# Ants in the OCEAN: Modulating Agents with Personality for Planning with Humans

Sebastian Ahrndt, Armin Aria, Johannes Fähndrich, and Sahin Albayrak

DAI-Laboratory of the Technische Universität Berlin
Faculty of Electrical Engineering and Computer Science
Ernst-Reuter-Platz 7, 10587 Berlin, Germany
sebastian.ahrndt@dai-labor.de (Corresponding author)

**Abstract.** This work introduces a prototype that demonstrates the idea of using a psychological theory of personality types known as the Five-Factor Model (FFM) in planning for human-agent teamwork scenarios. FFM is integrated into the BDI model of agency leading to variations in the interpretation of inputs, the decision-making process and the generation of outputs. This is demonstrated in a multi-agent simulation. Furthermore, it is outlined how these variations can be used for the planning process in collaborative settings.

**Keywords:** User/Machine Systems, Human factors, Software psychology

## 1 Introduction

Human-Aware Planning (HAP) is mainly required when the situation involves artificial and natural agents in the same environment, the actions of the artificial agents being planned and those of the natural agents being predicted [10, p. 15:2]. We find such situations in collaborative application areas like Smart Homes inhabited by agents, robots and humans, e.g., when addressing the ageing of the population with socially assistive robotics [34]. Although making artificial agents a constituent part of human activities leads to more affiliated teamwork scenarios on the one hand, it also introduces several new challenges on the other (cf. [3, 6, 17, 18]). One of those challenges is the *predictability* of an agent's actions during the planning process. Predictability addresses the condition that an agent can only plan its own actions—which includes coordination activities—effectively if it is assessable what the others collaborators will do [6]. To address this challenge in human-agent teamwork the use of human-behavioural models provided by psychology studies was proposed as being beneficial, e.g., when determining the most likely next action of a person [1, 17].
Taking that into consideration, this work introduces a prototype that integrates a psychological theory of personality types into a popular computational model for the conceptualisation of human behaviour (see Section 5). The work is intended to show that the integration of personality leads to variations in the interpretation of inputs, the decision-making process and the generation of outputs (see

Section 6). In fact, it is essential to prove this assumption prior to applying it to the more complex problem of planning with humans. Afterwards, it is outlined how this model can be used to enhance HAP by using the information about the personality as a kind of heuristic during the actual planning process (see Section 7). However, before describing the applied mechanism and the future work we will first introduce the psychological theory of personality types used within the work, which is known as the Five-Factor Model [22] (FFM) (see Section 2). Subsequently, we will provide a literature overview exploring the use of personality theories in agent-based systems (see Section 3). After introducing the state-of-the-art we compare the two most-popular personality theories and explain the reason for applying the FFM, finally justifying the motivation for presenting this work (see Section 4).

## 2 Five-Factor Model

The Five-Factor Model of personality [21, 22] is a psychological theory that can be used to model human personality types and their influences on the decision-making process of humans. As suggested by the name, the FFM introduces five dimensions characterising an individual, which are briefly described in the following:

- ***O****penness to experience* describes a person's preference to vary their activities over keeping a strict routine and is also related to their creativity (e.g., inventive, emotional and curious behaviour vs. consistent, conservative and cautious behaviour).
- ***C****onscientiousness* describes a person's preference to act duteously over spontaneously. This directly relates to the level of self-discipline when aiming for achievements (e.g., efficient, planned and organised behaviour vs. easy-going, spontaneous and careless behaviour).
- ***E****xtraversion* describes a person's preference to interact with other people and to gain energy from this interaction over being more independent of social interaction (e.g., outgoing, action-oriented and energetic behaviour vs. solitary, inward and reserved behaviour).
- ***A****greeableness* describes a person's preference to trust others, to act helpful and to be optimistic over an antagonistic and sceptical mind set. This trait directly influences the quality of relationships with other individuals (e.g., friendly, cooperative and compassionate behaviour vs. analytical, antagonistic and detached behaviour).
- ***N****euroticism* describes a person's preference to interpret external stimuli such as stress as minatory over confidence and emotional stability. Neuroticism addresses the level of emotional reaction to events (e.g., sensitive, pessimistic and nervous behaviour vs. secure, emotionally stable and confident behaviour).

These dimensions are also named the Big Five personality traits leading to acronyms such as OCEAN, NEOAC, NEO-PI and NEO-PI-R, which are frequently used when referring to the FFM theory. To some extent the different acronyms indicate different assessment instruments. The characteristic of each dimension is defined as a variation from the norm, whereas each dimension is an overarching container subsuming different lower-level personality traits. For example, neuroticism is associated with subordinated traits such as anxiety, hostility and impulsiveness [22]. Taking this observation into account, one can argue that the FFM theory is a conceptual framework about human personality traits that can, for example, be used to integrate other theories about human personalities into its structure [16, 24].

## 3 Related Work

In the following we will explore the use of personality theories in agent-based systems. In particular we want to carve out whether or not there is existing work aiming to prove that different personalities act in different ways and how the cooperation between agents is affected by this.

In research on agent-based systems, formal models of human personality are comprehensively used for the implementation of (microscopic) traffic simulation frameworks [20] and the agent-based simulation/visualisation of groups of people [8, 13]. The work of *Durupinar et al.* [13] shows how the introduction of different personalities into agents influences the behaviour of a crowd. For this simulation the authors applied the OCEAN model. Other areas include human-machine interaction [11], in particular conversational agents/virtual humans [4, 14] and life-like characters [5]. The latter outlines three projects that apply two dimensions of the FFM (extraversion and agreeableness). The effects are interpreted in a rule-based or scripted manner.

