller number and a larger number of 'starting number of problems' were selected to see if this change in variability would have an impact on the model dynamics. In addition, in order to provide an even plain field, when choosing the initial values for the SA it was decided that there should be at least 3 times more problems than the number of teams, so that a lack of problems would not cause a team to perform poorly when compared to others.

- *Selection cap* - The values used for the SA with regards to the selection cap was based on the premise of wanting to see how the number of applicants called in for selection would have an impact on the proposed approach. Accordingly, a smaller number, a moderately higher number and a larger number of applicants per each round was selected for the selection pool.

- *Selection threshold* - The values used for the selection threshold (for the SA) was based on the need to determine the impact the variability in strictness of such a threshold would have on the proposed approach and the whole selection process as a whole. Thus, in order to satisfy these needs of this inquiry, thresholds that are very strict, mildly strict and moderately relaxed were chosen for the SA.

- *Docility condition selector* - Since the primary focus was on the general impact of docility in capturing the *organizational cognition* of a team opposed to the individual impacts of its preconditions, DPGEN (which represents the collective encapsulation of its preconditions) was chosen as the proxy in which was used by O-C fit to capture the relevant levels of *organizational cognition* in the associated R&S process.

- *Selection approach* - The values used for this parameter was quite straightforward, essentially the O-C fit approach (both variants as used in *Chapters 4* and *5*) and the base approach which did not utilize an O-C fit approach, were all considered in order to examine their respective impact on team problem solving and the recruitment and selection process as a whole.

- *Information transparency* - Given that the information flow of a team problem-solving environment (e.g. organization) could have an influence on the working of a team (Che *et al.* 2019; Stevenson and Gilly 1993; Pfeffer 1992), it made sense to also inquire if such an influence would have a drastic impact on the proposed O-C fit approach and the R&S process as a whole. Accordingly, when parametrizing this, the rationality behind this process was very straight forward as well, especially because the goal was to test what impact transparency in the information flow might have on the model dynamics. Therefore, (a) an option to have information transparency in the team information flow and (b) another option to not have information transparency in the team information flow, were both included as parameter options for the model in order to assess the impact they might have on the overall model dynamics.

Submodels

The O-C fit model is not based on any other prior models as all the concepts and functionality are developed in direct relation to this study and its relevant literature and concepts. Therefore, no other models were used in the development of this model and it was developed from scratch for the purpose of this study. Moreover, the model features two primary sub-models (i.e. Team problem solving, Recruitment & selection) as discussed in detail in section 'Process overview and scheduling'. Therefore, in this section I will not reiterate the same information provided in that section but rather I will highlight the modeling blocks associated with each of the above-mentioned sub models.

Modeling Blocks for the Team problem solving sub-model:

- *go_problem_solve* – This block works as a primary block that connects all the other blocks related to problem solving. Therefore, in other words all the blocks below that are associated with team problem solving are called from this block.
    - *pick_work_group* – This block creates at link between a leader and a problem.
    - *leader_consume* – As explained in section 'Process overview and scheduling', the leader extracts information from the problem in this block.
    - *step1_consume* – Here the *team members* learn information regarding the problem from the leader.

- *step2_consume* – This block initiates the team problem solving component of the model, where the *team members* work with one another as explained in detail in section ‘Process overview and scheduling’.
- update_team_info_consumed – Here once the team problem solving has come to an equilibrium, the mean (average) of all the team members information learned (in regard to problem solving) will be taken and passed on to the leader.
- solve_task – Here as explained in the ‘Process overview and scheduling’ section, the leader will process and finalize the problem at hand based on the work done by its respective team.
    - *solved* – This block moves the solved problems to its designated area and marks them as solved.
- refill_info – This block refills the problem space with new problems when the existing problems are solved to have a constant supply of new problems.

Modeling Blocks for the Recruitment & selection sub-model:

- *selection2* – This block works as the primary block that connects all things related to the R&S process. In other words, the blocks represented below are called from the *selection2* block.
    - *move_applicants* – This block moves the applicants in the job applicant market.
    - *call_for_interview* – Here a link is established from a leader to an applicant, from the job applicant market for the interview process.
        - inform_newcomers – Assigning the team label to the interviewees and preparing (making the current team rWG statistic visible to the

interviewees in order to create a new rWG) them for the R&S process.

- *interview1* – Here the *new-rWG* is calculated for each interviewee. This process is referred to as the interview process.
- *selection_2* – Finally this block initiates the selection process, where a suitable candidate is selected if all the criteria is met (see section Process overview and scheduling).
    - *update_location* – This block re-updates and relocates the location of the newly hired applicant, so that it joins the team.
    - *reject* – This block marks the rejected applicants as unfit and moves them to the unfit applicant space.

- *refill_applicants* – This block refills new *applicants* if the number of available *applicants* gets low, this resembles new *applicants* joining the job market (e.g. a new batch of graduates entering the job market).

7.2.2. Calibration of the O-C Fit Model

This section will explain how the exact parameter settings used in this chapter were obtained. Accordingly, although the model's operation is relatively straightforward, the multitude of parameter combinations can produce varying results at times, therefore model calibration is needed to identify more suitable parameter values (Edmonds and Meyer, 2017). Hence, the *O-C fit* model was calibrated by executing a sensitivity analysis (Ten Broeke *et al.*, 2016). The modeling of the *O-C fit* model (*OC_fit_model*) along with the sensitivity analysis was performed by using *Netlogo 6.1.1*. In order to compute the highly resource demanding SA calculations for the *O-C fit* model, the HPC *Abacus 2.0* Danish supercomputer (located in university of Southern Denmark, Odense) was used.

Sensitivity Analysis (SA)

It should be mentioned that a pilot SA was performed prior to the SA mentioned here, so the SA presented here is derived from the prior SA. The initial SA revealed that the variability of the chosen parameter values did not vary much to explain what was happening as the R^2 was extremely low. Therefore, the variability of the parameters was increased, as were a few parameter tweaks such as making the mean *dpc* maneuverable opposed to the standard deviation, making *competence* a maneuverable parameter opposed to being non-maneuverable, and making the *problem difficulty* and the *number of problems* maneuverable. As a result of this effort, the SA represented below explains upwards of 75% (R^2), meaning that the new parameter values are more meaningful and have fixed the prior issues.

The model file used is 'OC_fit_model.nlogo' and it was used to run 6 computational experiments on Abacus 2.0; with some even taking around 48 HPC hours to complete, the experiments in total added up to 81 gigabytes with each experiment (cal_1.csv, cal_2.csv, cal_3.csv, cal_4.csv, cal_5.csv, cal_6.csv) generating files roughly around 13.5 gigabytes. Please refer to the 'Info' tab of the model file 'OC_fit_model.nlogo' in NetLogo and *Chapter 4* for additional details with regards to the features of the model.

Table IX. Parameter notations, values, and description

Parameter	Not.	Values	SA	Description
Sense of community	*mean_dpc*	*~ N (mean_dpc, 0.5)* *mean_dpc = [0, 1.5, 3]*	*[0, 1.5]*	The mean attitude towards sense of community.
Shared standards	*mean_dpis*	*~ N (1.5, 0.5)*	-	The mean attitude towards shared standards of team-based cultural milieu.

