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Meta-Analyzed Intercorrelation Matrix Based Traitspace Similarity for Traits Extension of Schelling Model of Segregation

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Abstract

This research extends the High Dimensional Personality Schelling Model (HDPSM) by implementing a meta-analyzed Five Factor Model (FFM) intercorrelation matrix, to construct the personality vectors that are used to compare similarity between an agent and its neighbor. In the previous iteration of HDPSM, all personality values were generated randomly. This research utilizes three well known matrices proposed by Ones (1993), Mount (2005), and van der Linden (2010). Along with that, it also utilizes a synthetic intercorrelation matrix and compares its effectiveness in generating the clustering behavior of agents. The results displayed that all three matrices produced significant, high, and consistent effect sizes across all matrices. In addition, the van der Linden matrix proved to have a higher effect than both Ones and Mount, which corroborated previous literature stating the matrix's high correlation values. Further analysis showed the synthetic matrix outperformed the three existing matrices, in terms of effect size, and providing strong evidence for usage of synthetic intercorrelation matrices when simulating personality-based Schelling models. The authors also conclude by presenting an exploratory analysis of statistical and spatial changes, when correlated personality matrices were introduced.

Keywords: agent based modelling, schellings model, computational modelling, multi-agent simulation, five factor model, personality intercorrelation matrix

1 Introduction

The "Introduction to Traits Extension of Schelling Model of Segregation" [1] (p. 1) introduced the High-Dimensional Personality Schelling Model (HDPSM) mechanics to study agent clustering dynamics in the presence of a personality model. This research served as an extension to the HDPSM's traitspace inputs and utilized meta-analyzed correlation matrices to construct the Five Factor Model (FFM) personality vector that determined inter-agent similarity. The five factors of this model are: Openness (O), Conscientiousness (C), Extraversion (E), Agreeableness (A), and Neuroticism (N). [2][3][4] The original extension compared results between the identicalness of the classical model (CSM), the multi-agent model (MASM), and the personality model (HDPSM) using a Cosine similarity equation, however one drawback that needed to be addressed was the nature of the inputs. The original traitspace comprised of randomized and uncorrelated values i.e. it did not follow any meta-analyzed intercorrelation matrix that is prevalent when conducting personality research. [5][6] This drawback reduced the applicability of the tool when utilizing personality as a predictor of task outcomes. In this research, the HDPSM is enhanced to include correlation matrices from three commonly used FFM matrices (Ones [7], Mount [8], and van der Linden [9]), as well as an Organizational Psychology focused intercorrelation matrix based on workplace related criteria, proposed by Park et. al. (2020)[10]. This research contributed towards laying the foundation for a traits-based agent framework for Agent Based Modelling (ABM) called MANTIS (Multi-Agent Needs and Traitspace Intelligence System), where the goal is to utilize personality data to predict behavior of individuals in a collective, when responding to external threat-based stimuli.

Historically, personality based research has cited the FFM as a robust measure that captured an individual's personality traits with minimal assumptions. [11][9] Meta-analysis of traits is a robust research topic that has been widely used to understand the influence of factors that contribute towards the development of a personality profile. Meta-analysis provides context to the relationship between lower-order facets of personality and the higher-order factors that are described by instruments such as the Five Factor Model.[12] Meta-analysis of the factors of FFM have enabled researchers to extrapolate sample-based insights to populations, by predicting organizational behavior [6], educational motivation [13] and performance [14], needs[?], and performance at the workplace [15]. This is an important consideration when building simulations with trait considerations, since the personality does not exist (or evolve) in isolation. Traits function as a facet of a person's life journey that potentially has the power to shape the way they engage in their lifestyle. [16][17] Similarly, the personality factors do not contribute in isolation, rather the interplay shapes different criteria that are imbued in the contextual decision-making processes of humans. One of the major problem areas of Agent Based Models with respect to traits has been its heavy reliance on rule-based (or scripted) behavior of the agents in the model. [18] Another issue that needed to be addressed often is the frequently implemented "single-use" agent based models that neither are generalizable [19] nor utilize a scientifically robust framework such as FFM. [20] The proposed MANTIS framework is aimed at extending the predictive behavior of intercorrelated personality matrices and address this problem-space by

laying its foundations based off principles derived from Industrial and Organizational Psychology, within the context of trait-driven workplace related behavior.