The mentioned approaches focus either on supplying personality to agents that interact with human users or applying personality theories to simulation environments to analyse more global effects. They implement the effects of personalities specifically for the individual use-case, without proving that this can be done in a more generic manner. Another branch of research focuses on modelling and examining the effects of personalities on interactions between agents and their environments. In particular, the effects of personalities in cooperative settings as addressed by this work are examined.

*Talman et al.* [33] present a work that illustrates the use of a rather simple abstraction of personality types. Personalities of agents are determined by the two dimensions cooperation and reliability, which are used to measure the helpfulness of an agent. The agents have to negotiate and cooperate as cooperation is an inherent part of the game they play. During repeatedly played games the agents reason about each other's helpfulness along the two dimensions. As an effect they try to respond more effectively by customising their behaviour appropriately for different personalities. *Campos et al.* [7] present a work employing the Myers-Briggs Type Indicator [23] (MBTI) model, which is here restricted to two of its dichotomies. It is integrated into the reasoning process of a BDI agent and the work proves that different personality characteristics lead to variations in the decision-making process in a simulation specifically designed for the paper's

use-case. In an early work, *Castelfranchi et al.* [9] present a framework to investigate the effects of personalities on social interactions between agents, such as delegation and help. The agents apply opponent modelling in terms of personality traits to motivate interactions. However, the work discusses personality traits as an abstract concept without relation to psychological theories. The work that is most closely related to our work, answering the question whether individuals with different personalities act in different ways, is presented by *J. Salvit* and *E. Sklar* [29, 30]. That is the case because the authors established an experiment validating the impact of the MBTI onto the decision-making process of agents. In order to do so, the MBTI is integrated into a sense-plan-act structure and the behaviour of each MBTI type is analysed in a simulation environment called the 'Termite World'. The results underline the hypothesis of the paper that the different personality types act in quite different ways. One consequence is 'that some agent personality types are better suited to particular tasks—the same observation that psychologists make about humans' [30, p. 147].
To conclude, there is evidence that proves the hypothesis addressed. Nevertheless, the literature overview also shows that the majority of works addressing the hypothesis apply the MBTI theory. The others use simplified models that are not based on psychology findings. In the following, we will carve out why we applied the OCEAN model and explain why MBTI should no longer be used within the agent community, thus giving the motivation for presenting this work.

## 4 Comparison of OCEAN and MBTI

To start with, the FFM emerged from empirical observations and analysis leading to the introduced formal model of human personality, whereas MBTI emerged from theoretical considerations, which were proven through user studies [26]. Another difference is the use of personality types on the one hand and personality traits on the other. The use of types presents the advantage of being distinct, but at the same time presents the disadvantage of being disjoint. This means that being classified as extrovert (E) clearly distinguish an individual from being introvert (I) and adds such an individual to its specific cluster, without giving any hint about the degree of extroversion. Still, this information might be important when this individual was close to the 'artificial' border that disjoints the dichotomies or when someone wants to compare persons of the same type. At this point a continuous scale as presented by FFM delivers more information, but misses the advantage of introducing standardised clusters to compare groups of people, making the implementation of FFM into agents challenging.
The completeness of a theory is another important characteristic that implies whether such a theory is broad enough to understand/describe the different human personalities. Here, it was shown that there are some characteristics of humans that the MBTI fails to cover [15, 22]. In particular the missing preference of being emotionally stable is criticised. In contrast, FFM presents a more generic structure, which is nevertheless also criticised for neglecting some domains of a human personality like honesty or religiosity [25] (also applies to MBTI). In both

cases, these criticisms are still an open discussion among psychologists and are subject to further investigation.
Beside the completeness of a theory, reliability is at least equally important. On the one hand, reliability addresses the consistency of the results when assessing an individual using self-assessment, questionnaires and professional assessments. On the other hand, it addresses the consistency when performing the same assessment repeatedly with some temporal distance, which is also named test-retest reliability. MBTI suffers in both categories, as it does not deliver constant results using the different assessment techniques. Also, experiments about the test-retest reliability have shown that there is a chance of 50% to be classified as another MBTI type when repeating the test after a period of only five weeks [26]. Here, FFM delivers more accurate results for short term intervals (1 week) [19] and long-term intervals (10 years) [35], which supports the finding that a developed personality is stable over the life span of a human [36].
Balancing the presented arguments and taking into account the possibility to integrate MBTI into FFM comes down to the point 'that it may be better [...] to reinterpret the MBTI in terms of the five factor model' [21, p. 37, according to [15]]. This is an advice we follow and that should be recognised by the agent community. One argument here might be that the use of psychological theories is not of relevance when the goal is to produce different artificial agent traits. We want to respond to this by highlighting the fairly long tradition of knowledge transfer between psychology and agent research and that newer findings should not be ignored.

