LUIZ FERNANDO BRAZ

Personalify: A framework for implementing MBTI agents

São Paulo
2023

LUIZ FERNANDO BRAZ

Personalify: A framework for implementing MBTI agents

(Revised Version)

Dissertation presented to the Graduate Program at the Escola Politécnica da Universidade de São Paulo to obtain the degree of Master of Science.

São Paulo
2023

LUIZ FERNANDO BRAZ

PERSONALIFY: A FRAMEWORK FOR IMPLEMENTING MBTI AGENTS

(Revised Version)

Dissertation presented to the Graduate Program at the Escola Politécnica da Universidade de São Paulo to obtain the degree of Master of Science.

Concentration Area:
Computer Engineering

Advisor:
Prof. Dr. Jaime Simão Sichman

São Paulo
2023

Autorizo a reprodução e divulgação total ou parcial deste trabalho, por qualquer meio convencional ou eletrônico, para fins de estudo e pesquisa, desde que citada a fonte.

Este exemplar foi revisado e corrigido em relação à versão original, sob responsabilidade única do autor e com a anuência de seu orientador.

São Paulo, 5 de Fevereiro de 2024

Assinatura do autor:

Assinatura do orientador:

Catalogação-na-publicação

Braz, Luiz Fernando
Personalify: A framework for implementing MBTI agents / L. F. Braz -- versão corr. -- São Paulo, 2023.
148 p.

Dissertação (Mestrado) - Escola Politécnica da Universidade de São Paulo. Departamento de Engenharia de Computação e Sistemas Digitais.

1.Sistemas Multiagentes 2.Simulação Baseada em Agentes 3.MBTI 4.BDI 5.Formação de Times I.Universidade de São Paulo. Escola Politécnica. Departamento de Engenharia de Computação e Sistemas Digitais II.t.

ACKNOWLEDGMENTS

First, I would like to express my gratitude to God, who has granted me life and the opportunity to have this incredible experience.

I want to extend my heartfelt appreciation to my advisor, Prof. Dr. Jaime Sichman, for supporting and guiding me throughout this journey and always providing constructive feedback that helped me evolve.

I would like to acknowledge Prof. Dra. Cristina Bachert for her enormous collaboration and for imparting many teachings. Her suggestions and knowledge were invaluable and fundamental to the development of this work.

I am deeply grateful to my wife Natália and my children, Luiza and Leo, who are the reason for my existence. Thank you for being with me in all the critical moments.

To my parents and all the family members who supported me so much, thank you for the words of encouragement.

I would like to extend my sincere appreciation to Prof. Dra. Diana Adamatti and Prof. Dr. Sigmar Malvezzi for making such a valuable contribution.

I would like to thank Prof. Rafael Silva for helping me with the English revisions.

I would also like to express my gratitude to Prof. Dra. Anarosa Brandão, Prof. Dra. Anna Reali, and all my colleagues at Laboratorio de Tecnicas Inteligentes (LTI) of Escola Politécnica for their contributions.

I would like to express my gratitude to the entire VAGAS team, especially Mário Kaphan, for introducing me to USP/Poli and for your encouragement. I would also like to thank Wesley Barreto, Sidney Monreal, and Pedro Zanni for their support and recommendations. To the entire Data Science team, Jaqs, Sidão, Zé, Bruno, BS, Kuma, Luis, Sand, and Ronie, thank you for inspiring and motivating me. This work has a bit of each of you; all the teachings and contributions are present in every dedicated effort.

Thanks to the entire Microsoft team, especially my managers Chris Faig, Carlos Abramo, Fernando Lemos, Thais Hidaib, Michel Pereira, Will Murphy and Marie Brunet, who encouraged me and were patient with my dedication. To all colleagues who inspired and contributed to the work's success every single day, Fonseca, Tokoi, Alfeu, André, Pedro, Luis Renato, Lari, Aninha, Malhano, and João.

Thanks to Jordan Salvit, for his important contributions.

Thanks to the anonymous reviewers who brought valuable insights and suggestions to improve this work.

And to all my academic and professional colleagues who helped me directly or indirectly with advice and suggestions.

All of you were essential to the construction of this work!

Thank you very much!

"Imagination is more important than knowledge. Knowledge is limited. Imagination encircles the world"

-- Albert Einstein

RESUMO

O uso da Inteligência Artificial para evolução do estudo do comportamento humano vêm recebendo grande atenção dos pesquisadores ao longo dos anos. O estudo de técnicas que permitam a simulação de características humanas com o uso de computadores têm contribuído para um melhor entendimento de diversos fatores, entre eles os tipos de personalidade e preferências comportamentais das pessoas. Neste sentido, instrumentos como o Myers-Briggs Type Indicator (MBTI) têm sido utilizados, buscando classificar e categorizar as preferencias comportamentais dos indivíduos como forma de descrever suas particularidades e apoiar em uma maior compreensão do fator humano em diferentes contextos, como por exemplo no trabalho. Estudos demonstram que o capital humano é um dos recursos mais críticos para as organizações que apesar disso ainda carecem de meios que lhes permitam compreender de forma ampla os fatores associados à formação de times de alto desempenho. O uso de ferramentas que permitam aos indivíduos um maior auto-conhecimento de suas preferências e características pode ajudar em adaptações que criem ambientes mais harmônicos e propícios ao trabalho em equipe, impactando positivamente os resultados dos times. Neste trabalho, buscou-se explorar através do uso de simulações baseadas em agentes a observação de aspectos comportamentais que possam influenciar as decisões e consequente desempenho de times de agentes artificiais. Em particular, foi proposto uma estrutura denominada Personalify que estende a arquitetura Belief-Desire-Intentions (BDI) de modo a incorporar múltiplos atributos de decisão projetados com características descritas no modelo MBTI. O Personalify foi implementado na plataforma Gama, e testado em diversos cenários de compra e venda de produtos, que apresentam similaridades com contextos de trabalho visando proporcionar simulações mais próximas às realidades organizacionais. Desta forma, espera-se que o estudo contribua de forma significativa para um melhor entendimento de elementos que possam influenciar o comportamento de agentes modelados com personalidades inspiradas na teoria do MBTI, observando como certas características podem ter maior impacto nas decisões tomadas pelos agentes e como estas poderiam ter relação com os resultados gerais apresentados pelo time.

Palavras-Chave: Sistemas Multiagentes. Simulação Baseada em Agentes. MBTI. BDI. Comportamento Humano. Formação de Times.

ABSTRACT

The use of Artificial Intelligence for the evolution of the study of human behavior has been receiving great attention from researchers over the years. The study of techniques that allow simulation of human characteristics using computers has contributed to a better understanding of several factors, including people's personality types and behavioral preferences. In this sense, instruments such as the Myers-Briggs Type Indicator (MBTI) have been used, seeking to classify and categorize individuals' behavioral preferences to describe their particularities and support a greater understanding of human factors in different contexts, such as in work. Studies show that human capital is one of the most critical resources for organizations that, despite this, still lack means that allow them to broadly understand the factors associated with the formation of high-performance teams. The use of tools that allow individuals greater self-knowledge of their preferences and characteristics can help in adaptations that create more harmonious environments and are favorable to teamwork, positively impacting teams' results. In this work, we sought to explore, through agent-based simulations, the observation of behavioral aspects that can influence decisions and the consequent performance of artificial agent teams. In particular, we propose a framework called Personalify, which extends the Belief-Desire-Intentions (BDI) architecture in order to incorporate multiple decision attributes designed with characteristics described in MBTI model. The Personalify was implemented on the Gama platform, and tested in various buyers and sellers scenarios, which have similarities with work contexts, aiming to provide simulations closer to organizational realities. In this way, it is expected that the study will contribute significantly to a better understanding of elements that can influence modeled agent behavior with personalities inspired by MBTI theory, observing how certain characteristics can have a greater impact on the decisions made by agents and how these could be related to overall results presented by the team.

Keywords: Multiagent systems. Agent-based simulations. MBTI. BDI. Human Behavior. Team Building.

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

ABSS Agent-Based Social Simulation.

AI Artificial Intelligence.

BDI Belief-Desire-Intention.

BEN Behavior with Emotions and Norms.

DAI Distributed Artificial Intelligence.

DSMR Design science research methodology.

FFM Five-Factor Model.

GAMA GIS & Agent-Based modeling Architecture.

GAML Gama Modeling Language.

GIS Geographical Information System.

HPT High-Performance Team.

IS Information Systems.

LST-MAX Linear Scale Transformation - Max.

MAS Multi-Agent Systems.

MBTI Myers Briggs Type Indicator.

OCEAN Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism.

WS Weighted Sum.

CONTENTS

1 INTRODUCTION

The study of human behavior in organizations has been the subject of several researchers who seek to understand how behavioral factors can influence decision-making and consequent actions of work teams in an organizational context. Since the emergence of the fatigue studies laboratory in 1889 by Luigi Patrizi, which aimed to study psychophysiological aspects associated with fatigue and later with the Organizational and Work Psychology area, problems related to performance, worker health, life quality, job impact, and working conditions, has been studied in order to obtain valuable knowledge of human factor in organizations (ZANELLI; BORGES-ANDRADE; BASTOS, 2014). Topics such as organizational efficiency and work performance were studied by researchers who sought to develop more efficient working methods. One of the best-known contributions is the study of time and movement by Frank and Lillian Gilbreth, who inspired by Frederick Winslow Taylor's ideas on productivity at work, created the study of time and motion intending to develop more efficient ways of working (SPECTOR, 2009). Since then, studies on human behavior have significantly evolved, focusing on different areas and seeking a better understanding of various issues associated with people and their relationship with work.

One of these studies, carried out by Katherine Briggs and Isabel Myers and inspired by Carl Jung's theory of psychological types, focused on developing an instrument that would allow people to have clearer awareness of their own behavioral characteristics and preferences. They had a shared vision of enabling individuals to grow through an understanding and appreciation of the differences in a healthy personality and to enhance harmony and productivity among diverse groups. As part of the study, they created an instrument that would allow people to access this knowledge (MYERS et al., 1998).

Myers-Briggs Type Indicator (MBTI) is a self-report instrument designed to make Jung's theory of psychological types understandable and useful in everyday life. With it, it is possible to identify individuals' behavioral characteristics and particularities. It can be applied to a wide variety of situations and purposes, such as self-understanding and development, career development, diversity, multicultural training, team building, among others (MYERS, 1998). With MBTI, it is possible to observe characteristics that represent how individuals perceive the world around them and make decisions influenced by these characteristics.

Some other studies have sought to combine ideas inspired from MBTI with Artificial Intelligence techniques that let assess some of these human characteristics and behaviors in the laboratory through computer simulations. In this sense, *Multiagent systems (MAS)* have been used to develop artificial agents that can represent certain particularities of different personality types described in the MBTI theory, supporting the development of scenarios close to real life and allowing the observation of behaviors derived from these characteristics modeled on the agents (BRAZ; SICHMAN, 2022c).

In this work, we presented *Personalify*, a framework for implementing an agent-based model inspired by MBTI theory. The framework is based on multiple decision attributes designed with characteristics described in MBTI. We also explored the extension of the model through the Seller-Buyer scenario for modeling Seller agents with personality types introduced from *Personalify* and that interact with Buyer agents. Simulations and experiments are conducted to study the behavior of Sellers agents in environments based on similarities with real-world work contexts.

1.1 Motivation

The evolution of knowledge about human behavior allows the development of more effective actions to solve or mitigate problems found in several areas. As an example, MBTI use by organizations can help leaders and employees recognize practices and evolve actions regarding organizational problems. Organizations' most common use cases involve improving communication, enhancing problem-solving and decision-making, dealing with conflicts, recognizing and managing stress, and team development activities. It is observed that organizations that use MBTI can have a clearer view of how individuals seek information (perception) and how they prioritize information in decision-making (judgment). Through it, people can better understand their own work styles while constructively identifying vulnerabilities and possible blind spots they were not previously aware of. The instrument also makes it possible to identify development paths useful in working groups and coaching team leaders. The constructive use of differences can be helpful in today's global and diverse organizations as well as supporting building positive and affirmative actions to help teams respect differences (MYERS, 1998).

Work teams have a fundamental impact on organizational results (SUNDSTROM; MEUSE; FUTRELL, 1990) and “a vast array of research concerning teamwork is conclusive: teams are capable of outstanding performance and are the primary unit of performance for increasing numbers of organizations” (CASTKA et al., 2001). Building environments where teams can maximize their potential is essential for organizations. Teamwork is not only a factor of motivation and employee satisfaction, but it is also the most efficient way of dealing with day-to-day tasks in organizations (SUNDSTROM; MEUSE; FUTRELL, 1990). It is a factor of high importance, especially as the activities of organizations become complex and an individual depends more and more on other individuals. Working as a team makes team members evolve in terms of skills, knowledge, and abilities, resulting in higher productivity, better problem solving, and consequently higher performance (MANZOOR et al., 2011).

The formation of high-performance teams is an essential factor for organizations in a highly competitive market. According to (SHARP et al., 2000), some enablers such as team member competencies, interpersonal skills, communication, personality preferences, among others, are very important in team-building. Furthermore, teams that manage to develop their full potential generally have a shared vision, working in creative environments, sharing common purposes and objectives in which a strong sense of commitment and ambition help them to complement themselves in terms of skills, facilitating the group’s objective to be achieved more efficiently. Despite that, “high-performance teams are a rarity” (CASTKA et al., 2001) and several obstacles prevent its successful implementation in organizations. Factors related to individuals’ culture, knowledge, skills, performance metrics, and teamwork are essential for workgroups to develop their full potential. Several authors argue that the correct management of this balance is necessary for the right balance of corporate and individual needs. Thus, they suggest analyzing differences and personal preferences using tools such as MBTI to evolve in understanding these differences. Through this, consequent actions could be taken that can lead to improvements in the group’s performance as a whole, thus creating more effective teams (CASTKA et al., 2001).

1.2 Objectives

The use of computational simulations, in which artificial agents are modeled with human characteristics, has allowed significant advances in a better understanding of aspects that can influence certain human behaviors. The study of factors associated with these behaviors and the observation of agent interactions developed with attributes inspired by theories that address human personality traits has supported the knowledge advancement regarding this topic.

The main objective of this work is to advance these studies and provide the scientific community with a framework capable of representing personality types inspired by MBTI in artificial agents that behave and make decisions directly influenced by the characteristics of the personalities modeled on them.

To advance in this aspect, simplified scenarios inspired by daily life found in companies are created, as described in later sections. The interactions between artificial agents modeled with MBTI-based personality characteristics are analyzed through computational simulations seeking to observe and study the agent's behavior in work contexts.

In particular, we designed several experimental Seller-Buyer scenarios, aiming to analyze whether the performance of agent teams was affected by different personality types and/or environmental conditions. Hence, in this work, we sought to answer the following research questions:

RQ1 Can personality types impact the Seller's agent team behavior?

RQ2 Can the environmental conditions impact the Seller's agent team behavior?

RQ3 Can personality changes influence the Seller's agent team behavior?

Forming harmonious work teams that can perform at their maximum potential as a team is a fundamental factor for organizations to achieve strategic objectives. In this sense, advancing studies that allow us to observe some behavior patterns can contribute to more effective actions to support team-building. It is crucial to point out that MBTI is an instrument for the voluntary assessment of individuals and should never be used as an instrument to select, promote, or fire employees (MYERS, 1998). In (COE, 1992), the author cites that sometimes instrument is misused by companies that use it to unjustly stereotype individuals, excluding those who do not have specific behavioral characteristics for a particular function. It is a misuse of the tool totally discouraged by the creators of MBTI theory.

On the other hand, the author also comments that this tool can be handy to help team-building, for example, supporting companies in actions that help their employees learn to respect differences and thus create environments of greater harmony, using MBTI as an instrument of support and not exclusion.

Our work sought to analyze and understand some behavioral differences of personality types described in MBTI, but without proposing or defining, directly or indirectly, any use of the theory as a form of selection or exclusion of any type. The work objective had the exclusive intention of understanding how specific characteristics of agent's personality types can lead to some behaviors without any intention to assess whether a personality type is better or worse for performing tasks.

1.3 Expected contributions

The main contribution of this work involved the proposal of a generic framework that can be used in agent-based systems with entities modeled from personality types inspired by the MBTI.

The modular development of the framework allows its extension to be used in different scenarios where researchers can adapt their models to compose agents with personality types derived from the defined MBTI-based model. The decoupled *Personalify* framework from the Seller-Buyer scenario can contribute to other studies, supporting broader scopes not covered in this work.

Through Artificial Intelligence, this work also sought to contribute to an evolution in studying human-inspired behavior in work contexts, observing how different personalities could influence agent teams' actions and outcomes toward common goals. Thus, it could be possible to understand better how factors associated with the characteristics and particularities of specific personality patterns could impact the decisions taken and the consequent behavior of the agent teams.

1.4 Document structure

The document is organized into nine chapters and two appendices. Following the introduction, Chapter 2 addresses the adoption of the Design Science Research Methodology for conducting the research. It describes the six steps involved, from identifying the problem and motivation to defining the objectives, designing and developing the framework, demonstrating and analyzing the results, and communicating to the Science community through academic publications.

Chapter 3 addresses the theoretical foundations used in the work, describing the main concepts applied as a basis for developing the models. Base topics are covered, such as

Multi-Agent Systems, the simulation of human behavior through computation, and the use of Belief-Desire-Intention architecture.

Chapter 4 explores the most popular Personality Assessment Models. It approaches the Five Factor Model and MBTI concepts for classifying personality types based on dichotomies. It describes all the sixteen personality types and how to use the instrument in Work contexts. It also explores some misuses and limitations regarding MBTI theory.

Chapter 5 covers the main related works analyzing developed models to simulate personalities in artificial agents. Works that address the use of MBTI and Five-Factor model as a basis for agent modeling are analyzed in order to understand the challenges involved and opportunities to approach new study avenues.

Chapter 6 describes our proposal and discusses the development of an MBTI-based agent framework named *Personalify* along with the Seller-Buyer scenario. The decision attributes and Market Types are also described.

Chapter 7 discusses the *Personalify* framework implementation, discussing the core architecture components and the framework integration with Seller-Buyer scenario.

Three experiments and several formulated hypotheses are approached in Chapter 8. The obtained results of each experiment are demonstrated using performance data metrics.

Finally, Chapter 9 discusses the conclusions, contributions, and possible future work.

As a supplementary material, appendices A and B respectively present the *Personalify* framework code and the Seller-Buyer scenario code.

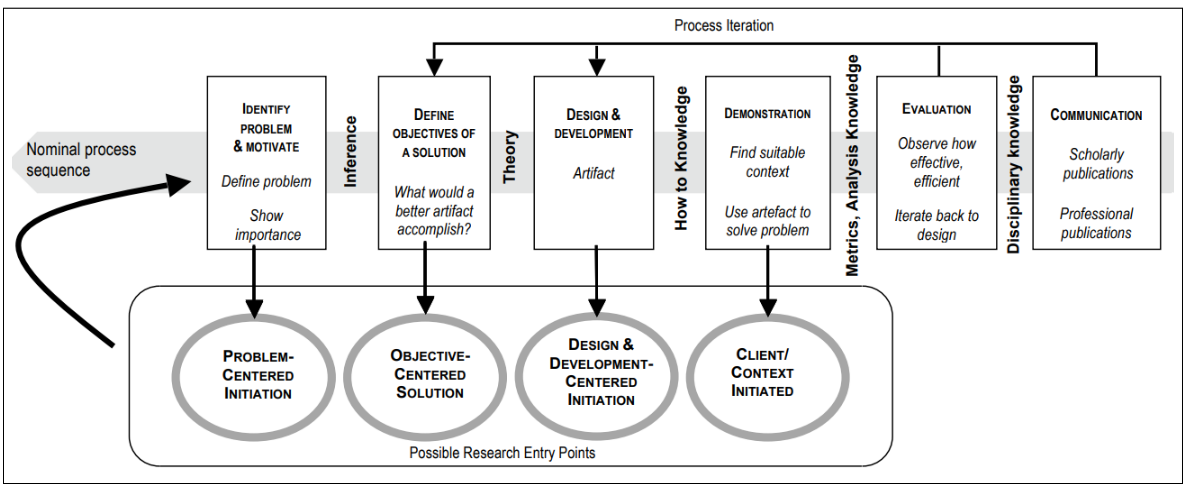
2 METHODOLOGY

The study has been conducted by developing simulations and experiments in an agent-based model using the *Design science research methodology (DSRM)* (PEFFERS et al., 2007). This framework has been widely used in Information Systems (IS) projects and describes a methodology for presenting and evaluating IS design science research.

Multidisciplinary studies involving areas such as Computer Science, Social Science, among other disciplines, are commonly applied to IS to progress in solving organizational problems using Information Technology. With the methodology, a set of principles, practices, and procedures may be structured, bringing elements that support the research development following explicitly designed methods for IS projects.

The proposed methodology involves six main steps: Identification and motivation of the problem; objectives definition of the solution; design and development of the artifacts that will compose the proposal; demonstration of the proposed solution; analysis and results communication. Figure 1 shows each of these steps and their process interaction.

Figure 1: Design Science Research Methodology (DSMR) Process Model (PEFFERS et al., 2007)



This current work aims to analyze phenomena related to the behavior of agent teams modeled with different personality types, thus providing a better understanding of factors that may influence the behavior of work teams in corporate contexts. To advance in this study, we will use DSRM to structure the research process and provide adequate means for conducting the studies. Experiments and simulations based on agents will be created to progress in the defined objective. The subsequent sections will address the details of each step of the methodology applied to the current research.

2.1 Identifying the problem

Several researchers have been studying the theme of developing agent-based models to simulate particularities inherent to human beings' behaviors. In particular, the work of Salvit and Sklar (SALVIT; SKLAR, 2010, 2012; SALVIT, 2012) provided a significant advance in the development of agents modeled behind MBTI-inspired personality types. With these advances, new lines of research emerged from the studies carried out. Expanding the scope for environments that simulate other specificities is promising to explore their adaptation for broader purposes than those originally analyzed.

In this sense, it is important to explore how agents modeled with personality types inspired by the MBTI behave in environments that represent similarities with the corporate world. This study can help expand knowledge of fundamental aspects regarding the relationship between agents' behavior and designed attributes in the environment.

Despite the various studies conducted, as we will detail in Chapter 5, the analysis of particularities inherent to agents' behavior in work contexts is still scarce. Extending these studies can help us improve the knowledge of factors associated with the presented behaviors and envision possible actions to address found gaps.

2.2 Defining objectives

As an organizational tool, MBTI has proven effective in supporting the formation of more efficient and harmonious work teams. Studies have shown that its use in corporate environments for team-building can contribute to the patterns identification and to building workspaces that are more harmonious and conducive to coexistence, respecting the particularities of each individual and seeking a better integration in the working groups (YANG, 2022).

Therefore, the proposed framework in this work can help evolve the study of factors that may be associated with certain behaviors influenced by characteristics described in the MBTI. For this, we approach the development of a model to represent aspects described in theory through artificial agents that portray some of these characteristics. Furthermore, through the Seller-Buyer scenario, we address the use of the framework in settings that represent similarities with corporate contexts.

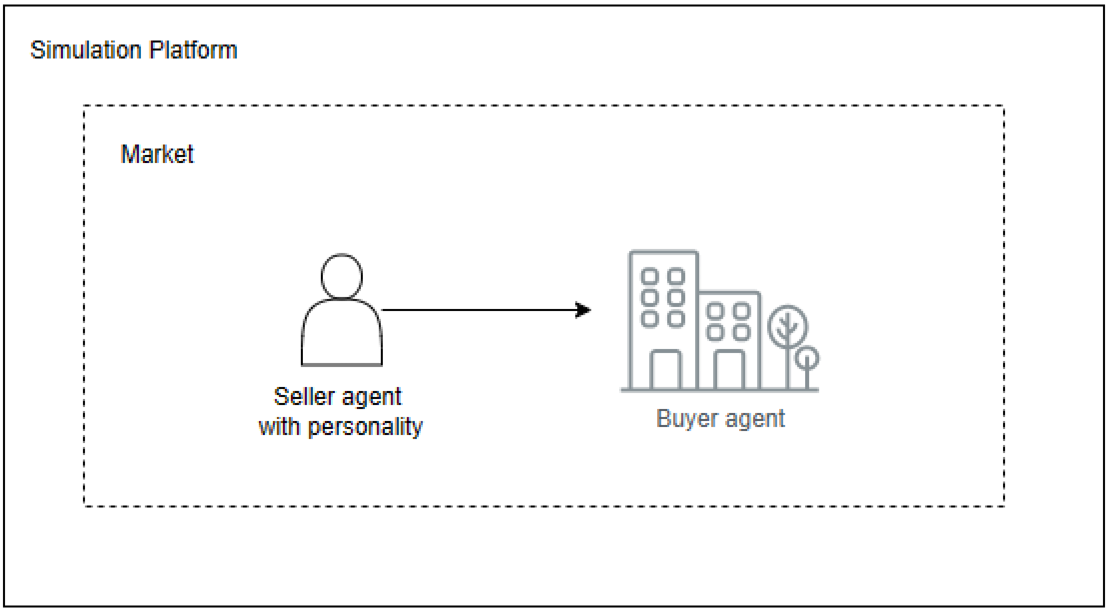
2.3 Design and development

The development of a framework capable of implementing MBTI-inspired features in artificial agents that interact and simulate human behavior, albeit in a simplified way, is possible through the construction of agent-based modeling architectures.

Multi-agent systems technology facilitates the design and development of autonomous and intelligent entities that relate to each other according to the modeling attributes reproducing the desired characteristics. Researchers can then observe, through computer simulations, the behaviors presented by these entities, called agents, to analyze the intended research questions (PALANCA et al., 2020).

The proposed model is guided by the same approach mentioned above. The construction of the framework is based on the development of two agents, Sellers and Buyers, who interact with each other in environments defined as markets, created computationally to mimic certain aspects of the real world. The designed architecture allows the observation of these interactions with simulations that use an agent modeling platform which, on the one hand, allows the representation of complex and dynamic environments with multi-level capabilities and, on the other hand, is also a platform thus facilitating its extension through other studies by the scientific community (DROGOUL et al., 2013a). Figure 2 demonstrates a high-level vision of the architectural design.

Figure 2: High-Level Architecture Design



2.4 Demonstration

In this phase of the DSRM methodology, the framework is demonstrated through computational simulations, defining experiments for each proposed scenario. The experiments describe the specificities to be studied, modeling artificial agents with personality types inspired by the MBTI. In each experiment, simulation environments are designed and used to provide favorable situations for the desired analyses.

Environments, defined as Market Types, are used to analyze the agents' reactions to different attributes. The interaction of Sellers and Buyers agents is directly influenced by these attributes, and the purpose is to observe, at the end of the simulations, the results presented by Seller's agent teams resulting from these interactions.

2.5 Evaluation

Performance metrics are used to evaluate the experiment results and observe the impact on interactions between sellers and buyers' agents in each Market Type.

These metrics are used solely and exclusively to analyze differences between behaviors influenced by the personality types modeled in the agents. It is known that the scope of the term performance can be quite broad. Companies have generally used the term performance to measure how much impact certain actions can influence their goals and strategic objectives. However, given the diverse nature of the actions, the measurement forms can be very distinct depending on the context considered. In this sense, studies have demonstrated different approaches to performance, seeking to consider it as a multidimensional concept (SONNENTAG; FRESE, 2002).

This work uses a more simplistic view of performance, focusing only on observing this metric to consider behavior differences between agent teams modeled with different personality types. The purpose is to be able to analyze the impact of certain attributes modeled on agents given the circumstances of the environments in which they are found.

Evaluations must be entirely limited to the context of this work. They cannot, and should not, be extrapolated to interpretations directly related to the real world. The analysis purpose is to help in a better understanding of characteristics that may be associated with certain aspects of personality types. Still, they should not be interpreted in the sense of stereotyping or excluding individuals, which would even represent a misuse of the MBTI (COE, 1992).

2.6 Communication

The first study on the use of MBTI for modeling multi-agent systems in support of organizational processes was presented and published in the annals of the **14th Workshop-School on Agents, Environments, and Applications** (WESAAC, 2020) and organized by the Federal Technological University of Paraná (UTFPR) and by the Federal Center for Education and Technology Celso Suckow (CEFET-RJ), winning the *Honorable Mention award* in the Post-Graduate category (BRAZ; SICHMAN, 2020).

As an award result, the authors were invited to a new publication in the Section *Selected Papers - WESAAC 2020* of **Revista de Informática Teórica e Aplicada** (RITA, 2022) in which a new article was published addressing the simulation of the formation of high-performance work teams in companies (BRAZ; SICHMAN, 2022c).

The extension of BEN architecture for modeling MBTI agents was presented and published at **1st conference GAMA Days 2021** (BRAZ; SICHMAN, 2021). Another work was also presented and published at **2nd conference GAMA Days 2022** addressing a MBTI-based agent model in a Buyer-Seller scenario (BRAZ; SICHMAN, 2022a).

The simulation of human behavior in work contexts using MBTI agents was presented at the **16th annual Social Simulation Conference** (SSC, 2022) and published in the conference proceedings (BRAZ; SICHMAN, 2022b).

Some improvements and adaptations to the agent‘s decision attributes and Seller-Buyer scenario were implemented, and new studies and simulations of work teams using MBTI agents were presented at the **23rd International Workshop on Multi-Agent-Based Simulation** (MABS, 2022) and published in the conference proceedings (BRAZ; BACHERT; SICHMAN, 2022).

PART I

FOUNDATIONS

3 MULTI-AGENT SYSTEMS

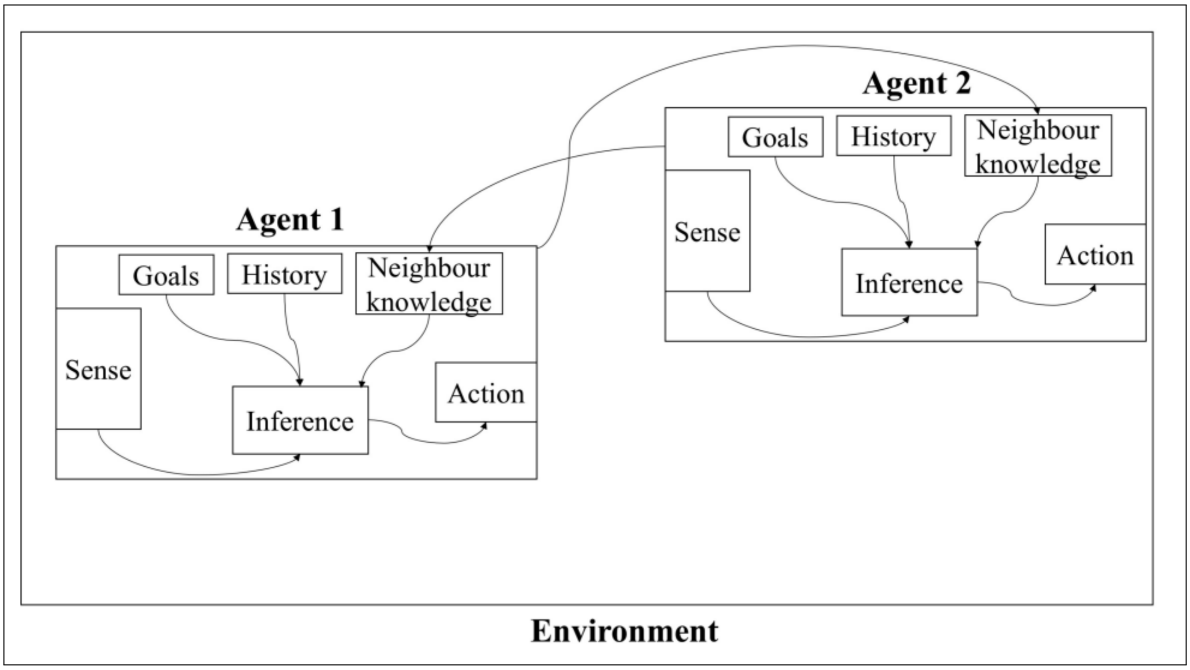
Human behavior simulation has been a significant challenge for many researchers over the years. The evolution of Artificial Intelligence (AI) techniques has contributed to the development of systems capable of representing certain characteristics of the human being and thus supporting people in different day-to-day situations. From image recognition to building self-driving cars, AI has been widespread, helping people make decisions in different scenarios and use cases. AI enables computer systems to have the ability to interpret external data and learn from them, using these data to achieve the goals and tasks for which they were developed (HAENLEIN; KAPLAN, 2019). In a classic approach of AI, an intelligence model based on individual human behavior is used. Other approaches, such as Distributed Artificial Intelligence (DAI), have also been highlighted, giving a greater focus on social behavior, with an emphasis on actions and interactions between artificial agents; that is, while classical AI is based on the individual, DAI seeks to study the relationships and social interactions, using autonomous entities named as agents (ALVARES; SICHMAN, 1997).