As of this research (excluding its predecessor [1]), there has yet to exist another piece of literature that applies high dimensional traits based inputs in the context of multi-dimensional Schelling’s Model. The major contribution of this research is to establish a foundation for ABM frameworks to incorporate correlated personality data and apply it to the context of crowd-based threat response models. This research also attempted to analyze the pre and post simulation Local Moran’s I spatial arrangements of the agents and compare the effect of uncorrelated inputs to correlated inputs.

2 Literature Review

Section 2.1 provides an overview of the Schelling’s Segregation Model which is the core algorithm behind HDPSM. Section 2.2 provides an overview of the five factors that the agent’s personality comprises of and a brief history on the meta-analysis conducted previously to develop intercorrelation matrices, that serve to provide a more realistic personality vector for the agents. This section also provides the context on the relevancy of using correlated values when working with personality-based ABM and social simulation.

2.1 Schelling’s Segregation Model and Extensions

Schelling’s Model of Segregation was one of the oldest and most influential models that simulated human nature in the field of Agent Based modelling. [21][22] The core idea proposed was that minor preferences at the micro-level of an agent (representing a human) over time could lead to macro-patterns being perceived as segregation. The resultant arrangement could communicate to an observer that the agent deliberately had high affinity towards it’s same type rather than a small preference (33 percent). [22] This core idea has been pivotal in understanding social dynamics in the field of residential segregation [23] and social network preferences. [24] Multiple models have traditionally limited themselves to binary agent systems to investigate tolerance towards values and ethnicity [25], multicultural segregation [26], and applying game theory concepts to the core algorithm (segregation was the result of the best-responses of the agents) [27], and this has been one of the major problem-spaces of Schelling’s Model research.

One of the earliest multi-dimensional identity based theories within the a spatial context was by [28]. According to [29] majority of the current studies assumed an unchanged ”identity” of an agent across a simulation, which limited the dynamic behavior of the agent. [30] presented research related to multi-dimensional Schelling Models which noted that if demand for similar neighbors was left uncontrolled, it could destabilize an otherwise stable system of arrangement for agents. The research also concluded that similarity with neighbor, rather than being identical, played an important role, when agents converged to a stable system with no segregation. This result was also corroborated in [1] where the HDPSM with uncorrelated personality vectors formed a lesser segregated stable system when switched to comparison with Cosine similarity rather than equality. [1] also found that as the number of agent types

increased, the threshold of acceptance for each agent type decreased to attain stability. [31] explored Schelling’s model with multi-dimensional preference-based agents within the context of urban dynamics. The research noted that heterogeneity in individual desires for socio-environmental factors contributed to urban segregation patterns. Higher diversity of spatial hubs resulted in lower segregation indices based on absolute differences in agent type proportions per hub and the mean proportion.

One of the other areas that has lacked in the application of the Schelling Model, is personality based social simulation. [32] in their research conducted an empirical analysis of the role of individual characteristics in segregation of seating arrangement, in the absence of an evident criterion. This did not employ personality factors directly, however the behavior was implied to be affected by the psychological background of the individual, which is influenced by personality [17]. A recent study [29] applied a behavioral layer to the multi-dimensional identity based Schelling Simulation, to investigate the effects of evolving identities’ role in segregation behavior. However, the limitation still remained of having a binary agent-type system and non-existent behavioral factors for all agents in the salience rules for the identity guide. [33] presented guidelines on the development of fine-grained human behavior models for ABM simulations. The authors defined fine-grained as the ability to represent behavior as an aggregate of personality, affect, and stress. The research however, did not elaborate upon the lower-order factors for the components. It provided significantly robust foundation to follow for frameworks such as MANTIS, to simulate more accurate models of human behavior.

Regardless of the limitations, Schelling’s Segregation Model has remained one of the strongest and most applicable ABM techniques to study macro-behavior based on micro-level preferences. One of the primary reasons for consideration of the Schelling Model as the base simulation driver for this research can be attributed to its adaptability and applicability in addressing problem spaces that go beyond social simulation, such as liquid models [34], spin models [35], fractals [36], topology analysis [37], social network analysis [38] among others.