## 5 Modulating BDI Agents with Personality

To integrate the personality of humans we embed the FFM theory into the BDI model of agency [28], a popular model for the conceptualisation of human behaviour. BDI agents separate the current execution of a plan from the activity of selecting a plan using the three mental concepts belief, desire and intention. The life-cycle of a BDI agent comprises four phases, namely the *Belief Revision*, the *Option Generation*, the *Filter Process*, and the *Actuation*. In our model, the phases of the BDI cycle are influenced by the characteristics of a personality in different ways. For instance, the trait conscientiousness strongly influences the goal-driven behaviour of an agent, whereas the trait extraversion influences the agent's preference to interact with others. Table 1 lists the influences of the different characteristics of FFM on the different phases of the BDI life-cycle. These influences address the intensity by which one personality trait influences a phase and thus (only) highlights the traits that are most influential.
In the following, to explain the model, we represent a BDI cycle as a sequence of states. Therefore let each state be a set of variables (syntax follows $\mathcal{LORA}$ [37]):

- $P : Per$ is the collection of personality traits the agent has, *i.e.* the actual characteristics for this agent according to the dimensions of the FFM;
- $\rho : Percepts$ is the information that the agent perceives/receives in its environment;

Table 1: In order not to value the influence in terms of being negative or positive, the list only highlights the traits that are most influential in each phase. Indeed, this classification is discussable as it reflects our own interpretation of the FFM traits in comparison with the BDI phases.

| | **O** | **C** | **E** | **A** | **N** |
|---|---|---|---|---|---|
| Belief Revision | × | | | × | |
| Option Generation | | × | | × | × |
| Filter Process | × | × | × | × | × |
| Actuation | × | × | × | | |

- $B : \wp(Bel)$ is the set of beliefs, *i.e.* the current assumptions about the state of the environment;
- $D : \wp(Des)$ is the set of desires, *i.e.* the set of intended goals the agent wants to fulfil;
- $I : \wp(Int)$ is the set of intentions, *i.e.* the set of desires the agent is committed to fulfil;
- $\pi : Act^*$ is the current sequence of actions taken from the set of plans over some set of actions *Act* this agent has chosen, *i.e.* the current plan; and
- $\alpha : Act$ is the action that is executed.

Algorithm 1 shows an adapted BDI life-cycle that involves personality as an influence during the different stages. All personality traits are considered during the process. Furthermore, we assume that the personality does not change during the life-cycle of an agent. This assumption is based on the finding that we as humans have a stable personality over our lifespan as adults [36].

**Algorithm 1** A BDI cycle that incorporates personality into the decision making process.

**Input:** $B_{init}$, $I_{init}$, $P$; **Output:** -

$B \leftarrow B_{init}$, $I \leftarrow I_{init}$
**while** true **do**
    $\rho \leftarrow$ percept($Env$, $Msg$)
    $B \leftarrow$ beliefRevision($B$, $\rho$, $P$)
    $D \leftarrow$ options($B$, $I$, $P$)
    $I \leftarrow$ filter($B$, $D$, $I$, $P$)
    $\pi \leftarrow$ plan($B$, $I$, $P$)
    **while** not empty($\pi$) **do**
        $\alpha \leftarrow$ hd($\pi$)
        execute($\alpha$, $P$)
        $\pi \leftarrow$ tail($\pi$)
    **end while**
**end while**

The cycle starts with the perception of information. During this stage the agent receives new information from the environment ($Env$) using its sensors, which also comprises messages ($Msg$) from other agents (communication acts). The perception is not affected by the personality, as humans are not able to restrict their perception during the cognition. This is a deliberate process taking place in the next step of the cycle. Formally, the signature of the perception function *percept* is defined as:

$$\mathit{percept} : Env \times Msg \rightarrow \mathit{Percepts}.$$

The next step of the BDI life-cycle is the *Belief Revision*. That means that given the new perceptions ($\rho$) an updated belief set ($B$) is computed with respect to the current personality ($P$). The belief revision function *beliefRevision* is defined as:

$$beliefRevision : \wp(Bel) \times \mathit{Percepts} \times Per \rightarrow \wp(Bel).$$

After this step the set of beliefs can contain information about the environment, the state of the agent itself (e.g., energy level, injuries like sensory malfunctions) and facts that were received via communication. In our model the **O** and **A** characteristics influence this phase most frequently, as they influence the interpretation of what the new measurement means for the agent and how trustful the agent is when receiving information from others. One essential reason to distinguish between perceptions/beliefs derived from the environment and perceptions/beliefs derived from other agents is the characteristic of the personality trait agreeableness, which indicates the preference to trust others.[1] We implemented this behaviour (the influence of the trait **A** during the belief revision) for our simulation environment using the characteristic of the personality trait as likelihood. For example, an agent with $A = 1.0$ would always trust information received via communication acts, whereas an agent with $A = 0.0$ would always reject them.

The next step is the *Option Generation*, where the agent generates its desires ($D$) taking into account the updated beliefs, the currently selected intentions ($I$) and the personality. The option generation is mainly influenced by the **C**, **A** and **N** characteristics, as these traits indicate the preferences to follow picked goals, the tendency to act selfishly or generously, and the reaction of the agent to external influences. This deliberation process is represented by the function *options* with the following signature:

$$\mathit{options} : \wp(Bel) \times \wp(Int) \times Per \rightarrow \wp(Des).$$

The generated desires are a set of alternatives (goals) an agent wants to fulfil, which are often mutually exclusive. As the option generation should produce all options available to the agent, the influence of the personality is restricted

[1] In fact, it might be hard to clearly distinguish the information sources. That is because other agents are part of the environment and the observation of the behaviour of other agents might thus be both an observation of the environment and an (implicit) communication act.

to the persistence of already selected intentions. Again, we implemented this by interpreting the traits as likelihood, e.g. an agent with $C = 1.0$ will always maintain an intention as an option regardless of the current beliefs about the world.

