Simulating Work Teams using MBTI agents

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Abstract. The study of human behavior in organizational environments has been the focus of researchers who seek to identify factors that may influence high-performance team building. In this context, agent-based simulations have been used to model artificial agents with human personality profiles based on the MBTI model. This work aimed to investigate whether MBTI personality types and different scenarios could influence the teams' outcomes, observing how agents' behaviors might impact the overall group performance. The results demonstrated that the scenario can decisively impact agent teams' performance, and certain personality type characteristics also influence these results.

Keywords: Multi-agent systems · MBTI · BDI · Human Behavior.

1 Introduction

The use of multi-agent systems to simulate human behavior has allowed a significant evolution in the study of human relationships in work environments [3] [4] [5]. The BDI architecture, which allows representing the decision-making process in agents, has enabled significant advances in understanding the influence of specific human characteristics on decisions taken in contexts such as work. In this sense, the MBTI [17] created from Carl Jungs' theory of personality types has stood out as an important instrument for a better understanding of peoples' characteristics and preferences in different situations.

In this work, we seek to explore the development of artificial agents that represent the various personality types described by MBTI theory, using studies [3] [4] [5] [21] [22] [23] considering different scenarios that demonstrate the creation of multi-agent systems based on Myers and Briggs' model. The purpose is to observe how different personalities could influence the performance of agent teams that have common goals and are formed with different personality compositions, thus advancing in the better understanding of characteristics that could decisively impact on teams performance. The paper is organized as follows: in section 2, we describe the MBTI and its relationship with the high-performance team building. Section 3 discusses the use of multi-agent systems to simulate the groups of agents with personalities presenting a model proposal considering

closer situations to what we see in similar situations experienced in organizational context. In this section, we also present the formulation of the hypotheses that will be tested. Section 4 describes the research methodology and results of the experiments carried out. Section 5 is dedicated to discussing the results obtained, addressing future works, and commenting on the limitations of the current study.

2 MBTI and High Performance Teams

The Myers Briggs Type Indicator (MBTI) is a personality inventory that allows identifying a set of characteristics a person uses in spontaneous and comfortable way to act in their daily life [17]. It is a widely used as a self-knowledge resource because it allows recognition of talents and skills. These skills, in turn, could be strengthened or modified aiming at personal improvement [16]. Based on Jungs' theory, Myers and Briggs classified the typical attitudes of an individual, randomly distributed in the general population [13] in four dimensions, represented by dichotomies, which can often be observed in people, regardless of cultural or social factors.

We will use the same type of description adopted in previous studies [3] [4] [5], considering that the prevalence of one dichotomy pole in each of the four dimensions indicates the person's preferred mode of living. In this sense, the sixteen personality types defined by the MBTI are based on the following factors:

Extraversion (E) - Introversion (I) In this first dichotomy, it is seen that Extraverted individuals tend to act faster based on the external world using more evident and superficial information. They feel comfortable and confident even in unfamiliar environments. Introverts are the opposite. They use their ideas, personal values, and thoughts to define how to act, demonstrating a slower and more cautious reaction due to their reflective attitude. They prefer quieter environments and forms of communication that allow less direct contact with others.

Sensing (S) - Intuition (N) This dichotomy involves the perception and processing of information. The Sensing (S) type tends to be more focused on measurable and tangible data, which often allows them to make practical and pragmatic perceptions. While the Intuition (N) type relies on understanding the big picture seeking new possibilities with the information they have.

Thinking (T) – Feeling (F) This dichotomy leads with the decision-making process. Thinking (T) type individuals tend to make more impersonal decisions, based on socially valued principles and rules. In contrast, we can notice in Feeling (F) type individuals that decisions are based on empathy and conflict avoidance in interpersonal relationships.

Judgment (J) – Perceiving (P) Finally, the last dichotomy involves the way a person deals with everyday situations, including unforeseen events and

routine changes. Judging (J) type people feel more comfortable acting from previously defined goals and planned actions in a methodical and organized way. While those with Perceiving (P) type are more flexible and agile in dealing with unforeseen circumstances. In these moments, instead of focusing on difficulties, they seek positive points and opportunities that can replace the original plan. Due to this more open attitude, they tend to have difficulties planning actions in a more organized way.

Each psychological type can be recognized as a personal way of acting in each of the instances defined here and can be identified early on life. The more frequently used skills tend to become dominant – however the arrangement is not permanent and can be intentionally modified based on environmental demands perceived by the individual. The changing indicates a person's better adaptation [13] to the environment, and it could be understood as a performance improvement based on the development of skills and talents [18].