2.2 Meta-Analysis of Personality and Applicable Criteria

Meta-analysis has proved to be an important tool for investigating the relationship between personality and other aspects of human lives, such as personal and social constructs. [39] Statistical reviews of the existing literature of personality have provided correlation between personality and criteria such as motivation [8], academic performance [13], organizational performance [10], culture[5], and leadership [40]. Meta-analysis, within the context of this research, was important to understand the population-level effects between personality and criteria and evaluate its generalization and applicability across domains. [6] Meta-analysis also enabled researchers to conduct multivariate analysis and regression analysis, to analyze whether traits can function as predictors of the criteria being investigated. [41]

[10] conducted one of the most robust meta-analysis on personality factors’ inter-correlations on work performance and outcomes. Their research provided important insight into three existing FFM intercorrelation matrices that have been used in multi-variate analysis with respect to Organizational Psychology criteria to predict

workplace performance. The Ones matrix [7], Mount matrix [8], and van der Linden matrix [9] were found to be commonly used matrices that were referenced widely by other researchers to "reduce second-order sampling error and provide more precise estimates of FFM intercorrelations." [10] (p. 1491) These intercorrelation matrices could also be used in weighted equation modeling and path modeling for multivariate analysis of personality factor variables as mentioned in [41]. [10] investigated the impact of FFM matrix choice on meta-analytic multivariate analysis, generation of new meta-analysis based specifically on employee data, and sources of differences in FFM intercorrelations. They presented their findings in the form of a framework to select meta-analytic FFM matrix specific to the context that required it. For the purposes of this research, according to the proposed guidelines, since only explicit FFM measures were used as the source of data and the criteria being evaluated is workplace performance, utilizing their analyzed values [10] (p.1497) would be sufficient.

[13] in their study conducted a meta-analysis of the FFM model of personality and academic performance relationships. They stated that meta-analytical approaches to prior literature and factorial models of personality, including FFM, proved pivotal in changing the earlier viewpoint of personality and academics not being related. [42] They state prior literature that moderately relates Agreeableness with cooperation in learning processes, effort, and focus on learning [43] [44]. Conscientiousness was related to achievement pursuit [45] and goal setting [46]. [43] also stated that highly neurotic individuals had reduced academic performance, and highly extroverted individuals had increased performance due to higher desire to learn. Openness was cited as representation of an "ideal" student [44]. The authors concluded with suggesting that personality should have a more important role when considering research related to academic performance, due to its high associativity. They stated that Conscientiousness had the strongest correlation with academic performance, however researchers must account for moderating factors of academic level, age, and any interaction effects between the simulation variables.

[33] for their research investigated building "fine grained" multidimensional human behavior models for simulation. This entailed the model being based on valid real-world observed values, and derived from past literature in social sciences and behavioral studies. They stated that such agents formed the basic computational unit for Fine-Grained Agent Based Simulation Models (FG-ABSM) which helped study macro-level effects derived from complex pairs of behavior-outcome based simulations. Prior literature for FG-ABSM had explored human performance [47], military training [48], and individual cognition and affect driven agents [49]. Meta-analysis of personality i.e. application of intercorrelated matrices can be utilized to address one of the limitations in the proposed multidimensional model in the "Connecting the Fragments" and "Quantification of the model" steps of [33] where the domain expert's role was paramount to analyze and calculate the simulation parameters.

The history of meta-analysis of personality has provided more foundational knowledge for this research. Pre-existing literature has been used to generate the correlation matrices to establish a relationship between personality variable and the criteria under investigation or a relationship between the factors of FFM.

3 Methodology

3.1 Model Formalization

This research built upon the High Dimensional Personality Schelling Model (HDPSM) [1] which drew its foundation from [50] and [23]. The core of the HDPSM lay in the personality vector attribute of each of the population type, that drove the Schelling Behavior. This research utilized intercorrelation matrix derived personality factors rather than the original research’s random values.