In this approach, an agent is defined as “a computer system that is situated in some environment, and that is capable of autonomous action in this environment in order to meet the design objectives” (WOOLDRIDGE; JENNINGS, 1995). Acting autonomously, an agent has the ability to rationally decide which goals to pursue, formulating actions that could be taken to achieve these goals. For this, agents can perceive and partially have a representation of the environment, interacting and communicating with other agents (ALVARES; SICHMAN, 1997).

Multi-agent Systems (MAS) is a subarea of the DAI and, according to (ALVARES; SICHMAN, 1997) aims to study “generic models from which agents, organizations and interactions can be conceived”. In this type of system, agents act collaboratively to solve tasks, have learning capabilities, and make autonomous decisions that help them complete their goals. Agents use their knowledge of the environment to decide and perform actions toward their allocated tasks. These tasks may have restrictions; for example, a particular agent may have to complete a task in a specific predetermined time. To complete complex tasks, agents can also share knowledge with other agents and request information to expand their environment learning. Agents can then use their acquired knowledge to predict situations and, based on them, make decisions seeking future gains that help them to complete their objectives. Although an agent can work individually, the most significant benefit is found when they seek to work collaboratively, thus seeking to help each other to solve complex tasks (DORRI; KANHERE; JURDAK, 2018).

Agents have relative autonomy considering the activities they need to perform. Their autonomy is related to their ability to make their own decisions, choosing actions or activities they will perform, when they will perform activities, what type of information they intend to communicate to other agents, and how to interpret the information received. This autonomy can have limits and established restrictions. The limits can be built by design or come by the interactions in an environment (LESSER, 1999). Each agent also has incomplete information or capabilities about an environment, with a limited view restricting its decision-making. There is no global control system in a MAS, the data is decentralized, and the computational processing is asynchronous. An agent's objective is to solve a task to which it has been assigned. For this, it has the ability to sense the parameters of the environment in which it is located. With the perceived data, an agent can build a knowledge base containing the environment data. This knowledge and the history of previous actions feed an inference engine used to decide the best action to be taken toward a predefined objective. The actions can also involve interaction with other neighboring agents (DORRI; KANHERE; JURDAK, 2018), as shown in Figure 3. These features allow dealing with highly complex problems in a modular form, increasing computational efficiency, reliability, extensibility, flexibility, and reuse of system components (SYCARA, 1998).

Figure 3: The structure of an agent (DORRI; KANHERE; JURDAK, 2018)



Due to the flexibility of use of the MAS, its concepts can be used in different areas of study that, aligned with multidisciplinary fields, can significantly expand its effectiveness. Areas such as social sciences, psychology, and cognitive sciences have explored the use of MAS in order to complement their studies and expand their impact potential. As an example, studies involving the representation of emotions, such as happiness, anger, and fear, have been conducted looking for more advanced ways of simulating human aspects through computation (MARTINEZ-MIRANDA; ALDEA, 2005). Other researchers have also explored agent-based approaches to representing other human characteristics, including personality. In this aspect, several studies were conducted (SALVIT, 2012; BRAZ; BACHERT; SICHMAN, 2022; BRAZ; SICHMAN, 2022b; FARHANGIAN, 2018; FARHANGIAN et al., 2014) seeking to observe characteristics of human personalities in artificial agents. To observe these aspects, simulation models can be created to analyze the behavior of agents modeled with different personality characteristics. These characteristics can be derived from existing theories in the areas of psychology and instruments such as the MBTI. Thus, it is possible to analyze through computer simulations the behavior of multiple agents, which are modeled with human-inspired personalities helping observe the particularities of each one and the decision-making process influenced by them.

3.1 Simulation of human behavior through computation

Simulations involving computational tools, with the objective of better understanding reality and its inherent characteristics, have been of great importance in numerous researches involving a wide range of application domains. MAS deals with the domain of computing that describes entities called agents, which can have autonomous and proactive behavior, interacting with an environment designed to observe circumstances conducive to various analyses. This peculiarity makes MAS a highly relevant study field for understanding, modeling, designing, and implementing different kinds of autonomous and distributed systems. Using a programming paradigm to develop complex and dynamic systems, MAS enables effective means of simulating the real world (MICHEL; FERBER; DROGOUL, 2018).

The broad applicability of MAS makes this approach suitable for developing systems that simulate human behavior in different contexts. MAS utilizes the same foundational ideas and concepts of human habits and societies. It is common to have systems made up of agents that interact and collaborate with each other in order to complete common goals for the group, in the same way we see human beings in the real world (ABBAS; SHAHEEN; AMIN, 2015).

Representing human behavior involves several challenges. Each individual has distinct characteristics and particularities that make them unique (BRAZ; SICHMAN, 2022c). In addition to a complex decision-making process, intelligence and emotions differentiate us from other beings. When a computer seeks to simulate human behavior, not only the decision-making process must be emulated. Emotions, personalities, and other characteristics inherent to the complexities of human beings must also be considered in order to represent these particularities (MARTINEZ-MIRANDA; ALDEA, 2005) more effectively.

From the nineties, Agent-Based Social Simulation (ABSS) became popular in modeling societies inspired by human beings containing several levels of abstraction of the individual's behavior. Several studies have also been carried out analyzing human behavior in contexts such as natural disasters (ADAM; GAUDOU, 2017), egress simulations in emergencies (SHARMA et al., 2018), crowd simulations (LUO et al., 2008), and many others.

Modeling these complex systems in multi-agent systems involves frameworks that make it possible, albeit simplistically, to represent some of these characteristics of individuals and thus enable the observation of phenomena resulting from the interactions between artificial agents and the environment, as discussed in the subsequent section.

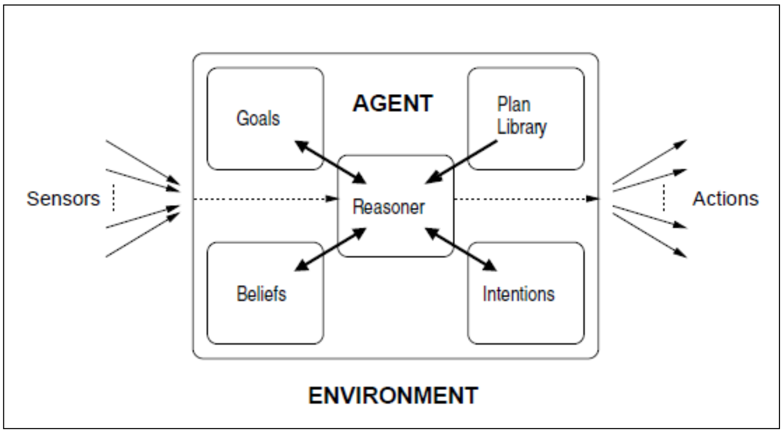
3.2 Belief-Desire-Intention Architecture

Some theories have stood out in the field of MAS, supporting the development of autonomous agents capable of simulating human behavior. *Belief-Desire-Intention architecture (BDI)* (BRATMAN; ISRAEL; POLLACK, 1988) has played an essential role in this regard, helping represent reasoning and decision process in agents (NORLING; SONENBERG, 2004). In this architecture, an abstraction of the reasoning process is proposed considering data structures that allow representing agents' beliefs, desires, and intentions. For this, agents can perceive internal and external events that define their mental state (RAO; GEORGEFF et al., 1995). According to (NORLING; SONENBERG, 2004), "The BDI framework is based upon a folk-psychological view of reasoning, that is, the way people think that they think, as opposed to the actual mechanics of the way that the brain works", which basically express the concept of abstraction used to simulate the idea we have about human reasoning, which may not actually represent what happens in reality.

In a BDI architecture, agents have beliefs, desires, and intentions that will define their behavior in an environment. Beliefs describe the information that agents have about the world around them, that is, their beliefs about the environment in which they find themselves. These beliefs are not necessarily true and may be incomplete or incorrect given agents' perception limit. Desires represent the actions that the agent would like to perform, or in other words, the goals that they intend to achieve. With these formulations, agents have intentions, representing the desires that agents have committed to achieving (HOEK; WOOLDRIDGE, 2008). Most BDI architectures also have a plan library that abstracts specifications for achieving goals or subtasks that may derive from a given (PADGHAM; LAMBRIX, 2000) goal. Figure 4 demonstrates the key components of a BDI agent in which it is noticed that given a perception of input sensors, agents then formulate their beliefs, desires, and intentions that directly influence their actions, that is, their behavior in the environment.

In developing a BDI agent-based, a set of initial beliefs and plans are specified. The agent then can fulfill a goal or respond to changes arising from environmental stimuli. Plans are defined as a sequence of steps towards a predetermined objective and may

Figure 4: The key components of a BDI agent(NORLING; SONENBERG, 2004)



contain actions and subgoals (SILVA; MENEGUZZI; LOGAN, 2020). The plan contains action directives that can directly influence the environment or sub-goals that can be expanded into other plans when necessary. This chain of objectives and plans allows agents to build complex hierarchies in decision-making (ADAM; GAUDOU, 2016).

To represent the dynamic structures described in the BDI, (RAO; GEORGEFF et al., 1995) proposes an abstraction of the architecture to combine them with the input of an event queue. The authors explain that this proposal provides updating and consulting operations in the three structures – Beliefs, Desires, and Intentions – ensuring that the mental state of the agents is fulfilled. An interpreter to represent the structures of events, beliefs, desires, and intentions as demonstrated in Algorithm 1.

Algorithm 1: BDI interpreter (RAO; GEORGEFF et al., 1995)

```
1:  initialize-state();
2:  repeat
3:      options = option-generator(event-queue);
4:      selected-options = deliberate(options);
5:      update-intentions(selected-options);
6:      execute();
7:      get-new-external-events();
8:      drop-successful-attitudes();
9:      drop-impossible-attitudes();
10: end
```

In this algorithm proposal, an option generator reads an event queue for each execution cycle (lines 1-3), returning the options that the agent must evaluate. Next, the deliberator selects a subset of the available options (line 4), considering the most viable ones. With this, the agent's intentions are updated (line 5), and the most appropriate action is then performed (line 6). New external events can occur during this process (line 7), and the agent must consider them in the event queue. Finally, the agent removes successful intentions (line 8) and desires and impossible ones (line 9). This architectural abstraction is based on the practical reasoning components proposed by (BRATMAN, 1987) and allows a more simplified representation of the rational reasoning (RAO; GEORGEFF et al., 1995) process in agents.

The abstract reasoning capabilities provided by BDI significantly contribute to the development of autonomous agents capable of demonstrating complex behaviors applied to different problems. According to (PADGHAM; LAMBRIX, 2000) these capabilities can also provide agents with relevant skills to understand their relationship with other agents in the same environment.

In a Multi-agent System, each agent could have the ability to share information with others, cooperating and absorbing knowledge that may be relevant in achieving mutual goals. (LENG; FYFE; JAIN, 2006) cites that the BDI architecture has been used by large-scale applications and is recognized as one of the most successful architectures in the development of complex and dynamic systems. Its implementation in agents enables the representation of proactive and reactive behaviors, providing complex interactive environments for simulations.

3.3 Extending BDI with affective states

Human capabilities involve aspects that go beyond intelligence. Emotions and affective states play an important role in individuals' decision-making processes. In work environments, personality traits influence professional skills performed by individuals. Skills such as self-awareness, emotional awareness, self-assessment, self-confidence, self-control, trustworthiness, conscientiousness, and adaptability, among others, are generally critical in ensuring excellent performance in dynamic and highly competitive environments.

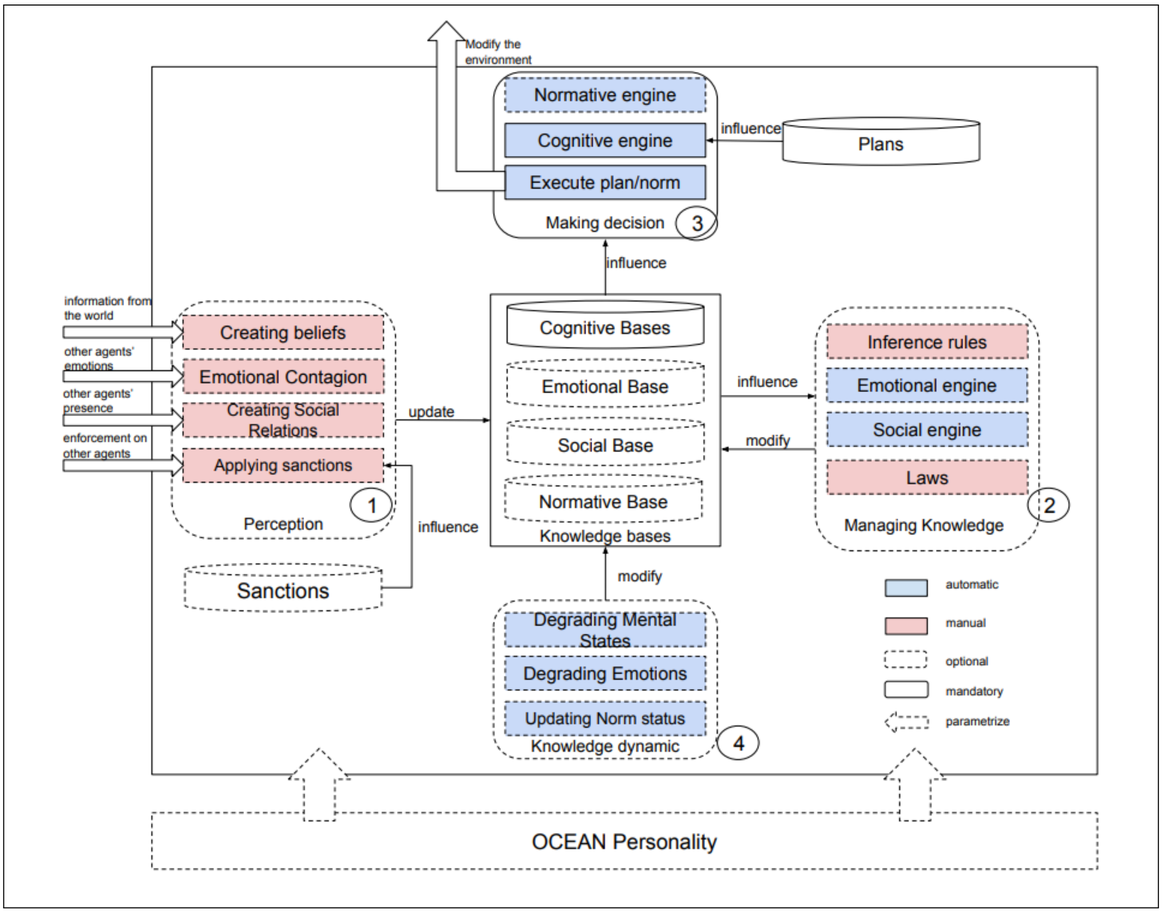
Given the importance of affective factors in human behavior, representing these aspects in a more realistic way in computer simulations allows the creation of systems closer to those observed in the real world. The development of artificial agents that demonstrate affections similar to those found in people is based on techniques that seek to express the observed main affective and emotional attributes. For example, the creation of agents with personality traits that portray behavior patterns and beliefs that dictate how they should react to environmental stimuli have been used to observe the impact of certain behavioral elements (MARTINEZ-MIRANDA; ALDEA, 2005).

Several architectures have been proposed over the years to address the challenges of representing human behavior through computation. As previously mentioned, BDI has stood out in this direction, enabling the development of agents with advanced abilities. Researchers have also sought to extend the capabilities of the BDI to illustrate specific affective elements. For example, the development of agents based on the BDI and modeled with social attributes such as cognition, emotions, norms, social relationships, and personalities have emerged through frameworks that use the precepts defined in the BDI as a basis for implementation.

The BEN (Behavior with Emotions and Norms) architecture was introduced to address the representation of these aspects in agent-based models. Agents with cognitive capabilities can be modeled with features that allow the environment perception and knowledge acquisition about social interactions with other agents and environmental stimuli. In their decision-making process, BDI agents take actions considering facts and situations that occurred concerning their beliefs, desires, and intentions, formulating their mental cognitive state. To connect this state with other social features, BEN integrates this structure with other capabilities that depict social relations, emotions, norms, and personalities defining the agent's behavior in simulations (BOURGAIS; TAILLANDIER; VERCOUTER, 2020).

In this kind of architecture, agents are built with dynamic structures that ensure the implementation of mechanisms for the environment perception, the decision-making process, and the agents' knowledge base management. In BEN, agents' behavior is influenced by their personality, which is the basis for all implemented structures, as described in Figure 5.

Figure 5: Diagram of the BEN architecture (BOURGAIS; TAILLANDIER; VERCOUTER, 2020)



The modularity of BEN's architecture makes modelers open to implementing other routines that play similar roles to those defined in the diagram shown. The standard architecture defines the OCEAN, or Five-Factor model as the implementation base for the development of agents; however, in this work, it will be proposed to customize the personality definition mechanisms based on the MBTI model, as explained in the Chapter 6.

4 PERSONALITY ASSESSMENT MODELS

This Chapter covers the main personality assessment models, presenting two popular models commonly used: The Five Factor Model (FFM), also known as the Big-Five or OCEAN Model, and the Myers Briggs Type Indicator (MBTI). Both instruments aim to classify specific individuals' personality characteristics based on their predominant attitudes.

4.1 Five Factor Model

The Five-Factor Model (FFM) is a model that classifies individuals' personality traits into five dimensions in a hierarchical organization: Extraversion (E), Agreeableness (A), Conscientiousness (C), Neuroticism (N), and Openness to Experience (O) (VOROBYEVA, 2011). The model has been used by researchers to predict behavior patterns in various areas and domains (ROCCAS et al., 2002). The FFM covers a vast conceptual space of human behavior, analyzing contexts such as power, love, work, affect, and intellect. It is an instrument that addresses fundamental questions about people and how they react to everyday situations (MCADAMS, 1992).

Each factor is composed to provide an accurate description of the personality dimensions. The combination of factors provides a useful framework for the study of human personality as well as an important instrument for personal development (VOROBYEVA, 2011).

Extraversion (E) The first FFM dimension describes how assertive, dominant, energetic, talkative and enthusiastic people are. Individuals with a high level of extraversion tend to enjoy interacting with large groups of people, are happy, and seek stimulation and excitement. On the other hand, people with a low level of extraversion tend to like spending more time alone. They are reserved, quiet, and independent (ZHAO; SEIBERT, 2006).

Agreeableness (A) The Agreeableness dimension describes individuals in terms of generosity, appreciation, forgiveness, kindness, sympathy, and trust (VOROBYEVA, 2011). People with a high level of Agreeableness are altruistic, sympathetic towards others, and believe that others will mutually reciprocate what has been given to them. People with a low level of Agreeableness, on the other hand, are egocentric, competitive and skeptical of the other's intentions (ROTHMANN; COETZER, 2003).

Conscientiousness (C) The Conscientiousness dimension describes how individuals deal with organization, persistence, hard work, and motivation to achieve goals. Some researchers see this dimension as the ability to work hard. The motivation to achieve results is also commonly seen as a driver for entrepreneurial attitudes (ZHAO; SEIBERT, 2006). People with a high level of Conscientiousness are linked to efficient, responsible, reliable, organized, and planful attitudes (VOROBYEVA, 2011). Low levels of Conscientiousness do not necessarily lack these principles, but they are less likely to apply them (ROTHMANN; COETZER, 2003).

Neuroticism (N) This dimension indicates the general tendency of individuals to experience negative affects such as fear, sadness, embarrassment, anger, guilt, and disgust (ROTHMANN; COETZER, 2003). Neuroticism describes individual differences in emotional adjustment and stability. High levels of Neuroticism indicate a tendency for people to experience negative emotions such as anxiety, depression, and impulsivity, among others. Individuals with a low level of neuroticism tend to be calm, self-confident and to demonstrate emotional stability (ZHAO; SEIBERT, 2006).

Openness to Experience (O) The last FFM dimension describes how people are actively imaginative, aesthetically sensitive, attentive to inner feelings, have a preference for variety, have intellectual curiosity and independence of judgment. Openness to Experience individuals are curious and seek new experiences. High levels of this dimension indicate that people are creative, innovative, imaginative, reflective, and unconventional (ZHAO; SEIBERT, 2006). On the other hand, people with a low level of Openness to Experience tend to have conventional behavior and prefer not to show emotional responses (ROTHMANN; COETZER, 2003).

FFM is an instrument that can be used in different domains to predict human behavior, including work contexts such as job and leader performance (VOROBYEVA, 2011). Its use for self-evaluations and work motivation has also been highlighted in studies that analyze how personality can correlate with work motivation factors (BIPP, 2010). It is a tool that contributes to a better understanding of people's natural behavioral factors and provides important insights into individuals' personality patterns.

4.2 Myers Briggs Type Indicator

MBTI is a personality inventory created by Isabel Myers and her mother, Katharine Briggs, based on Carl Jungs' theory of psychological types (JUNG, 2013). The instrument applies theoretical bases proposed by Jung so that they can be used as a resource for self-knowledge. The information provided allows individuals to have a better understanding of themselves, their motivations, natural strengths, and potential areas of growth. It is one of the most used instruments globally for understanding personality differences, and due to its dynamic characteristics, it has been used for a wide variety of purposes (MYERS, 1998). According to the authors, the instrument aims to address two main issues: identifying behavioral preferences of individuals following four proposed dichotomies, either implicitly or explicitly by Jung, and identifying and describing sixteen different types of personalities that result from interactions around these preferences (MYERS et al., 1998).

The authors also add that although these behavioral preferences represent our predilection for dealing with situations, they are not static and immutable. There is no right or wrong regarding our preferences. Each style has its particularities that are extremely valuable and characterize our personalities and how we prefer to deal with everyday situations. People tend to develop their behaviors, skills, and attitudes according to their experiences, learning to deal better with situations that are often difficult to live with, given their behavioral preferences. Each personality type has its peculiarities, strengths, and development points. Knowing how to accept and live with differences between different styles is essential for harmonious coexistence between people.

Based on the ideas of Jung's theory, Myers and Briggs classified typical human attitudes (JUNG, 2011) into four dimensions, called *dichotomies*. They are grouped to demonstrate individuals' preference between two opposing tendencies. The preference of individuals for one of the poles does not mean that they have that attitude all the time (MYERS et al., 1998). For example, extraverted individuals will have a greater tendency to be more sociable and expressive - characteristics of extraversion - compared to introverted individuals. However, they may not always exhibit this behavior (BRAZ; SICHMAN, 2022c). Dichotomies describe how individuals tend to demonstrate their behavioral styles, make decisions, and perceive the world around them, representing the way people deal with everyday situations in their lives. In this work, we used the same descriptive types already approached in previous studies (BRAZ; SICHMAN, 2020; BRAZ; BACHERT; SICHMAN, 2022; BRAZ; SICHMAN, 2022b, 2022c), analyzing particularities of each of the proposed dichotomies. Table 1 shows the characteristics of each dichotomy and behavior preference, as detailed described in the next sections.

Extraversion (E) - Introversion (I) The first dichotomy, Extraversion and Introversion, explains how individuals tend to direct their energies by interacting with the outer world, of people and activities, or the inner world of experiences and ideas. Extraverts are primarily oriented to the outer world. They direct their energy and attention outward, receiving energy from interacting with people and from taking action. Extraverted individuals are generally sociable, prefer to communicate through talking, have broader interests, and seek initiative at work or in relationships. They feel comfortable and confident even in unfamiliar environments. On the other hand, introverts tend to focus on their own inner world of ideas and experiences. They direct their energy and attention inward and receive energy from reflecting on their thoughts, memories, and feelings (MYERS, 1998). They generally prefer to communicate using forms of communication with less direct contact with others, like private and contained environments, and seek initiative when the situation or problem is very important to them (MYERS et al., 1998).

Sensing (S) - Intuition (N) The Sensing and Intuition dichotomy deals with how people perceive and process information, that is, how they seek information through their interactions with the environment around them. Sensing individuals prefer to collect information about what is real and concrete, focusing on what can be perceived by their five senses. They rely on experience and tend to be oriented to present realities, more conducive to short-term gains. Intuition individuals tend to perceive patterns and interrelationships, perceiving information more abstractly and focusing on the big-picture. They usually interpret the world in a more subjective way, which leads to less obvious paths and possibilities that may reflect long-term gains (MYERS et al., 1998).

Thinking (T) - Feeling (F) The dichotomy Thinking and Feeling explains how people make decisions. Thinking individuals base their decisions on logical conclusions and following principles and standards that can be used for similar situations. They tend to decide impersonally based objectively on the logical consequences of their decision. They are usually analytical, solve problems logically, and want everyone

Table 1: The characteristics of each preference (MYERS, 1998; BRAZ; SICHMAN, 2022c)

Dichotomy	Behavior Preference	Characteristics
E-I	Extraversion	Attuned to external environment Prefer to communicate by talking Work out ideas by talking them through Learn best through doing or discussing Sociable and expressive Readily take initiative in work and relationships Drawn to their inner world
E-I	Introversion	Prefer to communicate in writing Work out ideas by reflecting on them Learn best by reflection, mental “practice" Private and contained Take initiative when the situation or issue is very important to them
S-N	Sensing	Oriented to present realities Factual and concrete Focus on what is real and actual Observe and remember specifics Build carefully and thoroughly toward conclusions Understand ideas and theories through practical applications Trust experience
S-N	Intuition	Oriented to future possibilities Imaginative and verbally creative Focus on the patterns and meanings in data Remember specifics when they relate to a pattern Move quickly to conclusions, follow hunches Want to clarify ideas and theories before putting them into practice Trust inspiration
T-F	Thinking	Analytical Use cause-and-effect reasoning Solve problems with logic Strive for an objective standard of truth Reasonable Can be “tough-minded" Fair—want everyone treated equally
T-F	Feeling	Empathetic Guided by personal values Assess impacts of decisions on People Strive for harmony and positive interactions Compassionate May appear “tenderhearted" Fair—want everyone treated as an individual
J-P	Judging	Scheduled (have well-defined schedules) Organize their lives Systematic Methodical Make short- and long-term plans Like to have things decided Try to avoid last-minute stresses
J-P	Perceiving	Spontaneous Flexible Casual Open-ended Adapt, change course Like things loose and open to change Feel energized by last-minute pressures

to be treated equally. Feeling individuals are the opposite, making decisions based on personal or social values and considering what may be important to them and others around them. Their goal is to create an environment of harmony by treating each person as a single individual. They are generally empathetic, seek positive interactions, and want everyone to be treated as an individual (MYERS et al., 1998).

Judging (J) - Perceiving (P) The last dichotomy describes the way people deal with the outside world, that is, everyday situations, including unexpected events and routine changes. Judging individuals prefer previously well-defined and methodically constructed goals and plans. They tend to have their lives well organized and structured and feel good about getting things done. They are generally systematic, make short and long-term plans, and try to avoid last-minute changes. On the other hand, Perceiving individuals are spontaneous. They tend to look for more flexible and open paths to change, identifying opportunities that may arise in this journey. They adapt well to unplanned demands and are comfortable with last-minute pressures (MYERS, 1998).

4.2.1 Personality types

The combination of each behavioral preference described in the presented dichotomies constitutes sixteen MBTI personality types ($4^2 = 16$). MBTI uses letters to identify each behavioral preference and thus compose a distinct personality type; that is, each individual is classified according to a sequence of four letters in which each one corresponds to one of the opposite behavioral preferences of each dichotomy (MYERS, 1998). This structure describes each person's unique personality type. For example, a person classified as Extraverted, Sensing, Thinking, and Judging would be associated with the ESTJ personality type. Table 2 shows all personality types composed from possible combinations of behavioral preferences.

Table 2: The personality types (MYERS, 1998; SALVIT; SKLAR, 2010; BRAZ; SICHMAN, 2020))

		Sensing (S)		**iNtuition (N)**	
		Thinking (T)	**Feeling (F)**	**Thinking (T)**	**Feeling (F)**
Introverted (I)	**Judging (J)**	ISTJ	ISFJ	INTJ	INFJ
	Perceiving (P)	ISTP	ISFP	INTP	INFP
Extraverted (E)	**Judging (J)**	ESTJ	ESFJ	ENTJ	ENFJ
	Perceiving (P)	ESTP	ESFP	ENTP	ENFP

Each personality type defined in the MBTI has its own particularities considering the behavioral preferences that compose it. The personality type has its dominant attitudes reflected in this composition. Usually, these particularities are portrayed in a combined way to express the common characteristics of each group. These characteristics are important for analyzing dominant behavior patterns (MYERS et al., 1998).

To verify each individual's personality type, it is initially necessary to analyze the description of behavioral preferences, as described earlier. The definition of the personality type will be estimated from the peculiarities of the behaviors. For example, ISTJ individuals generally are quiet and serious, use logic to decide what should be done, are organized, and work in an orderly manner, valuing traditions and loyalty. On the other hand, ENFP individuals are generally imaginative and enthusiastic, see life as full of possibilities, quickly make connections between events, and are confident in the patterns they identify in these events. They are flexible, spontaneous, and confident in their verbal and improvisational skills (MYERS, 1998).

Identifying personality types allows individuals to develop skills in areas that may not be their natural preferences. Its use can positively impact the development of professionals who seek to explore new skills and thus amplify their actions. The constructive use of MBTI has been widely explored, from supporting the development of more effective learning methods considering individual styles (MUPINGA; NORA; YAW, 2006) to its use in work contexts, as explored in the next section.

4.2.2 MBTI applied to Work Context

MBTI's flexibility and multidisciplinary nature make it an instrument with wide applicability. In this sense, its application in corporate and work contexts has stood out for several use cases. Some common use cases involve self-understanding and development, career development, team-building, management and leadership training, problem-solving improvement, education and curriculum development, diversity and multicultural training, among many others.

People tend to be more satisfied with careers where they have opportunities to express their preferences. At the same time, knowing how to appreciate the positive value that differences can bring in relationships with people of distincts personality types helps to build more harmonious environments, encouraging individuals to respect differences and work together (MYERS, 1998).

Applying MBTI to build workplaces that are more connected with individual aspirations helps to increase the level of team engagement, influencing the positive impact on the business. The challenges in retaining talents also require organizations to work on actions to reduce turnover. Building highly engaged work teams supports organizations maximize their investments in human capital, reducing turnover and costs with recruiting, replacing, and training people (LOCKHART, 2021).

MBTI for team-building also plays a fundamental role in building more consonant teams. The effectiveness of teams depends on numerous factors, and knowing each one's unique characteristics can benefit the team as a whole (DIAB-BAHMAN, 2021). MBTI can be used for team-building in order to capture dominant factors hidden behind behavioral differences between individuals (YANG, 2022). Introducing MBTI to understanding each other's motivations and core values assists in building more energized teams. Recognizing, accepting, and encouraging coexistence with differences is essential for any successful team. Each personality has its strengths (PANAIT; BUCINSCHI, 2018), and teams with diverse skills can complement each other, working cooperatively and exploring ways to amplify the effectiveness of their joint actions (MYERS et al., 1998).

According to the MBTI theory creators, all of us can develop skills in nonpreferred areas. At the same time, the fact that each individual is classified with a certain personality type is not an excuse to avoid or not accept certain task types because of the personality type. Thus, this instrument cannot and should not be used to filter or stereotype individuals, as detailed in the next section.

4.2.3 Misuses and Limitations

Although MBTI is a widely popular instrument used by thousands of companies, several studies have shown that it must be applied prudently (BRAZ; SICHMAN, 2022c). In (COE, 1992), the author brings several implications of incorrect MBTI use. First, the instrument does not provide indications about the personal values and motivations of each one, which can bring an incomplete view of individual preferences. Second, the MBTI does not measure pathology; sane people may have the same personality type classification as those with some pathology. The author also argues that the instrument does not measure how well a person performs their preferred functions. For example, an extravert who likes to communicate verbally with others does not necessarily have empathy and communicates well, such as a Thinking individual could be better at math and logic. Finally, the author mentions that the instrument does not measure how well we perform shadow functions, or in other words, how much unconscious states influence us (THURMOND, 2012). MBTI should not be viewed as an either/or proposition. All eight functions constantly influence people. MBTI helps identify preferred characteristics of personality types, but it does not mean that a person will always exhibit a certain behavior. An extravert will have situations where they prefer to be alone and focus on the inner world, and the same will happen for all other preferences.