The third stage is the *Filter Process* where the agent chooses between competing desires and commits to achieve some of them next. The filter process is influenced by the preference to vary activities over keeping a strict routine (**O**) and the level of self-discipline (**C**), the need to act in harmony with other agents (**A, N**) and even the tendency to generally interact with others (**E**). For example, variations of **C** influence an agent's preference to detach the previously selected intentions. As another example, variations of **A** and **E** influence an agent's preference to commit to selfish/altruistic goals. The *filter* function is defined as:

$$filter : \wp(Bel) \times \wp(Des) \times \wp(Int) \times Per \to \wp(Int).$$

The personality helps to prioritise the different intentions and for example indicates to what extent an agent acts goal-driven, prefers interaction and varies the activities. It selects the best option from the agent's point of view based on the current beliefs, with respect to the previously selected option. Again interpreting the traits as likelihood, the filter process was implemented by, e.g., prioritising intentions that imply interaction with others using the characteristic of **E**.

The last stage is the *Actuation*, in which the agent creates/selects the plan ($\pi$) and influences the environment performing actions ($\alpha$). This phase is mainly influenced by the creativity level of the agent (**O**), the tendency to apply actions in a decent manner (**C**) and the preference to interact with others (**E**). The actual plan is then generated for the selected intentions and executed, which is defined as:

$$plan : \wp(Bel) \times \wp(Int) \times Per \to Act^*.$$

The execution of actions as plan-elements directly influences the environment and the personality indicates how accurately an agent behaves (**C**), which however is a rather vague argument for agents. To set an example, imagine a robot that performs a motion from one point to another in a specific time frame. The level of conscientiousness can then be used to implement a noise level added to the target location or time frame borders. Indeed, this seems to be curious when considering artificial agents but is one important difference between humans. The actuation function *execute* is formally defined as:

$$execute : Act \times Per$$

The algorithm explained here is one variant of a BDI agent following a blind-commitment strategy and being overcommitted to both the ends and means. As the chosen evaluation domain is tick-based and the plans are rather short, this commitment strategy is acceptable. However, using the provided explanation the algorithm can be adapted to produce reactive and single- or open-minded behaviour, which might be either bold or cautious. These variations of the BDI life-cycle are described by *M. Wooldridge* [37, pp. 31] and the modifications are straightforward.

## 6 Evaluation

To evaluate the model we implemented it for the multi-agent simulation environment AntMe![2]. The main objective of each ant colony is to collect as much food (apples, sugar) as possible and to defend their own anthill from enemies such as other ant colonies and bugs. Each simulation run encompassed 5000 time-steps, where each ant in each time-step completes the BDI cycle of sensing its environment, updating its beliefs, desires and intentions and executing. The ants are able to sense their location, to recognise whether or not they are transporting food, and to determine the the location of food, other ants, scent-marks, and enemies within their range of sight. The scent-marks are used to determine what other ants of the own colony are targeting and to highlight the occurrence of enemies. The possible actions are goStraight, goAwayFromPOI, goToPOI, goToNest, turnToPOI, turnByAngle, turnAround, turnToGoal ('turn actions'), pick-up and drop-off food, attack, and put scent-mark. Fig. 1 shows a screenshot of the simulation environment.

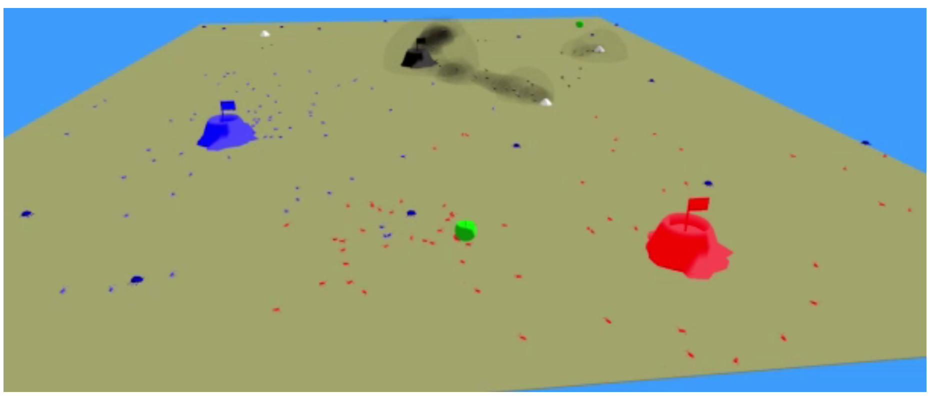


Fig. 1: Screenshot from an AntMe! simulation with three ant colonies (red, blue, black). Carrying apples (green) is a teamwork task and white cubes are sugar. The black dust is the visualisation of scent-marks, here used to highlight sugar. Such scent-marks disappear after a while.

Using the introduced model we expect that the ants' behaviours vary when adjusting the personality traits. In particular we expect that an ant population with high values in the trait openness (O+) does more exploration than a population with low values (O-).[3] That means that O+ ants are expected to find sugar and apples earlier. At the same time, we expect the O- ants to harvest

[2] For further information about the simulation environment the interested reader is referred to `http://www.antme.net/`.

[3] The $-$, $+$ label represent a value in the interval $[0.0, 0.5)$, $[0.5, 1.0]$ respectively.