The HDPSM is a traits based extension of the classical Schelling’s model [1] [21] in which the agents possess a five-dimensional weighted personality vector (1), that it utilizes to compare its similarity with its neighbors. The fraction of similar neighbors dictates the movement of the agent, which leads to clustering behavior. One of the limitations mentioned in the original study was the usage of purely random, independent weights in the personality vector derived from a Central Personality Value Matrix (CPVM) (See Section 3.3). The current research addresses this pitfall by implementing HDPSM with weights derived from multiple linear regression from an intercorrelated matrix. This intercorrelation matrix was extracted from meta-analysis of prior research conducted on the Five Factor Model of personality and the personality-criteria relationships studied in fields such as Industrial and Organizational Psychology, as stated in Section 2.2. For a general agent G , w_k ($k = 1, 2, 3, 4, 5$) are the associated weights of the five personality factors and can be represented as:

$$P_G = \{w_1O, w_2C, w_3E, w_4A, w_5N\} \quad (1)$$

The similarity between agent G and the neighbor n is calculated using Cosine Similarity between the personality vectors (4). Each agent at cell h has a threshold value for this similarity (T_{sim}), which can be adjusted to reflect how accepting the agent is of its neighborhood $U(h)$. Once all the neighboring agents that equal or exceed T_{sim} are noted (based on a 3x3 Moore Neighborhood [51]) it is used to calculate the satisfaction ($f_G(h)$) generated by the current neighborhood (2). The agent’s decision to move or not lies on whether f_G exceeds the acceptance threshold (T_G) as defined for that agent.

$$f_G(h) = \frac{SimilarNeighbors(h)}{TotalNeighbors(h)} \quad (2)$$

where

$$SatisfiedAgent(G) = \begin{cases} 1, & \text{if } f_G \geq T_G, \\ 0, & \text{if } f_G < T_G. \end{cases} \quad (3)$$

$$Similarity(\mathbf{P}_G, \mathbf{P}_n) = \frac{\mathbf{P}_G \cdot \mathbf{P}_n}{\|\mathbf{P}_G\| \|\mathbf{P}_n\|} \quad (4)$$

For a more detailed model formalization of HDPSM and its differences with respect to Classical Schelling’s Model, please refer to Section 3.1 and Section 3.2 in [1].

The major change in HDPSM is the introduction of intercorrelation matrices to generate personality vector of the agent. As stated in Section 2.2, prior researchers

have investigated the interdependence of the five FFM traits on each other via meta-analysis to generate intercorrelation matrices. This research's simulation utilized a multiple regression model for each factor, and used the remaining factors to derive regression weights using a predictor correlation matrix (and its inverse). From a larger intercorrelation matrix, the predictor correlation matrix (R_X) is extracted to compute the β coefficient vector. The regression coefficients (β_X) for each factor was used to define the interaction prediction equations in terms of the remaining factors. Then the coefficient of determination (R^2) for each factor was calculated to evaluate the predictive strength of each equation and representing the extent to which a target factor can be represented based off the remaining factors. For example, the predictor correlation matrix for Openness (R_O) (5), the openness correlation vector (r_O) (6), and the coefficient vector (β_O) is given below (7). The agent in this simulation contains three types of personality vectors that are used based on the information provided:

- The pure personality vector which is comprised of random values for O,C,E,A,N (initial personality vector)
 - The CPVM was used in accordance to prior research [52], as the starting value for personality.
- The predicted personality vector, obtained by using the β coefficient vector of standard multiple regression as weights
- The criteria correlated predicted personality vector, obtained by adding a portion of the correlation between a specific factor and criteria

$$R_O = \begin{bmatrix} 1 & r_{CE} & r_{CA} & r_{CN} \\ r_{EC} & 1 & r_{EA} & r_{EN} \\ r_{AC} & r_{AE} & 1 & r_{AN} \\ r_{NC} & r_{NE} & r_{NA} & 1 \end{bmatrix} \quad (5)$$

$$r_O = \begin{bmatrix} r_{OC} \\ r_{OE} \\ r_{OA} \\ r_{ON} \end{bmatrix} \quad (6)$$

$$\beta_O = R_O^{-1} r_O$$

$$\beta_O = \begin{bmatrix} \beta_C \\ \beta_E \\ \beta_A \\ \beta_N \end{bmatrix} \quad (7)$$

The standardized multiple regression coefficients are used to develop prediction equations (8) which present each factor as a linear combination of the remaining factors.