Considering the urgent need to compose and strengthen high-performance teams, the use of MBTI in the organizational context allows professionals to identify and understand the influence that certain characteristics of their personality can have on their work. It is also useful to identify learning needs and choose strategies that can be more effective to improve skills, knowledge, and attitudes [31] that facilitate their performance in an unstable, complex, competitive, and constantly changing environment [24].

Hence the importance of using the MBTI to build and develop teamwork skills with self-knowledge goals. This tool allows a better understanding of the influence that certain personality qualities can have on the way each person performs their duties and interacts with teammates [24]. Although important, a persons' personality type is not a crucial factor in their professional success. Studies indicates that market conditions, available technology and organizational climate are factors that can overcome individual characteristics [11], making it difficult to adapt working conditions to the employees' psychological type [31].

3 Using an Agent-Based Approach to Simulate Work Teams

Multi-agent systems (MASs) have been widely used to study individual human behavior through computer simulations [27]. Autonomous agents, having their own independent existence, are conceived to represent entities capable of carrying out a particular process and interacting with other agents. The objective of multi-agent systems is to conceive the means to ensure that these agents want to cooperate and effectively do so in order to solve specific problems as soon as they are presented to the system [1].

The representation of rational behavior, in which the production of actions that further the goals of an agent, based upon their conception of the world, has been receiving attention from researchers, who seek means to describe, through the use of Artificial Intelligence techniques, the rational human behavior [2]. In

this sense, the BDI (Belief-Desire-Intention) architecture has played an essential role in developing intelligent artificial agents to represent complex reasoning [19] [28] possessing capabilities to take decisions in complex dynamic environments [20].

3.1 BDI Model Proposal

Some studies were carried out using the BDI architecture as a basis for modeling multi-agent systems [3] [4] [5] [21] [22] [23]. In these, the authors modeled agents with behaviors derived from concepts seen in the MBTI theory, in which they sought to extend the BDI architecture by representing in the agents the different types of personalities described in the MBTI.

In a first approach the authors [21] [22] [23] model agents containing functions that define how the BDI process can influence their behavior and decisions. In this model, the agent first senses the environment through a perception function receiving input values (e.g., distance to other agents). After that, the agent interprets these data in the context of their personality type preferences, thus formulating their beliefs. The agent then evaluates its beliefs defining its desires, taking into account its internal state, short- and long-term goals, and personality type. Finally, with its defined desires and attainable goals, the agent evaluates the best decision to make by converting its desires into intentions [4] [21].

In a second perspective [3] [4] [5] that we will also use in this work, it sought to adapt and extend the framework proposed by Salvit and Sklar to cover a broader scope considering a scenario closer to organizational realities. In addition, adaptations were proposed in the decision-making process of agents considering the use of multi-attribute decision making (MADM) [25] so that agents can evaluate different alternatives and rank them according to prioritization criteria adjusted following the MBTI theory [3].

In this proposal, multiple attributes are used to define the behavioral preferences of the agents based on the dichotomies described in the MBTI theory. For each attribute, it was sought to consider factors more consistent with a scenario of Sellers and Buyers distributed in the scenario (explained in more detail in the subsequent section). In this situation, each distinct agent will process the data perceived in the environment, and the information processing, conditioned to personality type, will influence its behavior.

3.2 The Seller-Buyer Model

Several researchers have already used the approach with entities defined as Sellers, and Buyers [7] [29] [32] to observe situations closer to the daily life seen in many organizations. In this model, two types of agents are defined, Buyers and Sellers, having distinct particularities and generally interacting over a predefined time interval. The possibilities of actions derived from these interactions are many, but in this work, we will use the same approach already demonstrated in [3].

Buyers Buyers represent companies, and they are distributed in fixed locations (they do not move). Their role is to wait for a Sellers' visit so they can perform a purchase transaction. They can only make purchases when their demand is greater than zero, and with each transaction, their purchase demand is reduced.

Sellers Sellers have personalities conceived through the MBTI theory, and these decisively influence how they behave and decide. Initially, they wander the environment looking incessantly to visit Buyers and consequently make a sale. A priori, every visit from a Seller to a Buyer generates a sale transaction and subsequent purchase by the Buyer. Sellers also have a demand to sell, and as new transactions are made, their demand is also reduced. When it reaches the stipulated initial demand, the Seller is automatically removed from the environment.

3.3 Agent Decision Attributes

Following the architecture of the BDI and its subsequent extension to include the personalities types [21] adaptations have been made to the model [3] so that the Sellers agents could better assess their perceived inputs from the environment. In this way, five main attributes are used in the Sellers decision-making process:

Distance to the Buyer (A1) This attribute represents the Euclidean distance between a Seller and a Buyer and is considered as a cost attribute in MADM. As Sellers have a limited view of their environment, they cannot perceive all existing Buyers. This threshold also influences all other attributes.