Table IX. Parameter notations, values, and description

Public domain	*mean_dppd*	*~ N (1.5, 0.5*	-	The mean attitude towards the notion of a shared domain.
Competence	*mean_com*	$\begin{cases} 0 \leq \text{mean\_com} \\ \dfrac{\sim \text{N (mean\_com, } 1)}{1} \end{cases} \in \text{N}$	same	This is the level of competence that is attributes to each agent. Its distributed values are then rounded off, to eliminate decimal points. Also, If any value is lower than 0 it will be reassigned to 0.
Difficulty of problem	*mean_info_dif*	$\begin{cases} 90 \leq \text{mean\_info\_dif} \leq 119 \\ \dfrac{\sim \text{N (mean\_info\_dif, } 5)}{1} \end{cases} \in \text{N}$	same	The difficulty of the problem/task. It's distributed from 90 to 119, if any values go above or below these values they will be reassigned to their respective margins.
Number of team member	*teammember_size*	*[5, 10, 15]*	*[5, 15]*	The number of team members in each work team.
Number of teams	*team_size*	*5*	-	The number of teams in the simulation.
Number of applicants	*applicant%*	*[1, 10, 20]*	*[1, 10]*	This parameter is used to increase and decrease the starting number of applicants in the applicant market.
Number of starting problems/tasks	*information*	*[15, 30]*	30	The number of starting problems/tasks in the simulation.
Selection cap	*selection_cap*	*[2, 5, 10]*	*[2, 5]*	The number of applicants that will be considered for the section pool.
Selection threshold	*selection_threshold*	*[0.01, 0.1, 0.25]*	*[0.01, 0.25]*	The threshold used to determine how close to the existing group value, the new group value with the potential recruit should be (0.01 = 1%, 0.05 = 5% and 0.1 = 10%).
Docility condition selector	*DP-Selector*	*[DPGEN]*	-	This parameter is used to select which variation from dpc, dpis, dppd and dpgen is used for the selection process.
Selection approach	*selection_type*	*[Closest, Random, Furthest]*	*[Closest, Random,]*	This parameter is used to select which approach should be used to select the recruits (closest = OC fit, random = non-O-C fit).
Information transparency	*info_trans*	*[on, off]*	same	This represents the level of information transparency in the teams. If it is set as 'on' then all available problem information is passed to the

Table IX. Parameter notations, values, and description

				team, and if it is set as 'off' only access controlled information is passed on to the team.

Outcome Variable

The outcome variable used for the SA of the model is the number of problems solved. This was chosen as the outcome variable due to the study's interest in knowing if hiring an *O-C fit* individual will result in more problems solved when compared to not hiring one.

Accordingly, as a first step, a power analysis (PA) was conducted to determine the number of runs required for the SA (Secchi and Seri 2017; Seri and Secchi 2017). The PA revealed that 87480 runs were required. As a result of the high number of runs required for the sensitivity analysis, the experiment was further broken in to 6 experiments; so that a) it provided simultaneous processing, and b) provided an added layer of protection in case of computational errors and other unforeseen issues. Appropriately, the experiments were broken based on the parameter values 'no-app' and 'info-trans' (see Table X).

Table X: Experimental log scheme

exp#	Selection type	Mean problem difficulty	Selection cap	Mean competence	Selection threshold	No. of Team members	Mean dpc	No. of Problems	No. of applicants	Information transparency
Cal 1	Clo/Ran/Fur	[94, 115]	[2, 5, 10]	[2, 5, 8]	[0.01, 0.1, 0.25]	[5, 10, 15]	[0, 1.5, 3]	[15, 30]	1	on
Cal 2	Clo/Ran/Fur	[94, 115]	[2, 5, 10]	[2, 5, 8]	[0.01, 0.1, 0.25]	[5, 10, 15]	[0, 1.5, 3]	[15, 30]	1	off
Cal 3	Clo/Ran/Fur	[94, 115]	[2, 5, 10]	[2, 5, 8]	[0.01, 0.1, 0.25]	[5, 10, 15]	[0, 1.5, 3]	[15, 30]	10	on
Cal 4	Clo/Ran/Fur	[94, 115]	[2, 5, 10]	[2, 5, 8]	[0.01, 0.1, 0.25]	[5, 10, 15]	[0, 1.5, 3]	[15, 30]	10	off
Cal 5	Clo/Ran/Fur	[94, 115]	[2, 5,	[2, 5, 8]	[0.01, 0.1,	[5, 10, 15]	[0, 1.5,	[15, 30]	20	on

			10]		0.25]		3]			
Cal 6	Clo/Ran/Fur	[94, 115]	[2, 5, 10]	[2, 5, 8]	[0.01, 0.1, 0.25]	[5, 10, 15]	[0, 1.5, 3]	[15, 30]	20	off

Based on the above indicated experiments, Table XI shows the completion rate for each simulation per experiment. It shows that only a very few runs did not complete till the last time step (referred to as a tick in Netlogo), meaning that it was acceptable and ready for the SA.

Table XI: Runs completion table

Exp.	Applicants	Information Transparency	No. of Runs (required 14580)	Missing runs at final step (1919)
Cal.1	**1**	**on**	**14577**	**3**
Cal.2	**1**	**off**	**14572**	**8**
Cal.3	**10**	**on**	**14580**	**0**
Cal.4	**10**	**off**	**14580**	**0**
Cal.5	**20**	**on**	**14580**	**0**
Cal.6	**20**	**off**	**14580**	**0**

The sensitivity analysis was conducted per each parameter. In other words, the sensitivity for each parameter across each experiment was analyzed to identify if the same effect is carried on from one to another. Accordingly, the sensitivity analysis was conducted for the 9 parameters excluding the selection-type as it is the parameter which determines if either *O-C fit* is used or not.

Mean problem difficulty (Mean_info_dif)

In Table XII it can been seen that there is an average of around 0.043 difference in the R^2 between the two parameter values for all the experiments. More importantly further investigation also shows that when the *mean problem difficulty* changes from 94 to 115 the beta coefficient seems to vary to an extent where the signs change from one to another (e.g. in Cal 1 the selection type ‘Closest’ changes from – 0.187 to 0.261). These findings indicate that both the parameter variations do in fact provide valuable insight and has an interesting effect on the simulation. Therefore, it was decided to keep both variations for the full-scale study.