$$\begin{aligned}
O_{pr} &= \beta_C C + \beta_E E + \beta_A A + \beta_N N \\
C_{pr} &= \beta_O O + \beta_E E + \beta_A A + \beta_N N \\
E_{pr} &= \beta_O O + \beta_C C + \beta_A A + \beta_N N \\
A_{pr} &= \beta_O O + \beta_C C + \beta_E E + \beta_N N \\
N_{pr} &= \beta_O O + \beta_C C + \beta_E E + \beta_A A
\end{aligned} \tag{8}$$

A second added component to the correlation based equations is the correlation between the personality factors and an evaluation criteria that provides the context for the measured factor intercorrelation. For example, prior research has found various intercorrelation matrices for different criteria such as job performance, education, etc (see Section 2.2). The HDPSM accounts for criteria-based correlation for specific facets of the personality factors in question (for example leader effectiveness, job satisfaction, self-efficacy, etc.) which have been elaborated in [10]. This criteria also contributes to MANTIS's "Need" component, which will enable researchers to structure the correlation matrices based on the "need to fulfill" a facet of personality (for example a need to achieve high job satisfaction if considering the One's intercorrelation matrix applied to Organizational Psychology).

The associated criteria possessed correlation values with all five factors of personality was then used to calculate the overall correlated personality vector (9) possessed by an agent. For each active criteria being accounted for (determined by the researcher before runtime), the current value of the predicted criteria value for a personality factor (X_i) is updated by adding a proportion r_i of itself, which is the correlation between factor and criteria. Once the value is set for one criteria, this updated value is then used as input for calculating the predicted criteria value of the same factor for the next criteria(X_{i+1}).

$$X_{i+1} = X_i(1 + r_i) \quad \begin{cases} i = 0, \dots, n \\ X = \{O, C, E, A, N\} \end{cases} \tag{9}$$

The starting randomized personality equations, correlation based prediction equations, and criteria correlation based prediction equations were all normalized using Euclidean Normalization [53] to unit length (10). This enabled the vectors to treat the weights as coefficients indicating the importance of the factor in the overall equation. This also mapped each factor to their own directions in a multidimensional space, since prior research has shown the orthogonal relationship between the five factors in FFM (see Section 2.1).

$$x_{i\text{norm}} = \frac{x_i}{\sqrt{\sum_{j=1}^n x_j^2}} \quad i = 0, \dots, n \tag{10}$$

where $n = 5$ based on the five factors of FFM (Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism).

In the event that there was no intercorrelation matrix provided, the simulation assigned randomized weight values to be used in place of the β coefficient vector. In the event that there were no personality-criteria correlation data, the agent’s predicted personality equations were the same as the criteria-based predicted personality equations.

3.2 Implementation

This research utilized the same platform used to develop HDPSM. The simulation was made in Unity game engine (version 2022.3.62f3) and all code was written in C# language. The simulation space involved a grid of 50x50, for a total of 2500 occupiable spaces. The Moore’s Neighborhood was 3x3 Queen Contiguity. Each simulation iteration lasted for one tick of the default Update function of Unity, and simulations were allowed to run until either the system became stable or 2500 iterations had been completed.

The computation process utilized Unity’s Scriptable Object feature that allowed for creating the two primary persistable and serializable data structures used in the simulation. The first was the Correlation Profile that contained data related to the intercorrelation matrix, metadata of meta-analysis source, and calculations required for obtaining the multiple regression coefficient vector. The second was the Agent type, that contained a reference to the Correlation Profile, the initial FFM personality structure, the three personality vectors (pure, prediction, criteria-correlated), and the rest of the agent metadata such as ID, color, satisfaction threshold, and agent type. The calculation of the multivariate regression coefficients, R^2 scores, and personality equations were done before the simulation started for each agent type.

The inputs of the simulation’s personality equations were based on three widely used FFM based intercorrelation matrices to calculate the prediction and criteria-based personality equations (Equation 8), as well as R^2 values (per factor). The matrices were derived from [7] (Table 3, p. 129), [8] (Table 3, p. 463), and [9] (Table 3, p. 319) and the corrected values were used as presented in [10] (Table 1, p. 1493). This research treated the Neuroticism (N) component as the inverse of the reported Emotional Stability (ES) by reversing the sign, which is consistent with existing FFM literature. [10] in their research also presented guidelines to generate synthetic intercorrelation matrices to use in multivariate analysis and used the methodology to generate a synthetic matrix for FFM-work performance related research [15]. This research adds this synthetic matrix as a fourth source for prediction equations. The Correlation Profile Scriptable Object holds this information in separate objects to facilitate modularity and easy swapping of profiles for agents.