Psychometric criticisms and limitations are also described by authors who warn about the indiscriminate use of the instrument. Research suggests that the theory does not provide norms based on continuous scores and that much of the evidence described in the MBTI manual is questionable as to its validity (BOYLE, 1995). Other works also explain that the MBTI researches are not based on adequate scientific methods that guarantee the validity of their assumptions (PITTENGER, 2005) being necessary supplementary works that evolve the analysis in this direction.

In parallel to these limitations, the MBTI has been misused in various scenarios. Its use for screening and selecting candidates based on their personality types is an objective and clear example of the misuse of this instrument, which, as previously stated, should not be used for stereotyping purposes. There is no bad or wrong personality type for a particular job type. This conclusion is misguided and based on a misunderstanding of the MBTI (COE, 1992; MYERS, 1998).

However, knowing how to recognize the inherent limitations of the instrument and using it constructively can be extremely useful in helping people identify differences and improving the development of skills that help them respect these differences and work to mitigate eventual gaps. The use of MBTI as a support, and not an exclusion tool, can benefit organizations in building more harmonious and diverse teams, promoting team growth, and positively impacting companies (COE, 1992; BRAZ; SICHMAN, 2022c).

5 RELATED WORK

This Section presents related works, analyzing relevant studies that explored agent-based models inspired by personality theories. Studies that used the Five-Factor and MBTI models are discussed, approaching concepts related to behavior factors modeled into the agents.

5.1 Modeling agents with personalities

Artificial agents modeled with personalities have aroused the interest of researchers who seek to integrate characteristics inspired by human behavior in computational models. Using BDI to simulate the human being reasoning and decision-making process has helped the scientific community to conduct experiments that are closer to reality. The framework extension to represent complex behavioral aspects such as cognition and emotional reactions has also expanded the scope of analysis to increasingly complex scenarios (AHRNDT; FÄHNDRICH; ALBAYRAK, 2015).

The representation of emotional states and personality traits in agents has supported the development of models in numerous contexts involving agents that demonstrate behaviors influenced by their personalities. The agent modeling with personalities involves the intersection of several study areas, such as Biology, Psychology, and Artificial Intelligence (TRAPPL; PETTA, 1997).

The modeling of emotions and personalities in agents has several motivations. Incorporating more complex human aspects than the standard rational logic of the BDI architecture complements essential aspects to demonstrate more realistic agent behaviors. From entertainment-oriented applications to creating educational and training programs, agent-based simulations considering agents with personalities have been used in various scenarios (PADGHAM; TAYLOR, 1996). In the following sections, we will explore MAS works based on two popular theories concerning individuals' personality types and traits.

5.2 FFM-based models

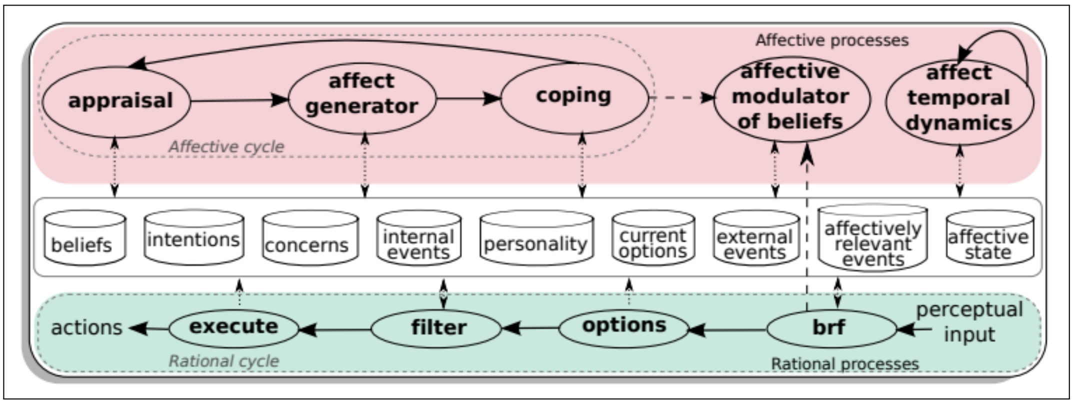
MAS scientific community has widely explored the BDI extension to add features inspired by people's personalities. Models based on human psychology theories that explain our behavior by describing personality traits and types have been developed to simulate these characteristics in computational agents (AHRNDT; FÄHNDRICH; ALBAYRAK, 2015). The Five-Factor Model (FFM), also known as Big-Five or OCEAN model, describes a conceptual and empirical model in the personality psychology field. Five factors are presented: Surgency (Extraversion), Agreeableness (Warmth), Conscientiousness (Will), Emotional Stability (Neuroticism), and Culture (Intellectance, Openness to Experience), demonstrating personality traits observed in individuals. These traits represent typical behaviors and cover a wide range of human behavior patterns (MCADAMS, 1992).

As seen earlier in Section 4.1, the FFM dimensions are defined according to behavioral particularities. Extraversion represents the search for sensations provided by the intensity of interpersonal relationships. People with extraversion are generally sociable, energetic, need stimulation, warmth, and tend to experience positive emotions, in contrast to introverted individuals. Agreeableness is related to people who prefer to be friendly, cooperative and compassionate, instead of being analytical, antagonistic, and less altruistic. Conscientiousness relates to people's preferences for organization, planning, and efficiency versus individuals' tendency to be more spontaneous and careless. Neuroticism characterizes people in terms of their tendency to experience negative emotions, such as nervousness, pessimism, and insecurity. Finally, Openness represents individuals' behavioral preferences for being inventive, curious, and emotional. People with low Openness are less likely to experiment new ideas and experiences (SMITH et al., 2019; BARAŃCZUK, 2019; AHRNDT; FÄHNDRICH; ALBAYRAK, 2015).

The use of the FFM as a basis for modeling agents with personalities has received attention from several researchers in the area, as well as the extension of the BDI through incorporating elements described in the theory. *GenIA*^{3} is an architecture proposed as an extension of BDI and aims to facilitate the design of effective agents focusing on characteristics and processes related to expressing emotions and personalities in agents (ESPINOSA, 2017). The architecture of *GenIA*^{3} uses classic concepts seen in BDI and offers a default design that incorporates FFM for representing personalities in agents. 6 shows the sequences (solid line arrows), subprocess (dashed line arrows), and information exchange (dotted line arrows) involved in the architecture.

Personality traits are represented as a set of traits followed by the agent's rationality

Figure 6: The $GenIA^3$ architecture (ESPINOSA, 2017)



level and a list of coping strategies. Despite being extensible, the architecture initially does not use personalities in the agents' cognitive process, and other authors have explored implementations in this direction.

The proposed $GenIA^3$ extension seen in (TAVERNER et al., 2018) allows modeling different personality profiles that can influence the agent's decision-making process and behavior. The personality traits of openness, conscientiousness, extraversion, agreeableness, and neuroticism are modeled as ranges corresponding to intervals of values that indicate the tendency of each dimension. The architecture was also modified so that the agent plan selection process considers intentions defined from the modeled personality profiles. Intents can be modeled on agents for each distinct personality profile. In addition to personalities, the authors also consider aspects related to emotional representation, such as surprise, fear, and sadness, among others.

Other works also considered FFM a basis for implementing personalities in agent-based models. (DOCE et al., 2010) proposed a FFM-based model for creating agents with distinguishable personalities. In this kind of model, personality traits are used to define the predisposition that a given agent has to feel certain emotions. Four cognitive/behavioral processes are elucidated as being strongly influenced by the FFM personality dimensions: emotions, coping behavior, planning, and body expression. In Neuroticism, for example, associations are made with how individuals demonstrate emotions such as anxiety and sadness. In this dimension, agents with a greater predisposition to Neuroticism demonstrate aspects related to insecurity and self-punishment. The other FFM dimensions are also studied, associating them with different emotions representations such as love, admiration, hate, and gratification.

Finally, in (AHRNDT; FÄHNDRICH; ALBAYRAK, 2015), the authors discuss FFM integration in BDI agents, describing the influence of FFM dimensions into the four phases of the BDI life-cycle, Belief Revision, Option Generation, Filter Process, and Actuation. Table 3 shows the influence of each FFM dimension, Openness, Conscientiousness, Extraversion, Agreeable, and Neuroticism, on the BDI phases.

Table 3: Influence of the FFM dimensions in each BDI phase (AHRNDT; FÄHNDRICH; ALBAYRAK, 2015))

	O	**C**	**E**	**A**	**N**
Belief Revision	x			x	
Option Generation		x		x	x
Filter Process	x	x	x	x	x
Actuation	x	x	x		

In this proposal, two versions of the BDI algorithm implementation are presented. A naive one and one that balances the commitment between means and ends. In the naive approach, an adaptation of the BDI life-cycle is described, considering the personality aspects of each stage. The cycle starts with the perception of information collected from the environment using the agents' sensors. At this stage, agents' perceptions are not affected by their personality type. In the next step, in the Belief Revision stage, the perceptions are computed taking into account the agent's personality, thus updating its current beliefs.

Beliefs contain information about the environment, the state of the agent, and received events. The Openness and Agreeable dimensions are the ones that most influence the interpretation of the results at this stage. For example, agents with a high A value will always tend to trust incoming information, while agents with a low A value will tend to always reject it. In the next stage related to Option Generation, the formulation of the agent's desires will take into account the updated beliefs, the selected intentions, and finally, its own personality. At this stage, the Conscientiousness, Agreeable, and Neuroticism dimensions have greater influence in defining the agents' preferences to follow the chosen goals, whether they will act selfishly or altruistically, and how they will react to external events and influences. The resulting desires are represented as a set of goals that agents must seek to complete. In this stage, its personality influences only the selected intentions, and as in the previous stage, high and low values associated with each dimension will determine its intentions.

In the Filter Process stage, agents choose the desires and commitments they must achieve. All dimensions influence this stage, defining the level of self-discipline (Openness and Conscientiousness), the need for harmony with the group (Agreeable and Neuroticism), and the tendency to interact with other agents (Extraversion). The agent's personality directly influences its decision-making process, helping to prioritize different intentions and, consequently, the goals that can be achieved. In the last stage, Actuation, agents create and select the plan and influence the environment by performing actions. At this stage, the Openness dimension will influence the agent's creativity level, the Conscientiousness dimension the agent's tendency to apply actions decently, and the Extraversion dimension, its preference in interacting with other agents. The actions in the selected plan will directly influence the environment, and the agent's personality indicates how accurately an agent behaves, influenced mainly by the Conscientiousness dimension.

In this proposal, the authors describe yet another variant of the BDI algorithm, adapting the life cycle so the agents are not overcommitted to intentions or plans. For this, the Actuation stage is extended with the Perception and Belief Revision stage. As the actions take a certain amount of time to be performed by the agent, the environment in which it acts may change during the task execution, making the current plan no longer relevant. The previously discussed method does not consider this sort of situation, and the adaptations proposed in this variant introduce methods so that the agent can reconsider its current intention, eventually deciding to change its plan. This approach will also be used in the current work considering the influence of the MBTI J-P dichotomy, as we will see in detail in the Chapter 6.

5.3 MBTI-based models

The MBTI, previously described in the Section 4.2, has also been widely used by researchers in the MAS area for modeling agents with personalities. The main characteristics of each MBTI dichotomy are modeled in agents based on the extension of the BDI architecture, exploring aspects inspired by the behavioral preferences described in the instrument.

In (CAMPOS et al., 2009), the authors present a process-oriented approach for creating agents with personalities based on MBTI. A model is proposed in which agents have a decision-making process founded on reasoning strategies defined according to their personality types. In this approach, agents create and select plans following a preferred reasoning process. It is a different approach from other proposals focused on the agent's preferences for a set of actions. To define the strategies, the BDI architecture and MBTI are used as a theoretical basis for modeling the personality-based reasoning process. Two dichotomies are used in the model: Sensing-Intuition and Thinking-Feeling. The first seeks to represent two distinct characteristics of behavioral preferences. While Sensing individuals have a preference for what is concrete and tangible, Intuition individuals prefer to be open to possibilities. The second dichotomy is used to represent the differences between Thinking individuals, who use logic in decision-making, and Feeling individuals, who prefer to base their decisions on subjective aspects related to person-centered values.

The authors developed an agent-based simulation to test the described concepts and evaluate a simple use case illustrated through a firefighting scenario. In this scenario, a firefighter agent must define the reasoning strategy to help a person calling for help in a burning building. Two options are possible: put up a safety net and wait for the person to jump into the net, or enter the building and bring the person out safely. Both situations involve uncertainties. Even with the safety net, the individual may decide not to jump, and the firefighter agent entering the building may find it impossible to proceed further into the burning building. The proposed simulation seeks to analyze different action plans that agents modeled with distinct personality types designed. The demonstrated results could reproduce expected behaviors following personality characteristics without defining behavioral preferences over a set of possible actions. The methods used were also flexible and could be adopted in other domains of agent-based systems.

Other researchers also addressed the modeling of agent personalities using MBTI precepts. Salvit and Sklar (SALVIT; SKLAR, 2010; SALVIT, 2012; SALVIT; SKLAR, 2012) explored the modularization of agent behavior through MBTI-inspired personalities. The BDI Architecture was used to design functions that define agents' beliefs, desires, and intentions influenced by their personality types. In this model, MBTI is applied to the BDI architecture by adapting each of its phases. Initially, as demonstrated in the equation 5.1, the agent is modeled with a perception function that will be used to sense the environment (ε) and interpret the meanings of the raw input data (S) captured:

$$sense \leftarrow \varepsilon \times S \tag{5.1}$$

Next, the agent interprets the input data using a set of values that define its personality type (γ). The Sensing-Intuition dichotomy is used to interpret the data, as seen in the equation 5.2, thus composing the agent's beliefs.

$$beliefs \leftarrow sense \times \gamma \tag{5.2}$$

After defining its beliefs, the agent will define its desires, and for that it uses its beliefs, its internal state (I), a set of short and long-term goals (G), and its personality type (γ). At this stage, the Thinking-Feeling dichotomy plays a major role, as it is described as fundamental in the decision-making process. The 5.4 equation shows the relationship between the variables for defining the agent's desires.

$$desires \leftarrow beliefs \times I \times G \times \gamma \tag{5.3}$$

Finally, the agent compiles a list of intentions, still using the T-F dichotomy to select the desires and convert them into intentions, as seen in the **??** equation.

$$intentions \leftarrow desires \times beliefs \times G \times \gamma \tag{5.4}$$

The plan's definition for executing the agents' intentions is defined also considering their personality; in this case, the Judging-Perceiving dichotomy influences the definition of plans according to the agent's behavioral preferences, determining how committed the agent is to its beliefs, desires, intentions and the formulated plan itself. The Extraversion-Introversion dichotomy also plays a role in each function, determining the agent's behavior in the environment. Extraverted agents will seek to interact with other agents, biasing their decisions towards the outer world. On the other hand, introverted agents will seek to focus their attention on their own inner world of individual goals and thoughts. The Table 4 shows how each MBTI dichotomy influences the BDI stages.

Table 4: MBTI influences in BDI process (SALVIT; SKLAR, 2012)

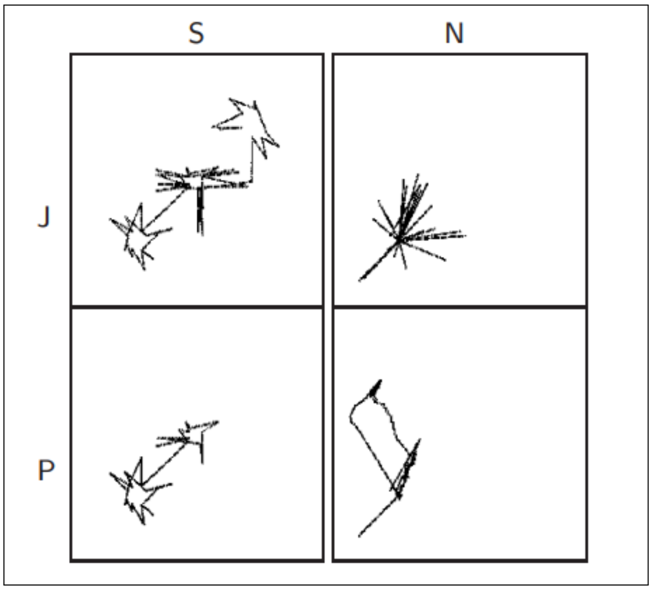
	E-I	**S-N**	**T-F**	**J-P**
sense environment and update beliefs	x	x		
update desires and intentions	x		x	
update plan and select actions	x			x

The framework proposed by (SALVIT; SKLAR, 2010) seeks to evaluate how agents, influenced by their behavioral preferences derived from the psychological types described in MBTI, act in relation to the achievement of a certain task, analyzing the performance of each agent in different scenarios simulated. The authors demonstrate that even when performing a simple task, agents with different personalities can follow different paths in achieving these same tasks, consequently making the resulting performance also impacted by these behavioral differences.

To simulate the proposed model, the authors defined a scenario in which agents must pile food particles scattered around the environment on predefined bases at the beginning of the simulations. At each simulation step, the agent senses the environment, decides what to do, and performs the action.

Despite a simple simulation scenario, the proposed model demonstrated that the agent's personality types impacted the agent's behavior in terms of decisions taken during the simulations and performance measured. Several simulations demonstrate differences between the behaviors presented in scenarios with different compositions of personality types in the agents, demonstrating that the personalities influenced the decisions taken and, consequently, the agents' performance. Figure 7 shows the typical paths taken by agents modeled with personality types composed by the S-N and J-P dichotomies, in which one can see the different paths chosen influenced by the agents' personalities.

Figure 7: Typical paths taken by each agent personality (SALVIT; SKLAR, 2012)



The work presented here uses concepts addressed by the mentioned authors and explores avenues of study related to the analysis of agent teams and not only the agents individually. Modeling work teams can contribute to the observation of collaborative aspects considering broader contexts and scopes.

PART II

PROPOSAL

6 *PERSONALIFY* FRAMEWORK

This Chapter presents the work proposal based on the objectives mentioned earlier. We presented *Personalify*, an MBTI-based agent framework that can be used in different domains and contexts.

Our work explored its use in contexts similar to organizational realities. For this, the Seller-Buyer scenario is used, representing entities that simulate in a simplified way, characteristics found in the buying and selling relationship commonly seen in corporate environments. We explored the modeling of agents' decision-making process by applying MBTI concepts and introduce the agent's decision attributes that comprise a decision matrix using the Multi Attribute Decision-Making method. Then, we addressed the scope expansion of MBTI agent-based simulations for scenarios that consider work teams and Market Types, addressing situations that illustrate buying and selling demand constraints. Finally, we presented a Pseudo-algorithm proposal using the formulated decision attributes to model the Sellers' agent decision process.

6.1 Introduction

In this work, we proposed an extension of the framework developed by Salvit and Sklar (SALVIT; SKLAR, 2010; SALVIT, 2012; SALVIT; SKLAR, 2012) to cover a broader scenario than originally used by the authors.

The framework proposes the use of the Multi Attribute Decision-Making (MADM) method to develop agent's decision attributes that enable a more complex and dynamic decision-making process, considering the combination of multiple attributes.

6.2 Multi attribute decision-making

Complex problems usually involve analysis of multiple factors in a decision-making process. The ability to consider factors of different natures and scales in a single, flexible, and dynamic mechanism enables more assertive decisions considering multiple dimensions. In this sense, Multi-Criteria Decision-Making methods have evolved to provide applications of different types to use the benefits of a centralized decision-making mechanism. The improvements in these methods allowed researchers to have access to advanced decision analysis. Despite being advanced, the simplification of these techniques has contributed to being applied in different contexts and use cases, in which benefits such as scalability, easy adaptation, and simplicity of use have been highlighted as advantages of using these methods (VELASQUEZ; HESTER, 2013).

Multi attribute decision-making (MADM) is one of these methods to deal with multiple decision factors in a centralized way. According to (STANUJKIC; MAGDALINOVIC; JOVANOVIC, 2013) MADM "refers to screening, prioritizing, ranking, or selecting a set of alternatives usually under independent, incommensurate or conflicting attributes" and thus provides multiple alternatives to be considered and ranked in order to select the best possible actions according to the given input attributes. The method has two phases. In the first phase, the decision-maker needs to define which attributes will be considered and the performance metric for each of them. The Weighted Sum method and a distance-based procedure are applied in the second phase to determine the alternatives' overall performance rating.

A MADM matrix can then be formalized to represent defined criteria and alternatives, as shown in matrix 6.1.

$$S = \begin{array}{c} \\ A_1 \\ A_2 \\ . \\ . \\ . \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & ... & C_n \end{array} \\ \begin{bmatrix} c_{11} & c_{12} & \dots & c_{1n} \\ c_{21} & c_{22} & \dots & c_{2n} \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ c_{1n} & c_{2n} & . & c_{mn} \end{bmatrix} \end{array}, \tag{6.1}$$

$$W = \begin{bmatrix} w_1, & w_2, & ..., & w_n \end{bmatrix},$$

The matrix S follows a similar structure proposed in MADM, where A_1, A_2, ..., A_n

are feasible alternatives. The criteria are represented as C_1, C_2, ..., C_n characterizing the attributes (criteria) that must be measured for each of the alternatives. Weights (significance) w_1, w_2, ..., w_n can also be defined for each attribute to add the weighted relevance.

In MADM, attributes can be classified into two categories: benefit attributes and cost attributes. For benefit attributes, the highest performance score is assigned to the alternative; that is, the higher the value associated with the attribute, the better its score. For example, in a scenario where one intends to choose the best car for a race, in which cars with higher speed values are likely to be preferred. For cost attributes, on the other hand, the highest score is assigned to the alternative with the lowest value associated with the attribute. In the car racing example, it can be considered that cars with the lowest fuel consumption would be a better choice. The best alternative will be the one with the best performance, comprising both cost and benefit attributes.

With the defined attributes, the next phase is to apply the Weighted Sum (WS) method, also known as Simple Additive Weighted. Although other methods can be used, WS has been one of the most famous methods applied to MADM. The WS method proposes to obtain the sum of the performance ratings of each alternative considering all attributes, so the overall performance rating is calculated for each alternative with the formula shown in equation 6.2.

$$S_i = \sum_{j=1}^{n} w_j \cdot r_{ij}, \tag{6.2}$$

where S_i contemplates the overall performance of each alternative ith; w_j is the weight of jth attribute; and r_{ij} is a normalized performance rating of ith alternative with respect to jth attribute.

An important requirement for using the equation is the application of performance rating normalization procedures to avoid computational problems that may be caused by differences in the unit metrics used in the decision matrix. Different normalization techniques can be applied together with the WS method since this method will not differentiate the normalization procedure used. The Linear Scale Transformation - Max (LST-MAX) is one of the simplest methods adopted for normalization. With it, cost and benefit attributes can be normalized following the equations 6.3 and 6.4.

$$r_{ij} = \frac{x_{ij}}{x_j^+} \tag{6.3}$$

$$r_{ij} = x_j^- / x_{ij} \tag{6.4}$$

In equation 6.3, a procedure to normalize benefit attributes is shown, where x_{ij} is a performance rating of ith alternative with respect to jth attribute; and x_j^+ is the largest performance rating of jth attribute. In equation 6.4, the cost attribute normalization procedure is applied where x_j^- is the smallest performance rating of the considered attribute. With the defined performance rating, the normalized attributes, and the overall ranking of each alternative calculated, the final stage of the MADM process involves obtaining the most acceptable alternative (STANUJKIC; MAGDALINOVIC; JOVANOVIC, 2013), that is, the one with the highest value of S_i, where the best alternative A^* can be obtained as follows in the equation 6.5.

$$A^* = \max_i S_i = \max_i \sum_{j=1}^{n} w_j \cdot r_{ij} \tag{6.5}$$

6.3 Agent's Decision Attributes

In *Personalify*, the agent's decision attributes are formulated by modeling the different MBTI personality types as part of the agents' decision-making process. The model uses the MADM approach to support agents to be able to select, prioritize, rank, or select alternatives that best apply to its context (STANUJKIC; MAGDALINOVIC; JOVANOVIC, 2013). For this purpose, it is formalized a matrix based on MADM that allows the agents to make decisions considering their various psychological types derived from MBTI, as seen in the following equation 6.6.

$$S = \begin{array}{c} \\ T_1 \\ T_2 \\ . \\ . \\ . \\ T_n \end{array} \begin{array}{c} \begin{array}{cccc} A_1 & A_2 & ... & A_n \end{array} \\ \begin{bmatrix} a_{11} & a_{12} & ... & a_{1n} \\ a_{21} & a_{22} & ... & a_{2n} \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ a_{n1} & . & . & a_{nn} \end{bmatrix} \end{array} \tag{6.6}$$

This matrix follows the same structure proposed in MADM, where T_1, T_2, ..., T_n are feasible alternatives (STANUJKIC; MAGDALINOVIC; JOVANOVIC, 2013) that adapted to an agent-based scenario will represent the possible agent's Target. Also following the same concept demonstrated in MADM, the criteria will be represented as the attributes A_1, A_2, ..., A_n characterizing the criteria that must be measured for each of the alternatives. The results from each criterion, applied to each possible Target agent, will compose the S matrix.

As the used criteria in modeling the agents' personalities have different units measurement, a Linear Scale Transformation Method (LST-Max) (NIJKAMP; DELFT, 1977; ZAVADSKAS; TURSKIS, 2008) is used to transform the benefit and cost attribute values. The attribute normalization is then represented in the S matrix, as shown in the equation 6.7.

$$S^{norm} = \begin{array}{c} \\ T_1 \\ T_2 \\ . \\ . \\ . \\ T_n \end{array} \begin{array}{c} \begin{array}{cccc} A_1 & A_2 & ... & A_n \end{array} \\ \begin{bmatrix} a_{11}^{norm} & a_{12}^{norm} & ... & a_{1n}^{norm} \\ a_{21}^{norm} & a_{22}^{norm} & ... & a_{2n}^{norm} \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ a_{n1}^{norm} & . & . & a_{nn}^{norm} \end{bmatrix} \end{array} \tag{6.7}$$

After determining the structure of S MADM matrix and its normalization procedure, it is necessary to define the attributes that compose the agents' decision making process. In this sense, five attributes are defined, as discussed in subsequent sections.

6.3.1 Distance to the Target-Agent (A1)

This attribute represents the Euclidean distance ($\sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$) between the coordinates of an agent and a Target agent given by the attribute value $\mathrm{a}_{\mathrm{i}1}$. As the agents normally have a limited time to complete their objective, they should prioritize Targets where the distance is smaller, aiming to consume fewer movement cycles. Agents also have a limited view of the environment, so they can only calculate the distance to the Target agents within its perception radius. Its threshold also influences all other attributes. It is considered a cost attribute in the normalization procedure for the MADM matrix, given that the smaller the distance, the higher its score will be. Equation 6.8 shows the normalization procedure for this attribute.

$$A_{\mathrm{i1}}{}^{norm} = min(A_1)/a_{\mathrm{i1}} \tag{6.8}$$

The A1 attribute is also present in the general scoring process for the other attributes A2, A3, and A4, having influence in all dichotomies.

6.3.2 Exploration or Exploitation (A2)

The second attribute represents the influence of the Extraversion-Introversion dichotomy in which agents will demonstrate two sorts of attitudes given their personality type: Exploration or Exploitation. This kind of approach is commonly seen in machine learning scenarios and helps to represent the attitude which an agent may have of exploring new options instead of staying within a familiar region (OSUGI; KIM; SCOTT, 2005; DESAI, 2015).

Extraverted agents are more prone to Exploration. Whenever possible, they seek to interact with Target agents they have never visited before. They seek to take the initiative in exploring unknown spaces, thus expanding their potential to create new relationships and broaden their range of interests. On the other hand, Introverted agents will try to interact with Target agents they already know, maintaining relationships they already have prior experience with and taking the initiative to expand their network when the situation is very important to them. This attribute seeks to represent the notions of the inner and outer world described in MBTI theory (MYERS, 1998).

The number of interactions (a_{i2}) made is used to calculate this attribute. For Extraverted agents, the metric is calculated as a cost attribute, while for Introverted agents it is considered as a benefit attribute, as seen in equation 6.9

$$A_{\mathrm{i2}}{}^{norm} = \begin{cases} min(A_2)/a_{\mathrm{i2}}, & \text{if } Preference = Extraverted \\ a_{\mathrm{i2}}/max(A_2), & \text{otherwise} \end{cases} \tag{6.9}$$

With the normalized values, the next step is to calculate the $\mathrm{S^{E\text{-}I}}_{\mathrm{i}}$ values. It is used the sum of $A_{\mathrm{i1}}{}^{\mathrm{norm}}$ and $A_{\mathrm{i2}}{}^{\mathrm{norm}}$ for each i value, as seen in the equation 6.10.

$$S^{\mathrm{E\text{-}I}}{}_{\mathrm{i}} = A_{\mathrm{i1}}{}^{\mathrm{norm}} + A_{\mathrm{i2}}{}^{\mathrm{norm}} \tag{6.10}$$

6.3.3 Cluster Density and Proximity to the Perception Edge (A3)

The third attribute addresses some of the particularities described in the Sensing-Intuition dichotomy. Firstly, agents will consider the density of the Target agents clusters (a_{i3^a}) around them, and with that, they will be able to abstract the possibility of future gains. That is, is it worth for an agent to travel a longer distance to find a Target agent since it is close to several other possible Target agents? To answer this question, agents will consider, through the modeling of decision attributes, the factors that will be most relevant in their decision-making process according to their behavioral preferences. Intuitive agents will prioritize cluster density focusing on some data patterns and on future possibilities, while Sensing agents will focus on what is actual, real, and concrete, prioritizing closer Targets. Cluster density is always calculated as a benefit attribute, as observed in the equation 6.11.

$$A_{i3^a}{}^{norm} = (a_{i3^a})/max(A_{3^a}) \tag{6.11}$$

To calculate A3 attribute, it is necessary to define a Density Weight. It must be done because the same benefit attribute must be applied for both personality types (S or N); however, for Intuition agents, the possibilities for long-term gains will be stronger than for Sensing agents. In this case, we apply a weight of 0.25 for iNtuition and 0.1 for Sensing. Equation 6.12 shows the weighting calculation. These factors were defined empirically, portraying the opposition between both behavioral preferences. The same weight value will also be applied to other attributes that seek to represent opposite poles. In future work, parameter optimizations can be made for greater robustness of analyses and observations.

$$DensityWeight = \begin{cases} 0.25, & \text{if } Preference = iNtuition \\ 0.1, & \text{otherwise} \end{cases} \tag{6.12}$$

Another characteristic measured in this attribute refers to the number of Target agents near the Agents's perception edge (a_{i3^b}). Intuition agents are more imaginative and will try to prioritize Target agents near the edge as they believe there are other targets beyond their vision limit close to the original target. In turn, Sensing agents will continue to focus on closer Targets. As it is seen in the equation 6.13, this is considered a benefit attribute in MADM.

$$A_{i3^b}{}^{norm} = a_{i3^b}/max(A_{3^b}) \tag{6.13}$$

Intuition agents prioritize proximity to the perception edge, and Sensing agents prioritize distance to Target agents. To address this situation, its applied the same concept seen earlier, associating weight values for each preference, as demonstrated in the equation 6.14.

$$AgentsClosestToEdgeWeight = \begin{cases} 0.25, & \text{if } Preference = iNtuition \\ 0.1, & \text{otherwise} \end{cases} \tag{6.14}$$

The distance measure (used to calculate $\mathrm{A_{i1}}^{\mathrm{norm}}$) will compose the remaining part of the weight calculation, as seen in equation 6.15.

$$DistanceWeight^{\text{S-N}} = 1 - DensityWeight - AgentsCloseToEdgeWeight \tag{6.15}$$

After the weights definition, it is necessary to gather the normalized values of the number of agents contained in each of the identified clusters($\mathrm{A_{i3}}^{\mathrm{norm}}$). A clustering method was applied to identify the clusters using the Gama function *simple_clustering_by_distance* as it will be described in Section 7.1. This function is similar to the concept of *hierarchical clustering* (MURTAGH; CONTRERAS, 2012) but applied to the current topology to compute the distances. The number of agents close to the edge of the agents' perception radius is also used ($\mathrm{A_{i3^b}}^{\mathrm{norm}}$) so that the calculation can be composed with the weight associated with this factor. Finally it is possible to calculate $\mathrm{S^{S\text{-}N}}_{\mathrm{i}}$ using the equation 6.16.

$$S^{\text{S-N}}{}_{\text{i}} = (A_{\text{i1}}{}^{\text{norm}} * DistanceWeight^{\text{S-N}}) + (A_{\text{i3}^{\text{a}}}{}^{\text{norm}} * DensityWeight) + (A_{\text{i3}^{\text{b}}}{}^{\text{norm}} * AgentsClosestToEdgeWeight) \tag{6.16}$$

6.3.4 Agents Close to the Target-Agent (A4)

This attribute represents the characteristics of the Thinking-Feeling dichotomy. Feeling agents are empathetic, seek environment harmony, and will consider what other agent colleagues might aim for, seeking to avoid target agents that are close to their peers. On the other hand, Thinking agents tend to be more logical and rational, focusing on their own goals over other factors. This attribute permits agents to act, even indirectly, collaboratively. Feeling agents will consider what other agents on the team may have as a plan and thus can avoid visiting Target agents who will eventually be visited first by other colleagues.