Table XII: Sensitivity analysis for the parameter mean problem difficulty

Dependent variable: **No. of Problems solved,** SA variable: **Mean problem difficulty**												
	Cal 1		**Cal 2**		**Cal 3**		**Cal 4**		**Cal 5**		**Cal 6**	
	= 94	= 115	= 94	= 115	= 94	= 115	= 94	= 115	= 94	= 115	= 94	= 115
Closest	-0.187***	0.261***	-0.130**	0.001	-0.229***	0.351***	-0.358***	-0.484***	0.313***	0.105**	-0.574***	-0.323***
	(0.058)	(0.043)	(0.058)	(0.042)	(0.058)	(0.042)	(0.058)	(0.042)	(0.057)	(0.042)	(0.057)	(0.042)
Furthest	-0.043	-0.037	-1.496***	-0.002	-0.584***	-0.106**	0.124**	-0.722***	-0.012	-0.166***	-0.412***	-0.566***
	(0.058)	(0.043)	(0.058)	(0.042)	(0.058)	(0.042)	(0.058)	(0.042)	(0.057)	(0.042)	(0.057)	(0.042)
Mean dpc	56.010***	37.182***	55.954***	36.930***	55.934***	36.977***	55.959***	37.019***	55.925***	37.024***	55.992***	36.949***
	(0.019)	(0.014)	(0.019)	(0.014)	(0.019)	(0.014)	(0.019)	(0.014)	(0.019)	(0.014)	(0.019)	(0.014)
Selection cap	-0.002	0.123***	0.031***	0.050***	0.111***	0.009*	0.039***	0.053***	0.138***	-0.034***	0.033***	0.034***
	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)
Mean competence	34.345***	22.403***	34.262***	22.355***	34.467***	22.324***	34.389***	22.329***	34.172***	22.404***	34.240***	22.294***
	(0.010)	(0.007)	(0.010)	(0.007)	(0.010)	(0.007)	(0.010)	(0.007)	(0.010)	(0.007)	(0.010)	(0.007)
Selection threshold	1.021***	0.919***	-0.493**	-0.175	-1.378***	0.715***	-0.773***	3.484***	1.773***	-1.460***	0.783***	-0.312*
	(0.238)	(0.175)	(0.239)	(0.174)	(0.238)	(0.174)	(0.238)	(0.174)	(0.236)	(0.173)	(0.237)	(0.174)
No. of team members	1.558***	1.340***	1.620***	1.300***	1.617***	1.277***	1.530***	1.348***	1.656***	1.366***	1.529***	1.358***
	(0.006)	(0.004)	(0.006)	(0.004)	(0.006)	(0.004)	(0.006)	(0.004)	(0.006)	(0.004)	(0.006)	(0.004)
No. of Problems	0.001	0.002	0.037***	-0.005**	-0.023***	0.012***	0.001	-0.051***	-0.004	0.022***	-0.013***	-0.006***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
Observations	6,951,786	6,954,671	6,949,837	6,957,535	6,984,397	6,987,275	6,990,153	6,989,193	6,991,110	6,990,151	6,990,151	6,988,234
R^2	0.754	0.709	0.752	0.711	0.754	0.709	0.753	0.711	0.754	0.712	0.754	0.709
R^2 Difference	0.045		0.041		0.045		0.042		0.042		0.045	
Note: *p**p***p<0.01												

Selection cap (selection_cap)

When looking at Table XIII it can been seen that there is barely any difference in the R^2 between the 3 parameters across all the experiments. However, upon further investigation of the beta coefficients of the parameter variations across all the experiments, it can be seen that all parameter variations in fact have an interesting effect on the simulation (e.g. when looking at the selection type ‘Closest’ it can be seen that throughout the experiments, each parameter variation seems to change the + or – signs of the beta coefficients). Therefore, given the fact that there is barely any difference in the R^2 but due to the interesting insight of the beta coefficients it was decided to only exclude one parameter value and keep *selection cap* 2 and 5 for the full-scale simulation.

Table XIII: Sensitivity analysis for parameter selection cap

Dependent variable: **groups_solved**, SA variable: **selection_cap**																		
	Cal 1			**Cal 2**			**Cal 3**			**Cal 4**			**Cal 5**			**Cal 6**		
	=2	= 5	= 10	=2	= 5	= 10	=2	= 5	= 10	= 2	= 5	= 10	=2	= 5	= 10	=2	= 5	= 10
Closest	0.373***	-0.079	-0.247***	-0.580***	0.394***	0.196***	-0.110*	-0.366***	0.656***	-0.377***	-0.644***	-0.221***	-0.143**	0.753***	0.016	-1.016***	0.415***	-0.727***
	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.065)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)
Furthest	0.009	-0.292***	0.290***	-1.144***	-1.051***	0.039	-1.104***	-0.119*	0.100	-0.144**	-0.317***	-0.428***	-0.457***	0.256***	-0.055	-0.845***	0.029	-0.642***
	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.065)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)
Mean problem difficulty	-3.431***	-3.440***	-3.389***	-3.418***	-3.391***	-3.403***	-3.422***	-3.424***	-3.460***	-3.435***	-3.422***	-3.427***	-3.374***	-3.422***	-3.442***	-3.418***	-3.424***	-3.418***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Mean dpc	46.499***	46.221***	47.078***	46.559***	46.305***	46.419***	46.403***	46.374***	46.578***	46.327***	46.562***	46.574***	46.381***	46.584***	46.458***	46.225***	46.607***	46.586***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Mean compe-tence	28.352***	28.318***	28.453***	28.311***	28.207***	28.379***	28.342***	28.364***	28.473***	28.277***	28.373***	28.424***	28.225***	28.302***	28.339***	28.176***	28.380***	28.249***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Selection threshold	3.032***	-0.444	0.474*	-1.490***	-2.170***	2.286***	-0.447	0.065	-0.443	1.189***	1.172***	1.621***	-0.543**	-0.322	1.294***	-0.734***	0.872***	0.551**

	(0.273)	(0.271)	(0.274)	(0.274)	(0.271)	(0.271)	(0.272)	(0.271)	(0.273)	(0.271)	(0.272)	(0.273)	(0.269)	(0.271)	(0.270)	(0.271)	(0.271)	(0.272)
No. of team members	1.434***	1.465***	1.433***	1.508***	1.484***	1.367***	1.441***	1.463***	1.438***	1.469***	1.402***	1.443***	1.568***	1.484***	1.482***	1.484***	1.429***	1.415***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
No of Problems	0.009***	0.004	-0.011***	-0.003	0.027***	0.029***	-0.025***	0.009**	0.001	-0.003	-0.026***	-0.045***	-0.0003	-0.010***	0.037***	-0.047***	0.0001	0.019***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observa-tions	4,627,160	4,638,692	4,640,605	4,626,161	4,633,893	4,647,318	4,654,987	4,657,863	4,658,822	4,658,824	4,660,741	4,659,781	4,660,740	4,660,740	4,659,781	4,658,823	4,659,781	4,659,781
R^2	0.736	0.738	0.736	0.734	0.737	0.737	0.735	0.737	0.736	0.736	0.736	0.735	0.738	0.736	0.738	0.735	0.737	0.735
Note: *p**p***p<0.01																		

Mean competence (mean_comp)

Table XIV shows that the R^2 for all three parameters seem to vary and that this pattern is repeated for all the experiments. Accordingly, *mean competence* = 2 seemed to have the highest R^2 throughout all the experiments, while *mean competence* = 8 had the second highest and *mean competence* = 5 had the lowest. Given these finding it was decided to select the two extreme values of the R^2 [*mean competence* = 2, 5] for the full-scale simulation.