Finally, the spatial relation was calculated at the beginning of the simulation and at the end (when stability was achieved) and the results were evaluated using the Local Moran’s I Index of Spatial Association [54][23] to classify clustering behavior.

3.3 Evaluation & Validation

The HDPSM was generated for $T_G = 0.33$ since this was the value mentioned in Classical Schelling’s Model where the system first attained stability. The HDPSM had five types of agents, all equally distributed over the grid tiles (18% each with remaining 10% empty spaces) and the composition of the core personality vector for all five types was done pre-start of the simulation. The similarity threshold for all HDPSM agents was set as $T_{sim} = 0.8$.

The CPVM was used to set the starting values for all factors of the pure personality vector. Each row of the CPVM represented one of the agent types (A, B, C, D, E) and each row’s elements represented one of the FFM factors. The dominant-trait CPVM ($CPVM_d$) one of the elements in each row was set to 0.9 to set it as the dominant-trait in the personality vector. For future research, the non-dominant trait CPVM ($CPVM_{nd}$) would have all the elements as 0.5, to not bias the personality vector towards a specific vector and let the dominant traits emerge organically after the randomized shifts. For the purposes of this research, only the $CPVM_d$ was used to generate the pure personality values.

Two layers of randomized shifts were applied (each during a specific stage) to create unique personality vectors at the individual agent level. Equation 11 is the first layer of randomized shift along the central personality value (for dominant traits). This is applied directly to the CPVM, and the resultant absolute value is taken (to ensure the scale remains between 0 and 1). This shift is done before simulation start to prepare it for generating the predicted personality vector (using β -coefficients). The shift range was chosen arbitrarily and did not reflect any empirical estimates.

$$shift_d(P_G) = \begin{cases} [-0.1, 0.05], & \text{if } P_{ij} = 0.9, \\ [-0.3, 0.3], & \text{if } P_{ij} = 0.1 \end{cases} \quad (11)$$

The second shift was applied to the final personality vector (which can be either the pure vector, the prediction vector, or the criteria-based prediction vector) using the Box-Muller Transform [55] (13) when the agents first got initialized during the setup phase of the simulation (i.e. during runtime). This ensured randomization within agents belonging to one type of agent that shared the predicted personality vector. The precursor to this research [1] also induced random perturbations in per-agent personality, using the same method.

$$z_1 = \sqrt{-2 \ln(u_1)} \sin(2\pi u_2) \quad (12)$$

$$x' = x + z_1 \sigma \quad (13)$$

where u_1 and u_2 are independent samples from the unit interval, x' was the resultant shifted value of factor value x , and σ is the user defined standard deviation in the range of $[0.1, 0.3]$ (determined arbitrarily). The clamped values (in the range of $[0.1, 0.9]$) after the Box-Muller shift introduced a departure from an ideally normalized distribution at the boundaries. The constraint reflected the theoretical limits of the construct being modeled and steers away from invalid trait values. The HDPSM

simulation outputs were analyzed using Moran’s I Index of Spatial Association which is a local spatial autocorrelation statistic that classifies spatial cluster arrangements in a worldspace. The Local Moran’s I (14) was used to analyze differences in clustering and outlier effects when comparing agents with intercorrelated trait scores. The trait scores are nominal in nature and the Moran’s analysis follows the same procedure as stated in [1].

$$I_i = \frac{(x_i - \bar{x})}{S_i^2} \sum_{j=1}^N w_{ij}(x_j - \bar{x}) \quad (14)$$

where N represents total agents, j represents a neighbor agent, x_i is the post-encoded value at current cell’s location, $\bar{x}$ is the global mean, w_{ij} is the weight matrix (if neighbor then 1, else 0), and S_i^2 is defined as

$$S_i^2 = \frac{1}{N} \sum_k w_{ik}(x_k - \bar{x}) \quad (15)$$

The Moran’s encoded values can be classified into four local spatial patterns, based on an agent’s current value and it’s neighborhood spatial lag (weighted average of neighbors). All scores were permutation tested for significance (99 iterations and $p < 0.01$) to eliminate non-significant clusters. All classifications were color coded for visual significance. (Table 1)