To calculate this dimension, agents will consider the number of other colleague agents close to a Target (a_{i4}). This attribute is considered a cost attribute in MADM, as seen in the equation 6.17, given that the more co-workers close to the Target, the lower associated value.

$$A_{i4}{}^{norm} = a_{i4}/max(A_4) \tag{6.17}$$

A weight is also applied in order to differentiate the behavior of Feeling agents, who will consider more important the fact of having teammates close to possible Targets, from Thinking agents, who will consider their own distance a factor of greater relevance. The equation 6.18 shows how the weights are distributed according to the behavior preference, representing opposite poles.

$$SellersCloseToBuyerWeight = \begin{cases} 0.8, & \text{if } Preference = Feeling \\ 0.2, & \text{otherwise} \end{cases} \tag{6.18}$$

The distance measure also composes the remaining part of the weight calculation, as shown in the equation 6.19.

$$DistanceWeight^{\text{T-F}} = 1 - SellersCloseToBuyerWeight \tag{6.19}$$

After the weights application, it is possible to calculate $S^{\text{T-F}}{}_{\text{i}}$ using the equation 6.20.

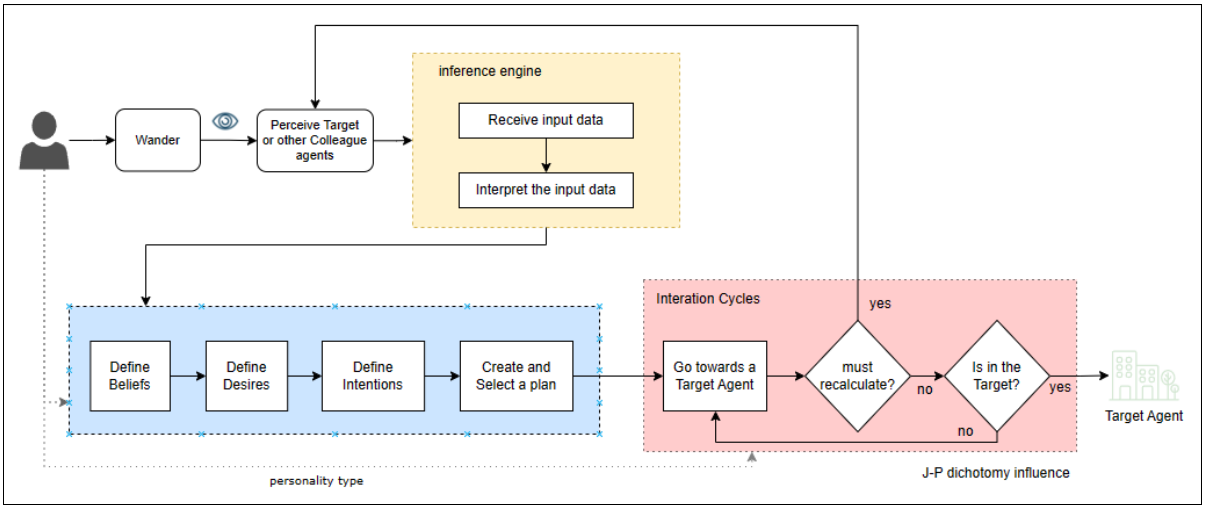
$$S^{\text{T-F}}{}_{\text{i}} = (A_{\text{i1}}{}^{\text{norm}} * DistanceWeight^{\text{T-F}}) + (A_{\text{i4}}{}^{\text{norm}} * SellersCloseToBuyerWeight) \quad (6.20)$$

6.3.5 Probability to recalculate the plan (A5)

The last attribute relates directly to the Judging-Perceiving dichotomy. Perceiving agents can constantly reconsider the original plan being open to new options and alternatives that may arise in their journey to the Target agent. Judging agents will be highly committed to their original plan unless they realize their goal is unattainable. It is the only attribute not considered in the MADM matrix, being implemented in the system as a probability of recalculating the agents' plans at each execution cycle.

Figure 8 shows the Agents' decision process now considering the influence of the J-P dichotomy. When an agent decides on a specific Target, it creates and selects an action plan to reach this objective. The agent can reconsider this decision or continue its journey toward the chosen Target agent. This choice occurs at each interaction cycle (a step the agent takes towards the Target agent), and the personality type directly influences it. Judging agents are committed to the decision made and not very susceptible to plan changes. Perceiving agents constantly reconsider their decisions, considering new possibilities. These attitudes can influence the agent's success in achieving their goals. For example, an agent who has decided to follow a long journey to reach a Target agent who is close to several other agents may discover, in the middle of the journey, that there are several other agent's colleagues close to the Target and thus give up this choice and choose another goal. Judging agents have 80% probability of maintaining their choice and 20% of recalculating the original plan; the opposite occurs with Perceiving agents, having 80% probability of recalculating their choice and 20% of maintaining the original plan. These parameters have been chosen empirically and seek to represent the opposite preferences among the two attitudes.

Figure 8: Agent decision-making process with J-P influence



6.3.6 Decision Function

With the S_i outcomes from the three dichotomies, it is necessary to calculate the final decision score. According to the MADM method, equivalence weights for all dichotomies are used. In this case, we chose to apply the same weights to all dichotomies to maintain a balance between all influences, as shown in equations 6.21, 6.22 and 6.23. This work does not consider concepts related to the dominance of main and auxiliary functions addressed by the MBTI. A potential study path could be applying different weights to represent these aspects in the MADM matrix. The weights defined are applied for each S_i, as detailed in the equation 6.24.

$$Weight^{\text{E-I}} = 1/3 \tag{6.21}$$

$$Weight^{\text{S-N}} = 1/3 \tag{6.22}$$

$$Weight^{\text{T-F}} = 1/3 \tag{6.23}$$

$$S^{\text{Final}}{}_{\text{i}} = (S^{\text{E-I}}{}_{\text{i}} * Weight^{\text{E-I}}) + (S^{\text{S-N}}{}_{\text{i}} * Weight^{\text{S-N}}) + (S^{\text{T-F}}{}_{\text{i}} * Weight^{\text{T-F}}) \tag{6.24}$$

According to these steps, the $S^{\text{Final}}{}_{\text{i}}$ will represent a ranking of alternatives based on the preferred performance ratings where the best alternative will be the one with the highest value of $S^{\text{Final}}{}_{\text{i}}$ (STANUJKIC; MAGDALINOVIC; JOVANOVIC, 2013), as we can see in the equation 6.25.

$$S^{\text{Best}} = max(S^{\text{Final}}{}_{\text{i}}) \tag{6.25}$$

6.4 Applying *Personalify* to a Seller-Buyer scenario

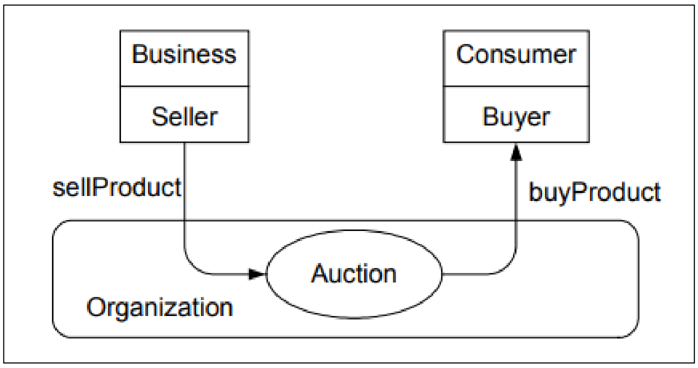
We used the Seller-Buyer scenario to apply the *Personalify* franework considering situations closer to organizational contexts.

This scenario contains two entity types: Sellers and Buyers. This approach, already used in several other studies (BRATMAN; ISRAEL; POLLACK, 1988; XU; SHATZ, 2001; TRAN; COHEN, 2002; ZHANG; COHEN; LARSON, 2008), allows design scenarios in which Buyers and Sellers agents interact with each other, seeking to carry out a sales transaction.

Researchers have used models with entities called Sellers and Buyers to develop agent-based simulations considering scenarios close to those seen in the organizational real world. Buyers and Sellers represent entities, such as companies and consumers, who seek to carry out business transactions with each other. A selling agent is usually autonomous, making decisions independently, without user intervention; on the other hand, buying agents seek to find and buy what they are looking for according to their interests (CHAVEZ; MAES, 1996). In general, Sellers have the main objective of selling products, and they seek to complete sales transactions with Buyers. These, in turn, seek to buy products that are offered to them. Although quite simple, this scenario allows several real-world problems to be explored in order to observe the behavior derived from these relationships.

Adaptations in the characteristics of both Buyers and Sellers can also be implemented, seeking to analyze certain particularities of problems, and in this sense, studies have been conducted exploring different situations. In the (TRAN; COHEN, 2002) study, the authors simulate a marketplace environment with Buyers and Sellers who are free to enter and exit the market. Sellers can sell the same products with different qualities, and Buyers must learn to avoid the risk of purchasing low-quality products to maximize the benefit of the transaction. In (XU; SHATZ, 2001), the authors explore the concept of Buyers and Sellers for developing an agent-based model in which communication protocols are analyzed synchronously and asynchronously. (KÖNIG et al., 2008) study electronic trading systems approaching the concept of Buyers and Sellers negotiating with each other in multiple auction scenarios and (DELOACH, 2002) use Buyers and Sellers to denote an agent class diagram demonstrating purchase and sale transactions carried out through an auction, as can be seen in Figure 9.

Figure 9: Sellers and Buyers (DELOACH, 2002)

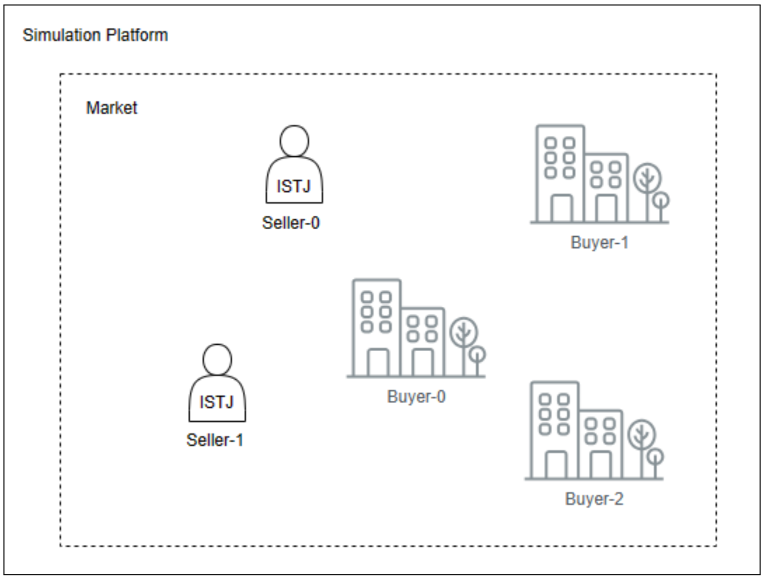


The Buyer and Seller scenario can be applied in use cases to study interactions between entities that, for example, represent similarities with real-life companies and consumers. Its flexibility makes it a perfect scenario for several implementations on agent-based models. More broadly, it is also possible to explore scenarios that represent the markets in which these agents are inserted, thus enabling not only the analysis of interactions between agents but also studies of the influence of market factors, such as pricing, demand, seasonality, among others.

In addition, more complex negotiation and auction mechanisms could be added, providing sophisticated means of simulating human behavior. The use of organizational rules with existing methodologies of multiagent systems can also be explored to investigate how the integration of goals, roles, tasks, agents, and conversations could be integrated with organizational rules and tasks (DELOACH, 2002). These approaches provide significant advances in the representation of structures found in organizations in conjunction with already consolidated methodologies of multiagent systems.

There are several possibilities of analysis derived from this Seller-Buyer scenario; however, in this work, we sought to study how Seller agents with personalities inspired by MBTI, will behave. The approach is a simplified representation of buying and selling situations, similar to those seen in organizations from different segments. Figure 10 shows an example of the environment design with two Sellers and three Buyer agents. Each Seller

Figure 10: Seller-Buyer simulation environment



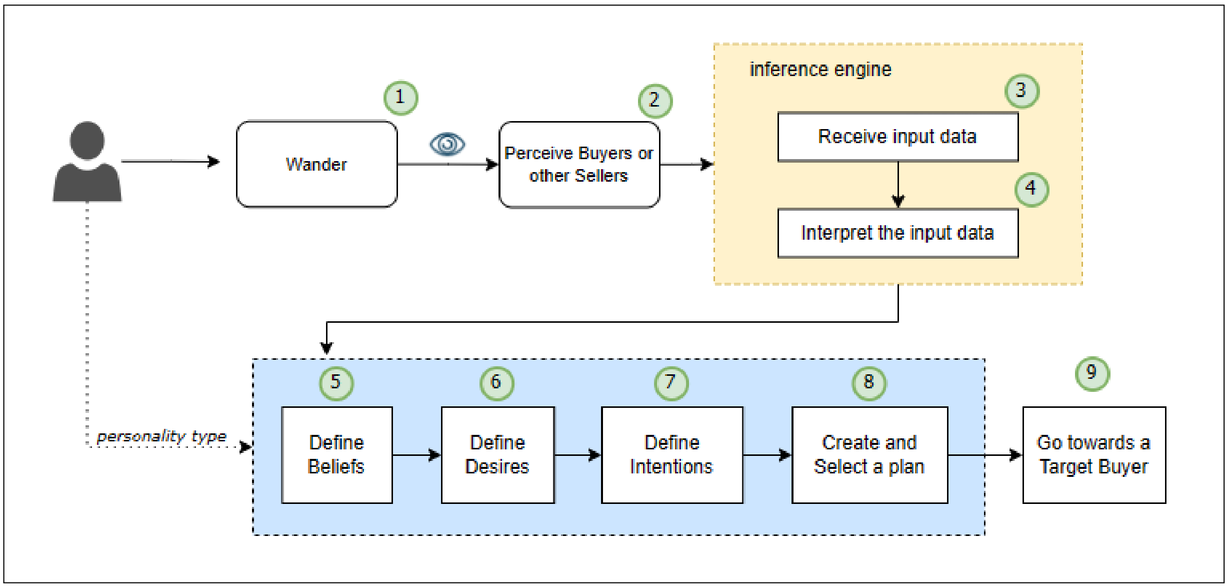
is modeled with a personality type. The modeled characteristics represent aspects of each behavioral preference described in MBTI. These attributes influence agents' behavior in the environment as they are part of their decision-making process, as detailed in Section 6.3.

Sellers Agents with personalities inspired by MBTI theory. Their personality types influence how they behave and make a decision. The Sellers' agent objective is to find and interact with what they consider the best Buyer agent, one who is in the best position according to their BDI reasoning process. Seller agents have an initial sales demand and aim to make as many sales as possible.

Buyers They represent companies and play the role of waiting for the visit of Seller agents and thus be able to purchase a product. Buyer agents are defined with an initial purchase demand suitable for the market type they are located.

The Sellers' objective is to find Buyer agents spread around the environment looking for interaction and consequently make a sales transaction. To achieve their goal, Seller agents will constantly wander the environment (1) looking for Buyers. They have a perception radius that limits how much they can see of the environment around them; that is, their perception radius restricts them from having a complete view of the whole scenario. This constraint can lead the agents to make certain decisions in a more abstract way. When a Seller agent perceives (2) Buyers, or other Seller agents, their perception

Figure 11: Seller decision-making process



function feeds the inference engine. Using its perception function, an agent senses the environment, receiving input data (3) such as its distance from other agents, the distance between other Sellers and target Buyers, among others. Subsequently, the agent interprets these input data (4), define their beliefs (5) that are directly influenced by their particular personality type. After their beliefs are defined, the Sellers' decision-making process will consider them to define their desires (6) and intentions (7) following the BDI architecture stages. In this process, they will consider the best decision given the information they have about the environment and influenced by their personality type, following an approach similar to the Framework proposed by (SALVIT; SKLAR, 2012). After this, the Seller creates and selects a plan (8) to target the chosen Buyer. Then, the Seller goes towards a Buyer (9).

During this journey, depending on its personality type, it may or may not reconsider the decision made, as will be explained later in Section 6.3. External factors to the agents can change the environment. For example, a Target Buyer may unexpectedly receive a visit from another Seller during its journey, preventing it from completing the objective as planned. If the objective is achieved as planned, the Seller will then sell a product to the respective Buyer, reducing its purchase demand by one item.

For simplicity reasons, characteristics such as product quality, price, variety, among others, will not be considered in the model, and these aspects can be better explored in future works. After completing the product's sale and still having sales demand, the

Seller will continue its search cycle for new Buyers, restarting the process as explained.

In this scenario, Buyer agents have a much simpler role since the main objective of this work is to analyze the behavior of Seller agents. Buyers are distributed throughout the environment with the unique purpose of acquiring products sold by Sellers. Also, for simplicity, they do not have a sophisticated decision process, acquiring products as new Sellers interact with them. Both Buyer and Seller agents have an initial demand for products they must sell or buy. This demand can have an important impact on the resulting performance, being a fundamental aspect of the configuration of Market Types, as detailed in Section 6.4.2.

6.4.1 Agent work teams

Another important aspect considered in the current work is the composition of agent teams working together for a common objective. This theme differs from other related studies that use MBTI-based models to observe individuals' agent behavior.

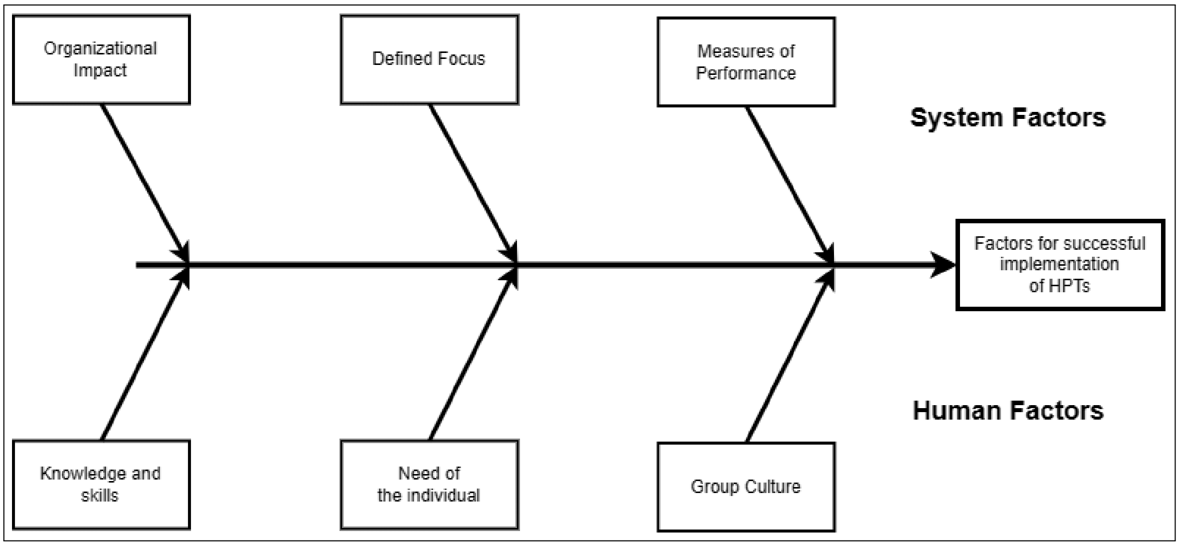
Work teams, defined as "interdependent collections of individuals who share responsibility for specific outcomes for their organizations" (SUNDSTROM; MEUSE; FUTRELL, 1990) have been considered over the years as the foundation of organizations in terms of effectiveness and outcomes. Several studies have demonstrated the association of work teams with tangible corporate results related to productivity, quality of work, creativity, and efficiency (MATHIEU et al., 2017). Work teams are groups composed of two or more individuals performing relevant tasks to an organization who share one or more common goals, interact socially, exhibit task interdependencies – goals, outcomes, and workflows – and have defined organizational constraints on performing tasks boundaries (KOZLOWSKI; BELL, 2003).

As the basis for any organization, team-building has received attention from many researchers who have studied aspects of team composition such as personality factors, values and abilities. Personal development has also been demonstrated to add important value to organizations. People who have opportunities to develop skills and knowledge can usually bring greater benefits to organizations. Thus, individuals development has a consequent direct impact on the teams' results. Knowing how to identify the development needs of each team member is of fundamental importance for teams to be more effective (BELL, 2007).

One of the central attitudes of managers and leaders in organizations is recognizing each team member's development needs, supporting their professional growth through practical actions, such as training and development activities (WILLIAMS, 2007). A leader must inform how each team member can apply their knowledge and skills to the organization's goals and model the team according to actions that will be more effective to meet business demands (WING, 2005). The rich variety of human nature makes personal and professional relationships so diverse, interesting, stimulating, and challenging. Knowing how to understand the particularities and differences of each one can help organizations to be more effective in their actions. All people have different approaches and attitudes during life, which does not mean one person is right, making another person wrong. In fact, it just means that we are all different. Recognizing and accepting these differences is one of the main keys to building high-performance teams, understanding each one's competencies, roles, and responsibilities, and helping to develop them (WILLIAMS, 2007).

A high-performance team is "a team of people who have unleashed their potential toward their stakeholders shared purpose" (SHARP et al., 2000) and despite knowing its importance, it is still unclear which specific characteristics are decisive in the team design that may affect performance (BELL, 2007). (SHARP et al., 2000) cites that High-Performance teams "demand strong group culture, which is based on empowerment, shared vision, creativity, participation, learning ability, trust, and shared consensus", among main success factors for team-building, the authors also mention aspects related to both environmental and human factors. Figure 12 shows the critical factors of implementing High-Performance Teams (HPT).

Figure 12: Factors affecting successful implementation of HPTs (SHARP et al., 2000)



Among the considered aspects, meeting the needs of each member requires team alignment. It is necessary for each individual to have the necessary conditions of empowerment for decision-making so that it can reflect beneficially on the whole group. That is, each team member needs to recognize and understand the needs of others so the team can benefit as a whole. This attitude represents one of the main points in the team's development. Knowing how to balance individual needs with the team's common goals reflects on the group's conditions to work together to achieve organizational goals. In this sense, correctly managing this balance helps teams to be more effective (SHARP et al., 2000). Teamwork has been increasingly important for organizations. Organizations are increasingly involved in complex activities that require cooperation and knowledge sharing. Teamwork helps advance skills, abilities, and knowledge, making the whole team grow together (MANZOOR et al., 2011).

Training and development actions must be performed to support the teams in developing more cooperative attitudes and teamwork. These actions can help mitigate day-to-day problems such as conflicts and miscommunication. Environments conducive to employee learning and development help achieve organizational goals and objectives more effectively. At the heart of these training programs is supporting team members to understand and better deal with differences in personality preferences. Some key enablers often are found in high-performance teams (SHARP et al., 2000):

- Team member competencies

- Skills, processes, tools and techniques
- Interpersonal skills, communication, personality preferences
- Value system
- Shared vision, purpose, goals, direction
- Organizational values including openness

Given the key HPT enablers, it is noticed that factors related to interpersonal skills and personality preferences are relevant in forming high-performance teams. To advance these studies, instruments such as MBTI allow a better understanding of different personality types and have been applied to support teams in identifying behavioral characteristics and preferences. Researchers have found evidence demonstrating that team members feel much more protected in trusting each other when they understand the reasons for these personality differences. For example, understanding opposing personality characteristics can lead individuals to know each other better and understand each other's needs, resulting in a healthier and more positive relationship. In some cases, understanding personality preferences is seen as the missing link to improve interpersonal relationships between team members, directly contributing to the formation of more effective work teams (SHARP et al., 2000).

In this way, using MBTI as an instrument for individual self-knowledge is encouraged to facilitate mitigating natural barriers arising from differences in people's personality types. The tool helps people better understand behavioral factors associated with a work environment, such as teamwork, communication styles, and learning preferences. It can also support organizations in personal development actions (MYERS, 1998). Its constructive use can collaborate to evolve the understanding of team members' differences, facilitating creation of more harmonious environments conducive to development and positively impacting organizations.

Complex projects often involve coordinating tasks and activities that need to be carried out, aiming at a strategic objective for the team and not only for an individual. A work team must be able to successfully complete actions that consider mutual and shared objectives. Despite this, numerous factors can influence the team's good performance. The main aspects can be grouped into three categories: individual characteristics, social characteristics, and temporal and economic costs. Individual characteristics consider that each person has a professional level and a degree of specialization in certain tasks. They will portray the task types that can be performed, the time required for resolution, and the costs involved. Social characteristics deal with how much a team member is willing to work in a group, thinking about the collective good and not only regarding their own personal goals. An individual may, for example, be a great specialist in their expertise area, but if they cannot work in a team, they may compromise the results achieved, regardless of their level of specialization. Finally, time costs deal with issues related to efficiency. Projects often have time constraints and limited financial resources. Finding an optimal balance allows work teams to work efficiently (MORENO; VALLS; MARÍN, 2003).

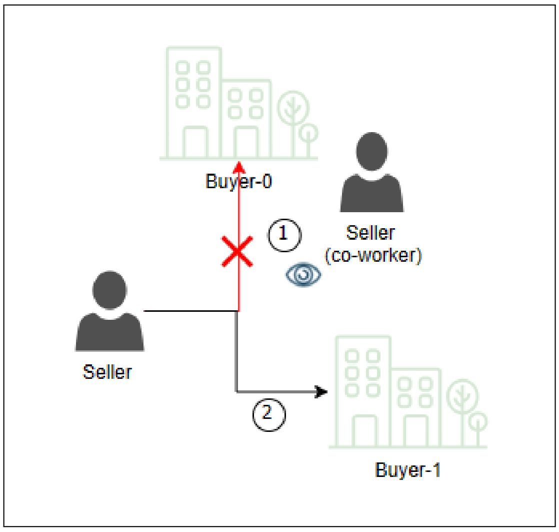
Using the concept of work teams in agent-based models provides ideal conditions for observing complex behaviors involving interactions between agents seeking to achieve shared goals. Several approaches using agent teams are possible. MAS applications offer taxonomies considering team size, communication topology, team composition, and heterogeneity. Collaborative learning using Machine Learning and Reinforcement Learning techniques has also been demonstrated in studies analyzing how collaborative and cooperative attitudes can feed learning models based on shared rewards. Agents are computational mechanisms capable of performing actions with a certain degree of autonomy. They can have attitudes that affect not only their objectives. The multi-agent learning technique, for example, deals with problem domains involving multiple agents that, through their interactions, trigger small changes in the environment that can result in macro-level properties affecting the group as a whole (PANAIT; LUKE, 2005).

Other strategies, for example, the Ad Hoc autonomous agent teams, where multiple agents with different knowledge and skills find themselves in situations where they have shared goals, have also been explored, expanding the teams' collaboration forms. In this approach, agents meet with other teammates without establishing a priori coordination mechanism. Having a common objective, agents must coordinate their actions, even indirectly, to achieve the group's common objective. One can imagine a situation where an individual is faced with a car accident. Many actions are necessary, and eventually, help from others will be needed to increase the chances of success in helping the victim. One person can call an ambulance, another can help with first aid, and another can bring the required support items. However, there was no prior organization of these actions. Given the situation, the individuals simply began to coordinate actions that led directly to the objective to be achieved, in this case, saving the accident victim. This kind of approach applied to Multi-Agent Systems is called *ad hoc team setting* and allows the simulation of scenarios involving work teams without the need to develop coordination mechanisms designed a priori (STONE et al., 2010).

This work used a similar approach to forming the agent's teams. Team members do not know each other a priori, but according to their behavioral preferences, they can collaborate toward a common objective. In our proposal, the developed scenarios provide an environment where agents can interact and perceive each other's actions. The calculations of decision attributes take into account both the individual agent and its interpretation of the context in which it is located. This context involves its its own goals and also what its co-workers might contemplate. Although each Seller agent individually has their own objective, portrayed as the amount of sales demand they need to fulfill, the team's objective will only be successfully completed if they manage to maximize the group's actions. For this, they are modeled with personality types that influence their decisions and make it possible to act collaboratively.

In this sense, the T-F dichotomy plays a fundamental role in representing some collaborative aspects modeled in agents. The A4 decision attribute considering Sellers Close to the Target-Buyer makes it possible to take into account shared objectives, even indirectly, that can impact the common Seller‘s team objectives. For instance, a Feeling Seller can target an interaction with a specific Buyer, shown in figure 13. In this way, it realizes that there is another Seller closer to the same Buyer previously chosen as Target. It has two options: continue the path toward the already chosen Buyer (1) or change the established original plan towards another Buyer (2) imagining that its teammate may have the same goal, which does not bring long-term benefits to the team. These choices have associated risks. The Seller does not know if the teammate actually has the same objective; at the same time, it does not know if, eventually the purchase demand of the other Buyer may have been exhausted by the time it reaches the destination.

Figure 13: Feeling Seller



The involved uncertainties in these interactions make simulations useful for observers to analyze the consequences of certain behaviors and actions on the environment. In this work, several simulations are performed to analyze how the agent's personality types can influence their attitudes and, consequently, the team's overall outcomes.

6.4.2 Market Types

In order to create environments closer to organizational realities, scenarios inspired by the Law of Supply and Demand (HEAKAL, 2015) are used, helping to observe behaviors influenced by the available demand for both Buyer and Seller agents. For simplicity, factors related to prices and quality of products are not considered, and the main aspect analyzed will be the variation in the demand level available in the Market. In this sense, three Markets were formulated with different demand configurations:

Balanced Market In this Market Type, both Seller and Buyer agents have similar buying and selling demand; that is, the market has a general demand balance.

Supply Market The second Market Type has a configuration where Seller agents have higher sales demand than Buyers, which is a more challenging scenario for Sellers' teams as there are restrictions on the market potential.

Demand Market The last Market Type considers a scenario in which Buyer's demand is greater than Seller's demand, existing an imbalance between them in which Buyers will not have their demand fully satisfied.

The analyses considering Market Types with different demand levels offer environments with circumstances that will force agents to seek new alternatives and options depending on the situation. The adaptive topic is of fundamental importance to identify behavioral aspects that contribute to a better adaptation of individuals. When we analyze the real world, this adaptation to the environment can be understood as the development of talents and skills (MYERS; MYERS, 2010) that help individuals to better deal with situations encountered in their daily lives. Progressing in the comprehension of factors that may be conducive to this adaptation helps to understand better both individual and environment-related aspects that influence this adaptation. (MYERS et al., 1998) explains that an important aspect of Jung's theory is to consider that individuals can develop personality characteristics throughout their lives.

As new experiences emerge, people can devote energy to making progress in developing weaknesses and, thus, skills that they are not comfortable with. This development offers the individuals new perspectives and experiences they previously did not consider. The environment in which individuals find themselves can discourage the development of their skills and also suppress people's preferred talents. People may feel less competent in environments that do not favor their behavioral preferences or are not open to personal development. Understanding the differences of each one and the identification of means of harmonious coexistence is essential for creating environments conducive to personal development (MYERS et al., 1998).

6.4.3 Pseudo-Algorithm

According to the precepts previously discussed, a proposal for an algorithm for modeling the decision-making process of Seller's agents is then presented. The defined decision attributes are used to compose the agents' reasoning process following the BDI architecture. The pseudo-algorithm 2 demonstrates the Seller's decision-making process abstraction.