Table 2: Correlation matrix between measured items and personality traits (upper part) and collected information for an example set of ant populations.

| | **Apple** | **Sugar** | **Eaten** | **Starved** | **Bugs** |
|---|---|---|---|---|---|
| **O** | -0.068 | -0.444 | -0.043 | -0.209 | 0.027 |
| **C** | 0.545 | 0.425 | -0.454 | 0.893 | -0.027 |
| **E** | -0.150 | 0.072 | 0.002 | -0.119 | -0.009 |
| **A** | 0.261 | 0.501 | -0.430 | 0.107 | -0.554 |
| **N** | 0.305 | 0.114 | -0.436 | 0.125 | -0.554 |
| *values below are ordered according to the OCEAN acronym* | | | | | |
| (0,0,0,0,0) | 8.4 | 18.4 | 281.6 | 6.0 | 2.5 |
| (0,1,0,0,0) | 19.0 | 75.6 | 117.4 | 146.9 | 3.3 |
| (0,1,1,0,0) | 19.0 | 52.9 | 98.3 | 162.9 | 2.1 |
| (0,1,1,1,0) | 16.5 | 181.0 | 65.9 | 174.6 | 0.0 |
| (0,1,1,1,1) | 16.0 | 175.7 | 64.2 | 175.9 | 0.0 |
| (1,0,0,0,0) | 8.5 | 8.1 | 285.4 | 0.0 | 3.0 |
| (1,0,1,0,0) | 7.9 | 6.5 | 283.9 | 0.1 | 3.5 |
| (1,0,1,1,1) | 15.8 | 39.9 | 75.0 | 0.0 | 0.0 |
| (1,1,1,1,1) | 19.3 | 75.8 | 54.2 | 188.4 | 0.0 |
| $(\frac{1}{2},\frac{1}{2},\frac{1}{2},\frac{1}{2},\frac{1}{2})$ | 9.7 | 17.1 | 270.8 | 19.5 | 1.5 |

sugar faster as a consistent behaviour is favourable for this task, which includes walking the same route multiple times. We expect that high values in the trait conscientiousness (C+) lead to more collected food, as such ants will not drop food when facing other goals such as attacking/running away from bugs. At the same time, we expect low valued ants (C-) to have a lower chance of starving during the search for food as collecting food is the most important desire. Extroverted ants (E+) are expected to communicate more frequently with other ants by putting scent-marks as markers for the occurrence of sugar, apples and bugs more frequently. However, this effect correlates with the effect of the trait agreeableness, indicating whether an ant trusts information received from other ants (A+) or not (A-). We expect that high valued ants in both traits collect food more frequently. The neuroticism trait indicates the ants' emotional stability. We expect high valued ants (N+) to avoid dangerous situations such as bugs and hostile ants – resulting in lower numbers of eaten ants and killed bugs. However, the effect of this trait correlates with the level of trust (A+ vs. A-) and the level of self-discipline (C+ vs. C-).

Table 2 shows the correlation matrix for all personality traits and the measurable features of an AntMe! simulation. For this we simulated the permutation of the minimum and maximum values for each trait, resulting in $2^5 = 32$ ant populations. The features comprise the collected apples and the collected sugar, the number of eaten and starved ants, and the number of killed bugs. For each permutation the values were averaged over 50 simulation runs, where each simulation run started with the same point of origin of the ant hill, apples, and sugar.

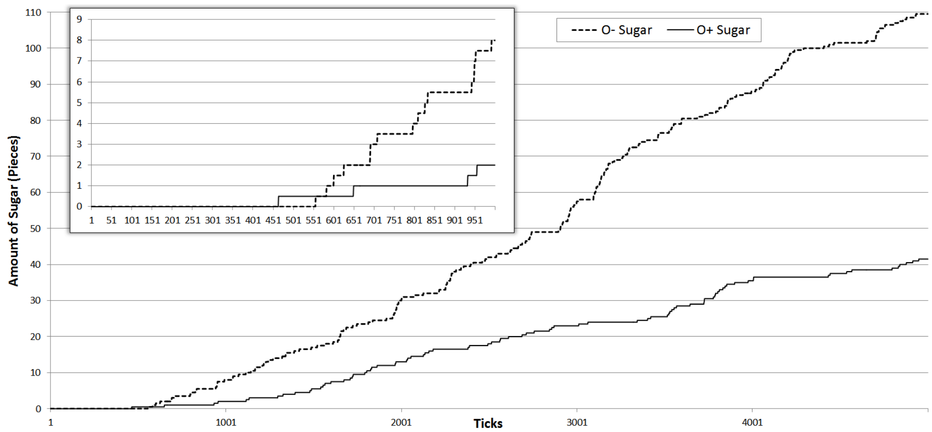
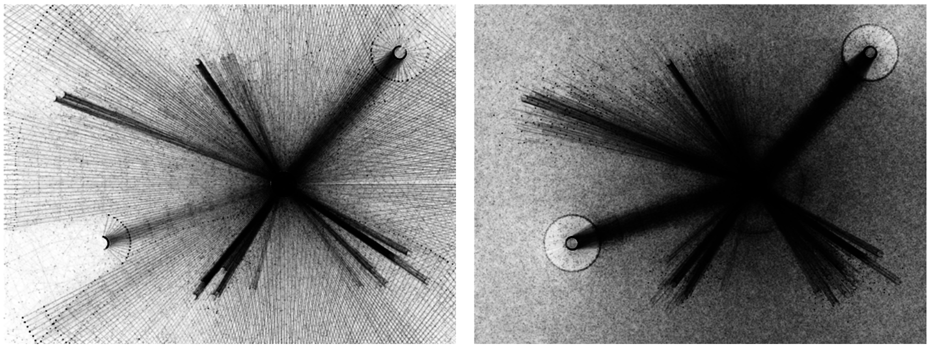



Fig. 2: Tick-based cumulation of O+ (average for 10000, 11111) and O- (average for 00000, 01111) ant populations and their process of collecting sugar. The values are averaged over the 50 simulation runs performed for each population. One can see that O+ ant populations start approximately 2% earlier with the collection (the smaller diagram shows the relevant segment) but collect food slower than O- ant populations.