Table 1 Local Indicators of Spatial Association classification and color code

Agent Value	Spatial Lag	Classification	Color
High	High	HH (Cluster)	Red
High	Low	HL (Outlier)	Light Red
Low	High	LH (Outlier)	Light Blue
Low	Low	LL (Cluster)	Blue
None	None	Empty	Black
Any	Any	Not Significant	White

4 Results

All simulations were run until atleast 3 stable end-configurations were achieved for each of the correlation matrix types. [1] stated that for the HDPSM, $T_G = 0.5$ was the critical threshold, thus each profile was simulated with this value and the original Schelling’s acceptance threshold value of $T_G = 0.33$. For this research, the pure personality vectors generated for each agent type was kept consistent throughout all simulations, with the Correlation Profiles and acceptance threshold values being the only attributes that changed for an agent type. The initial pure personality vectors were generated from the dominant trait $CPVM_d$ (Section 3.3, and these were used as inputs for multiple regression model. Across all models, the R^2 values ranged from

meaningful to exceptionally high (0.14 – 0.51) indicating that the underlying intercorrelation matrix based personality equations provided significant explanatory power for the interacting factors of each simulation. The classification scores for pre-simulation and post-simulation Moran’s I, the number of iterations needed to achieve a stable configuration, and the number of unsatisfied agents per iteration was also captured. Finally, the pre-simulation and post-simulation classification percentages were analyzed using a repeated-measures Analysis of Variance (ANOVA). For this research, the scope was limited to use only the prediction equations (8), and the personality-criteria correlation values (Equation 9) were used only for an initial exploratory analysis.

4.1 HDPSM and Non-Criteria Based Personality

In total, 60 different sets of values for HH, HL, LH, and LL were analyzed for each of the intercorrelation matrices with two levels of satisfaction thresholds of agents $T_G = 0.33$ and $T_G = 0.50$, after a total of 24 simulations (3 simulations each for 4 types of matrices, and each simulation had 2 thresholds). Figure 1 and Figure 2 provide summarized box-plots for both threshold values.

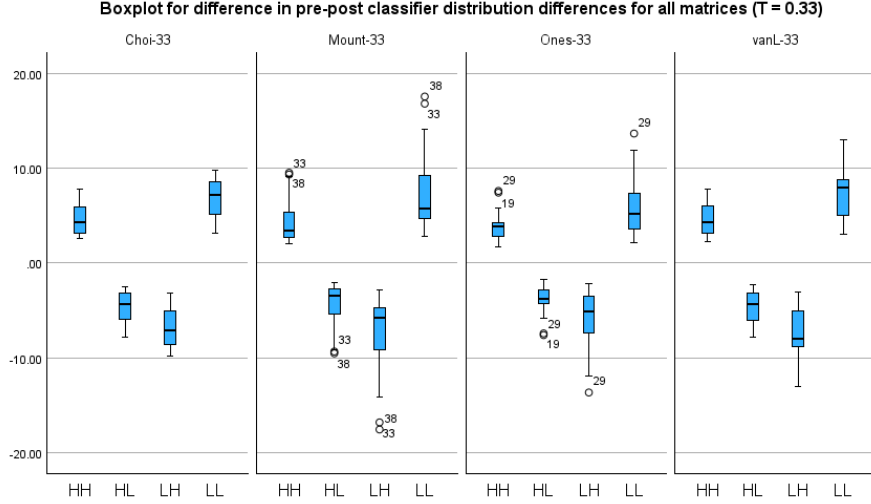


Fig. 1 Boxplot for difference in pre-post classifier distribution differences for all matrices ($T = 0.33$) (all 60 values obtained after 12 simulations)

The first set of values related to all simulations with $T_G = 0.33$. The mean, standard deviation, and standard error for HH ($M_{HH} = 4.496$, $SD_{HH} = 1.953$, $SE_{HH} = .252$), HL ($M_{HL} = -4.496$, $SD_{HL} = 1.953$, $SE_{HL} = .252$), LH ($M_{LH} = -7.034$, $SD_{LH} = 3.377$, $SE_{LH} = .436$), and LL ($M_{LL} = 7.034$, $SD_{LL} = 3.377$, $SE_{LL} = 0.436$) was calculated. Shapiro-Wilk tests revealed significant departures from normality ($p < .001$) however visual inspection of Q-Q plots only suggested moderate deviations from the normal distribution. Based on the large observed effect sizes, the analysis was retained.