Table XIV: Sensitivity analysis for parameter Mean competence

Dependent variable: **groups_solved**, SA variable: **mean_comp**																		
	Cal 1			**Cal 2**			**Cal 3**			**Cal 4**			**Cal 5**			**Cal 6**		
	=2	= 5	= 8	=2	= 5	= 8	=2	= 5	= 8	= 2	= 5	= 8	=2	= 5	= 8	=2	= 5	= 8
Closest	-0.085***	-0.183***	0.063	0.081***	-0.373***	0.354***	0.028***	-0.389***	0.511***	0.046***	0.350***	-1.604***	-0.089***	0.153***	0.563***	-0.202***	-0.213***	-0.931***
	(0.008)	(0.024)	(0.050)	(0.008)	(0.024)	(0.050)	(0.008)	(0.023)	(0.050)	(0.007)	(0.024)	(0.050)	(0.008)	(0.024)	(0.050)	(0.008)	(0.024)	(0.050)
Furthest	-0.248***	0.074***	0.213***	0.055***	-0.687***	-1.333***	-0.128***	-0.389***	-0.562***	0.110***	0.366***	-1.392***	0.083***	-0.050**	-0.296***	-0.055***	-0.157***	-1.195***
	(0.008)	(0.024)	(0.050)	(0.008)	(0.024)	(0.050)	(0.008)	(0.023)	(0.050)	(0.007)	(0.024)	(0.050)	(0.008)	(0.024)	(0.050)	(0.008)	(0.024)	(0.050)
mean_info_dif	-1.806***	-3.243***	-5.210***	-1.805***	-3.220***	-5.202***	-1.804***	-3.230***	-5.274***	-1.809***	-3.223***	-5.253***	-1.817***	-3.242***	-5.179***	-1.805***	-3.239***	-5.216***
	(0.0003)	(0.001)	(0.002)	(0.0003)	(0.001)	(0.002)	(0.0003)	(0.001)	(0.002)	(0.0003)	(0.001)	(0.002)	(0.0003)	(0.001)	(0.002)	(0.0003)	(0.001)	(0.002)
mean_dpc	8.221***	35.927***	95.782***	8.153***	35.654***	95.396***	8.192***	35.545***	95.649***	8.140***	35.777***	95.529***	8.231***	35.912***	95.280***	8.120***	35.917***	95.387***
	(0.003)	(0.008)	(0.017)	(0.003)	(0.008)	(0.017)	(0.003)	(0.008)	(0.017)	(0.002)	(0.008)	(0.017)	(0.003)	(0.008)	(0.017)	(0.003)	(0.008)	(0.017)

selection_cap	-0.010***	0.082***	0.073***	0.017***	-0.037***	0.122***	0.005***	0.072***	0.102***	-0.014***	0.052***	0.095***	0.014***	0.048***	0.094***	0.033***	-0.005*	0.068***
	(0.001)	(0.003)	(0.006)	(0.001)	(0.003)	(0.006)	(0.001)	(0.003)	(0.006)	(0.001)	(0.003)	(0.006)	(0.001)	(0.003)	(0.006)	(0.001)	(0.003)	(0.006)
selec-tion_threshold	1.092***	3.303***	-2.271***	1.498***	-0.540***	-2.994***	-0.216***	-0.127	-0.766***	0.852***	0.777***	2.205***	-0.471***	1.306***	-0.383*	0.871***	0.232**	-0.435**
	(0.031)	(0.100)	(0.206)	(0.031)	(0.097)	(0.207)	(0.031)	(0.097)	(0.206)	(0.031)	(0.099)	(0.207)	(0.031)	(0.100)	(0.204)	(0.031)	(0.100)	(0.206)
teammem-ber_size	0.484***	1.119***	2.670***	0.464***	1.198***	2.690***	0.459***	1.217***	2.672***	0.486***	1.194***	2.634***	0.471***	1.207***	2.856***	0.480***	1.131***	2.713***
	(0.001)	(0.002)	(0.005)	(0.001)	(0.002)	(0.005)	(0.001)	(0.002)	(0.005)	(0.001)	(0.002)	(0.005)	(0.001)	(0.002)	(0.005)	(0.001)	(0.002)	(0.005)
information	-0.002***	0.012***	-0.010***	-0.002***	0.009***	0.036***	0.008***	0.009***	-0.039***	-0.004***	-0.020***	-0.048***	0.003***	-0.005***	0.029***	-0.002***	0.012***	-0.039***
	(0.0004)	(0.001)	(0.003)	(0.0004)	(0.001)	(0.003)	(0.0004)	(0.001)	(0.003)	(0.0004)	(0.001)	(0.003)	(0.0004)	(0.001)	(0.003)	(0.0004)	(0.001)	(0.003)
Observations	4,637,724	4,636,764	4,631,969	4,630,980	4,639,637	4,636,755	4,659,781	4,654,027	4,657,864	4,659,782	4,658,822	4,660,742	4,660,740	4,660,740	4,659,781	4,659,782	4,658,822	4,659,781
R^2	0.912	0.873	0.897	0.912	0.877	0.895	0.913	0.878	0.897	0.914	0.874	0.896	0.913	0.873	0.898	0.913	0.873	0.897

Note: *p**p***p<0.01

Selection threshold (selection_threshold)

Table XV indicates that there is no significant change in the R^2 between the parameters across all the experiments. However, when looking at the beta coefficients of the parameter variations across all the experiments, the parameter variations in fact have an interesting effect on the simulation (e.g. each parameter variation of variable selection type ‘Closest’ seem to at times change the signs of the beta coefficients from + or – to the other). Given the low R^2, yet the interesting beta coefficients, it was decided to exclude *selection threshold* = 0.1 and use the two extreme values (*selection threshold* = 0.01. 0.25) for the full-scale simulation.

Table XV: Sensitivity analysis for parameter Selection threshold

Dependent variable: **groups_solved**, SA variable: **selection threshold**																		
	Cal 1			**Cal 2**			**Cal 3**			**Cal 4**			**Cal 5**			**Cal 6**		
	=0.01	= 0.1	= 0.25	=0.01	= 0.1	= 0.25	=0.01	= 0.1	= 0.25	=0.01	= 0.1	= 0.25	=0.01	= 0.1	= 0.25	=0.01	= 0.1	= 0.25
Closest	-1.117***	-0.352***	1.517***	-0.656***	0.400***	0.266***	0.549***	0.014	-0.381***	-0.462***	-0.615***	-0.165**	0.250***	0.369***	0.007	-0.357***	0.074	-1.044***
	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.065)	(0.066)	(0.065)	(0.066)	(0.066)	(0.066)
Furthest	-0.391***	0.147**	0.255***	-1.619***	0.141**	-0.674***	-0.074	-0.361***	-0.687***	-0.919***	-0.352***	0.383***	-0.249***	-0.104	0.097	-0.466***	-0.458***	-0.535***
	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.065)	(0.066)	(0.065)	(0.066)	(0.066)	(0.066)

mean_info_dif	-3.422***	-3.417***	-3.422***	-3.401***	-3.412***	-3.399***	-3.458***	-3.418***	-3.430***	-3.450***	-3.433***	-3.401***	-3.389***	-3.419***	-3.429***	-3.403***	-3.436***	-3.420***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
mean_dpc	46.633***	46.610***	46.555***	46.506***	46.385***	46.392***	46.359***	46.478***	46.518***	46.482***	46.271***	46.710***	46.423***	46.651***	46.349***	46.500***	46.387***	46.531***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
selection_cap	0.091***	0.046***	0.023***	-0.010	0.013	0.110***	0.100***	0.001	0.082***	0.040***	0.042***	0.054***	0.001	0.088***	0.068***	-0.037***	0.120***	0.018**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
mean_comp	28.404***	28.423***	28.299***	28.360***	28.376***	28.161***	28.388***	28.405***	28.387***	28.410***	28.234***	28.430***	28.263***	28.327***	28.276***	28.279***	28.294***	28.233***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
teammember_size	1.301***	1.451***	1.581***	1.454***	1.486***	1.419***	1.377***	1.492***	1.473***	1.401***	1.514***	1.399***	1.536***	1.478***	1.520***	1.430***	1.459***	1.439***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
information	0.027***	-0.022***	-0.003	0.019***	0.023***	0.011***	-0.010***	0.001	-0.006*	-0.009***	-0.011***	-0.053***	-0.014***	0.028***	0.013***	-0.034***	-0.007*	0.012***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	4,639,644	4,631,972	4,634,841	4,633,871	4,634,833	4,638,668	4,656,905	4,654,986	4,659,781	4,659,782	4,659,781	4,659,783	4,659,781	4,660,740	4,660,740	4,660,740	4,656,905	4,660,740
R^2	0.735	0.737	0.737	0.735	0.736	0.736	0.736	0.735	0.736	0.737	0.735	0.736	0.737	0.737	0.738	0.736	0.737	0.735

Note: $^{*}p^{**}p^{***}p<0.01$

No. of team members (teammember_size)

When looking at Table XVI it can been seen that the difference in R^2 is relatively small. Yet again the beta coefficients of the parameter variations across all the experiments seems to show interesting variations across all parameter values (e.g. the variable *selection threshold* in cal 2 seems to change from -1.093 (at member size 5) to 2.788 (at member size 10) and then to -2.889 (at member size 15, which seems to represent a ‘U’ shaped curve). However, given the small difference in R^2 it was decided to exclude the *No. of team members* = 10 and keep the two extremes (*No. of team members* = 5, 15) for the full-scale simulation.