Algorithm 2: *Sellers' agent decision process* pseudo-algorithm

```
1: while Number of Buyers >0 and My Demand >0 do
2:   if TargetBuyer not defined then
3:     Perceive Buyers and other Sellers in my perception radius
4:     for all Buyers do
5:       Calculate the distance to the Buyer {A1 attribute}
6:       Get the number of interactions to the Buyer {A2 attribute}
7:       Calculate cluster density and proximity to the perception edge {A3 attribute}
8:       Check if there are other Sellers close to the Buyer {A4 attribute}
9:     end for
10:    Calculate Scores
11:    TargetBuyer ← Buyer with max(score)
12:    Go towards TargetBuyer
13:  else
14:    if My personality type is Perceiving then
15:      TargetBuyer ← Recalculate TargetBuyer {A5 attribute}
16:    end if
17:    Go towards TargetBuyer
18:  end if
19: end while
```

In the *Pseudo-Algorithm*, it is observed that Seller agents will constantly seek to interact with Buyer agents while they have available sales demand and exists Buyers available, with purchase demand (line 1), in the environment. If they have not yet defined a Target Buyer (line 2), that is, defined a plan to visit a chosen Buyer, they will observe the environment around them, perceiving all the Buyers and other Sellers within their perception radius (line 3). For each Buyer (line 4), they calculate the four proposed decision attributes. First, they calculate the distance to the considered Buyer, prioritizing those with the shortest distance (line 5). Next, they calculate the decision attribute *A2* with the influence of the E-I dichotomy considering the number of visits already made to the Buyer (line 6). In this dimension, Extraverted agents will prioritize Buyers who have not been interacted, while Introverted agents will prefer Buyers they already know.

In the next step, Sellers calculate the density of the Buyers clusters within their perception radius, as well as their distance to the edge of their perception radius, contemplated in the decision attribute *A3* (line 7). Intuition agents will try to abstract future gains considering that the Buyers cluster could be even larger than they can see, prioritizing those close to the edge of their perception radius.

In order to calculate the *A4* attribute, the agents evaluate whether there are other Sellers close to the considered Buyer (line 8). Feeling agents will prioritize other Buyers who are not close to their teammates while Thinking agents will give less importance to this aspect. The scores are calculated following the MADM method with all the input data (line 10). Then, the most feasible Buyer will be chosen (line 11). With the decision made, the Seller can go towards the Buyer (line 12). External events may occur, such as other Sellers heading toward the same Buyer or new Buyers appearing in the Sellers' perception radius.

Finally, *A5* decision attribute is evaluated. Perceiving agents are pruned to recalculate their original plan (line 14). As they are opened to new options, they will consider whether it is worth changing their decision, reconsider their choice, and choose another Buyer they consider better, moving towards this new target. At the same time, Judging agents are more committed to the original choice they made, rarely reconsidering their options (lines 15-17).

7 *PERSONALIFY* IMPLEMENTATION

7.1 Gama Platform

The present work used Gama platform (GIS & Agent-based Modeling Architecture) to develop and implement the *Personalify* framework. Gama is an Open Source agent-based modeling and simulation platform that provides a complete development environment with ready-to-use abstractions for diverse needs, containing decision architectures, generic behavior models, and multi-level capabilities. The platform is based on three main components. A meta-model, used to represent complex environments and multi-level models; GAML, a high-level modeling language; and a virtual machine for model executions and simulations execution. Its main advantage over other platforms is providing a multi-level architecture to represent highly complex environments. It can be developed with a language (GAML) that is easy to develop and understand (DROGOUL et al., 2013a).

The platform has been widely used in scenarios and uses case involving domains such as ecology, economics, and socio-environmental systems. Its modularization capabilities and integration with external plugins ensure extensibility for various situations (TAILLANDIER et al., 2019). As a flexible and dynamic platform has allowed researchers to use it in scenarios such as traffic simulations (TAILLANDIER, 2014; SAVAL et al., 2023), building evacuation (MACATULAD; BLANCO, 2014), and urban growth prediction (TSAGKIS; PHOTIS, 2018). It has been recently used to develop simulations regarding the evolution of the COVID-19 Pandemic, helping researchers understand its dangers and effects (BAN et al., 2020). This work uses the platform for prototyping and developing models, experiments, and agent-based simulations.

7.2 *Simple_BDI*

The development of agent-based simulations using BDI architecture often demands expensive computational resources. The complexities involved in the simulation of human behavior pose significant challenges to operationalizing complex systems that faithfully simulate the behavior of multiple individuals and that, at the same time, do not make research projects unfeasible in financial terms. Parallel to this issue, paradigms based on BDI architecture are generally highly complex to be understood and used by people who do not have a deep technical knowledge of this domain. To deal with these barriers, an architecture integrated into the GAMA platform was developed to simplify the development of agent-based models. Using a simple language to be used by modelers and flexible enough to develop agents with complex behaviors, the architecture also allows the development of systems with low computational cost (TAILLANDIER et al., 2017).

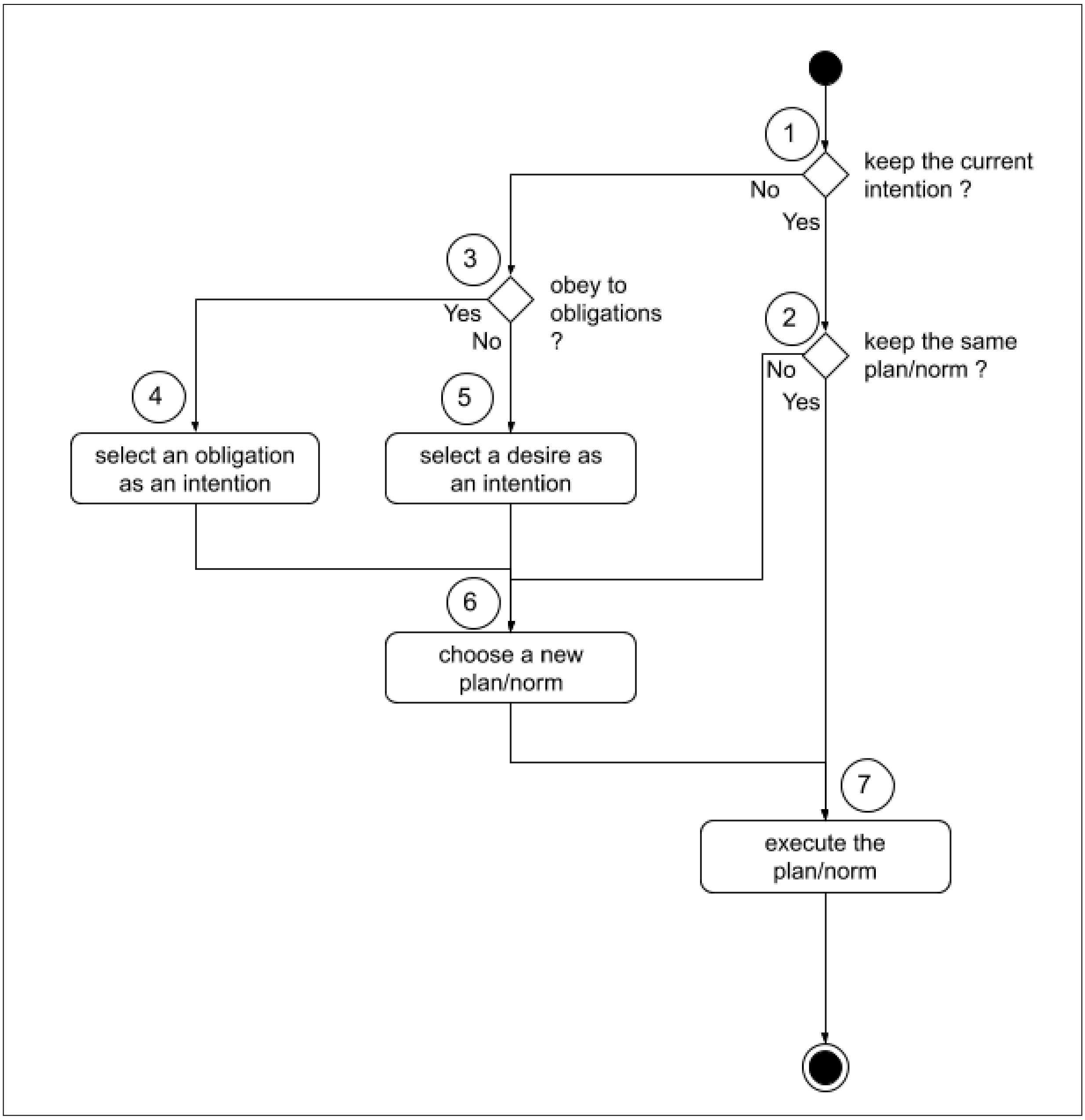
The *simple_BDI* architecture provides an environment conducive to the development of fast and efficient models, from the design of agents to the development of complex and dynamic models. Its basic structure includes all the stages of traditional BDI architectures. An agent will have beliefs, desires, and intentions formulated from the basic definitions of its architecture composing its knowledge base, called predicates.

Beliefs represent what the agent thinks, that is, the knowledge an agent has of the environment. Desires deal with what the agent wants to accomplish, or in other words, the goals it seeks to complete. Desires can have priorities and be dynamic according to the conditions agents encounter. Finally, the intentions are portrayed by what the agent chooses to do. Intents can be put on hold when, for example, they need other actions to be completed before they begin.

In addition to beliefs, desires, and intentions, *simple_BDI* agents' behavior is based on their perceptions and plans. Perceptions are functions used in each interaction. With them, an agent can perceive environment stimuli and react to them, updating its knowledge base. Agents also have a set of plans defining their behavior to complete their desires (CAILLOU et al., 2017).

Therefore, the agent decision-making process must obey the basic structure described in the BDI. First, an agent will infer its current intention, analyzing whether it should proceed with its current plan. Next, the current plan or norm is analyzed to evaluate its viability. The inference engine must then check whether the agent must obey some obligation corresponding to a norm described a priori. If so, the agent will select an obligation as an intention. Otherwise, it will continue with the fulfillment of its desire. The plan or rule is then chosen to be executed, and finally, the agent performs the corresponding action. These steps do not necessarily need to be deterministic; probabilistic behaviors can be modeled in the selection stages of norms or desires, as well as in their execution (LESQUOY, 2022). Figure 14 demonstrates each step described in the decision-making process in the *simple_BDI* architecture.

Figure 14: The decision-making process in the *simple_BDI* architecture (LESQUOY, 2022)

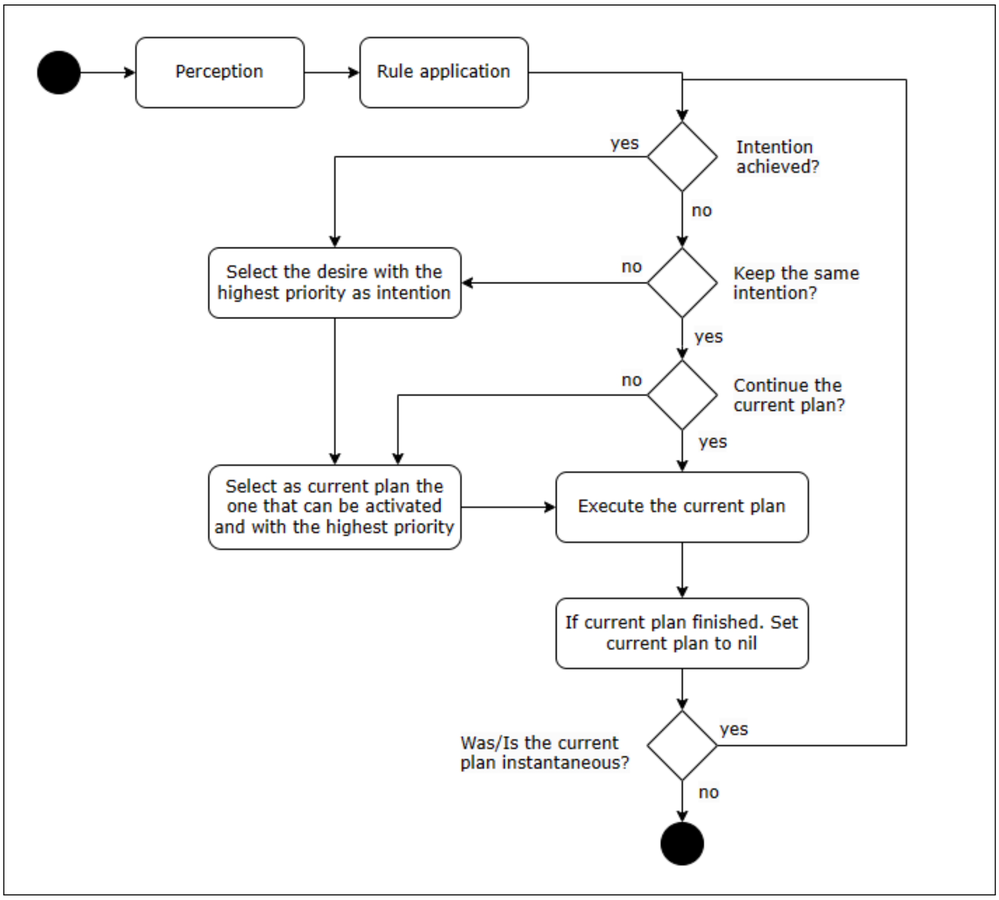


Given the complexities involved in modeling agents with human characteristics, it is necessary to use tools that allow high levels of abstraction. The package *simple_bdi* available on Gama platform is used in order to simplify the agent modeling and the architecture development described in BDI. The entire structure of agents' beliefs, plans, desires, and intentions, proposed in BDI theory, can be applied through this kind of approach.

In *simple_bdi*, beliefs, desires, and intentions are illustrated using predicates. They can have a set of name-value pairs that define a particular attribute and its associated value. For example, in the Gold Miner scenario, available for learning purposes on the platform, a mining agent has an initial desire to find gold scattered throughout the environment. To find gold, it carries out its action plan, which is initially to wander around the environment. When it perceives gold, it stores this information in the beliefs db, adding the location coordinates where it was found. That is, the agent now has the belief that there is gold, and with *simple_bdi*, a new predicate containing the coordinate values is created. At this point, the agent must put the current intention on hold and add a new intention, in this case, extract gold.

To complement the BDI, agents have three types of databases: a belief_base, containing obtained data related to the environment and which represents what the agent knows about the world around it; a desire_base, containing the goals that the agent seeks to fulfill; and an intention_base, with the actions that the agent chose to perform. In addition to bases, agents also contain structures that help define their behavior in the environment. The perception function is executed at each interaction cycle and is used so that the agent can observe changes that occur in the environment. The rule is a function executed at each interaction to infer new beliefs or desires from an existing one. Finally, an agent has a set of plans that define its behavior to accomplish selected intentions (TAILLANDIER et al., 2016). Figure 15 shows the activity diagram regarding this approach.

Figure 15: Activity Diagram (TAILLANDIER et al., 2016)



Applied to the context of this work, we use *simple_bdi* in the same way as previously described. The Seller agents are modeled with perception functions sensitized from the observation of Buyers, or other Sellers, present in the environment and within their perception radius. The Buyers and Sellers locations are stored using predicates defined as *location_buyer* or *location_seller*. Beliefs, Desires, and Intentions of Seller agents are also defined based on structures inspired by the Gold Miner model, as explained in greater detail in subsequent sections.

7.3 Environment

The Gama platform allows the representation of complex and dynamic environments with different types of topologies (grid, graph or continuous). This feature allows modelers to create agents based on spatial data with reality consistent attribute values. Developers can also manipulate and use geometries with a high level of transformation as well as represent primitive movements in the environment (DROGOUL et al., 2013a) .

Gama language also supports a rich graphical interface that facilitates the development of complex models and visualization of computer simulations from various perspectives. 2D or 3D environment views allow observing the agents' behavior and monitoring and debugging their states throughout the simulations. Agents can have simple (point, polyline or polygon) or complex (several sub geometries) 3D vector geometry formats (DROGOUL et al., 2013b).

In the developed models in this work, we used the Gama platform to create an environment conducive to the interaction of the agents, Sellers and Buyers, developed. This simulation environment, represented as a two-axis plane (x,y) in a fixed-size grid, is used to observe the behavior of Sellers agents randomly scattered around the environment, who constantly seek to interact with Buyers.

Environmental conditions throught control parameters are applied to enable agents interacting influenced by certain factors modeled in the scenario. Thus, at the beginning of the simulations, pre-defined parameters are used, portraying aspects such as the available demand for buying and selling, the density of Sellers and Buyers present in the environment, the maximum number of cycles, the distance that each Seller agent has as a limit to its perception radius, among other aspects. Section 8.2 deals in greater detail with all the parameters used in the environment and in agent modeling.

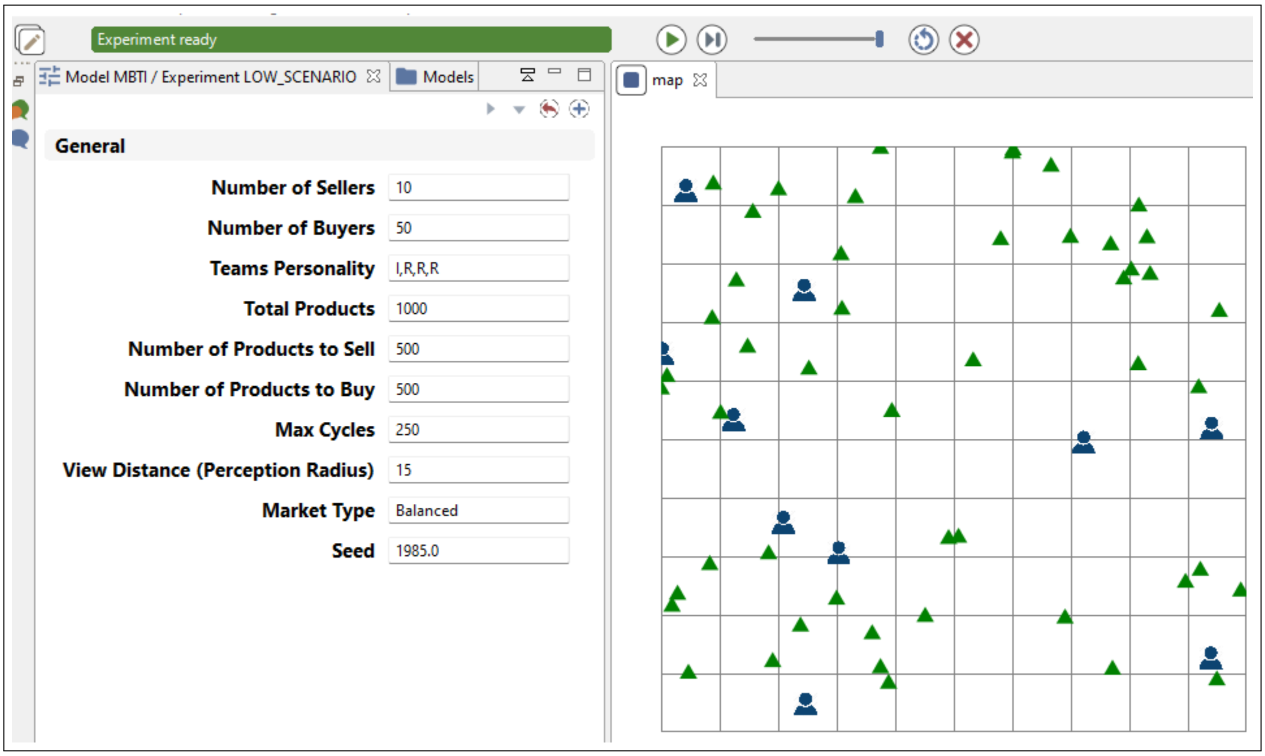
It can be seen in Figure 16 a simple example of the initial simulation environment containing ten Sellers and fifty Buyers in a 10x10 grid size. The green triangle icons represent the Buyer agents, and the person-shaped icons in blue represent the Seller agents.

7.4 Extending the ***Personalify*** framework

In this work, we used a modularization approach to develop the scenarios. The *Personalify* framework can be used regardless of the considered domain. In other words, researchers may use this framework without necessarily applying the Seller-Buyer scenario together. The agents of a specific species, actions, behaviors, and skills are built in a generic way and can be inherited from other developed Gama models.

The basic idea of the *Personalify* framework is to portray, in generic agents, the personality types designed from the already described MBTI concepts. Agents are built with generic skills that are easily extensible by other models that inherit their characteristics. In the aforementioned example, the Gold Miner model could inherit *Personalify* to cre-

Figure 16: Initial Environment



ate mining agents with MBTI-inspired personalities. Thus, their personality traits could influence their behaviors and actions in the environment.

On Gama platform, agents are depicted through species, a prototype of agents that defines both the agent internal state and their behavior (TAILLANDIER; DROGOUL, 2010). In *Personalify* we create a generic agent associated with a species named Person. This species has skills and performs actions that illustrate its behavior in the environment.

Person In this type of agent, we consider a generic species that can be inherited by other models to implement personalities in other agent species. A Person agent has attributes that define its personality type inspired by the MBTI. Four Boolean attributes are associated with a Person: *is_extraverted*, *is_sensing*, *is_thinking* and *is_judging*. These attributes portray the poles of behavioral preferences of each of MBTI dichotomies. When instantiating *Personalify*, other models must define the personality type of their derived agents. For this, they use a method named *set_my_personality* passing the personality type as a parameter. This parameter is a list of Strings; for example, to define an agent with the ISTJ personality type, the model can call the method *set_my_personality* passing the list [“I”, “S”, “T”, “J”] as parameter. It is also possible to define whether a probabilistic factor will be considered in the definition of the personality type. A boolean parameter named *use_probability* is used then. If the value is set to True, a probability factor of 80-20% is used to define the agent's personality. That is, an agent will have 80% probability of keeping a given behavioral preference and 20% probability of changing it. According to the MBTI, a predominantly extraverted person will not necessarily exhibit this behavior all the time and this function allows modelers to consider situations considering these behavioral changes.

Finally, generic global parameterizations are applied to the Person species to control the modeling of behavioral preferences following the defined decision attributes. For example, the E-I dichotomy, represented in the decision attribute *A2*, has two global parameters that respectively define the number of cycles an agent needs to wait before returning to an already visited agent and the maximum number of interactions an agent can make to another previously visited agent. This parameterization is important to prevent introverted agents from always acting in the same region, forcing this tendency to occur only in a predefined maximum number of cycles and interactions. Other parameterizations are also applied for the other decision attributes, as explained in later sections.

Actions, Behaviors, and Skills

A Person agent has predefined actions, behaviors, and skills. The defined actions reproduce the defined concepts in the decision attributes to influence the agent's reasoning process. In Gama, an action is a function or procedure run by an instance of species. It can return values or not, and are usually called functions or procedures in other programming languages. In the current work context, actions were created to define the decision attributes application following the MADM method. For each decision attribute, an equivalent action is implemented to influence a given preference on the agent's behavior. For example, to calculate the decision attribute A3 has been created an action the involved calculations. As part of this process, we call the Gama function *simple_clustering_by_distance* to calculate the clusters and all the other decision calculations.

A behavior, or reflex, is a set of statements which is called automatically at each time step by an agent. This behavior can be associated with a certain architecture, such as BDI. In *Personalify* we use this concept to define, for example, when a personality type should be reconsidered in an agent through the reflex *must_change_personality*.

A Person agent also has an associated Skill. Skills are built-in modules that provide a set of related built-in attributes and built-in actions to the species that declare them (GAMA, 2023). *Personalify* implements only the single Skill *moving*, that allows an agent to move in a defined topology.

The Seller-Buyer scenario was implemented separately from the *Personalify* framework. As previously mentioned, this is done to contribute to research projects involving other domains.

This approach inherits *Personalify* by creating agents with theory-based personality types. Seller agents have the objective of selling all the products they have. They need to visit as many Buyer agents as possible within a predetermined time, defined in the model with a parameter of the maximum number of cycles. Each visit to a Buyer generates a consequent sale for the Seller, a very simplified interaction process. In future works, sophisticated negotiation and auction mechanisms may be developed in order to analyze more complex situations.

To achieve their goal, Sellers wander the environment looking for possible target Buyers. Its personality directly influences its behavior, modeled on the agent inheriting *Personalify*. As an example, when an Extraverted and an Introverted agent are observed, disregarding the influence of the other dichotomies, it is noticed that the first will prefer to have more exploratory attitudes; that is, it will seek to interact with Buyers who have not visited previously. On the other hand, introverted Sellers will seek to interact with Buyers they already know, strengthening their connections.

Two species are created in the model, Sellers and Buyers. Each one is used to represent the Seller-Buyer scenario explained earlier in Section 6.4.

Seller This species uses the *parent species* concept, inheriting the Person species from the MBTI model and standing as a *child species*. In GAML language, it is used to structure the codes better so that the child species can only contain the differences between the two species. This behavior can even be redefined in the child species if necessary. This structure allows modularization and model extensibility, reducing code reuse complexity. In addition to inheriting the Person attributes and skills, the Seller species adds an architectural control based on *simple_bdi*. Control architectures will allow the modeler to use a specific control architecture for a species in addition to the typical behavior structure (GAMA, 2023). Predicates are also included in the BDI structure of beliefs, desires, intentions, and plans. The listing 7.1 shows a sample of the agent structure represented by the Seller species.

```
species Seller parent: Person control: simple_bdi{

  // Define agent behavior
  predicate wander <- new_predicate("wander");
  predicate define_item_target <- new_predicate("define_item_target
   ");
  predicate define_buyer_target <- new_predicate("
   define_buyer_target");
  predicate sell_item <- new_predicate("sell_item");
  predicate say_something <- new_predicate("say_something");
  predicate met_buyer <- new_predicate("met_buyer");

  // How many items the Seller can sell
  int current_demand <- copy(nb_items_to_sell);

  list<point> possible_buyers;
  point target;

  init{
    do add_desire(wander);
  }
}
```

Listing 7.1: Seller agent structure

Sellers implement perception functions to perceive other agents, Buyers and Sellers, within their perception radius. Listing 7.2 shows the implementation of the Buyer's perception function considering only those with purchase demand greater than zero. When a Buyer is perceived, the agent removes its current intention *wander*.

```
perceive target:Buyer in: view_distance {
    if(self.current_demand > 0){
      focus id:"location_buyer" var:location;
      ask myself {do remove_intention(wander, false); }
    }
  }
```

Listing 7.2: Example of a Seller's Perception Function

Agent Sellers also implement their action plans based on their intentions. In addition to the initial *wander* plan, two other plans are defined: *choose_buyer_target* and *sellItem*. The *choose_buyer_target* plan is based on the *define_buyer_target* intention and is responsible for defining the Buyer target choice. The agent uses actions defined in the Person parent species, containing all the implementations of the decision attributes explained previously. GAML implements *super* and *invoke* calls to be able to interact with actions defined in the parent species (GAMA, 2023). At the end of the plan, the agent defines the Buyer by adding to the belief database the coordinates of its position and a new wish called *sell_item*, which is associated with the plan *sellItem*.

With the target Buyer definition, the Seller can move to interact and consequently complete a sale transaction with the chosen Buyer. The *sellItem* plan addresses this process and possible external influences on the agent's journey to its destination. The J-P dichotomy, depicted in the decision attribute A5, plays a major role in defining whether or not an agent should recalculate its original plan. Perceiving agents have an 80% probability of recalculating their plan, while Judging agents have the opposite.

Buyer This agent is implemented to represent companies in the buying and selling process. They are developed from a simple species that contains only two attributes: a Boolean indicating whether the Buyer has already been visited and another that indicates the amount of purchase demand that the Buyer has. When a Seller visits a Buyer, current demand is reduced for an item. The listing 7.3 shows the agent implementation.

```
species Buyer{
  rgb color <- blue;
  bool visited <- false;
  int current_demand;

  init{
    current_demand <- copy(nb_items_to_buy);
  }

  aspect default {
    draw triangle(3) color: current_demand=0? red : color at:{location.x,location.y};
  }
}
```

Listing 7.3: Buyer implementation

PART III

RESULTS

8 EXPERIMENT RESULTS

Several experiments were planned to enable different study compositions. Environments with conducive conditions to the analysis were designed to simulate artificial agents performing the designated roles with appropriate circumstances to the desired observations.

As previously explained in Chapter 7, the Gama platform was used to implement the experiments and simulations following specific requirements for each situation. In the next sections, we discussed how these simulations were specified, which parameters were adopted, and which performance metrics were used to compare the results of the different teams. More specifically, three experiments were carried out to analyze the behavior of Sellers' agent teams considering various behavior aspects.

8.1 Simulation settings

The simulations based on the Seller-Buyer scenario and *Personalify* framework must import the Gama model and implement scenarios established on parameters that determine the applied environmental conditions.

Buyer and Seller agents have initial demands for both purchase and sale, defined according to the Market Type. These restrictions are applied at the beginning of the simulations directly in the environment, as detailed in the Section 8.2. The action *calculate_market_demand* controls how the demand is distributed in each Market Type as seen in the listing 8.1.

```
action calculate_market_demand(string market_type, int total_demand){
    if (market_type="Balanced"){
      total_sellers_demand <- (total_demand/2);
      total_buyers_demand <- (total_demand/2);
    } else if (market_type="Supply>Demand"){
      total_sellers_demand <- ((2/3) * total_demand);
```

```
    total_buyers_demand <- (total_demand-total_sellers_demand);
  } else if (market_type="Demand>Supply"){
    total_buyers_demand <- ((2/3) * total_demand);
    total_sellers_demand  <- (total_demand-total_buyers_demand);
  }

  // Calculate selling-buying items according to the market
  nb_items_to_sell <- round(total_sellers_demand/nb_sellers);
  nb_items_to_buy <- round(total_buyers_demand/nb_buyers);
}
```

Listing 8.1: *calculate_market_demand* action

When beginning the simulations, it is necessary to indicate, in addition to the environmental conditions, the number of agents, the team's personality type, and the general parameters that define the agents' behavior concerning the decision attributes. The team composition can be homogeneous, with the same personality types, or heterogeneous, in which different personality types will make up the team. This attribute is controlled through the definition of the personality type itself. For example, to compose a team of Sellers agents with only the "I,S,T,J" personality type, the modeler can indicate this value directly into the *teams_mbti_string* variable. It is also possible to combine the letter "R" for random formations in the position of any of the behavioral preferences. Listing 8.2 shows an example of implementing a simulation.

```
model BuyerSellerExample
import "../buyer_seller.gaml"

global {
  string teams_mbti_string <- "E,R,R,R";
  int nb_sellers <- 10;
  int nb_buyers <- 3;
  int total_demand <- 1000;
  string market_type <- "Balanced";
  string scenario;
  int nb_number_of_cycles_to_return_interacted_agent;
  int nb_max_number_of_visits_to_a_interacted_agent;
  int nb_min_distance_to_exclude;

  init {
      // MBTI profile
      teams_mbti <- list(teams_mbti_string split_with ",");
```

```

    // Calculate Market Demand
    do calculate_market_demand(market_type, total_demand);

    create Seller number: nb_sellers {
        //do set_my_personality(teams_mbti, false); // Without using
 probability
        do set_my_personality(teams_mbti, true); // Using probability
        set view_distance <- 20;
        do set_global_parameters(
 nb_number_of_cycles_to_return_interacted_agent,
                     nb_max_number_of_visits_to_a_interacted_agent,
                     nb_min_distance_to_exclude
        );
    }

    create Buyer number: nb_buyers;
  }
}
```

Listing 8.2: Model initialization

In this example, ten Sellers and three Buyer agents are created. A total of 1.000 demand items are also defined in a balanced Market Type. When creating Seller agents, the action *set_my_personality* defines whether the agent will consider a probability factor, in the proportion 80-20%, to respect or not each of the defined behavioral preferences.

In Gama, experiments instantiate the models to run the simulations by passing parameters that define the environmental conditions. These parameters facilitate user interaction in determining the models global variables and the environment's attributes. The listing 8.3 displays an example of creating experiments for the Seller-Buyer scenario with interactive parameters. Initial values can be defined and modified later by users.

```
experiment BuyerSellerBalancedExperiment type: gui keep_seed: true
 autorun: true{

 // Parameters
 parameter "Teams MBTI" var: teams_mbti_string init: "E,R,R,R";
 parameter "Market Type" var: market_type init: "Balanced";
 parameter "Cycles to return to interacted agent" var:
  nb_number_of_cycles_to_return_interacted_agent init: 75;
 parameter "Max visits to a interacted agent" var:
```

```
    nb_max_number_of_visits_to_a_interacted_agent init: 3;
  parameter "Min Distance to Exclude" var: nb_min_distance_to_exclude init: 10.0;

  parameter "Sellers" var: nb_sellers init: 10;
  parameter "Buyers" var: nb_buyers init: 3;
  parameter "Total Demand" var: total_demand init: 100;
  parameter "Scenario" var: scenario init: "LOW";
  parameter "Max Cycle" var: max_cycles init: 250;
  parameter "View Distance" var: view_distance init: 20;

  output {
    display map {
      grid grille_low lines: #gray;
      species Seller aspect:default;
      species Buyer aspect:default;
    }
  }
}
```

Listing 8.3: Experiment Example

8.2 Simulation parameters

Several parameters are defined to control the simulation. Parameterizations allow the modelers to determine the conditions necessary to observe certain situations. In the Seller-Buyer scenario, parameters were defined to define the effect that particular circumstances applied to the simulation environment could result in. Table 5 shows the Parameters used to initialize the simulations.