Exploration or Exploitation (A2) The A2 attribute mainly impact the E-I dichotomy and was adapted from what was originally used in a previous study [3]. To better represent the influence of the Extraversion-Introversion dichotomy, we will represent here two types of attitudes: Exploration and Exploitation. Extraverted Sellers are more prone to Exploration. They tend to seek to meet Buyers they have never visited before. On the other hand, Introverts Sellers will seek the opposite, that is, to interact with Buyers they already know. This adaptation seems to be more coherent with the notions of inner and outer world described in MBTI [16] [17] [18]. To measure the attribute, we will use the number of visits made by the Seller to the respective Buyers; For extraverted agents it will be counted as a benefit attribute in MADM. At the same time, it will be a cost attribute for introverts.

Cluster Density and Proximity to the Perception Edge (A3) For this attribute, adaptations were also made to include characteristics closer to the S-N dichotomy. With this attribute, Sellers can perceive the density of the Buyers cluster, thus making it possible to abstract future gains. In this attribute, the proximity of Buyers to the edge of the Sellers' perception radius will also be considered, so more imaginative Sellers can think that other Buyers may be close to the limit of their perception radius, envisioning future gains. We calculate both as benefit attributes in MADM, however, Intuition Sellers will prioritize cluster density and proximity to the edge of perception, while Sensing Sellers will prioritize the distance to the Buyer.

Sellers Close to the Target-Buyer (A4) The T-F dichotomy has the main influence on this attribute, considered as a cost attribute in MADM. In this

attribute, Sellers will consider whether there are other co-workers close to the same objective (Buyer) who they have. Feeling Sellers prioritize what other Sellers can aim for, seeking out Buyers who are not close to their colleagues. Thinking Sellers tend to be rational and more concerned with the goals defined by the organization.

Probability to Recalculate the Plan (A5) This attribute is influenced by the J-P dichotomy and is directly implemented in agents as a probability of reconsidering their decisions. The attribute deals with how committed the Seller is to maintaining its original plan. Perceiving Sellers will constantly reconsider their decisions based on changing environment conditions. However, Judging Sellers will tend to keep to their original plan even if other alternatives appear along the way to the chosen Buyer.

3.4 Market Types

To evaluate the agents' performance, different scenarios were defined inspired by the Law of Supply and Demand [12]. For reasons of simplicity, we will not use the price variable; that is, in the experiments that will be demonstrated, all agents do not suffer the impact that an eventual price variation could cause in the market. Thus, we will analyze how the influence of demand variation may or may not impact the performance of Sellers agents, decreasing or not their delivery capacity. For this, three different market types were defined:

Balanced Market In this scenario, both agents, Sellers, and Buyers, have similar buying and selling demands, that is, the market has a general balance of demand.

Supply Market In this market, Sellers have a higher sales demand than the Buyers' purchase demand. This is a more challenging scenario for Sellers as there is a restriction on Buyers' purchasing potential.

Demand Market Finally, there may be a market in which the purchase demand is greater than the Sellers are able or need to meet, thus existing an imbalance in which the Buyers will not have their demand fully met.

3.5 Work Teams

Another essential aspect implemented in the current model is the notion of work teams. Previous studies noticed a focus on agents individually, analyzing the relationship between their performance and personality type. With the concept of work teams, we will seek to analyze how the composition of different agent teams with different personality type profiles can influence the groups' overall performance. Work teams are defined as interdependent collections of individuals who share responsibility for specific outcomes for their organizations [26]. Individuals in a team usually have one or more common goals and jointly seek to achieve these goals by performing tasks relevant to an organizational context [14] [15]. So, in this work, we will analyze the influence of the behavioral preference in teams of Sellers agents, observing the impact of the different personality type profiles on the performance of the teams.

3.6 Hypotheses

Given the challenges already discussed about forming high-performance teams, a first research question emerges: Can Seller agent teams modeled with different personality types present different performance levels? To advance this study, we will seek to analyze how teams of agents formed with opposite behaviors perform. For simplicity, we will focus on the Extraversion-Introversion dichotomy in which future studies may expand the scope to other dichotomies. This leads us to formulate the first hypothesis of the study.