Table XVI: Sensitivity analysis for parameter No. of team members

Dependent variable: **groups_solved**, SA variable: **teammember-size**																		
	Cal 1			**Cal 2**			**Cal 3**			**Cal 4**			**Cal 5**			**Cal 6**		
	=5	= 10	= 15	=5	= 10	= 15	=5	= 10	= 15	=5	= 10	= 15	=5	= 10	= 15	=5	= 10	= 15
Closest	0.374***	-0.189***	-0.151**	0.121**	0.083	-0.183***	-0.545***	0.090	0.637***	-1.131***	0.052	-0.157**	0.462***	0.025	0.139**	-1.308***	-0.103	0.089
	(0.062)	(0.067)	(0.068)	(0.061)	(0.067)	(0.067)	(0.061)	(0.067)	(0.068)	(0.061)	(0.067)	(0.068)	(0.061)	(0.067)	(0.068)	(0.061)	(0.067)	(0.068)
Furthest	-0.173***	-0.803***	0.984***	-1.438***	-0.415***	-0.297***	-0.846***	-0.426***	0.142**	-0.566***	0.056	-0.383***	0.110*	-0.068	-0.294***	-1.180***	-0.413***	0.126*
	(0.062)	(0.067)	(0.068)	(0.061)	(0.068)	(0.067)	(0.061)	(0.067)	(0.068)	(0.061)	(0.067)	(0.068)	(0.061)	(0.067)	(0.068)	(0.061)	(0.067)	(0.068)
mean_info_dif	-3.349***	-3.460***	-3.452***	-3.320***	-3.428***	-3.467***	-3.337***	-3.469***	-3.499***	-3.371***	-3.457***	-3.456***	-3.318***	-3.463***	-3.456***	-3.365***	-3.449***	-3.446***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
mean_dpc	42.695***	48.105***	48.981***	42.532***	48.192***	48.538***	42.435***	48.156***	48.760***	42.597***	47.967***	48.895***	42.587***	47.922***	48.914***	42.556***	48.015***	48.845***
	(0.021)	(0.022)	(0.023)	(0.021)	(0.023)	(0.022)	(0.020)	(0.022)	(0.023)	(0.020)	(0.022)	(0.023)	(0.020)	(0.022)	(0.023)	(0.020)	(0.022)	(0.023)
selection_cap	0.079***	0.016**	0.067***	0.140***	0.020**	-0.043***	0.090***	0.013	0.081***	0.047***	0.062***	0.026***	0.118***	0.018**	0.021**	0.117***	-0.053***	0.037***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
mean_comp	26.124***	29.180***	29.811***	26.013***	29.125***	29.743***	26.096***	29.300***	29.781***	26.167***	29.165***	29.742***	25.889***	29.112***	29.865***	25.985***	29.106***	29.713***
	(0.010)	(0.011)	(0.011)	(0.010)	(0.011)	(0.011)	(0.010)	(0.011)	(0.011)	(0.010)	(0.011)	(0.011)	(0.010)	(0.011)	(0.011)	(0.010)	(0.011)	(0.011)
selec-tion_threshold	-5.401***	2.564***	5.915***	-1.093***	2.788***	-2.889***	-1.312***	-1.657***	2.134***	0.641**	3.495***	-0.174	1.321***	-1.908***	1.002***	-0.622**	1.712***	-0.399
	(0.254)	(0.277)	(0.281)	(0.254)	(0.278)	(0.278)	(0.253)	(0.277)	(0.280)	(0.253)	(0.278)	(0.280)	(0.250)	(0.275)	(0.280)	(0.252)	(0.275)	(0.281)
information	0.012***	-0.028***	0.021***	0.072***	-0.025***	0.004	-0.013***	0.005	-0.007*	-0.065***	0.009**	-0.018***	0.026***	-0.003	0.003	-0.001	-0.018***	-0.010**
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
Observations	4,626,207	4,643,485	4,636,765	4,617,557	4,639,640	4,650,175	4,654,027	4,658,823	4,658,822	4,657,865	4,660,740	4,660,741	4,660,740	4,659,781	4,660,740	4,658,823	4,658,822	4,660,740
R^2	0.734	0.740	0.741	0.733	0.737	0.743	0.734	0.739	0.740	0.735	0.737	0.741	0.736	0.741	0.742	0.735	0.740	0.739
Note: *p**p***p<0.01																		

Mean dpc (mean_dpc)

When looking at Table XVII it can been seen that the R^2 between the parameter variations seem to share a common pattern, where *mean dpc* = 0 has the highest R^2 and *mean dpc* = 3 has the second highest, while *mean dpc* = 1.5 has the lowest. Therefore, it was decided to only use the parameters with highest and the lowest R^2 (*mean dpc* = 0, 1.5).