Table 5: Simulation Parameters

Parameter	Name	Type
P1	Teams MBTI	string
P2	Number of Sellers	int
P3	Number of Buyers	int
P4	Market Type	string
P5	Total Demand	int
P6	Number of Cycles to return to an interacted agent	int
P7	Max Visits to an interacted agent	int
P8	Max distance to notice a colleague	int
P9	Max number of Cycles	int
P10	View Distance	int
P11	Number of Cycles to reconsider the personality type	int

As previously stated, the *P1 - Teams MBTI* parameter defines the team's personality type and allows different combinations of comma-delimited values indicating the team's personality type. The parameters *P2 - Number of Sellers* and *P3 - Number of Buyers* are integers that control the number of agents, Sellers and Buyers, that will exist in the simulation environment. The *P4 - Market Type* defines how demand will be distributed between Buyers and Sellers according to the Market Type, explained previously in Section 6.4.2. A *string value* is defined as one of three options: Balanced, Supply > Demand, or Demand > Supply. The amount of demand to be distributed is given by the integer parameter *P5 - Total Demand* and defines how much demand will be distributed to the two teams of Sellers and Buyers. As an integer value, it may be rounded as the values are distributed equally to each of the agents.

The integer parameter *P6 - Number of Cycles to return to an interacted agent* controls the number of cycles a Seller agent needs to wait before it can return to a previously visited Buyer. The integer parameter *P7 - Max Visits to an interacted agent* controls the maximum number of visits a Seller can make to the same Buyer. Both parameters have a primary influence on the decision attribute *A2* as it prevents, for example, Introverted agents from deciding to remain forever in the same region of interaction, forcing them to search for new areas not yet visited after a certain time. The integer parameter *P8 - Max distance to notice a colleague* considers the maximum distance a Seller agent will consider to consider other teammates close to the same Target Buyer. This restriction mainly influences the decision attribute *A4* as it will define the action radius that Thinking-

Feeling agents will assume to consider or not their teammates.

Finally, the parameters *P9 - Max number of Cycles* and *P10 - View Distance* control general environment aspects and Seller agents behavior. The first indicates how many cycles a simulation will have, and the second is the maximum distance Sellers will have as their perception radius. Agents outside this radius are not considered in Sellers' decision attributes. The *P11 - Number of Cycles to reconsider the personality type* parameter enables a probabilistic factor to reconsider an agent's personality type. This parameter indicates how many cycles will be waited until the personality type is reconsidered.

All these combined parameters provide distinct simulation environments that allow observing different situations and the influence of certain aspects on team behavior and performance.

8.3 Seller Performance Metrics

The behavior of Seller agents directly influences the demand available in the environment. As they interact with Buyer agents, both the sales and purchase demand are reduced, impacting the environment and consequently influencing the agents' behavior. In this sense, it is necessary to develop metrics to observe how the Seller agents' actions' can impact the simulation environment. Agent teams modeled with different personality types can present distinct behaviors. Performance metrics can help identify the influence certain particularities can have on the environment.

As previously explained in Section 6.4.2, environments called Market Types are created to make the distribution of buying and selling demands to agents. It restricts agents' behavior according to the demand that each one has and the purchasing potential that the Buyers around them also have. In this work, we use a performance metric based on sales made by Sellers to measure the teams' impact. In other words, at the end of the simulations, how much demand the Seller agent team managed to deliver is analyzed.

The performance term has been commonly used by organizations worldwide, covering metrics that support them in measuring actions and expected outcomes that directly impact their strategic objectives. Performance is considered a multi-dimensional concept involving the individual actions of an organization's employees, the work context, and the tasks performed, among other factors (SONNENTAG; FRESE, 2002).

Numerous aspects can influence the work team's performance. In addition to individual aspects of performance, dependent variables such as job satisfaction, engagement, health, stress and work balance are essential characteristics that directly affect workers' performance (CAMPBELL; WIERNIK, 2015). Studies that investigate the correlation of personality traits and learning styles with job performance have also been conducted seeking to analyze how certain attributes can influence the behavior of individuals in a corporate context (FURNHAM; STRINGFIELD, 1993; FLEENOR, 1997; FURNHAM; CRUMP et al., 2015).

In this work, we used a simplistic view of the term performance. As mentioned previously, the complexities involved in measuring performance regarding broader aspects are not considered. We focus exclusively on the analysis that the decision attributes, modeled on Seller agents, can have on the behavior and, consequently, the agents' performance. The aim is to observe how certain patterns can influence the decisions and actions taken and the effects that can be produced from them.

In this context, performance measurement focuses on the sales demand distributed to the agent Seller teams. The sole and exclusive objective of the analyzes carried out at the end of the simulations is to observe the impact that certain behavioral characteristics, modeled on the agents, can have on the created environment. These analyses must be completely restricted to the created scenarios for agent-based simulations. Conclusions regarding these analyses cannot, and should not, be extrapolated to the real world and must be limited exclusively to the context of this work. In other words, the studies carried out do not indicate that a particular personality type is better or worse for the tasks. As seen previously in Section 4.2.3, MBTI cannot be used under any circumstances as an instrument for stereotyping or excluding people based on their personality types (COE, 1992).

8.4 Experiment I: Effect of different personality types

The simulation of human behavior through computing has allowed great advances in understanding aspects that may influence certain behaviors. The first experiment was developed to implement the concepts explained previously and analyze how artificial agents perform designated tasks in pre-designed environments with similar characteristics to organizational realities. In this way, it is expected to observe the agent's behavior to evolve in understanding how certain modeled factors can lead to particular behaviors and their impacts on the teams' overall outcomes. In particular, with this first experiment, we aimed to have an answer to research question **RQ1**, as described in Section 1.2.

8.4.1 Description

In the first experiment (BRAZ; SICHMAN, 2022b), Seller agent teams modeled with decision attributes inspired by MBTI were created following the previously described concepts. This experiment's main objective is to observe agent teams' behavior in multiple computer simulations, analyzing possible differences between the demonstrated behaviors. This initial experiment uses a simplification of the concepts explained previously, focusing on identifying similarities with achieved results in studies by other authors (SALVIT, 2012; SALVIT; SKLAR, 2012).

With the use of new methodologies focused on the combination of multiple decision attributes and the MADM method, the aim is to observe how the characteristics of personality types modeled in Seller agents can influence performance metrics in built environments. Furthermore, in this experiment, we also sought to observe how multiple simulations with similar environmental conditions can influence the teams' overall performance.

In the experiment conduction, a simplified version of the decision attributes was used, focusing on observing possible differences in behavior between the personality types modeled in the agents.

An agent-based simulation scenario using a two-plane axis (x,y) on a 160x160 grid was implemented on the Gama platform. The two types of agents, Sellers and Buyers, were developed. The first is modeled on concepts inspired by the MBTI. As a simplified version, we do not consider the concepts of Market Type explained in the section 6.4.2 in this experiment since the purpose is to analyze the behavior of agent teams without the influence of environment demand restrictions.

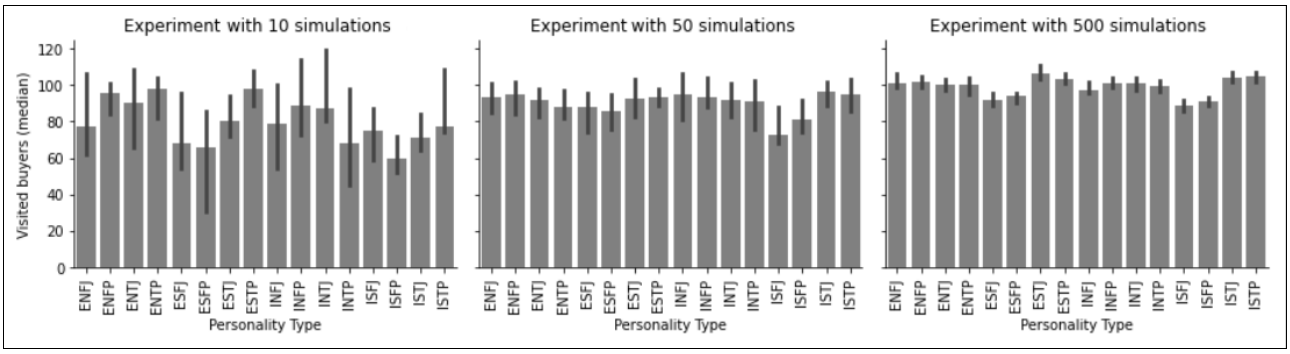
In each simulation round, teams of sixteen Seller agents were used, each one representing a distinct MBTI personality type. In the simulation scenario, a Random Seed is used to allow the experiment's reproducibility using the same initial environmental conditions. These positions indicate the location of each of the agents, randomly distributed but capable of reproduction considering the same Random Seed.

We adopted 2.500 cycles as the limit for each simulation, and a number of 1.280 Buyers was defined. This value represents an occupancy rate of 5% given that the grid size is $160 * 160$ =25,600. Three rounds of experiments were carried out with 10, 50, and 500 simulations, respectively. The results of each round were grouped, and performance metrics were extracted from these groupings. In this experiment, we consider how many visits Sellers made to Buyer agents as a performance metric. At the end of the simulations, with the grouped data, the median performance data (visits) was extracted for each simulation round. The median as a central metric aims to prevent outlier values from having a significant impact on the analyses.

8.4.2 Results

From the grouped data, we can analyze the obtained results for each round of simulations. Figure 17 shows three charts considering the experiment with 10, 50, and 500 simulations and grouping the data by each personality type. As previously stated, this experiment considered the median number of visits made to Buyers as a performance metric.

Figure 17: Experiment 1 - Sellers performance by personality type (BRAZ; SICHMAN, 2022b)



In the first round, we can see that considering ten simulations, there is a high variability between the performances obtained by each personality type modeled in Seller agents. The narrow black bar represents a 95% confidence interval and also demonstrates a high variation between each simulation for each personality type.

As more simulations are carried out, it can be seen that the variability between personality types reduces significantly. The experiment, considering 50 simulations, already demonstrates this reduction trend. We can observe that variability is drastically reduced by increasing the number of simulations tenfold. In this case, most personality types achieve similar results. Table 6 shows the minimum, maximum, median, mean, and standard deviation results achieved by each of the personality types in the third round of simulation with five hundred simulations.

Personality type	min	max	median	mean	std
ENFJ	73	147	101	102.9	14.1
ENFP	79	162	102	104.2	14.9
ENTJ	70	140	100.5	100.8	12.7
ENTP	78	165	100	100.4	14.2
ESFJ	37	127	92	92.7	15.9
ESFP	49	138	94	93.5	16
ESTJ	73	142	106.5	106.8	14.1
ESTP	79	143	103	104.5	13.3
INFJ	72	130	97	99.7	12.5
INFP	75	144	101	102.8	14.6
INTJ	63	156	101	101.8	16.8
INTP	65	135	99.5	99.5	14.4
ISFJ	59	121	89	88.3	12.8
ISFP	56	135	91	90.5	14.3
ISTJ	78	142	104	105.6	13.7
ISTP	70	138	104.5	104.5	13.7

Table 6: Sellers' Performance - 500 simulations

As more simulations are performed, it becomes clear that the differences in performance between personality types are closer. This approximation strongly indicates that the initial random conditions of the environment are more significant factors for performance than the agent personality types. As new simulations are carried out, favorable conditions for certain personality types can be created, enabling them to achieve greater performance in certain situations, thus the agents have to adapt themselves to the environmental conditions.

There is a great variation in the performance ranking between simulations. An agent with a certain personality type may lead to performance in a certain simulation, while in others, it may reach last. This alternation indicates that the initial positions of the Sellers and Buyers agents have a greater influence on the results than the modeled personality types. Over time, performance differences are reduced as new circumstances may emerge, favoring other characteristics modeled on agents.

8.5 Experiment II: Effect of Scenarios

In the second experiment, we sought to analyze how the personality types and the developed scenarios can impact the behavior of Seller agent teams and, consequently, their overall performance. In this experiment, we introduce the concepts of Market Types, previously explained in Section 6.4.2, seeking to observe how demand restrictions applied in the environment can influence the behavior and agent performance. *Personalify* decision attributes were also entirely considered, as described in Section 6.3. In particular, with this second experiment, we aimed to have an answer to research questions **RQ1** and **RQ2**, as described in Section 1.2.

8.5.1 Description

For a better understanding of the human factor in work contexts, the second experiment takes into account the developed Market Types to represent realities closer to organizations. Observing work teams, not just individuals, also allows broader analyses, enabling the identification of behavior patterns that can affect the group.

In this second experiment, we seek to observe how behavioral preferences, Extraversion and Introversion, modeled in Seller agents, can influence the teams' overall performance. Various team formations are composed to investigate how exploration or exploitation attitudes can affect behavior and impact the results achieved.

The addition of Market types provides favorable conditions for studies related to the influence of the environment on decisions made and the behavior of teams of agents. In this experiment, we also sought to observe the relationship between these conditions and the behaviors presented (BRAZ; BACHERT; SICHMAN, 2022).

In this experiment, hypotheses were formulated to assist the studies of the personality type influence on behavior presented by the Seller agents. These hypotheses aim to address important research questions related to the impact of certain agents' behavioral attitudes on team objectives, as well as the influence of environmental conditions on the behaviors and outcomes achieved.

Hypothesis 1 (H1): There is a performance difference between Teams composed of Extraverted and Introverted agents

The first hypothesis was formulated to identify whether there are differences in performance considering teams formed with opposite behavioral preferences, in this case, extroversion and introversion. The purpose is to observe whether the characteristics modeled in the agents can significantly influence the final team performance. As each of the behavioral preferences has opposite distinctions, the intent is to analyze the representative impact of different decisions made by agents modeled with both types of attitudes. Extroverted Seller Agents have a greater predilection for exploratory behaviors, seeking new regions and interactions in the environment. On the other hand, introverted Sellers tend to intensify their actions in areas of prior knowledge, strengthening pre-existing relationships.

Hypothesis 2 (H2): Markets with different Supply and Demand levels can impact the teams' performance

The second hypothesis aims to study the impact of environmental conditions on the agent's behavior and performance. Market Types represent restrictions on team actions, as they limit the number of interactions/sales made by each Seller agent. These limitations symbolize conditions closer to organizational realities, where employees are generally subject to market conditions that may or may not be favorable to good performance. In this hypothesis, we seek to respond to whether environmental demand restriction conditions can be significant for Seller agent teams.

In this experiment, the Gama platform was used to build a simulation scenario with a Grid Size of 125 x 125 and a maximum of 250 simulation cycles (*P9 Parameter*). Occupancy rates were set at 2% and 5% for Buyers and Sellers, totaling 313 Buyers (*P3 Parameter*) and 78 Sellers (*P2 Parameter*). With the addition of the Market Types (*P4 Parameter*), the number of products available for purchase and sale was defined at 4,688 (*P5 Parameter*), that is, a proportion of 30% of the environment. The parameter *P6 - Number of Cycles to return to an interacted agent* was set to 75 (30% of the total cycles), indicating how long a Seller agent needs to wait before returning to a previously visited Buyer agent.

The maximum number of visits to the same Buyer (*P7 Parameter*) was defined as three visits. The (*P8 Parameter*) that indicates the maximum distance to perceive a colleague from the same Seller team was set to ten, as well as the maximum distance of the Seller perception function (*P10 Parameter*) set to twenty. All these values were defined empirically according to observations in control simulations. In future studies, we expect new parameter combinations and optimizations to be carried out using sensitivity analysis methods. This experiment did not use the (*P11 Parameter*) since we did not explore possible changes in the agents' personality types and behavioral preferences.

The demand distributions for each of the Market Types follow the strategy previously explained in 6.4.2 section. The Balanced Market considers the division of global demand defined in (*P5 Parameter*) into two equal parts, that is, 2.344 products for sale and 2.344 products for purchase. In each group of Sellers and Buyers agents, these values were divided equally to the number of agents.

The distribution strategy applied to the Supply and Demand Markets considered the proportion of 2/3 of products. In other words, at Supply Market, we consider 2/3 of distribution for the Sellers agent team and 1/3 distributed to Buyers. The opposite was applied to the Demand Market, in which 2/3 of the demand was distributed to Buyers and the remaining 1/3 to the Sellers agent team.

8.5.2 Results

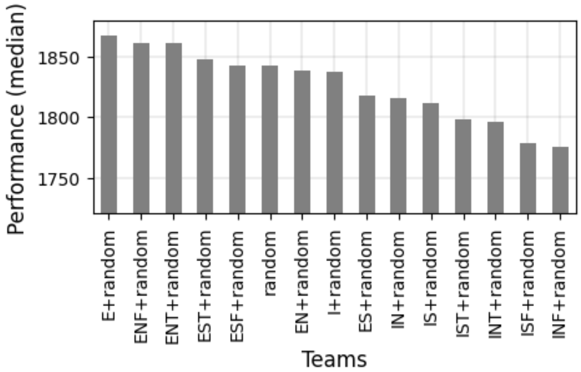
The formulated hypotheses were used as a basis for the simulations carried out in this experiment. Team profiles were formed to combine certain behavioral preferences to address the study scope. In this sense, extraversion and introversion attitudes were combined with random behavioral preferences to analyze the influence of certain aspects modeled on agents. A completely random team profile (PROF15) was also added to create a scenario with heterogeneous teams. Table 7 shows the composition of the team profiles:

Profile	**Attitude**	**Personality type**
PROF1	Extraverted	E+random
PROF2	Extraverted	ES+random
PROF3	Extraverted	EN+random
PROF4	Extraverted	EST+random
PROF5	Extraverted	ESF+random
PROF6	Extraverted	ENT+random
PROF7	Extraverted	ENF+random
PROF8	Introverted	I+random
PROF9	Introverted	IS+random
PROF10	Introverted	IN+random
PROF11	Introverted	IST+random
PROF12	Introverted	ISF+random
PROF13	Introverted	INT+random
PROF14	Introverted	INF+random
PROF15	Heterogeneous	random

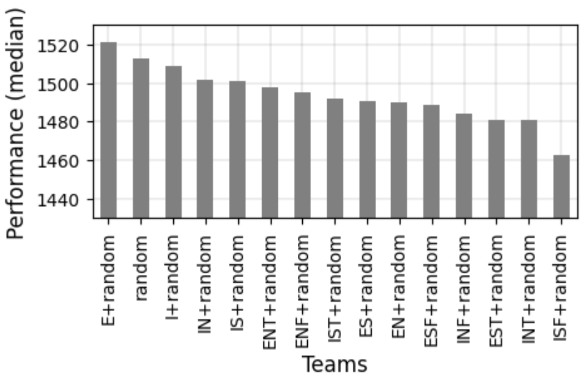
Table 7: Experiment Two - Team profiles

With the composition of the team profiles, three different scenarios were developed to cover each modeled Market Type. In this experiment, fifteen simulations were carried out for each of the scenarios, each one with a distinct team profile. For greater robustness in analyzing the results, we used five different Random Seeds to reduce the impact that initial environmental conditions may have on the studies. As previously seen in the first experiment, these conditions can decisively influence the agent team's performance, and it is important to mitigate the effect that these conditions may have on the final results measurement. As a consequence, 225 simulations in total (*15 simulations * 5 Random Seeds * 3 Market Types*).

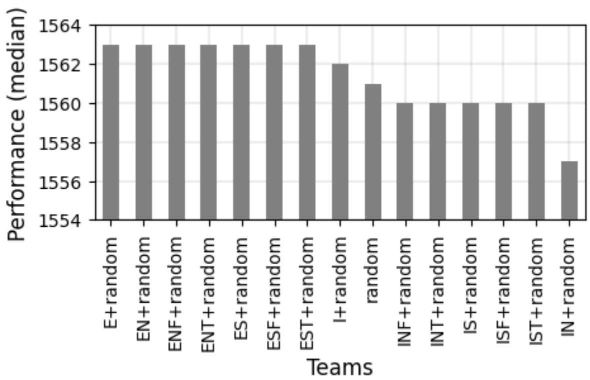
The results were grouped for each Market Type, and the median performance was extracted for each group. In this experiment, we considered the sales demand realized for the composite team profiles, as explained previously in 8.3 section. The obtained results are shown in Figure 18.



(a) Balanced Market



(b) Supply Market



(c) Demand Market

Figure 18: Team profile performance by Market Type

With the obtained performance data for each scenario, we applied the Wilcoxon test (WILCOXON, 1992) to validate the formulated hypotheses.

The first hypothesis *(H1)* considers whether there are performance differences between teams of extroverted and introverted agents. For this study, we used the obtained results among predominantly extroverted profiles, composed of profiles PROF1 to PROF7, comparing them with the team profiles predominantly introverted, composed of profiles PROF8 to PROF14. The PROF15 profile, which is completely random, was not used in this analysis.

According to the Wilcoxon test, *p-value* were obtained to quantify the probability of obtaining a certain set of observations if the null hypothesis is true, or in other words, to measure the strength of the collected evidence against the null hypothesis (DOREY, 2010). The calculated *p-value* for each Market Type helps us quantify the importance of the obtained data.

For the Balanced market, we obtained *p-value* $= 0.000023$, which indicates that we can reject the *Null Hypothesis* *(H_0)* and conclude that there are performance differences between the profiles of Extraverted and Introverts teams.

These results, analyzed with the performance charts, indicate that the exploratory characteristics, modeled in extraverted agents, possibly let them to achieve high performance in the Balanced scenario. Their predisposition to expand their territory, explore new regions, and create new connections allowed agents to expand their action's impact. The PROF6 and PROF7 profiles, composed of ENF and ENT personality types, achieved the highest performances after the E+random profile. It also indicates that the intuitive characteristic modeled in the agents, with a tendency to abstract long-term gains, helped them to achieve greater competitive advantage.

On the other hand, we noticed from the obtained data that Introverted agents presented the lowest performances. Their tendency to maintain pre-existing relationships with already known Buyers made it difficult to search for unexplored regions. It thus prevented them from creating new connections that would enable greater performance.

In the Supply market, a more challenging environment given that Supply is greater than Demand, we obtained $p\text{-}value = 0.229537$, indicating that we cannot reject the H_0 hypothesis. This data allows us to conclude that there are no differences in performance between the two Extraverted and Introverted teams. In a scenario where purchasing Demand is scarce, Introverted agents quickly need to change their posture to exploratory attitudes since Buyers' Demand will cease fast. This adaptation to environmental conditions allows them to perform equivalently to Extroverts, indicating there are no significant differences between the two teams. Compared to the real world, the development of skills and talents can help individuals adapt to the environments and work conditions in which they are situated. As a self-knowledge instrument, MBTI can help individuals develop skills in non-natural areas, allowing them to grow personally and professionally (MYERS; MYERS, 2010).

In the last studied Market Type, where Demand is greater than Supply, we obtained $p\text{-}value = 0.000272$, concluding that there are differences between team profiles. Despite this, it is important to analyze that the percentage of Demand reached by all teams was above 99% of the initial allocated Demand. In other words, we can conclude that all teams achieved excellence in performance and that personality type was not a relevant factor at the end of the simulations.

It is also interesting to note that in all three Market Types, the PROF15 random profile team has achieved reasonable results. This probably happened due to a heterogeneous profile that can lead to multiple behaviors, not reflecting a single aspect in particular. However, this specific characteristic must be better explored in further studies to investigate the specificities that influenced team performance.

A synthesis of these results may be seen in Table 8 where we show the associated p-value for each Market Type:

Market-Type	**P-Value**
Balanced Market	**0.000023**
Supply Market	0.229537
Demand Market	**0.000272**

Table 8: Wilcox Test *Hypothesis H1* E-I only

Hypothesis H2 was also analyzed using the Wilcoxon test. In order to validate if the modeled Market Types could impact the performance of Seller agent teams, we compared the fifteen team profiles on a two-by-two basis. In other words, the same team profiles were compared for each Market Type scenario. For example, for the PROF1 team profile, the achieved performance in the Balanced Market was compared with the performance in the Supply Market, the Balanced Market with Demand Market, and finally, the Supply Market with the Demand market. This kind of analysis was carried out successively for all fifteen team profiles.

As indicated in Table 9 in all comparisons analyzed, the obtained *p-value* was less than 0.00005, indicating that the *Null Hypothesis (H_0)* can be rejected and that there are in fact, differences in terms of performance when we analyze the same team profile in dissimilar scenarios.

Market-Type	**P-Value**
Balanced Market	**0.00002**
Supply Market	**0.00002**
Demand Market	**0.00002**

Table 9: Wilcox Test *Hypothesis H2* E-I only

This analysis makes it clear that the designed Market Types can significantly impact the team performance, being a decisive factor that directly influences the behavior of Seller agents and, consequently, the team performance.

In the real world, it is natural that work teams depend on external conditions that limit and directly influence their actions. Creating more harmonious environments conducive to professional development can help organizations create more effective working conditions that allow them to impact the results positively and the organizations' strategic objectives. The constructive use of MBTI can help individuals better understand aspects of each person's personality types, contributing to the construction of work environments that are more appropriate to each person's particularities (MYERS, 1998).

8.6 Experiment III: Effect of Personality Changes

So far, in our framework, each agent acts 100% of time according to its personality type. However, this does not occur in real life: even if agents have prevalent personality characteristics, there are situations where their behaviors do not match such specific characteristics. An extraverted agent, for example, may be tired and not willing to interact with other agents at that exact moment. Hence, in this last experiment, we explored how eventual changes in behavioral preferences can influence the decisions and actions of Seller agent teams. In particular, with this last experiment, we aimed to strengthen the research question **RQ1** study and to have an answer to research question **RQ3**, as described in Section 1.2.

8.6.1 Description

According to MBTI, people have natural behavioral preferences combined to form their personality types. These preferences represent predominant factors commonly observed in our daily lives and can be seen as tendencies to present certain types of behaviors. Thus, personality types reflect predominant behavioral preferences and our natural tendency to react to situations and environmental stimuli.

However, these preferences are not constant; that is, we do not necessarily always express the same types of behavior. Human beings, with all their complexities, can react differently according to specific situations in which they may be involved. For example, a predominantly extraverted individual may go through situations they are uncomfortable with and demonstrate attitudes that are opposite to their natural preference. At the same time, introverted individuals may, at times, show a preference for extroversion.

Anyone can develop skills in areas that are not their natural preference. MBTI describes that personality types should not be used as a way to avoid or refuse to perform certain types of tasks. The instrument is important for identifying areas of personal growth, helping individuals develop new skills by exploring aspects that eventually require greater focus and attention.

The dichotomies described in MBTI constitute opposite poles of behavioral preferences. Individuals can use both poles at different times and not with the same confidence level (MYERS, 1998).

This experiment explored how eventual changes in the agent's personality type could impact the observed behavior and team performance.

To evolve with the analysis regarding the influence of changes in agents' personality types, we formulate two hypothesis, as described below:

Hypothesis 1 (H1): There is performance difference between Sellers' agent teams composed of distinct personality types

The first hypothesis aims to bring greater robustness to the study described in Section 8.5. This study focused on analyzing the behaviors of teams with extraverted and introverted attitudes; it is also important to analyze whether other behavioral preferences would have the same performance pattern. *Hypothesis H1* seeks to analyze whether there are differences in performance between teams modeled with different personality types, considering the four dichotomies described in the MBTI.

Hypothesis 2 (H2): There is performance difference when considering the effect of personality type changes

hypothesis H2 aims to explore how personality changes modeled on agents can impact the teams' overall performance. It is important to analyze this aspect, given that in the real world, people do not have the same behavioral preferences all the time. Thus, this hypothesis seeks to analyze how personality changes that occur during agent-based simulations could influence the teams' overall performance.

In this experiment, we used the same simulation parameters from the previous study detailed in 8.5 section. To ensure greater robustness of the analyses, the same parameterizations were considered, applying new Random Seeds and a more significant number of simulations.

The parameter *P11 - Number of Cycles to reconsider the personality type* was added in this experiment to introduce the aspect of changing the agents' behavioral preferences during the simulations. In this parameter, we specify the number of cycles that are waited to reconsider the agents' personality type. This parameter is set to the value 25, representing 10% of the simulation cycles; in each simulation round, the agents' personality type will be reconsidered ten times.

Personalify framework implements an action called *set_my_personality* receiving a Boolean value *use_probability* that indicates when the personality type should use a deterministic or probabilistic factor. In this case, when *use_probability* is *True*, each behavioral preference will have an 80% probability of keeping the original preference. For example, an agent defined with the I,S,T,J personality type, upon reaching the twenty-fifth simulation cycle, will reconsider each of the behavioral preferences, having an 80% probability of remaining Introverted and a 20% probability of change to an Extraverted attitude, and so on for all defined behavioral preferences.

8.6.2 Results

The study of personality changes influence on the behavior and performance of Seller's agent teams was performed based on simulations for each of the Market Types already described in Section 6.4.2 and used to the experiment detailed in Section 8.5.

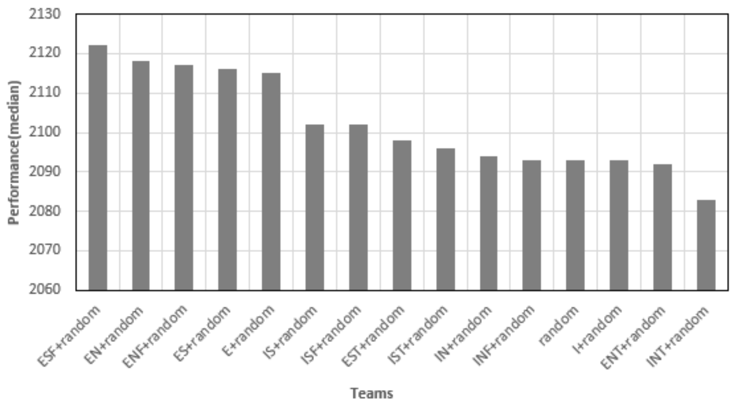
In the new experiment, *Hypothesis 1 (H1)* considers all dichotomies and requires new team profile compositions. Thus, six new profiles were added PROF15, PROF16, PROF17, PROF18, PROF19 and PROF20 as shown in Table 10. These profiles are necessary to compose the remaining behavioral preferences of S-N, T-F, and J-P dichotomies:

Profile	Personality type
PROF1	E+random
PROF2	ES+random
PROF3	EN+random
PROF4	EST+random
PROF5	ESF+random
PROF6	ENT+random
PROF7	ENF+random
PROF8	I+random
PROF9	IS+random
PROF10	IN+random
PROF11	IST+random
PROF12	ISF+random
PROF13	INT+random
PROF14	INF+random
PROF15	S+random
PROF16	N+random
PROF17	T+random
PROF18	F+random
PROF19	J+random
PROF20	P+random
PROF21	random

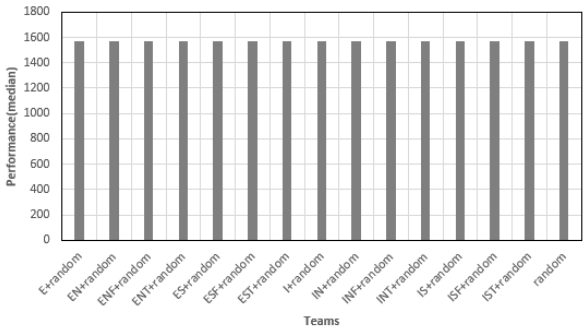
Table 10: Experiment Three - Team profiles

In the third experiment, new compositions of Random Seeds were also used in the simulations. As previously explained, the variation of Random Seeds is important to ensure that the initial environment's random conditions do not significantly impact the agent behavior. Thus, twenty-one simulations were run using different Random Seeds for each team profile and Market Type, totaling 1.953 simulations (*21 simulations * 31 Random Seeds * 3 Market Types*).

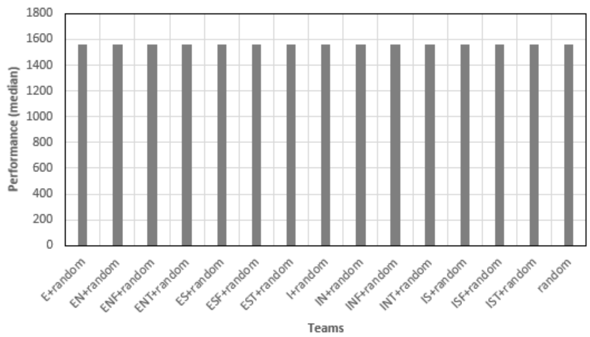
The continuity of the studies described in Section 8.5 and in (BRAZ; BACHERT; SICHMAN, 2022) contributes to the robustness of the analyses. The first simulation focuses on studying Extraverted and Introverted team profile performance. Figure 19 shows the measured data from the new simulations.