Occurrence of bugs is randomised and each deceased ant is instantly replaced with a new one. As indicated in the correlation matrix, the majority of effects that were postulated are observable in the simulation. To start with, the matrix indicates that O+ ants collect less food than O- ants and that this behaviour is most notable for the collected sugar. Still, we postulated that O+ ants will find sugar earlier. This effect is illustrated in Fig. 2, where the process of collecting sugar is depicted tick-wise.
Table 2 also lists the results for some selected ant populations and emphasises that different types of personality lead to different simulation results. For example, an ant population with maximum values (1,1,1,1,1) collects more apples and sugar, kills fewer bugs and loses fewer ants because of bugs than an ant population with minimum values (0,0,0,0,0). Still, for the latter a lower number of starved ants can be observed. Here, the traits **E** and **A** influence the occurrence of scent-marks and the interpretation (trust) of the very same thing. The trait **C** implies that already picked-up food is not dropped because of new percepts, as collecting food is the most important goal for the ants. The trait **N** affects the flight behaviour of the ants leading to fewer/more eaten ants/killed bugs, respectively.
The effects of the personality traits are also visible in the paths an ant population takes. Fig. 3 shows the path heat maps for the two discussed populations. It emphasises the effects of the trait **O**, which affects an ant's preference of acting exploratively vs. exploitatively or following a conservative vs. curious behaviour (*i.e.* staying in known areas vs. eager to explore new areas). At the same point,



(a) (0,0,0,0,0) (b) (1,1,1,1,1)

Fig. 3: The cumulated paths of two ant populations. As the occurrence of food and the location of the ant hill are fixed a comparable structure originates. Still, the effects of exploration vs. exploitation are visible (covered area, curious behaviour, broader paths). The artefacts denote the visibility range of the ants and the points where apples are spawned, giving an indication of the effects of scent-marks and the trustfulness of the ants.

the figure visualises how cooperatively the ants act, visible through the round artefacts highlighting the occurrence of apples – collecting apples is a cooperative task.
Taking these results into account we can conclude that different personalities affect the result of the simulation and that some personalities are better suited for particular tasks than others. That confirms the finding of *J. Salvit* and *E. Sklar* [30] with respect to the Five-Factor Model of personality. One implication might be that personality is a kind of basic heuristic that influences an agent's performance during the lifetime as it influences the interpretation of perceptions, the interaction with other agents, the decision-making process and even the actual actuation.

## 7 Personality and Human-Aware Planning

The basic idea to forward the information about the personality to the planning process is to provide a cost estimate for the capabilities. We refer to this idea as Dynamic Heuristic of Human-Behaviour (DHHB). DHHB is used to determine the likelihood that a task will be performed, *i.e.* lower cost indicates a higher likelihood and vice versa. Indeed, *Sisbot et al.* [32] already showed the usefulness of this idea in a human-aware robot motion planning setting. Such robots should avoid to approach humans from behind during the motion. To accomplish this the authors attached higher cost to actions in the back of humans and thus influenced the path-finding of the applied A* algorithm without changing it.

To enable this idea for HAP, we represent each natural agent as an avatar in the computing system that provides information for the actual planning process to the artificial agents. Doing this, we are enabled to use existing planning components and to influence the action selection of a planning process, while the actual planning procedure remains a black box. In a prior work [2], we already showed that this is possible; influencing the action selection process using an estimate of how helpful (in terms of cooperation and reliability) a human might be as an additional actor in a multi-actor Blocks-World domain. In particular, it is planned to integrate the model introduced within this work into the development environment presented in published work [2]. To provide some more details: The BDI model introduced here builds a decision-tree during the life-cycle as shown elsewhere [31]. In the current prototype this tree contains weights for the intentions, which are used to remember previously selected intentions and which depend upon the personality. Such weights can also be interpreted as likelihoods indicating which intention will be satisfied next by the represented human. In HTN planning, these intentions can be seen as either primitive or non-primitive tasks. Thus, such weights can also be used as one of the factors determining the likelihood of the next action. However, other factors like familiarization with specific actions or the timely execution of an action must be learned and added here. This leads to a theory- and data-driven approach, such as postulated by *R. Prada* and *A. Paiva* [27] for encouraging human-agent interaction. Thus major part of the integration will be experiments with real users to find a way to accurately infer the likelihood of a human's next steps from the proposed model.

## 8 Conclusion

This work demonstrated that the integration of the FFM into the BDI model of agency leads to variations in the interpretation of inputs and generation of outputs. The observation indicates that the decision-making process is influenced by the personality type and that agents with different personalities behave differently. That is the same observation that psychologists make about humans and was proven for the MBTI in a related work. It was argued why we applied the FFM and that psychologists tend to accept the FFM as a conceptual framework for describing human personality. The evaluation comprises the implementation of the model into the multi-agent based simulation environment AntMe!. Despite the fact that ants were simulated, the environment provides a completely adaptable test-bed for behavioural studies, which were used to show that personality affects all relevant phases of decision-making processes. Still, the actual implementation has shortcomings and it is important to mention that we presented a stepping-stone rather than a holistic solution. First of all, the effect of a personality is only based on the characteristic of the trait that decides how often such a trait influences the current stages in one of two ways. But in fact, the influence of a personality is always subject to the context of the individual. For instance, persons that are very calm in general, can become very temperamental given the right circumstance. Here a more realistic method must be found that includes the current context of the agent, which also comprises the effects of emotions or moods. Surprisingly, agent-based research that particularly emphasises the effects of emotions abandons the fact that emotions and its influences are contingent upon the personality. However, finding solutions for both problems is an open topic and requires both further theoretical work and empirical results obtained within user-studies. A first step in this direction is presented by *H. Du* and *M. Huhns* [12]. The authors examine whether the interaction of humans with both humans and agents depends on the humans' personality type according to the MBTI. The experiments done using the cake-cutting game show that the different personalities act in different ways, but also show that there is only little evidence that can be used to make correct predictions about possible behaviour based on information about personality. In future work, it will be interesting to examine whether a combination of theory-driven and data-driven approaches leads to more accurate results in the prediction of the next actions a human takes.