Table XVII: Sensitivity analysis for parameter Mean dpc

Dependent variable: **groups_solved**, SA variable: **mean_dpc**																		
	Cal 1			**Cal 2**			**Cal 3**			**Cal 4**			**Cal 5**			**Cal 6**		
	=0	= 1.5	= 3	=0	= 1.5	= 3	=0	= 1.5	= 3	=0	= 1.5	= 3	=0	= 1.5	= 3	=0	= 1.5	= 3
Closest	-0.040***	0.377***	-0.438***	-0.374***	-0.023	0.375***	-0.142***	-0.043	0.311***	-0.014	-0.759***	-0.434***	-0.350***	0.363***	0.613***	-0.177***	0.104***	-1.262***
	(0.011)	(0.032)	(0.055)	(0.012)	(0.032)	(0.056)	(0.011)	(0.032)	(0.056)	(0.011)	(0.032)	(0.056)	(0.011)	(0.032)	(0.055)	(0.012)	(0.032)	(0.055)
Furthest	0.270***	-0.608***	0.256***	-0.660***	-0.891***	-0.478***	-0.038***	-0.638***	-0.314***	-0.027**	-0.837***	-0.040	0.050***	-0.217***	-0.102*	-0.327***	0.430***	-1.525***
	(0.011)	(0.032)	(0.055)	(0.012)	(0.032)	(0.056)	(0.011)	(0.032)	(0.056)	(0.011)	(0.032)	(0.056)	(0.011)	(0.032)	(0.055)	(0.012)	(0.032)	(0.055)
mean_info_dif	-2.069***	-3.426***	-4.763***	-2.058***	-3.408***	-4.756***	-2.062***	-3.471***	-4.776***	-2.077***	-3.428***	-4.781***	-2.064***	-3.410***	-4.764***	-2.062***	-3.417***	-4.780***
	(0.0004)	(0.001)	(0.002)	(0.0004)	(0.001)	(0.002)	(0.0004)	(0.001)	(0.002)	(0.0004)	(0.001)	(0.002)	(0.0004)	(0.001)	(0.002)	(0.0004)	(0.001)	(0.002)
selection_cap	-0.026***	-0.062***	0.212***	-0.021***	0.145***	-0.032***	-0.011***	0.140***	0.052***	0.010***	0.023***	0.099***	0.010***	0.117***	0.028***	-0.001	-0.016***	0.117***
	(0.001)	(0.004)	(0.007)	(0.001)	(0.004)	(0.007)	(0.001)	(0.004)	(0.007)	(0.001)	(0.004)	(0.007)	(0.001)	(0.004)	(0.007)	(0.001)	(0.004)	(0.007)
mean_comp	8.393***	24.543***	52.189***	8.432***	24.363***	52.035***	8.411***	24.646***	52.143***	8.401***	24.572***	52.095***	8.402***	24.534***	51.927***	8.387***	24.405***	52.020***
	(0.002)	(0.005)	(0.009)	(0.002)	(0.005)	(0.009)	(0.002)	(0.005)	(0.009)	(0.002)	(0.005)	(0.009)	(0.002)	(0.005)	(0.009)	(0.002)	(0.005)	(0.009)
selec-tion_thresh-old	1.046***	0.972***	-0.066	-0.550***	0.929***	-1.659***	-1.472***	-0.231*	0.384*	0.959***	-1.671***	4.540***	0.998***	-0.073	-0.446**	0.235***	-0.415***	0.850***
	(0.047)	(0.133)	(0.228)	(0.048)	(0.130)	(0.230)	(0.047)	(0.133)	(0.230)	(0.046)	(0.133)	(0.229)	(0.047)	(0.131)	(0.227)	(0.047)	(0.131)	(0.228)
teammem-ber_size	0.547***	1.329***	2.424***	0.596***	1.345***	2.411***	0.537***	1.376***	2.432***	0.532***	1.355***	2.425***	0.636***	1.364***	2.534***	0.546***	1.350***	2.428***
	(0.001)	(0.003)	(0.006)	(0.001)	(0.003)	(0.006)	(0.001)	(0.003)	(0.006)	(0.001)	(0.003)	(0.006)	(0.001)	(0.003)	(0.006)	(0.001)	(0.003)	(0.006)
information	-0.023***	0.0003	0.014***	0.015***	0.030***	-0.001	0.009***	-0.049***	0.020***	0.005***	-0.007***	-0.070***	-0.007***	0.005***	0.030***	-0.016***	-0.009***	-0.005
	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)
Observations	4,632,925	4,635,811	4,637,721	4,631,007	4,633,864	4,642,501	4,656,905	4,658,822	4,655,945	4,659,782	4,659,781	4,659,783	4,660,740	4,659,781	4,660,740	4,659,781	4,659,781	4,658,823
R^2	0.898	0.860	0.889	0.897	0.863	0.887	0.899	0.861	0.887	0.902	0.860	0.887	0.898	0.863	0.889	0.897	0.862	0.888
Note: *p**p***p<0.01																		

No. of problems (problems/tasks)

When looking at Table XVIII it can been seen that there is no significant difference in the R^2 within the parameter variations across all the experiments. Moreover, when looking at the beta coefficients the parameter value change seems to have a slight effect but nothing substantial. Therefore, it was decided to only keep *No. of problems* = 30 for the full-scale study as it seems to have more significant beta coefficients. As a secondary benefit, choosing just the value 30 also eliminates the risk of having low problems at a given time, thus ensuring that it doesn't affect the time taken to solve problems.

Table XVIII: Sensitivity analysis for parameter No. of problems

Dependent variable: **groups_solved,** SA variable: **No. of problems**												
	Cal 1		**Cal 2**		**Cal 3**		**Cal 4**		**Cal 5**		**Cal 6**	
	= 15	= 30	= 15	= 30	= 15	= 30	= 15	= 30	= 15	= 30	= 15	= 30
Closest	-0.448***	0.480***	-0.0001	0.009	0.045	0.076	-0.598***	-0.230***	-0.043	0.460***	-0.486***	-0.399***
	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.053)	(0.054)	(0.054)	(0.054)
Furthest	0.238***	-0.234***	-0.939***	-0.495***	-0.475***	-0.272***	-0.091*	-0.501***	-0.263***	0.092*	-0.396***	-0.576***
	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.053)	(0.054)	(0.054)	(0.054)
mean_info_dif	-3.419***	-3.421***	-3.388***	-3.420***	-3.448***	-3.423***	-3.409***	-3.447***	-3.422***	-3.403***	-3.422***	-3.418***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
mean_dpc	46.464***	46.735***	46.464***	46.390***	46.406***	46.498***	46.672***	46.303***	46.381***	46.568***	46.441***	46.505***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
selection_cap	0.072***	0.034***	0.011	0.065***	0.040***	0.082***	0.084***	0.006	0.014**	0.091***	-0.025***	0.092***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
mean_comp	28.377***	28.373***	28.243***	28.355***	28.449***	28.338***	28.411***	28.304***	28.256***	28.321***	28.314***	28.223***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
selection_thresh-old	1.769***	0.272	-0.167	-0.744***	-0.359	-0.193	2.771***	-0.115	-0.562**	0.848***	-1.132***	1.591***
	(0.223)	(0.223)	(0.222)	(0.222)	(0.223)	(0.222)	(0.222)	(0.222)	(0.220)	(0.221)	(0.221)	(0.221)
teammem-ber_size	1.436***	1.453***	1.504***	1.402***	1.442***	1.452***	1.403***	1.473***	1.529***	1.494***	1.448***	1.436***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)

Observations	6,956,574	6,949,883	6,954,658	6,952,714	6,985,357	6,986,315	6,989,192	6,990,154	6,990,151	6,991,110	6,988,233	6,990,152
R^2	0.736	0.737	0.735	0.736	0.735	0.736	0.736	0.735	0.738	0.737	0.736	0.736
R^2 Difference	0.001		0.001		0.001		0.001		0.001		0	
Note: *p**p***p<0.01												

No. of applicants & information transparency

When comparing the difference of R^2 between cal 1 & cal 2, cal 3 & cal 4, and cal 5 & cal 6 (in Table XIX), the effect of *information transparency* can be observed. Where when it is ‘on’, the R^2 is higher between all the pairs, thus indicating that having *information transparency* on/off does in fact have a distinguishable effect on the simulation and that it should be included in the full-scale study.

Moreover, when comparing the difference of R^2 between cal 1, cal 3, cal 5 and cal 2, cal 4, cal 6 (in Table XIX), the effect of the *number of applicants* can be observed. It appears that there is only a very small difference between the R^2 of these variations. Also, it can be seen that, on the one hand that when *information transparency* is ‘on’, the *No. of applicants* = 1 and the *No. of applicants* = 20 have a similar R^2 while the *No. of applicants* = 10 is slightly lower. On the other hand, when *information transparency* is ‘off’, the *No. of applicants* = 1 and the *No. of applicants* = 20 yet again has a similar R^2 but the *No. of applicants* = 10 has a slightly higher $R^{2.}$ Therefore, due to this similarity in R^2 between the *No. of applicants* = 1 and the *No. of applicants* = 20, it was decided to only use the *number of applicants* = 1 along with the *No. of applicants* = 10 for the full-scale study.