(a) Balanced Market



(b) Supply Market



(c) Demand Market

Figure 19: Teams' performance By Market Type (Extraversion-Introversion influence)

Similar patterns can be observed from the obtained data to the previous experiments when comparing extraverted and introverted team profiles. The exploratory attitude modeled in extraverted teams continues to significantly influence the demonstrated performance by the team of agents in the Balanced Market Type. In other markets, all teams achieved performance excellence, corroborating previous data that indicated that the Market Type can significantly influence team performance.

When considering all dichotomies to study *Hypothesis 1 (H1)*, the Wilcoxon test is also applied for comparative analysis between each dichotomy. Therefore, we compare team profiles with opposite attitudes to analyze whether there are significant performance differences. The following comparisons were made: PROF1 with PROF8, PROF15 with PROF16, PROF17 with PROF18 and PROF19 with PROF20. The *p-value* obtained data can be seen in Table 11:

Extraversion and Introversion

Market-Type	P-Value
Balanced Market	**0.0011**
Supply Market	0.5014
Demand Market	—

Sensing and Intuition

Market-Type	P-Value
Balanced Market	0.7187
Supply Market	0.1901
Demand Market	—

Thinking and Feeling

Market-Type	P-Value
Balanced Market	**0.0146**
Supply Market	0.1791
Demand Market	—

Judging and Perceiving

Market-Type	P-Value
Balanced Market	0.8757
Supply Market	0.2675
Demand Market	—

Table 11: Wilcox Test *Hypothesis H1* with all dichotomies

With the significant *p-value* achieved by teams with Thinking or Feeling profiles, we graphically analyzed the team's performance with these attitudes considering only the Balanced market. The Figure 20 illustrates this chart:

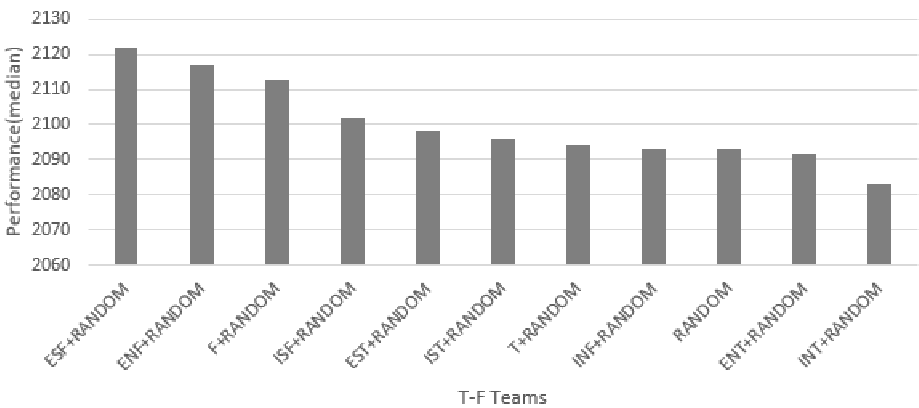
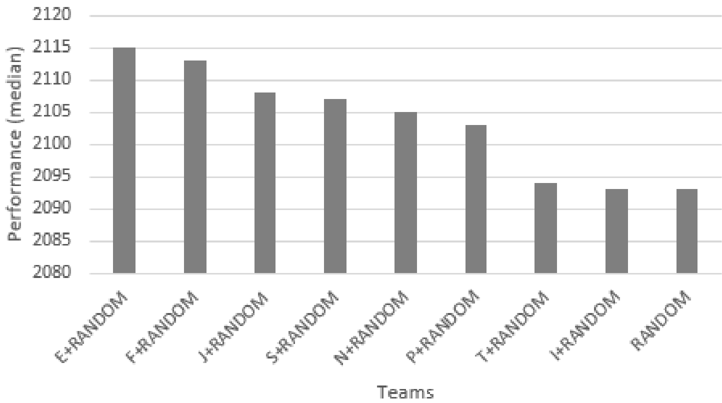
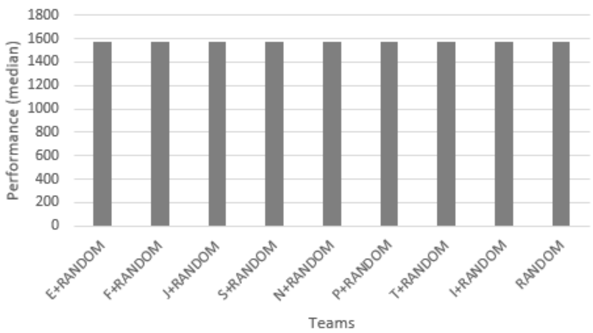


Figure 20: T-F Teams Performance (Balanced Market)

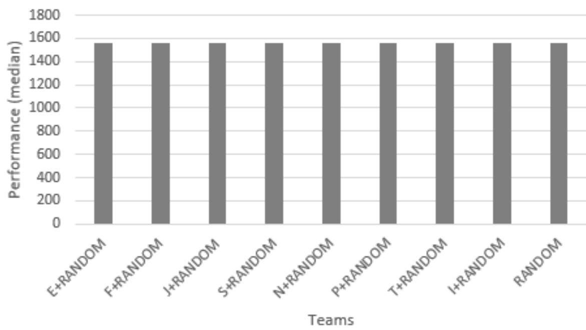
We also comparatively analyzed the performance of the eight teams composed of the behavioral preferences isolated from each of the dichotomies and the totally random team, as seen in Figure 21.



(a) Balanced Market



(b) Supply Market



(c) Demand Market

Figure 21: Teams' performance By Market Type (All Dichotomies)

The results demonstrated that in the Balanced market, the *Null Hypothesis* (H_0) can be rejected for the dichotomies E-I with *p-value* = 0.0011 and T-F with *p-value* = 0.0146, both lower than the threshold below 5% defined in the study. With the data, we can conclude that there are significant differences in performance between the profile teams for these dichotomies in the Balanced market.

The data confirm that the exploratory predisposition of extraverted agents could positively influence team performance. In the T-F dichotomy, it is clear that the opposite attitudes demonstrated by Thinking and Feeling agents resulted in significant comparative differences. Thinking teams, with a predisposition to be more logical and rational, had comparatively lower results than Feeling teams, which prioritize the possible objectives of their colleagues. It is interesting to note that the Feelings teams' collaborative characteristics significantly impacted overall performance.

In the Supply market, there were no significant differences in performance for any of the teams. In the Demand market, there were no variations in the median performance achieved by the teams. As seen in other studies (BRAZ; BACHERT; SICHMAN, 2022), the team performance above 99% indicates that the differences were not significant. It is relevant to note that in more challenging scenarios than the Balanced Market, environmental conditions are factors that decisively influence the agent's behavior who needs to adapt to new circumstances.

The Wilcoxon test was also used to analyze *Hypothesis 2 (H2)*. In this case, the focus is on validating the effects that personality changes introduced in agents during simulations can have on the team's presented results. Given there were no significant variations in other markets, we only considered the Balanced market in the analyses. For each behavioral preference, we compare the influence of *parameter P11*, which controls the verification of possible personality changes. That is, for each of the eight team profiles, considering only the influence of unique behavioral preferences, we compare simulations with and without the effect of personality changes. Table 12 shows the *p-values* results obtained:

Extraversion (PROF1)

Market-Type	**P-Value**
Balanced Market	0.3993

Introversion (PROF8)

Market-Type	**P-Value**
Balanced Market	**0.0045**

Sensing (PROF15)

Market-Type	**P-Value**
Balanced Market	0.4624

Intuition (PROF16)

Market-Type	**P-Value**
Balanced Market	0.4989

Thinking (PROF17)

Market-Type	**P-Value**
Balanced Market	0.0698

Feeling (PROF18)

Market-Type	**P-Value**
Balanced Market	0.4389

Judging (PROF19)

Market-Type	**P-Value**
Balanced Market	0.5765

Perceiving (PROF20)

Market-Type	**P-Value**
Balanced Market	0.1470

Table 12: Wilcox Test *Hypothesis H2* with all Behavior Preferences

Figure 22 also shows the performance chart comparing all behavioral preferences considering personality changes.

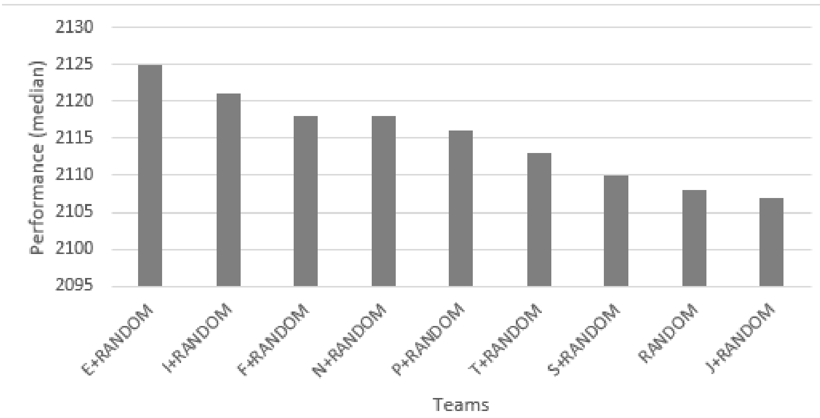


Figure 22: Teams Performance with Personality Changes

The obtained data shows that performance differences were observed only for introverted teams. These data are in line with other observations, given that this scenario considers Introverted agents who eventually act with Extraverted attitudes. In other words, they are agents that predominantly behave with exploitation attitudes, but they can also demonstrate exploratory attitudes in certain situations. These changes have a decisive impact on team's performance.

Although not the objective of this current work, these analyses are in line with MBTI theory, which indicates that individuals can adapt to environmental conditions and develop skills and talents that help them grow personally and professionally (MYERS, 1998; MYERS et al., 1998; MYERS; MYERS, 2010).

The PROF17 profile, predominantly Thinking, obtained a *p-value* $= 0.0698$, very close to the established Threshold. This data, analyzed with the comparative chart shown in Figure 22, allows us to glimpse that possibly Thinking agents that eventually act with collaborative Feelings attitudes can significantly impact long-term performance. However, more studies considering the impact of other parameterizations are necessary to evolve and confirm this analysis.

9 CONCLUSIONS AND FURTHER WORK

MBTI has been an important instrument of self-knowledge, helping people to better understand their behavioral preferences and develop new skills and talents. People tend to have greater satisfaction in more harmonious work environments that consider their preferences and personality types. A better understanding of factors that can influence people's behavior in work contexts can help build more collaborative environments in which people mutually respect and cooperate with each other, positively impacting organizations (MYERS, 1998).

This work explored the use of Artificial Intelligence to build agent-based simulations inspired by the real world. Seller-Buyer scenarios that mimic the buying and selling relationship were created to represent situations found in corporate environments, albeit in a very simplified way. In this context, several experiments were conducted to observe the behavior of Seller agent teams in Market Types developed with demand restrictions that directly influence the agents' behavior.

The decisions and behavior of Seller agents are also influenced by decision attributes inherited from *Personalify*, a framework to represent characteristics inspired by the behavioral preferences described in MBTI theory. Team profiles composed of different personality types were formed and used in the simulations. In the end, agent performance metrics were measured to determine the impact that the team's profile had on the built environment, comparatively evaluating the differences between the various profiles applied in the simulations. As detailed in Section 8.3, the performance metrics should not be interpreted to conclude whether a personality type is good or bad for carrying out tasks, which would indicate a misuse of the MBTI (COE, 1992). Results interpretations must remain exclusively in the presented work's context and not be directly extrapolated to the real world.

The *Personalify* framework implementation extended with the Seller-Buyer scenario allowed the observation of agent teams' behavior composed of diverse personality types. Three experiments were developed to address the research questions formulated at the beginning of the work and described in Section 1.3.

The first experiment, using a simplified version of the decision attributes (BRAZ; SICHMAN, 2022b) described in Section 6.3, demonstrated that Seller agents modeled with different personality types can present different performance levels and thus affirmatively respond to the first research question, whether personality types can impact the behavior of Seller's agent teams. Although using different methodologies and implementations from other authors, these results are similar to other related studies (SALVIT; SKLAR, 2010; SALVIT, 2012; SALVIT; SKLAR, 2012). However, the experiment also demonstrates that as new simulations are carried out, there is a tendency towards equalization of the achieved performances. In a scenario considering five hundred simulations, there is a great approximation of the measured performance for all personality types. This trend indicates that the initial positions of the agents, Sellers and Buyers, had a more relevant impact than the modeled decision attributes. Given that new random environmental conditions are configured, the differences between the modeled agent's characteristics are not decisive in the overall team performance.

With the development of more complex decision attributes and the construction of scenarios involving sales and purchase demand restrictions, other results could be observed in a second experiment. Two hypotheses were formulated, the first validating whether there are differences in performance between teams composed of extraverted and introverted agents. The second analyzes whether different buying and selling demand levels can impact the performance of Seller teams. The results demonstrated that the Exploration or Exploitation attitudes, implemented in decision attribute A2, significantly impacted the agent team performance in the Balanced Market. As Extraverted agents are more likely to establish new connections with Buyer agents, they had more significant results in terms of performance. It is interesting to note that in more challenging markets, such as the Supply Market, there were no performance differences between the teams. In the Demand Market, despite the hypothesis test demonstrating performance differences between the teams, it was observed that all teams presented above 99% demand achievement. This analysis demonstrates that the agent adaptation to environmental conditions made it possible to equalize the performance level by comparing different personality types. For the second hypothesis, the results also demonstrated that different Market Types can influence agents' performance. The demand restrictions applied in the environment decisively influenced the observed performance. Thus, it was also possible to address the second research question in which it can be seen that the environment can indeed impact the behavior of Seller's agent teams.

Finally, the last experiment sought to validate the observations made previously, expanding the scope of hypothesis testing to consider whether there are differences in performance considering all dichotomies. The study reinforced that Exploration or Exploitation attitudes, modeled on Seller agents, significantly impact performance in the Balanced Market. Another interesting finding in this market is that there were performance differences regarding Thinking and Feeling teams. The collaborative attitudes of the Feelings teams allowed greater overall performance results compared to the more logical and objective attitudes of the Thinking teams. In more challenging markets, the study also confirmed that the influence of personality type is reduced as agents need to adapt to new environmental conditions. In the Demand and Supply Markets, there were no significant differences in terms of performance. To conclude the study, a new hypothesis was formulated to analyze whether there are differences in performance, considering changes in the agents' personalities during the simulation cycles. In this case, only the Balanced market was considered, given that other studies have shown that it has the greatest impact on variations in agent performance. The obtained results demonstrated that only introverted teams, which eventually behave with extraverted attitudes, presented differences in performance. Thinking teams, which eventually behave like Feelings, had *p-values* very close to the defined threshold, but more studies are needed to analyze whether this behavior can be significant. In this case, it was also possible to answer the last research question in which we realized that personality changes can influence the behavior of Seller's agent teams, although in different ways depending on the considered personality type.

With the experiments, we can see that the personality characteristics modeled in agents influence their behavior and, consequently, their performance. However, their adaptive behavior to environmental conditions significantly contributes to ensuring that any gaps are mitigated and that, in the long term, there are no significant differences between the modeled personality types. The personality changes that occurred during the simulations also demonstrate that the adaptability of the agents is a factor that provides greater equalization of differences.

Based on our experiment results, we can now make a synthesis of the answers for our research questions introduced in Section 1.2:

RQ1 Can personality types impact the Seller's agent team behavior?
Answer: Based on the results of all experiments, it is evident that personality types can impact the behavior of Seller's agent teams.

RQ2 Can the environmental conditions impact the Seller's agent team behavior?

Answer: Based on the results of our second experiment, it is clear that the environmental conditions affect the behavior of Seller's agent teams decisively.

RQ3 Can personality changes influence the Seller's agent team behavior?
Answer: Based on the results of our third experiment, it was noticed that personality changes can influence the behavior of Seller's agent teams, although in different ways depending on the considered personality type.

Collaborative attitudes also positively impacted the agent teams who considered the objectives of their teammates, demonstrating that this is an important topic to consider when forming teams. MBTI is a self-affirming instrument that encourages cooperation with other individuals (MYERS, 1998). Teams that work collaboratively, understand each other's needs, have mutual trust, and share information have a greater chance of success. Personality differences can cause conflicts and miscommunication. Understanding and dealing with these differences is a key factor in creating high-performance teams (HPTs) (SHARP et al., 2000).

9.1 Contributions

The study contributed to the knowledge evolution of behavioral factors modeled in artificial agents. With them, we can better understand how certain characteristics, inspired by MBTI theory and introduced into agents through the decision attributes development, can influence their behaviors and decisions made.

The formulated research questions, described in Section 1.2, were answered through the framework development and the experiments. We observed that personality types, the environment, and personality changes can directly influence and impact agents' behavior. Agents can also adapt their behaviors according to situations and environmental conditions, helping to mitigate eventual differences between the diverse behavior preferences.

This work also contributed to developing *Personalify*, a generic and extensible framework that can be applied in other scenarios. Researchers can use MBTI-based framework independently of the Seller-Buyer scenario, applying the described concepts of personality types in broader agent scopes. The source code is accessible through Github repository: *https://github.com/lfbraz/mas-mbti-model*.

9.2 Future Work

Despite contributing to advancing the agent's behavior study, the current work has limitations that can be addressed in future work.

The parameterizations and weights used were empirically defined, and in the future, more efficient and robust methods can be employed to optimize and compose them. The concepts of primary and auxiliary functions, among other aspects regarding the different functions associated with the behavioral preferences from MBTI, have also not been considered and can be explored in future works.

Sensitivity analyses should be applied to calibrate parameters using methods such as Sobol's (NOSSENT; ELSEN; BAUWENS, 2011). Variations and new scenario compositions can also help analyze broader scopes of the Seller-Buyer scenario.

Other metrics and techniques for analyzing agents' behavior can help to investigate deeply how modeled attitudes can bring more assertiveness to the study's conclusions. Evolving with the development of proposed decision attributes can also allow the recognition of new patterns and behavioral aspects that help to create intelligent mechanisms closer to the behaviors demonstrated by human beings.

Advanced negotiation mechanisms between Sellers and Buyers can be implemented, and more complex market conditions can be created to simulate what happens in the real world. These mechanisms can help with in-depth analysis of factors that may be correlated with certain behavior patterns.

Finally, *Personalify* can be extended to represent other behavioral models, such as the Five-Factor Model. Thus, its implementation could cover numerous use cases involving two of the most popular models for classifying individuals' personality tendencies.

REFERENCES

ABBAS, H. A.; SHAHEEN, S. I.; AMIN, M. H. Organization of multi-agent systems: an overview. *arXiv preprint arXiv:1506.09032*, 2015.

ADAM, C.; GAUDOU, B. Bdi agents in social simulations: a survey. *The Knowledge Engineering Review*, Cambridge University Press, v. 31, n. 3, p. 207–238, 2016.

ADAM, C.; GAUDOU, B. Modelling human behaviours in disasters from interviews: Application to melbourne bushfires. *Journal of Artificial Societies and Social Simulation*, v. 20, n. 3, p. 12, 2017. ISSN 1460-7425. Disponível em: <http://jasss.soc.surrey.ac.uk/20/3/12.html>.

AHRNDT, S.; FÄHNDRICH, J.; ALBAYRAK, S. Modelling of personality in agents: from psychology to implementation. *Proceedings of the HAIDM*, p. 1–16, 2015.

ALVARES, L. O.; SICHMAN, J. S. Introduçao aos sistemas multiagentes. In: *XVII Congresso da SBC-Anais JAI'97*. [S.l.: s.n.], 1997.

BAN, T. Q. et al. Covid-19 disease simulation using gama platform. In: IEEE. *2020 international conference on computational intelligence (ICCI)*. [S.l.], 2020. p. 246–251.

BARAŃCZUK, U. The five factor model of personality and emotion regulation: A meta-analysis. *Personality and Individual Differences*, Elsevier, v. 139, p. 217–227, 2019.

BELL, S. T. Deep-level composition variables as predictors of team performance: a meta-analysis. *Journal of applied psychology*, American Psychological Association, v. 92, n. 3, p. 595, 2007.

BIPP, T. What do people want from their jobs? the big five, core self-evaluations and work motivation. *International journal of selection and assessment*, Wiley Online Library, v. 18, n. 1, p. 28–39, 2010.

BOURGAIS, M.; TAILLANDIER, P.; VERCOUTER, L. Ben: An architecture for the behavior of social agents. *Journal of Artificial Societies and Social Simulation*, JASSS, v. 23, n. 4, 2020.

BOYLE, G. J. Myers-briggs type indicator (mbti): some psychometric limitations. *Australian Psychologist*, Wiley Online Library, v. 30, n. 1, p. 71–74, 1995.

BRATMAN, M. Intention, plans, and practical reason. 1987.

BRATMAN, M. E.; ISRAEL, D. J.; POLLACK, M. E. Plans and resource-bounded practical reasoning. *Computational intelligence*, Wiley Online Library, v. 4, n. 3, p. 349–355, 1988.

BRAZ, L. F.; BACHERT, C. M. D. A.; SICHMAN, J. S. Simulating work teams using mbti agents. In: SPRINGER. *International Workshop on Multi-Agent Systems and Agent-Based Simulation*. [S.l.], 2022. p. 57–69.

BRAZ, L. F.; SICHMAN, J. S. Um estudo do myers-briggs type indicator (mbti) para modelagem de sistemas multiagentes no apoio a processos de recrutamento e seleção nas empresas. In: *Anais do XIV Workshop-Escola de SistemasAgentes, seus Ambientes e apliCações de Agentes, seus Ambientes e apliCações*. [S.l.]: Zenodo, 2020. p. 250–255.

BRAZ, L. F.; SICHMAN, J. S. Extending ben architecture for modeling mbti agents. In: *1st conference GAMA Days 2021*. [S.l.: s.n.], 2021.

BRAZ, L. F.; SICHMAN, J. S. Exploring a mbti-based agent model in a buyer-seller scenario. In: *2nd conference GAMA Days 2022*. [S.l.: s.n.], 2022.

BRAZ, L. F.; SICHMAN, J. S. Using mbti agents to simulate human behavior in a work context - in press. In: SPRINGER. *Advances in Social Simulation*. [S.l.], 2022.

BRAZ, L. F.; SICHMAN, J. S. Using the myers-briggs type indicator (mbti) for modeling multiagent systems. *Revista de Informática Teórica e Aplicada*, v. 29, n. 1, p. 42–53, 2022.

CAILLOU, P. et al. A simple-to-use bdi architecture for agent-based modeling and simulation. In: SPRINGER. *Advances in Social Simulation 2015*. [S.l.], 2017. p. 15–28.

CAMPBELL, J. P.; WIERNIK, B. M. The modeling and assessment of work performance. *Annu. Rev. Organ. Psychol. Organ. Behav.*, Annual Reviews, v. 2, n. 1, p. 47–74, 2015.

CAMPOS, A. M. et al. A process-oriented approach to model agent personality. In: *AAMAS (2)*. [S.l.: s.n.], 2009. p. 1141–1142.

CASTKA, P. et al. Factors affecting successful implementation of high performance teams. *Team Performance Management: An International Journal*, MCB UP Ltd, 2001.

CHAVEZ, A.; MAES, P. *Kasbah: An agent marketplace for buying and selling goods*. [S.l.]: Practical Application, 1996.

COE, C. K. The mbti: Potential uses and misuses in personnel administration. *Public Personnel Management*, SAGE Publications Sage CA: Los Angeles, CA, v. 21, n. 4, p. 511–522, 1992.

DELOACH, S. A. Modeling organizational rules in the multi-agent systems engineering methodology. In: SPRINGER. *Conference of the Canadian Society for Computational Studies of Intelligence*. [S.l.], 2002. p. 1–15.

DESAI, D. R. Exploration and exploitation: an essay on (machine) learning, algorithms, and information provision. *Loy. U. Chi. LJ*, HeinOnline, v. 47, p. 541, 2015.

DIAB-BAHMAN, R. The impact of dominant personality traits on team roles. *The Open Psychology Journal*, v. 14, n. 1, 2021.

DOCE, T. et al. Creating individual agents through personality traits. In: SPRINGER. *Intelligent Virtual Agents: 10th International Conference, IVA 2010, Philadelphia, PA, USA, September 20-22, 2010. Proceedings 10*. [S.l.], 2010. p. 257–264.

DOREY, F. *In brief: The P value: What is it and what does it tell you?* [S.l.]: Springer, 2010.

DORRI, A.; KANHERE, S. S.; JURDAK, R. Multi-agent systems: A survey. *Ieee Access*, IEEE, v. 6, p. 28573–28593, 2018.

DROGOUL, A. et al. Gama: A spatially explicit, multi-level, agent-based modeling and simulation platform. In: SPRINGER. *International Conference on Practical Applications of Agents and Multi-Agent Systems*. [S.l.], 2013. p. 271–274.

DROGOUL, A. et al. Gama: multi-level and complex environment for agent-based models and simulations. In: *international conference on Autonomous agents and multi-agent systems*. [S.l.: s.n.], 2013. p. 1361–1362.

ESPINOSA, B. A. *Agents with affective traits for decision-making in complex environments*. Tese (Doutorado) — Universitat Politècnica de València, 2017.

FARHANGIAN, M. *Capturing the effect of personality on teams with agent-based modelling*. Tese (Doutorado) — University of Otago, 2018.

FARHANGIAN, M. et al. Modelling the effects of personality and temperament in the team formation process. In: *the First International Workshop on Multiagent Foundations of Social Computing, at The 13th International Joint Conference on Autonomous Agents & Multiagent Systems, Paris*. [S.l.: s.n.], 2014. v. 6.

FLEENOR, J. W. The relationship between the mbti and measures of personality and performance in management groups. *Developing leaders: Research and applications in psychological type and leadership development*, Davies-Black Publishing Boston, p. 115–138, 1997.

FURNHAM, A.; CRUMP, J. et al. The myers-briggs type indicator (mbti) and promotion at work. *Psychology*, Scientific Research Publishing, v. 6, n. 12, p. 1510, 2015.

FURNHAM, A.; STRINGFIELD, P. Personality and work performance: Myers-briggs type indicator correlates of managerial performance in two cultures. *Personality and individual Differences*, Elsevier, v. 14, n. 1, p. 145–153, 1993.

GAMA. 2023. Available in: <https://gama-platform.org/wiki/> [Accessed: 2023-09-08].

HAENLEIN, M.; KAPLAN, A. A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California management review*, SAGE Publications Sage CA: Los Angeles, CA, v. 61, n. 4, p. 5–14, 2019.

HEAKAL, R. Economics basics: Supply and demand. *Investopedia. accessed September*, v. 28, 2015.

HOEK, W. Van der; WOOLDRIDGE, M. Multi-agent systems. *Foundations of Artificial Intelligence*, Elsevier, v. 3, p. 887–928, 2008.

JUNG, C. G. *Obras Completas de C. G. Jung*. [S.l.]: Editora Vozes Limitada, 2011.

JUNG, C. G. Tipos psicológicos. *Tipos psicológicos*, Trotta, p. 1–633, 2013.

KÖNIG, S. et al. Towards reputation enhanced electronic negotiations for service oriented computing. In: SPRINGER. *International Workshop on Trust in Agent Societies*. [S.l.], 2008. p. 273–291.

KOZLOWSKI, S. W.; BELL, B. S. Work groups and teams in organizations. *Handbook of psychology: Industrial and organizational psychology*, Wiley, v. 12, p. 333–375, 2003.

LENG, J.; FYFE, C.; JAIN, L. Teamwork and simulation in hybrid cognitive architecture. In: SPRINGER. *International Conference on Knowledge-Based and Intelligent Information and Engineering Systems*. [S.l.], 2006. p. 472–478.

LESQUOY, B. 2022. Available in: <https://gama-platform.org/wiki/Using-BEN-simple-bdi>.

LESSER, V. R. Cooperative multiagent systems: A personal view of the state of the art. *IEEE Transactions on knowledge and data engineering*, IEEE, v. 11, n. 1, p. 133–142, 1999.

LOCKHART, J. N. *Examining the Relationship between Individual Employee Engagement and Personality Type Using the Myers-Briggs Type Indicator (MBTI®)*. Tese (Doutorado) — Pepperdine University, 2021.

LUO, L. et al. Agent-based human behavior modeling for crowd simulation. *Computer Animation and Virtual Worlds*, Wiley Online Library, v. 19, n. 3-4, p. 271–281, 2008.

MABS. *Multi-Agent-Based Simulation XXIII*. [S.l.]: Springer Cham, 2022.

MACATULAD, E.; BLANCO, A. 3dgis-based multi-agent geosimulation and visualization of building evacuation using gama platform. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Copernicus GmbH, v. 40, p. 87–91, 2014.

MANZOOR, S. R. et al. Effect of teamwork on employee performance. *International Journal of Learning and Development*, Macrothink Institute, v. 1, n. 1, p. 110–126, 2011.

MARTINEZ-MIRANDA, J.; ALDEA, A. Emotions in human and artificial intelligence. *Computers in Human Behavior*, Elsevier, v. 21, n. 2, p. 323–341, 2005.

MATHIEU, J. E. et al. A century of work teams in the journal of applied psychology. *Journal of applied psychology*, American Psychological Association, v. 102, n. 3, p. 452, 2017.

MCADAMS, D. P. The five-factor model in personality: A critical appraisal. *Journal of personality*, Wiley Online Library, v. 60, n. 2, p. 329–361, 1992.

MICHEL, F.; FERBER, J.; DROGOUL, A. Multi-agent systems and simulation: A survey from the agent commu-nity's perspective. In: *Multi-Agent Systems*. [S.l.]: CRC Press, 2018. p. 17–66.

MORENO, A.; VALLS, A.; MARÍN, M. Multi-agent simulation of work teams. In: SPRINGER. *Multi-Agent Systems and Applications III: 3rd International Central and Eastern European Conference on Multi-Agent Systems, CEEMAS 2003 Prague, Czech Republic, June 16–18, 2003 Proceedings 3*. [S.l.], 2003. p. 281–291.

MUPINGA, D. M.; NORA, R. T.; YAW, D. C. The learning styles, expectations, and needs of online students. *College Teaching*, Routledge, v. 54, n. 1, p. 185–189, 2006. Disponível em: <https://doi.org/10.3200/CTCH.54.1.185-189>.

MURTAGH, F.; CONTRERAS, P. Algorithms for hierarchical clustering: an overview. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, Wiley Online Library, v. 2, n. 1, p. 86–97, 2012.

MYERS, I. B. *Introduction to type: A guide to understanding your results on the Myers-Briggs Type Indicator . Mountain View, CA: CPP*. [S.l.]: Inc, 1998.

MYERS, I. B. et al. *MBTI manual: A guide to the development and use of the Myers-Briggs Type Indicator*. [S.l.]: Consulting Psychologists Press Palo Alto, CA, 1998. v. 3.

MYERS, I. B.; MYERS, P. B. *Gifts differing: Understanding personality type*. [S.l.]: Nicholas Brealey, 2010.

NIJKAMP, P.; DELFT, A. van. *Multi-criteria analysis and regional decision-making*. [S.l.]: Springer Science & Business Media, 1977. v. 8.

NORLING, E.; SONENBERG, L. Creating interactive characters with bdi agents. 02 2004.

NOSSENT, J.; ELSEN, P.; BAUWENS, W. Sobol'sensitivity analysis of a complex environmental model. *Environmental Modelling & Software*, Elsevier, v. 26, n. 12, p. 1515–1525, 2011.

OSUGI, T.; KIM, D.; SCOTT, S. Balancing exploration and exploitation: A new algorithm for active machine learning. In: IEEE. *Fifth IEEE International Conference on Data Mining (ICDM'05)*. [S.l.], 2005. p. 8–pp.

PADGHAM, L.; LAMBRIX, P. Agent capabilities: Extending bdi theory. In: *AAAI/IAAI*. [S.l.: s.n.], 2000. p. 68–73.

PADGHAM, L.; TAYLOR, G. A system for modelling agents having emotion and personality. In: SPRINGER. *International Workshop on Intelligent Agent Systems*. [S.l.], 1996. p. 59–71.

PALANCA, J. et al. Spade 3: Supporting the new generation of multi-agent systems. *IEEE Access*, IEEE, v. 8, p. 182537–182549, 2020.