Hypothesis 1 (H1): *There is a performance difference between Teams composed of extraverted and introverted agents.*

With this hypothesis, we seek to analyze whether the two opposing behavioral preferences, extraversion and introversion, can lead Sellers' teams to have different performances given the common attitude of the group of agents. To be able to analyze if other factors associated with the environment could influence the performance of agent teams, we also formulated a second hypothesis:

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

In this case, we seek to analyze whether agent teams with different personality type profiles can be impacted, for example, by types of market in which there are demand restrictions, both for sale and purchase.

4 Methods and Results

The experiments were performed using a model developed and implemented in the Gama platform, making use of the architecture *simple_bdi* [28]. The platform allows a high-level language to build agent-based models, making it possible to observe behaviors and interactions between agents with different levels of abstraction [8]. Perception functions were also used to enable Sellers to perceive Buyers and also other Sellers around them. We defined a perception radius that limits the number of agents that they can perceive; thus, Sellers have a restricted view of what they can see around them. However, as they walk through the environment, they can visualize agents that they did not know before, thus expanding their knowledge of the environment.

Both Sellers and Buyers have initial locations defined through random seed, so we can use the same initial conditions for each simulation performed, changing only the different personalities type of the work teams we want to evaluate. We also used pre-defined cycles for each simulation, causing agents to have a time limit to complete their tasks. At the end of the simulations, we evaluate the Sellers' teams' performance, measuring the number of products sold to the respective Buyers.

4.1 Environment Setup

We used a Grid size of 125x125 with a maximum of 250 cycles for each simulation to carry out the experiments. We also set the rates for the number of Buyers and

Sellers respectively as 2.0% and 0.5%, thus totaling 313 Buyers and 78 Sellers. This choice was made to maintain an approximately four times higher ratio of Buyers to Sellers, representing a scenario with a low density of Buyers.

The total number of products to be sold by the Sellers and purchased by the Buyers was fixed and defined as 4.688 products. As Sellers can choose to revisit a Buyer, we define as three the maximum number of visits that a Seller can make to the same Buyer. We also added a parameter that defines the number of cycles a Seller needs to wait until they can revisit a Buyer, set this to 75 (30% of the total number of cycles). These initial parameters were empirically defined through observations carried out in several simulations. With the observations made it was possible to analyze, for example, how long it would take for 80% of Buyers to have at least one visit at the end of each simulation.

In further works, it is intended to explore other scenario configurations and variations of the initial parameters (such as the number of agents, grid size, agents' perception radius, initial agent's demand, among others), thus providing more robust analyzes considering other situations not addressed in the current work.

To handle the distribution of the products in the different market types, we defined a product division strategy following each market type. For the Balanced Market, the 4.688 products were divided into 2.344 products to be sold and other 2.344 to be purchased. In each group of Buyers and Sellers these values were equally divided amoung the agents. In the Supply Market, we divided 2/3 of the products to the Sellers and 1/3 to the Buyers, corresponding respectively to 3.120 sale products, and the Buyers with a demand of 1.565 products. The same numbers were applied in the Demand Market, switching these values: 2/3 of the products to the Buyers and 1/3 to the Sellers.

4.2 Experiments

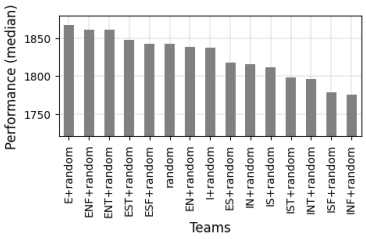
To evolve with the formulated hypotheses, we used different compositions of work team profiles, combining certain behavioral preferences with other random combinations, thus allowing us to analyze the influence of each agent teams' personality type. Table 1 shows these different team profiles. In addition to these fourteen teams, we will also consider a completely random profile (PROF15) aiming to also have heterogeneous team compositions.

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

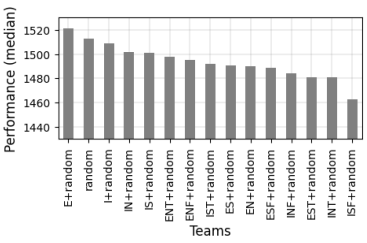
Table 1: Team profiles

For each scenario, we ran 15 simulations, each of them composed of a given team profile. In these experiments, we used a same random seed for all team

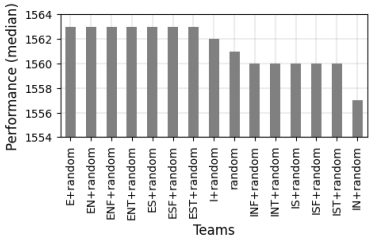
profiles, thus ensuring the same initial conditions for all simulations. Moreover, to mitigate the fact that a given random seed could benefit a specific profile, we performed these 15 simulations with 5 different random seed values, resulting in a total number of 75 simulations for each scenario. Thus, we obtained a sample larger than 30 observations to ensure greater significance in the statistical test. The obtained results for the Balanced, Supply and Demand Markets are shown respectively in Figures in Figure 1 (a), Figure 1 (b) and Figure 1 (c).