Table XIX: Sensitivity analysis for parameters No. of applicants & information transparency

Dependent variable: **groups_solved,** SA variables: **no-app & info-trans**						
	Cal 1	**Cal 2**	**Cal 3**	**Cal 4**	**Cal 5**	**Cal 6**
	No-app =1, info-trans = on	No-app =1, info-trans = off	No-app =10, info-trans = on	No-app =10, info-trans = off	No-app =20, info-trans = on	No-app =20, info-trans = off
Closest	-0.187***	0.261***	-0.130**	0.001	-0.229***	0.351***

	(0.058)	(0.043)	(0.058)	(0.042)	(0.058)	(0.042)
Furthest	-0.043	-0.037	-1.496***	-0.002	-0.584***	-0.106**
	(0.058)	(0.043)	(0.058)	(0.042)	(0.058)	(0.042)
mean_dpc	56.010***	37.182***	55.954***	36.930***	55.934***	36.977***
	(0.019)	(0.014)	(0.019)	(0.014)	(0.019)	(0.014)
selection_cap	-0.002	0.123***	0.031***	0.050***	0.111***	0.009*
	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)
mean_comp	34.345***	22.403***	34.262***	22.355***	34.467***	22.324***
	(0.010)	(0.007)	(0.010)	(0.007)	(0.010)	(0.007)
selection_threshold	1.021***	0.919***	-0.493**	-0.175	-1.378***	0.715***
	(0.238)	(0.175)	(0.239)	(0.174)	(0.238)	(0.174)
teammember_size	1.558***	1.340***	1.620***	1.300***	1.617***	1.277***
	(0.006)	(0.004)	(0.006)	(0.004)	(0.006)	(0.004)
information	0.001	0.002	0.037***	-0.005**	-0.023***	0.012***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
Observations	6,951,786	6,954,671	6,949,837	6,957,535	6,984,397	6,987,275
R^2	0.754	0.709	0.752	0.711	0.754	0.709
Note: *p**p***p<0.01						

Following the sensitivity analysis, the base number of runs with the new parameter configurations for the full simulation were calculated as shown below (see Table XX).

Table XX: Parameter value changes based on the SA

SA	WHAT	MD	COMMENTS
3 ×	selection-type	**2** ×	‘Furthest’ is not relevant for the article
2 ×	mean_info-dif	**2** ×	Same as before
3 ×	selection-cap	**2** ×	Selection caps of 2 & 5
3 ×	mean_comp	**2** ×	Mean competence of 2 & 5
3 ×	selection-thresh	**2** ×	Selection threshold of 0.01 & 0.25
3 ×	teammember-size	**2** ×	Number of team members of 5 & 15

3 ×	mean_dpc	**2** ×	Mean dpc of 0 & 1.5
2 ×	information	**1** ×	Starting problems/tasks of 30
3 ×	no-app	**2** ×	Number of applicants of 1 & 10
2 ×	info-trans	**2** ×	Same as before
=17496		**=512**	

Now that the base number of runs required is known, a statistical power analysis was conducted to estimate the number of runs required for the full-scale simulation (Secchi and Seri 2017; Seri and Secchi 2017). The power analysis indicated that 26 runs were needed to be on the safe side. Thus, it brought the total number of runs required to 13312.

7.3. Appendix – C

7.3.1. Supplementary fit

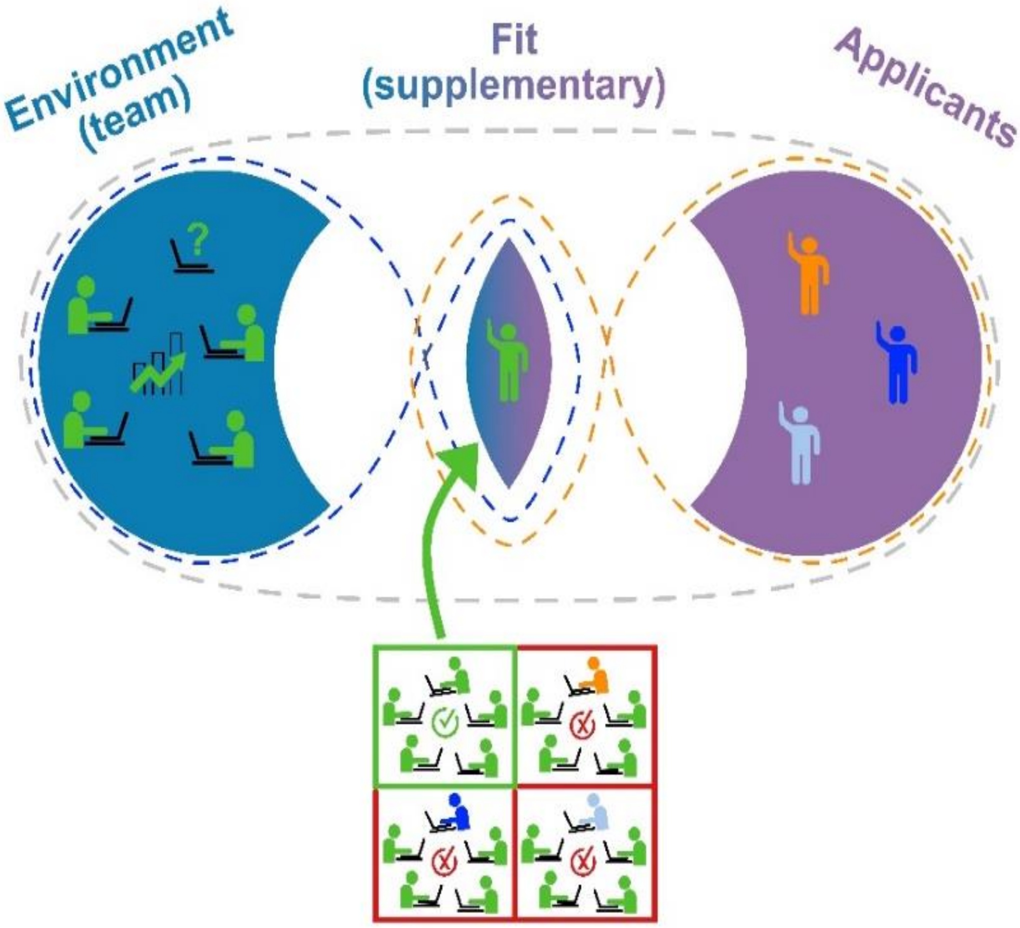
Supplementary fit is when there is a "similarity between the person and the environment, where the environment refers to other people individually or collectively in groups, organizations, or vocations" (Edwards *et al.*, 2006, p. 804). Thus, in other words *supplementary fit* exists when both the individual and the environment/others in the environment are similar or share matching characteristics (Cable and Edwards, 2004; Kristof-Brown *et al.*, 2005; Vogel and Feldman, 2009; Wingreen and Blanton, 2007; Muchinsky and Monahan, 1987). *Supplementary fit* is more generally studied in research surrounding value congruence between organizations and employees (Kristof, 1996), for example "whether an employee and an organization both consider autonomy important" (Cable and Edwards, 2004, p. 822). Moreover, it can also be considered as supplementary fit, if a company hires an individual with identical or matching characteristics to the already commonly possessed characteristics of the workforce (Cable and Edwards, 2004). Thus, majority of the studies on *supplementary fit* measure fit on the basis of characteristics such as personality, values beliefs and more (Chatman, 1991; Guan, Deng, Risavy, Bond, and Li, 2011; O'Reilly, Chatman, and Caldwell, 1991). Interestingly, Cable and Edwards (2004) based on their research indicate that both *supplementary fit* and *complementary fit* are interrelated, yet they both contribute independently to outcomes. Thus, indicating that the utility of these traditions should be used based on the desired outcomes (e.g. using *supplementary fit* when wanting to expand a team while maintaining a similar team dynamic).