## References


1. Ahrndt, S.: Improving human-aware planning. In: Klusch, M., Thimm, M., Paprzycki, M. (eds.) Multiagent System Technologies, pp. 400–403. No. 8076 in Lecture Notes in Artificial Intelligence, Springer Berlin Heidelberg (2013)
2. Ahrndt, S., Ebert, P., Fähndrich, J., Albayrak, S.: HPLAN: Facilitating the implementation of joint human-agent activities. In: Demazeau, Y., Zambonelli, F., Corchado, J.M., Bajo, J. (eds.) Advances in Practical Applications of Heterogeneous Multi-Agent Systems. The PAAMS Collection., Lecture Notes in Computer Science, vol. 8473, pp. 1–12. Springer International Publishing (2014), `http://dx.doi.org/10.1007/978-3-319-07551-8_1`
3. Ahrndt, S., Fähndrich, J., Albayrak, S.: Human-aware planning: A survey related to joint human-agent activities. In: Bajo, J., Corchado, J.M., Mathieu, P., Campbell, A., Ortega, A., Adam, E., Navarro, E.M., Ahrndt, S., Moreno, M., Julián, V. (eds.) Trends in Practical Applications of Heterogeneous Multi-Agent Systems. The PAAMS Collection., Advances in Intelligent Systems and Computing, vol. 293, pp. 95–102. Springer International Publishing (2014), `http://dx.doi.org/10.1007/978-3-319-07476-4_12`
4. Allbeck, J., Badler, N.: Toward representing agent behavior modified by personality and emotion. In: Proc. of the Workshop on Embodied Conversational Agents at the 1st Int. Conf. on Autonomous Agents and Multiagent Systems (AAMAS). ACM Press (April 2002)
5. Andre, E., Klesen, M., Gebhard, P., Allen, S., Rist, T.: Integrating models of personality and emotions into lifelike characters. In: Paiva, A., Martinho, C. (eds.) Proc. of the Workshop on Affect in Interactions  Towards a new Generation of Interfaces. pp. 136–149 (2000)
6. Bradshaw, J.M., Feltovich, P., Johnson, M., Breedy, M., Bunch, L., Eskridge, T., Jung, H., Lott, J., Uszok, A., Diggelen, J.: From tools to teammates: Joint activity in human-agent-robot teams. In: Kurosu, M. (ed.) Human Centered Design, Lecture Notes in Computer Science, vol. 5619, pp. 935–944. Springer Berlin Heidelberg (2009), `http://dx.doi.org/10.1007/978-3-642-02806-9_107`

7. Campos, A., Dignum, F., Dignum, V., Signoretti, A., Magaly, A., Fialho, S.: A process-oriented approach to model agent personality. In: Sierra, C., Castelfranchi, C., Decker, K.S., Sichman, J.S. (eds.) Proc. of the 8$^{\text{th}}$ Int. Conf. on Autonomous Agents and Multiagent Systems (AAMAS 2009). pp. 1141–1142. IFAAMAS, Budapest, Hungary (May 2009)
8. Canuto, A.M., Campos, A.M., M.Santos, A., Moura, E.C., Santos, E.B., Soares, R.G., Dantas, K.A.: Simulating working environments through the use of personality-based agents. In: Sichman, J.S., Coelho, H., Rezende, S.O. (eds.) Advances in Artificial Intelligence - IBERAMIA-SBIA 2006, pp. 108–117. No. 4140 in LNAI, Springer (2006)
9. Castelfranchi, C., de Rosis, F., Falcone, R., Pizzutilo, S.: Personality traits and social attitudes in multi-agent cooperation. Applied Artificial Intelligence 12(7-8), 649–675 (1998), Special Issue on 'Socially Intelligent Agents'
10. Cirillo, M., Karlsson, L., Saffiotti, A.: Human-aware task planning: An application to mobile robots. ACM Trans. Intell. Syst. Technol. 1(2), 15:1–15:26 (November 2010), http://doi.acm.org/10.1145/1869397.1869404
11. Dryer, C.: Getting personal with computers: How to design personalities for agents. Applied Artificial Intelligence 13(3), 273–295 (1999)
12. Du, H., Huhns, M.N.: Determining the effect of personality types on human-agent interactions. In: Web Intelligence (WI) and Intelligent Agent Technologies (IAT), 2013 IEEE/WIC/ACM International Joint Conferences on. vol. 2, pp. 239–244. IEEE (November 2013)
13. Durupinar, F., Allbeck, J., Pelechano, N., Badler, N.: Creating crowd variation with the OCEAN personality model. In: Padgham, Parkes, Müller, Parsons (eds.) Proc. of the 7$^{\text{th}}$ Int. Conf. on Autonomous Agents and Multiagent Systems (AAMAS 2008), pp. 1217–1220. IFAAMAS (2008)
14. Egges, A., Kshirsagar, S., Magnenat-Thalmann, N.: Generic personality and emotion simulation for conversational agents. Computer Animation and Virtual Worlds 15, 1–13 (2004)
15. Furnham, A.: The big five versus the big four: The relationship between the Myers-Briggs Type Indicator (MBTI) and NEO-PI Five Factor Model of personality. Pers Indiv Differ 21(2), 303–307 (August 1996)
16. John, O.P., Srivastava, S.: The big-five trait taxonomy: History, measurement, and theoretical perspectives. In: Pervin, L.A., John, O.P. (eds.) Handbook of Personality: Theory and Research, vol. 2, pp. 102–138. The Guilford Press (1999)
17. Kirsch, A., Kruse, T., Sisbot, E.A., Alami, R., Lawitzky, M., Brscic, D., Hirche, S., Basili, P., Glasauer, S.: Plan-based control of joint human-robot activities. KI – Künstliche Intelligenz 24(3), 223–231 (September 2010)
18. Klein, G., Woods, D.D., Bradshaw, J.M., Hoffmann, R.R., Feltovich, P.J.: Ten challenges for making automation a 'team player' in joint human-agent activity. Human-Centered Computing 19(6), 91–95 (November/December 2004)
19. Kurtz, J.E., Parrish, C.L.: Semantic response consistency and protocol validity in structured personality assessment: The case of the NEO-PI-R. J Pers Assess 76(2), 315–332 (2001)
20. Lützenberger, M., Albayrak, S.: Current frontiers in reproducing human driver behavior. In: Proc. of the 46$^{\text{th}}$ Summer Computer Simulation Conference 2014, pp. 514–521 (2014)
21. McCrea, R.R., Costa, P.: Reinterpreting the Myers-Briggs Type Indicators from the perspective of the Five-Factor Model of personality. J Pers 57(1), 17–40 (March 1989)