PANAIT, C.; BUCINSCHI, V. Myers-briggs type indicator influence in team buildings. *Review of the Air Force Academy*, Henri Coanda Air Force Academy, n. 1, p. 89–94, 2018.

PANAIT, L.; LUKE, S. Cooperative multi-agent learning: The state of the art. *Autonomous agents and multi-agent systems*, Springer, v. 11, n. 3, p. 387–434, 2005.

PEFFERS, K. et al. A design science research methodology for information systems research. *Journal of management information systems*, Taylor & Francis, v. 24, n. 3, p. 45–77, 2007.

PITTENGER, D. J. Cautionary comments regarding the myers-briggs type indicator. *Consulting Psychology Journal: Practice and Research*, Educational Publishing Foundation, v. 57, n. 3, p. 210, 2005.

RAO, A. S.; GEORGEFF, M. P. et al. Bdi agents: from theory to practice. In: *Icmas*. [S.l.: s.n.], 1995. v. 95, p. 312–319.

RITA. *Revista de Informática Teórica e Aplicada*. 2022. Disponível em: <https://doi.org/10.22456/2175-2745.110015>.

ROCCAS, S. et al. The big five personality factors and personal values. *Personality and social psychology bulletin*, Sage Publications Sage CA: Thousand Oaks, CA, v. 28, n. 6, p. 789–801, 2002.

ROTHMANN, S.; COETZER, E. P. The big five personality dimensions and job performance. *SA Journal of industrial psychology*, AOSIS, v. 29, n. 1, p. 68–74, 2003.

SALVIT, J. *Extending BDI with Agent Personality Type*. Tese (Doutorado) — The City University of New York, 2012.

SALVIT, J.; SKLAR, E. Toward a myers-briggs type indicator model of agent behavior in multiagent teams. In: SPRINGER. *International Workshop on Multi-Agent Systems and Agent-Based Simulation*. [S.l.], 2010. p. 28–43.

SALVIT, J.; SKLAR, E. Modulating agent behavior using human personality type. In: *Proceedings of the Workshop on Human-Agent Interaction Design and Models (HAIDM) at Autonomous Agents and MultiAgent Systems (AAMAS)*. [S.l.: s.n.], 2012. p. 145–160.

SAVAL, A. et al. Dealing with mixed and non-normative traffic. an agent-based simulation with the gama platform. *Plos one*, Public Library of Science San Francisco, CA USA, v. 18, n. 3, p. e0281658, 2023.

SHARMA, S. et al. Modeling human behavior during emergency evacuation using intelligent agents: A multi-agent simulation approach. *Information Systems Frontiers*, Springer, v. 20, p. 741–757, 2018.

SHARP, J. M. et al. Continuous organisational learning through the development of high performance teams. In: *ICSTM*. [S.l.: s.n.], 2000.

SILVA, L. D.; MENEGUZZI, F. R.; LOGAN, B. Bdi agent architectures: A survey. In: *Proceedings of the 29th International Joint Conference on Artificial Intelligence (IJCAI), 2020, Japão*. [S.l.: s.n.], 2020.

SMITH, M. M. et al. Perfectionism and the five-factor model of personality: A meta-analytic review. *Personality and Social Psychology Review*, Sage Publications Sage CA: Los Angeles, CA, v. 23, n. 4, p. 367–390, 2019.

SONNENTAG, S.; FRESE, M. Performance concepts and performance theory. *Psychological management of individual performance*, v. 23, n. 1, p. 3–25, 2002.

SPECTOR, P. E. *Psicologia nas organizações*. [S.l.]: Saraiva Educação SA, 2009.

SSC. *Advances in Social Simulation*. 2022. Disponível em: <https://link.springer.com/chapter/10.1007/978-3-030-92843-8_25\#chapter-info>.

STANUJKIC, D.; MAGDALINOVIC, N.; JOVANOVIC, R. A multi-attribute decision making model based on distance from decision maker's preferences. *Informatica*, Vilnius University Institute of Mathematics and Informatics, v. 24, n. 1, p. 103–118, 2013.

STONE, P. et al. Ad hoc autonomous agent teams: Collaboration without pre-coordination. In: *Twenty-Fourth AAAI Conference on Artificial Intelligence*. [S.l.: s.n.], 2010.

SUNDSTROM, E.; MEUSE, K. P. D.; FUTRELL, D. Work teams: Applications and effectiveness. *American psychologist*, American Psychological Association, v. 45, n. 2, p. 120, 1990.

SYCARA, K. P. Multiagent systems. *AI magazine*, v. 19, n. 2, p. 79–79, 1998.

TAILLANDIER, P. Traffic simulation with the gama platform. In: *International Workshop on Agents in Traffic and Transportation*. [S.l.: s.n.], 2014. p. 8–p.

TAILLANDIER, P. et al. A bdi agent architecture for the gama modeling and simulation platform. In: SPRINGER. *International Workshop on Multi-Agent Systems and Agent-Based Simulation*. [S.l.], 2016. p. 3–23.

TAILLANDIER, P. et al. A bdi agent architecture for the gama modeling and simulation platform. In: SPRINGER. *Multi-Agent Based Simulation XVII: International Workshop, MABS 2016, Singapore, Singapore, May 10, 2016, Revised Selected Papers 17*. [S.l.], 2017. p. 3–23.

TAILLANDIER, P.; DROGOUL, A. From gis data to gis agents, modeling with the gama simulation platform. In: *Technical Forum Group on Agent and Multi-agent-based Simulation: 1st meeting collocated with Eumas*. [S.l.: s.n.], 2010. v. 10.

TAILLANDIER, P. et al. Building, composing and experimenting complex spatial models with the gama platform. *GeoInformatica*, Springer, v. 23, p. 299–322, 2019.

TAVERNER, J. et al. Modeling personality in the affective agent architecture genia3. In: *ICAART (1)*. [S.l.: s.n.], 2018. p. 236–243.

THURMOND, D. B. The influence of carl jung's archetype of the shadow on early 20th century literature. 2012.

TRAN, T.; COHEN, R. A learning algorithm for buying and selling agents in electronic marketplaces. In: SPRINGER. *Conference of the Canadian Society for Computational Studies of Intelligence*. [S.l.], 2002. p. 31–43.

TRAPPL, R.; PETTA, P. *Creating personalities for synthetic actors: Towards autonomous personality agents*. [S.l.]: Springer Science & Business Media, 1997. v. 1195.

TSAGKIS, P.; PHOTIS, Y. N. Using gama platform and urban atlas data to predict urban growth. the case of athens. In: *13th International Conference of the Hellenic Geographical Society*. [S.l.: s.n.], 2018.

VELASQUEZ, M.; HESTER, P. T. An analysis of multi-criteria decision making methods. *International journal of operations research*, Citeseer, v. 10, n. 2, p. 56–66, 2013.

VOROBYEVA, A. The five-factor model: general overview. n. 4, p. 80–85, 2011.

WESAAC. *Anais do XIV Workshop-Escola de SistemasAgentes, seus Ambientes e apliCações de Agentes, seus Ambientes e apliCações*. Zenodo, 2020. Disponível em: <https://doi.org/10.5281/zenodo.4037413>.

WILCOXON, F. Individual comparisons by ranking methods. In: *Breakthroughs in statistics*. [S.l.]: Springer, 1992. p. 196–202.

WILLIAMS, K. *Developing High Performance Teams CMIOLP*. [S.l.]: Routledge, 2007.

WING, L. S. Leadership in high-performance teams: a model for superior team performance. *Team Performance Management: An International Journal*, Emerald Group Publishing Limited, 2005.

WOOLDRIDGE, M.; JENNINGS, N. R. Intelligent agents: Theory and practice. *The knowledge engineering review*, Cambridge University Press, v. 10, n. 2, p. 115–152, 1995.

XU, H.; SHATZ, S. M. An agent-based petri net model with application to seller/buyer design in electronic commerce. In: IEEE. *Proceedings 5th International Symposium on Autonomous Decentralized Systems*. [S.l.], 2001. p. 11–18.

YANG, Y. Research on the application of mbti in organization. In: ATLANTIS PRESS. *2022 7th International Conference on Social Sciences and Economic Development (ICSSED 2022)*. [S.l.], 2022. p. 1751–1754.

ZANELLI, J. C.; BORGES-ANDRADE, J. E.; BASTOS, A. V. B. *Psicologia, Organizações e Trabalho no Brasil-2*. [S.l.]: AMGH Editora, 2014.

ZAVADSKAS, E. K.; TURSKIS, Z. A new logarithmic normalization method in games theory. *Informatica*, Institute of Mathematics and Informatics, v. 19, n. 2, p. 303–314, 2008.

ZHANG, J.; COHEN, R.; LARSON, K. A trust-based incentive mechanism for e-marketplaces. In: SPRINGER. *International Workshop on Trust in Agent Societies*. [S.l.], 2008. p. 135–161.

ZHAO, H.; SEIBERT, S. E. The big five personality dimensions and entrepreneurial status: a meta-analytical review. *Journal of applied psychology*, American Psychological Association, v. 91, n. 2, p. 259, 2006.

APPENDIX A – *PERSONALIFY* FRAMEWORK - CODE

```

model personalify

species Person skills: [moving]{

  // Weights for each dichotomy considered in the MADM matrix
  float weight_e_i <- 1/3;
  float weight_s_n <- 1/3;
  float weight_t_f <- 1/3;

  // E-I constraints
  int number_of_cycles_to_return_interacted_agent <- 75;
  int max_number_of_visits_to_a_interacted_agent <- 3;

  // T-F constraints
  int min_distance_to_exclude;

  list my_personality;
  list<string> my_original_personality;

  bool is_extroverted;
  bool is_sensing;
  bool is_thinking;
  bool is_judging;

  string E_I;
  string S_N;
  string T_F;
  string J_P;

  map<agent, float> num_interactions_with_the_agent;
  map<point, float> agent_distance_norm_global;
```

```
list<point> interacted_target;
map<point, int> agents_interacted_within_cycle;
map<agent, float> agents_distance_norm_global;

list<agent> colleagues_in_my_view;
bool must_use_probability;

reflex must_change_personality when: every(25#cycle) and must_use_probability {
  do set_my_personality(self.my_original_personality, true);
}

list set_my_personality(list<string> mbti_personality,
            bool use_probability
){

  list<string> mbti_personality_treated <- copy(mbti_personality);
  self.my_original_personality <- mbti_personality_treated;
  must_use_probability <- use_probability;

  // Check if the MBTI should be randomized
  if(mbti_personality contains "R"){
    mbti_personality_treated <- randomize_personality(mbti_personality);
  }

  E_I <- mbti_personality_treated at 0;
  S_N <- mbti_personality_treated at 1;
  T_F <- mbti_personality_treated at 2;
  J_P <- mbti_personality_treated at 3;

  self.my_personality <- [];

  if (use_probability){
    // A Seller agent has 80% of probabability to keep its original MBTI personality
    is_extroverted <- E_I = "E" ? flip(0.8) : flip(0.2);
    is_sensing <- S_N =  "S" ? flip(0.8) : flip(0.2);
    is_thinking <- T_F =  "T" ? flip(0.8) : flip(0.2);
    is_judging <- J_P = "J" ? flip(0.8) : flip(0.2);
  }
  else{
    is_extroverted <- E_I = "E" ? true : false;
```

```
      is_sensing <- S_N =  "S" ? true : false;
      is_thinking <- T_F =  "T" ? true : false;
      is_judging <- J_P = "J" ? true : false;
    }

    add is_extroverted ? "E":"I" to: self.my_personality;
    add is_sensing ? "S":"N" to: self.my_personality;
    add is_thinking ? "T":"F" to: self.my_personality;
    add is_judging ? "J":"P" to: self.my_personality;

    return self.my_personality;
  }

  list<string> randomize_personality (list<string> mbti_personality) {
    if mbti_personality[0] = "R" {
        mbti_personality[0] <- rnd_choice(["E"::0.5, "I"::0.5]);
    }

    if mbti_personality[1] = "R" {
        mbti_personality[1] <- rnd_choice(["S"::0.5, "N"::0.5]);
    }

    if mbti_personality[2] = "R" {
        mbti_personality[2] <- rnd_choice(["T"::0.5, "F"::0.5]);
    }

    if mbti_personality[3] = "R" {
        mbti_personality[3] <- rnd_choice(["J"::0.5, "P"::0.5]);
    }

    return mbti_personality;
  }

  action set_global_parameters(int nb_number_of_cycles_to_return_interacted_agent, // E-I constraints
                  int nb_max_number_of_visits_to_a_interacted_agent, // E-I constraints
                  int nb_min_distance_to_exclude // T-F constraints
                  ){

    number_of_cycles_to_return_interacted_agent <- nb_number_of_cycles_to_return_interacted_agent;
    max_number_of_visits_to_a_interacted_agent <-
```

```
  nb_max_number_of_visits_to_a_interacted_agent;
    min_distance_to_exclude  <- nb_min_distance_to_exclude;
}

  action increment_interactions_with_agent(agent interacted_agent){
    add interacted_agent::num_interactions_with_the_agent[interacted_agent] + 1 to:
    num_interactions_with_the_agent ;
  }

  action add_interacted_target(point target){
    add target to: interacted_target;
  }

  action add_agents_interacted_within_cycle(pair<point, int>
  agents_cycle){
    add agents_cycle to: agents_interacted_within_cycle;
  }

  pair<agent, float> get_max_score(map<agent, float> agent_score){
    return agent_score.pairs with_max_of(each.value);
  }

  action show_my_personality {
    write self.my_personality;
  }

  map<agent, float> get_distances(list<agent> agents_in_my_view){
    return map<agent, float>(agents_in_my_view collect (each::self
  distance_to (each)));
  }

  list remove_interacted_target(list list_of_points, int cycle){
    map<point, int> agents_within_limit ;
    list<point> agents_to_remove;

    // We have a parameter to define the min cycles to consider before a
  Seller can return to an already visited Buyer
    agents_within_limit <- map<point, int>(
  agents_interacted_within_cycle.pairs where ((cycle - each.value) <
  number_of_cycles_to_return_interacted_agent));
    agents_to_remove <- agents_within_limit.keys;

    // We have a parameter to define the max number of visits to consider
```

```
as a limit to a seller be able to visit again the same buyer
  agents_within_limit  <- map<point, int>(num_interactions_with_the_agent.pairs where ((each.value) >=
max_number_of_visits_to_a_interacted_agent ));
  agents_to_remove <- (agents_to_remove union agents_within_limit.keys
);

  remove all:agents_to_remove from: list_of_points;

  return list_of_points;
}

float get_normalized_values(float value, map<agent, float>
 agents_values, string criteria_type){
  if criteria_type="cost"{
    return value>0 ? abs(min(agents_values) / value) : 1.0;
  } else {
    return value>0 ? abs(value / max(agents_values)) : 0.0;
  }
}

map<agent, float> get_agents_in_my_view(list<agent> list_of_agents){
  list_of_agents <- reverse (list_of_agents sort_by (each distance_to
 self));

  // Get the distance of each Buyer to the Seller and calculate the
 inverted norm score
  map<agent, float> agents_distance_to_me  <- get_distances(
 list_of_agents);
  map<agent, float> agents_distance_norm_global <-
 agents_distance_to_me.pairs as_map (each.key::(get_normalized_values(
 each.value, agents_distance_to_me, "cost")));

  return agents_distance_norm_global;
}

action calculate_score(list<agent> agents_in_my_view, int cycle){

  agents_in_my_view <- agents_in_my_view sort_by(each);
  agents_distance_norm_global <- get_agents_in_my_view(
 agents_in_my_view);


```

```
    // Calculate score for E-I
    map<agent, float> agents_e_i_score;
    if (self.E_I contains_any ["E", "I"]) {agents_e_i_score <- get_extroversion_introversion_score(agents_in_my_view);}

    // Calculate score for S-N
    map<agent, float> agents_s_n_score ;
    if (self.S_N contains_any ["S", "N"]) {agents_s_n_score <- get_sensing_intuition_score(agents_in_my_view);}

    // Calculate score for T-F
    // In T-F dichotomy we need to consider both, the target agents and our colleagues
    map<agent, float> agents_t_f_score;
    if (self.T_F contains_any ["T", "F"]) {agents_t_f_score <- get_thinking_feeling_score(agents_in_my_view, colleagues_in_my_view);}

    // Sum all scores
    map<agent, float> agents_score;

    agents_score <- map<agent, float>(agents_in_my_view collect (each::(agents_e_i_score[each]*weight_e_i) +
                                                (agents_s_n_score[each]*weight_s_n) +
                                                (agents_t_f_score[each]*weight_t_f)
    ));

    // We sort map to avoid diferent values between the simulations (when a tie happen on the scores)
    agents_score <- agents_score.pairs collect (each.key::each.value) sort_by(each.key) sort_by(each.value);

    return agents_score;
  }

  map<agent, float> get_extroversion_introversion_score(list<agent> agents_to_calculate){

    map<agent, float> score_e_i;
    map<agent, float> num_interactions_with_the_agent_init <- map<agent, float>(agents_to_calculate collect (each:: 0.0));
```

```
    num_interactions_with_the_agent <- map<agent , float >
  ((num_interactions_with_the_agent_init.keys -
  num_interactions_with_the_agent.keys) collect
  (each::num_interactions_with_the_agent_init[each])
                    + num_interactions_with_the_agent.pairs);

    // When there is a unique agent we can simply consider it as the max
  score
    if(length(agents_to_calculate)=1){
      score_e_i <-  map<agent , float>(agents_to_calculate collect (first
  (each)::1.0));
    }
    else {

      map<agent , float> num_interactions_to_the_agent_norm;

      string criteria_type;

      // According to the seller personality type the normalization
  procedure will change (cost or benefit attribute)
      criteria_type <- self.is_extroverted ? "cost" : "benefit";
      map<agent , float> num_interactions_with_the_agent_norm <-
  num_interactions_with_the_agent.pairs as_map (each.key::float(
  get_normalized_values(each.value , num_interactions_with_the_agent,
  criteria_type)));

      // Calculate SCORE-E-I
      score_e_i <- agents_distance_norm_global.pairs as_map (each.key::
  each.value+(num_interactions_with_the_agent_norm[each.key]));
    }

    return score_e_i;
  }

  map<agent , float> get_sensing_intuition_score (list<agent>
  agents_to_calculate){
    map<agent , float> score_s_n;

    // When there is a unique agent we can simply consider it as the max
  score
    if(length(agents_to_calculate)=1){
      score_s_n <-  map<agent , float>(agents_to_calculate collect (first
```

```
(each)::1.0));
 }
 else {

   // Calculate the density using simple_clustering_by_distance
technique
   list<list<agent>> clusters <- list<list<agent>>(
simple_clustering_by_distance(agents_to_calculate, 10));

   list<map<list<agent>, int>> clusters_density <-list<map<list<agent
>, int>>(clusters collect (each::length(each)));

   // We must navigate in three different levels because of the
structure of the list of maps of lists
   // Given that, we create a map of agents with the density of their own cluster
   map<agent, float> agents_density;
   loop cluster over:clusters_density{
     loop agents_by_density over: cluster.pairs{
       loop agent_unique over: agents_by_density.key {
         add agent_unique::agents_by_density.value to:agents_density;

       }
     }
   }

   float distance_weight;
   float density_weight;
   float agents_closest_to_edge_weight;

   density_weight <- self.is_sensing ? 0.1 : 0.25;
   agents_closest_to_edge_weight <- self.is_sensing ? 0.1 : 0.25;
   distance_weight <- 1 - density_weight -
agents_closest_to_edge_weight;

   // Normalize density as a benefit attribute
   map<agent, float> agents_density_norm;
   agents_density_norm <- agents_density.pairs as_map (each.key::(max
(agents_density)>1) ? get_normalized_values(each.value,
agents_density, "benefit") : 1.0);

   // Calculate closest cluster point to the edge (perception radius)
   list<point> cluster_list;
   agent agent_closest_to_edge;
```

```
    map<agent, float> agents_closest_to_edge;

    loop cluster over: clusters{
      cluster_list <- list<point>((cluster collect each));
      agent_closest_to_edge <- agent_closest_to(geometry(cluster)
 farthest_point_to(point(self)));
      add agent_closest_to_edge ::(agent_closest_to_edge  distance_to
 self) to:agents_closest_to_edge;
    }

    // Normalize buyers_closest_to_edge as a benefit attribute
    map<agent, float> agents_closest_to_edge_norm;
    agents_closest_to_edge_norm <- agents_closest_to_edge.pairs as_map
   (each.key::get_normalized_values(each.value, agents_closest_to_edge,
   "benefit"));

    // Calculate SCORE-S-N
    score_s_n <- agents_distance_norm_global.pairs as_map (each.key
 ::((each.value*distance_weight)
                                    +(agents_density_norm[each.key]*
 density_weight)
                                    +(agents_closest_to_edge_norm[
 each.key]*agents_closest_to_edge_weight)
    ));

   }

   return score_s_n;
 }

map<agent, float> get_thinking_feeling_score(list<agent>
 agents_to_calculate, list<agent> my_colleagues){
   map<agent, float> score_t_f;

   float inc_num_agents_close_to_target_agent <- 0.0;
   map<agent, float> num_agents_close_to_target_agent;

   // We sort the list to avoid different values between the simulations
   (when a tie happens on the scores)
   my_colleagues  <- my_colleagues sort_by(each);

   loop target_agent over: agents_to_calculate{ // targets
     loop agent_perceived over: my_colleagues{ // colleagues
```

```
        if(point(agent_perceived) distance_to point(target_agent) < min_distance_to_exclude){
          inc_num_agents_close_to_target_agent  <- inc_num_agents_close_to_target_agent + 1.0;
        }
      }
      add target_agent::inc_num_agents_close_to_target_agent to: num_agents_close_to_target_agent;
      inc_num_agents_close_to_target_agent <- 0.0;
    }

    // We give more weight for feeling agents
    float agents_close_to_target_agent_weight;
    float distance_weight;

    agents_close_to_target_agent_weight <- !self.is_thinking ? 0.8 : 0.2;
    distance_weight <- 1 - agents_close_to_target_agent_weight ;

    // Normalize num_agents_close_to_main_agent as a cost attribute and apply the weight
    map<agent, float> num_agents_close_to_target_agent_norm;
    num_agents_close_to_target_agent_norm <- num_agents_close_to_target_agent.pairs as_map (each.key::(get_normalized_values(each.value, num_agents_close_to_target_agent, "cost")));

    // Calculate SCORE-T-F
    score_t_f <- agents_distance_norm_global.pairs as_map (each.key::((each.value*distance_weight)+(num_agents_close_to_target_agent_norm[each.key]*agents_close_to_target_agent_weight)));

    return score_t_f;
  }

  point get_judging_perceiving(list<agent> agents_to_calculate, point current_target, int cycle){
    bool must_recalculate_plan;
    point new_target;

    // If is a perceiving agent it has 80% probabability to recalculate the plan
    must_recalculate_plan <- !self.is_judging ? flip(0.8) : flip(0.2);
```

```

    if(must_recalculate_plan and self.J_P contains_any ["J", "P"]){

      map<agent, float> new_agents_score;
      new_agents_score <- calculate_score(agents_to_calculate, cycle);

      if (!empty(new_agents_score )) {
        map<agent, float> max_agent_score <- get_max_score(
   new_agents_score);
        new_target <- point(max_agent_score.keys[0]);
      }
      return new_target;
    }

    return current_target;
  }

}
```

APPENDIX B – SELLER-BUYER SCENARIO - CODE

```
model buyer_seller
import "personalify.gaml"

global {

  // Vars received from parameters
  int nb_sellers;
  int nb_buyers;
  int nb_items_to_buy;
  int nb_items_to_sell;
  list<string> teams_mbti;
  string teams_mbti_string;
  int total_demand;
  string market_type;
  int nb_number_of_cycles_to_return_interacted_agent;
  int nb_max_number_of_visits_to_a_interacted_agent;
  float nb_min_distance_to_exclude;

  // Global environment vars
  int cycle <- 0;
  int view_distance;
  int max_cycles;
  string scenario;

  // Staging vars
  int total_sellers_demand;
  int total_buyers_demand;
  int performance;

  init {

```

```
  // Set teams MBTI profile
  teams_mbti <- list(teams_mbti_string split_with ",");

  // Calculate Market Demand
  do calculate_market_demand(market_type, total_demand);

}

action calculate_market_demand(string market_type, int total_demand){
  if (market_type="Balanced"){
    total_sellers_demand <- (total_demand/2);
    total_buyers_demand <- (total_demand/2);
  } else if (market_type="Supply>Demand"){
    total_sellers_demand <- ((2/3) * total_demand);
    total_buyers_demand <- (total_demand-total_sellers_demand);
  } else if (market_type="Demand>Supply"){
    total_buyers_demand <- ((2/3) * total_demand);
    total_sellers_demand  <- (total_demand-total_buyers_demand);
  }

  // Calculate the items to sell and buy according to the market
  nb_items_to_sell <- round(total_sellers_demand/nb_sellers);
  nb_items_to_buy <- round(total_buyers_demand/nb_buyers);
}

reflex stop when:cycle=max_cycles{
  list sellers_demand <- list(Seller collect  (each.current_demand));

  performance <- total_sellers_demand - sum(sellers_demand);
  write "PERFORMANCE: " + performance
      + " SCENARIO: " + scenario
      + " MARKET-TYPE:" + market_type
      + " TEAMS-MBTI: " + teams_mbti
      + " TOTAL-DEMAND: " + total_demand
      + " CYCLES-TO-RETURN: " +
 nb_number_of_cycles_to_return_interacted_agent
      + " MAX-VISITS-TO-AGENT: " +
 nb_max_number_of_visits_to_a_interacted_agent
      + " MIN-DISTANCE-TO-EXCLUDE: " + nb_min_distance_to_exclude
      + " SEED: " + seed;

  do pause;
}
```

```
}

species Seller parent: Person control: simple_bdi{

  // Define agent behavior
  predicate wander <- new_predicate("wander");
  predicate define_item_target <- new_predicate("define_item_target");
  predicate define_buyer_target <- new_predicate("define_buyer_target");
  predicate sell_item <- new_predicate("sell_item");
  predicate say_something <- new_predicate("say_something");
  predicate met_buyer <- new_predicate("met_buyer");

  // How many items the Seller can sell
  int current_demand <- copy(nb_items_to_sell);

  list<point> possible_buyers;
  point target;
  bool got_buyer <- false;

  bool default_aspect_type <- true;

  int view_distance;

  init{
    // Begin to wander
    do add_desire(wander);
  }

  //if the agent perceive a buyer in its neighborhood, it adds a belief
    concerning its location and remove its wandering intention
  perceive target:Buyer in: view_distance {
    // Seller only focus on Buyer if it has demand
    if(self.current_demand > 0){
      focus id:"location_buyer" var:location;
      ask myself {do remove_intention(wander, false); }
    }
  }

  perceive target:Seller in: view_distance{
    // We must validate that only our teammates would be considered (
    also remove the seller itself)
    if(myself.name != self.name){
      focus id:"location_seller" var:location;
```

```
    list<point> colleagues_in_my_view_points <- get_beliefs(new_predicate("location_seller")) collect (point(get_predicate(mental_state (each)).values["location_value"]));

    // We must populate the MBTI global var colleagues_in_my_view with the perceived Sellers
    colleagues_in_my_view <- get_sellers_from_points(colleagues_in_my_view_points); // <<< MBTI >>>>
    do remove_belief(new_predicate("location_seller"));
  }
}

//if the agent has the belief that there is a possible buyer given location, it adds the desire to interact with the buyer to try to sell items.
rule belief: new_predicate("location_buyer") new_desire: sell_item strength:10.0;

// plan that has for goal to fulfill the wander desire
plan letsWander intention:wander
{
  do wander amplitude: 60.0;
}

list get_buyers_from_points(list list_of_points){
  list<Buyer> list_of_buyers;
  loop buyer over: list_of_points{
    add Buyer(buyer) to: list_of_buyers;
  }

  return list_of_buyers;
}

list get_sellers_from_points(list list_of_points){
  list<Seller> list_of_sellers;
  loop seller over: list_of_points{
    add Seller(seller) to: list_of_sellers;
  }
  return list_of_sellers;
}

// plan that has for goal to fulfill the "sell_item" desire
plan sellItem intention:sell_item{
```

```
 // if the agent does not have chosen a target location, it adds the sub-intention to define a target and puts its current intention on hold
 // the agent will do the same if it has the perceiving personality, because it has to reconsider it current decision each cycle
 if (target = nil) {
   do add_subintention(get_current_intention(), define_buyer_target, true);
   do current_intention_on_hold();
 } else {

   if (Buyer(target).current_demand = 0){
     do remove_belief(new_predicate("location_buyer", ["location_value"::target]));

     target <- nil;
     do remove_intention(sell_item, true);
   } else {

   do goto target: target;

   // The J-P dichotomy is an indepent function and must be checked here
   // to calculate if the Seller needs to change the plan
   point new_target;
   list<Buyer> buyers_in_my_view <- get_buyers_from_points(possible_buyers);
   new_target <- super.get_judging_perceiving(buyers_in_my_view, target, cycle);

   if (target != new_target ) {
     // write "HAS CHANGED THE TARGET";
     // If the target has changed seller must move to this new direction
     target <- new_target;
     do goto target: target;
   }

   //if the agent reach its location, it updates it takes the item, updates its belief base, and remove its intention to get item
   if (target = location)  {
     got_buyer <- true;

     Buyer current_buyer <- Buyer first_with (target = each.location)
```

```
;
      if current_buyer != nil and current_buyer.current_demand > 0{

        // Update demand of the current buyer
        ask current_buyer {
          visited <- true;
          current_demand <- current_demand-1;
        }

        // Update demand of the current seller
        current_demand <- current_demand-1;

        // If there is no sellers' demand we kill the seller
        if current_demand = 0 {
          do die;
        }

        do add_belief(met_buyer);

        //                    «<< BEGIN-MBTI >»
        // We increment the number of interactions with the current_buyer
 to consider in E-I dichotomy
        invoke increment_interactions_with_agent(current_buyer);

        // We add the target (point) in the list of interacted targets

        invoke add_interacted_target(target);

        // We need to control the cycle a Seller visited a Buyer to be
able to remove it after the limit
        pair<point, int> agents_cycle <- point(current_buyer)::cycle;
        invoke add_agents_interacted_within_cycle(agents_cycle);

      }

      do remove_belief(new_predicate("location_buyer", ["
location_value"::target]));

      target <- nil;
      do remove_intention(sell_item, true);
      }
    }
 }
```

```
}

//plan that has for goal to fulfill the define item target desire. This plan is instantaneous (does not take a complete simulation step to apply).
plan choose_buyer_target intention: define_buyer_target instantaneous: true{

  possible_buyers <- get_beliefs(new_predicate("location_buyer")) collect (point(get_predicate(mental_state (each)).values["location_value"]));

  // Remove interacted targets according to the model constraints
  list<point> agents_to_calculate <- super.remove_interacted_target(possible_buyers, cycle); //  <<<<< MBTI >>>>
  list<Buyer> buyers_in_my_view <- get_buyers_from_points(agents_to_calculate);

  // Calculate the scores based on MBTI personality
  map<Buyer, float> buyers_score;
  buyers_score <- super.calculate_score(buyers_in_my_view, cycle); // <<<<< MBTI >>>>

  // It is important to check if there is any buyer to consider because T-F can remove all the possible agents
  if (empty(buyers_score)) {
    do remove_intention(sell_item, true);
    do remove_intention(define_buyer_target, true);
    do add_desire(wander);
  } else {

    // We get the max score according to the MADM method
    map<Buyer, float> max_buyer_score <- super.get_max_score(buyers_score);     //  <<<<< MBTI >>>>

    // Now find the target buyer from its location
    target <- point(max_buyer_score.keys[0]);

  }
  do remove_intention(define_buyer_target, true);
}

aspect default {
```

```
      if(default_aspect_type){draw circle(2) color: #purple;}
        else {draw square(2) color: #purple;}
     // enable view distance
       draw circle(view_distance) color:rgb(#yellow,0.5) border: #red;

       draw (string(self.my_personality)) color:#black size:4 at:{location.x-3,location.y+3};
  }
}

species Buyer{
  rgb color <- #blue;
  bool visited <- false;
  int current_demand;

  init{
    current_demand <- copy(nb_items_to_buy);
  }

  aspect default {
    draw triangle(3) color: current_demand=0? #red : color at:{location.x,location.y};
  }
}

grid grille_low width: 125 height: 125 {
  rgb color <- #white;
}
```