(a) Balanced Market



(b) Supply Market



(c) Demand Market

Fig. 1: Team profile performance in different scenarios

4.3 Obtained Results

In order to analyze the performance results of the experiments carried out, we applied the Wilcoxon [30] test to compare team profiles with an extraverted or introverted tendency and thus be able to answer the first hypothesis *(H1)* for each market. For this end, we have added the results obtained by PROF1-PROF7, typically extroverted, with the ones obtained by PROF8-PROF14, that correspond to the introverted type. The complety random profile PROF15 was not considered in this test.

For the Balanced Market, we obtained $p\text{-}value = 0.000023$, indicating that we can reject the *Null Hypothesis (H0)* and thus conclude that there is a difference between the extraverted and introverted profiles. For the Supply Market, we obtained $p\text{-}value = 0.229537$, indicating that in this case, we cannot reject *H0*, and thus we conclude that there are no differences between the profiles. For the Demand Market, the $p\text{-}value = 0.000272$ allows us to conclude that there are also differences between the profiles. Despite of these results, as we will see in Section 5, the difference does not seem significant when analyzing the percentage of demand reached by each agent team.

We also analyze the second hypothesis *(H2)* using the Wilcoxon test, comparing the performance of each of the fifteen team profiles in the three different scenarios, on a two by two basis. That is, we compare the same profiles in the scenarios: Balanced Market with Supply Market, Balanced Market with Demand Market and Supply Market with Demand Market. For all comparisons, we obtained *p-value* = 0.000002, indicating that we can reject the *Null Hypothesis (H0)*, i.e., there is indeed a performance difference when we analyze the same profile in different scenarios.

5 Discussion

Based on simulations carried out, the highest performances in the Balanced Market were obtained by Extravert agent teams, indicating that their Exploratory attitude with a predisposition to expand their sales area allowed them to obtain better results than Introverts agent teams. Because they are more shy, introverted Seller agents tend to relate to familiar Buyers, which makes it difficult to expand their sales area and consequently their performance. The second and third positions obtained by agent teams ENF and ENT also indicate that the intuitive characteristic with the tendency to abstract long-term gains, combined with the exploration profile, brought the teams a competitive advantage. We also see that Introverted Sellers had a lower performance in a Balanced Market scenario. This was probably due to their tendency to seek interactions with the same Buyers they already know. As they are more shy, they tend to keep their usual Buyers avoiding new unexplored regions.

In a more challenging market where Supply is higher than Demand, there is no difference between the Extraverted and Introverted agent teams. This result can be explained because, in a scarcer market, where Buyers quickly do not have more additional demand, Introverted Sellers should have an exploratory attitude in order to adapt to the given conditions, seeking new opportunities and consequently have greater performances. As seen earlier, this change can suggest a better adaptation of the agent teams to the environment, and although not the purpose of this study, it is in line with the understanding of the MBTI theory on the development of skills and talents [18].

When the scenario is changed to a market where Demand is higher than Supply, the results indicated that there are differences between the performances of Extraverted and Introverted Seller agents teams. Despite this, it is important to note that all teams achieved over 99% of their initial demands; we can consider that all teams had excellence in their performance and the personality type was not a relevant factor in this type of market. It was also clear from the experiments that the type of market can decisively influence the performance of the Sellers agents, limiting their ability to act and influencing their results.

It is essential to explain that the purpose of this model is not to assess whether certain types of personalities are better or worse for performing the tasks [3], which would even represent a misuse of the MBTI [6]. The analyses and interpretations carried out from this study should be restricted to the scope of the model shown, which is not a tool for selecting or stereotyping individuals.

The study is also limited to the analysis of artificial agent teams, and these do not represent reality; that is, although the study can support a greater understanding of characteristics associated with the personality types described in the MBTI, these should not be directly associated with people's life. The interpretations must be restricted to the scope of experiments based on agents considered in this work.

In further work, new metrics that allow the analysis of exploration and exploitation attitudes may also contribute to a greater guarantee of assertiveness in the conclusions about the results. Price variations in the markets and negotiation mechanisms between Sellers and Buyers agents could also be implemented, thus making it possible to observe more complex situations and close to those observed in organizational environments. Other approaches explored by studies such as [9] [10] can also be integrated to complement aspects related to the team composition as well as helping to a better understanding of factors that might be related to agents' performance.

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