22. McCrea, R.R., John, O.P.: An introduction to the five-factor model and its applications. J Pers 60(2), 175–215 (1992)
23. Myers, I.B., Byers, P.B.: Gifts Differing: Understanding Personality Type. Nicholas Brealey Publishing, 2 edn. (May 1995)
24. O'Connor, B.P.: A quantitative review of the comprehensiveness of the Five-Factor Model in relation to popular personality inventories. Assessment 9, 188–203 (2002)
25. Paunonen, S.V., Jackson, D.N.: What is beyond the big five? plenty! J Pers 68(5), 821–835 (October 2000)
26. Pittenger, D.J.: Cautionary comments regarding the myers-briggs type indicator. Consulting Psychology Journal: Practice and Research 57(3), 210–221 (2005)
27. Prada, R., Paiva, A.: Human-agent interaction: Challenges for bringing humans and agents together. In: Proc. of the 3rd Int. Workshop on Human-Agent Interaction Design and Models (HAIDM 2014) at the 13th Int. Conf. on Agent and Multi-Agent Systems (AAMAS 2014), pp. 1–10. IFAAMAS (2014)
28. Rao, A.S., Georgeff, M.P.: BDI agents: From theory to practice. In: Lesser, V., Gasser, L. (eds.) Proc. of the First Int. Conf. on Mutiagent Systems (ICMAS 1995). pp. 312–319. AAAI, The MIT Press (April 1995)
29. Salvit, J., Sklar, E.: Toward a Myers-Briggs Type Indicator model of agent behavior in multiagent teams. In: Bosse, T., Geller, A., Jonker, C.M. (eds.) Multi-Agent-Based-Simulation XI, Int. Workshop, MABS 2010, Toronto, Canada, May 2010, Revised Selected Papers. pp. 28–43. No. 6532 in Lecture Notes in Artificial Intelligence, Springer-Verlag, Berlin, Heidelberg (2011), `http://dl.acm.org/citation.cfm?id=1946224.1946228`
30. Salvit, J., Sklar, E.: Modulating agent behavior using human personality type. In: Proc. of the Workshop on Human-Agent Interaction Design and Models (HAIDM) at Autonomous Agents and MultiAgent Systems (AAMAS). pp. 145–160 (2012)
31. de Silva, L., Padgham, L.: A comparison of BDI based real-time reasoning and HTN based planning. In: Australian Conference on Artifical Intelligence'04. pp. 1167–1173 (2004)
32. Sisbot, E.A., Marin-Urias, L.F., Alami, R., Simeon, T.: A human aware mobile robot motion planner. IEEE Transactions on Robotics 23(5), 874–883 (2007)
33. Talman, S., Hadad, M., Gal, Y., Kraus, S.: Adapting to agents' personalities in negotiation. In: Pechoucek, M., Steiner, D., Thompson, S. (eds.) Proc. of the 4th Int. Joint Conf. on Autonomous Agents and Multiagent Systems (AAMAS). pp. 383–389. ACM, New York, NY, USA (2005)
34. Tapus, A., Matarić, M.J., Scassellati, B.: The grand challenges in socially assistive robotics. IEEE Robotics and Automation Magazin 14(1), 35–42 (March 2007)
35. Terracciano, A., Jr., P.T.C., McCrae, R.R.: Personality plasticity after age 30. Pers Soc Psychol B 32(8), 999–1009 (2006)
36. Wilks, L.: The stability of personality over time as a function of personality trait dominance. Griffith University Undergraduated Student Psychology Journal 1, 1–9 (2009)
37. Wooldridge, M.: Reasoning about Rational Agents. Intelligent Robotics and Autonomous Agents, The MIT Press (July 2000)