7.3.2. Operationalization of Supplementary fit in relation to O-C fit

In order to make the underlying logic of *supplementary fit* much clearer a visual representation of how *supplementary fit* is presented in Figure 23. Accordingly, it provides an example of a scenario of wanting to expand a team while maintaining a similar team dynamic. Similar to the visualization of complementary fit in *Chapter 5* (section 5.2.4.3.) Figure 23 can be thought of as a deconstructed Venn diagram, where the blue-colored crescent shape on the left represents the corporate team environment and the purple-colored crescent shape on the right representing the pool of potential candidates. The middle component represents the intersection (overlap) of the two spheres (i.e. environment and applicants), as well as the fit between them. Furthermore, the blue and orange dotted lines represent the relation between the two spheres as well as the intersection (respectively), while the grey-colored dotted line circling these three components represents the entire R&S process of finding the best match.

Accordingly, on the one hand, the symbol in the middle of the green-colored people (employees), represent how the team is performing, where in this example it symbols that the team is performing well. On the other hand, the color of the '***?***' in the corporate team environment shows what the team is seeking for. In other words, it shows the envisioned characteristics of the employee needed, as per the employers' requirements. Thus, given this example, the team is seeking an employee that shares a similar working dynamic to the existing team members. Here the colored squares below the three components play a role in this visualizing the selection process. Thus, each candidate's individual dynamic is combined with the existing team members, to assemble a new team dynamic per inclusion of each candidate. The four boxes represent the process where each candidate's individual dynamic is compared with another to find the candidate that has the required similar dynamic for the existing team. As a result, Figure 23 shows that the selection process selected a candidate that provides the most *supplementary fit* with the existing team.

Figure 23: Visual representation of Supplementary fit



7.4. References

Cable, D. M., & Edwards, J. R. (2004). Complementary and Supplementary Fit: A Theoretical and Empirical Integration. *Journal of Applied Psychology*, Vol. 89 No. 5, pp. 822-834.

Chatman, J. A. (1991). Matching People and Organizations: Selection and Socialization in Public Accounting Firms. *Administrative Science Quarterly*, Vol. 36 No. 3, pp. 459-484.

Che, T., Wu, Z., Wang, Y., & Yang, R. (2019). Impacts of knowledge sourcing on employee innovation: the moderating effect of information transparency. *Journal Of Knowledge Management*, Vol. 23 No. 2, pp. 221-239.

Edmonds, B. & Meyer, R., Eds. (2017). *Simulating Social Complexity. A Handbook*. Heidelberg: Springer, second edition.

Edmonds, B., Le Page, C., Bithell, M., Chattoe-Brown, E., Grimm, V., & Meyer, R. et al. (2019). Different Modelling Purposes. *Journal Of Artificial Societies And Social Simulation*, Vol. *22* No. 3.

Edwards, J. R., Cabe, D. M., Williamson, I. O., Lambert, L. S., & Shipp, A. J. (2006). The Phenomenology of Fit: Linking the Person and Environment to the Subjective Experience of Person-Environment Fit. *Journal of Applied Psychology*, Vol. 91 No. 4, pp. 802-827.

Grimm, V., Polhill, G., and Touza, J. (2017). Documenting social simulation models: The ODD protocol as a standard. In Edmonds, B. and Meyer, R., editors, *Simulating Social Complexity: A Handbook*, pages 349–365. Springer, Cham.

Grimm, V., Railsback, S. F., Vincenot, C. E., Berger, U., Gallagher, C., DeAngelis, D. L., Edmonds, B., Ge, J., Giske, J., Groeneveld, J., et al. (2020). The odd protocol for describing agent-based and other simulation models: A second update to improve clarity, replication, and structural realism. *Journal of Artificial Societies and Social Simulation*, Vol. 23 No. 2.

Guan, Y., Deng, H., Risavy, S. D., Bond, M. H., & Li, F. (2011). Supplementary Fit, Complementary Fit, and Work-Related Outcomes: The Role of Self-Construal. *Applied Psychology: An International Review*, Vol. 60 No. 2, pp. 286-310.

James, L., Demaree, R., & Wolf, G. (1984). Estimating within-group interrater reliability with and without response bias. Journal Of Applied Psychology, Vol. 69 No. 1, pp. 85-98.

Kristof, A. (1996), "Person-organization fit: an integrative review of its conceptualizations, measurement, and implications", *Personnel Psychology*, Vol. 49 No. 1, pp. 1-49.

Kristof-brown, A., Zimmerman, R. and Johnson, E. (2005), "Consequences of individuals' fit at work: a meta-analysis of person-job, person-organization, person-group, and person-supervisor fit", *Personnel Psychology*, Vol. 58 No. 2, pp. 281-342.

Muchinsky, P. M., & Monahan, C. J. (1987). What is person-environment congruence? Supplementary versus complementary models of fit. Journal of Vocational Behavior, Vol. 31 No. 3, pp. 268-277.

O'Reilly, C., Chatman, J. and Caldwell, D. (1991), "People and organizational culture: a profile comparison approach to assessing person-organization fit", *Academy of Management Journal*, Vol. 34 No. 3, pp. 487-516.

Pfeffer, J. (1992). *Managing with power: politics and influence in organizations*. Boston, Mass: Harvard Business School Press.

Secchi, D. & Seri, R. (2017). Controlling for ‘false negatives’ in agent-based models: A review of power analysis in organizational research. *Computational and Mathematical Organization Theory*, Vol. 23 No. 1, pp. 94–121.

Secchi, D. (2011), *Extendable Rationality*, Springer, New York.

Secchi, D. and Bardone, E. (2009), "Super-docility in organizations: an evolutionary model", *International Journal of Organization Theory & Behavior*, Vol. 12 No. 3, pp. 339-379.

Seri, R. & Secchi, D. (2017). How many times should one run a computational simulation? In B. Edmonds & R. Meyer (Eds.), *Simulating Social Complexity. A Handbook* (pp. 229–251). Heidelberg: Springer, 2nd edition.

Stevenson, W., & Gilly, M. (1993). Problem-Solving Networks in Organizations: Intentional Design and Emergent Structure. Social Science Research, Vol. 22 No. 1, pp. 92-113.

Ten Broeke, G., van Voorn, G., & Ligtenberg, A. (2016). Which Sensitivity Analysis Method Should I Use for My Agent-Based Model?. *Journal Of Artificial Societies And Social Simulation*, Vol. *19* No. 1.

Vogel, R. and Feldman, D. (2009), "Integrating the levels of person-environment fit: The roles of vocational fit and group fit", *Journal of Vocational Behavior*, Vol. 75 No. 1, pp. 68-81.

Wilensky, U. (1999). *NetLogo. Evanston*, IL: Center for connected learning and computer-based modeling, Northwestern University.

Wingreen, S. and Blanton, J. (2007), A social cognitive interpretation of person-organization fitting: The maintenance and development of professional technical competency, *Human Resource Management*, Vol. 46 No. 4, pp. 631-650.