A repeated-measures ANOVA also confirmed a significant effect of classifier type on pre-post simulation percentage ($p < .001$) and a large effect size (partial $\eta^2 = 0.823$). The Greenhouse-Geisser score for Mauchly's Test of Sphericity was also within accepted levels ($\epsilon_{GG} = 0.352$). Pairwise comparisons after Bonferroni adjustments also showed significance ($p < .001$) between each of the classifier types.

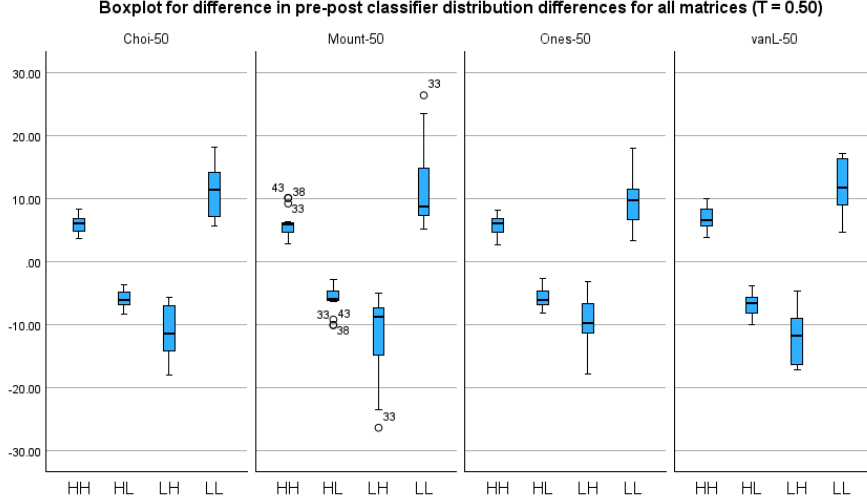


Fig. 2 Boxplot for difference in pre-post classifier distribution differences for all matrices ($T = 0.50$) (all 60 values obtained after 12 simulations)

The second set of values related to all simulations with $T_G = 0.5$. The mean, standard deviation, and standard error for HH ($M_{HH} = 6.12$, $SD_{HH} = 1.82$, $SE_{HH} = 0.24$), HL ($M_{HL} = -6.12$, $SD_{HL} = 1.82$, $SE_{HL} = 0.24$), LH ($M_{LH} = -11.11$, $SD_{LH} = 5.08$, $SE_{LH} = 0.66$), and LL ($M_{LL} = 11.11$, $SD_{LL} = 5.08$, $SE_{LL} = 0.66$) was calculated. Shapiro-Wilk tests reveal that HH and HL did not display significant deviation from normality ($p = .278$), however LH and LL deviated from normality ($p = .010$). This was confirmed by the Q-Q plots closely following the reference line suggesting approximate normality (for HH and HL). The LH and LL distributions exhibited minor deviations at the tails, which was consistent with the Shapiro-Wilk tests. Overall, departures from normality were moderate.

A repeated-measures ANOVA confirmed a significant effect of classifier type on pre-post simulation percentage ($p < .001$) and a large effect size (partial $\eta^2 = .849$). The Greenhouse-Geisser score for Mauchly's Test of Sphericity was also within accepted levels ($\epsilon_{GG} = .348$). Pairwise comparisons after Bonferroni adjustments also showed significance ($p < .001$) between each of the classifier types.

The following images (Figure 3) provide a clearer picture of the simulations before and after the main algorithm was run which utilized the underlying intercorrelation matrix based personality structure of an agent, to determine similar personality ($T_{csim} = 0.8$) between an agent and its neighbors (satisfaction threshold $T_G = 0.5$).

The simulations were carried out for the Ones, Mount, and van Linden matrices, as well as a synthetically generated Choi matrix. All simulations showed consistency in generating clusters of similar personalities post-simulation. The analysis also corroborated previous findings that higher the critical value, more prominent is the clustering effect.

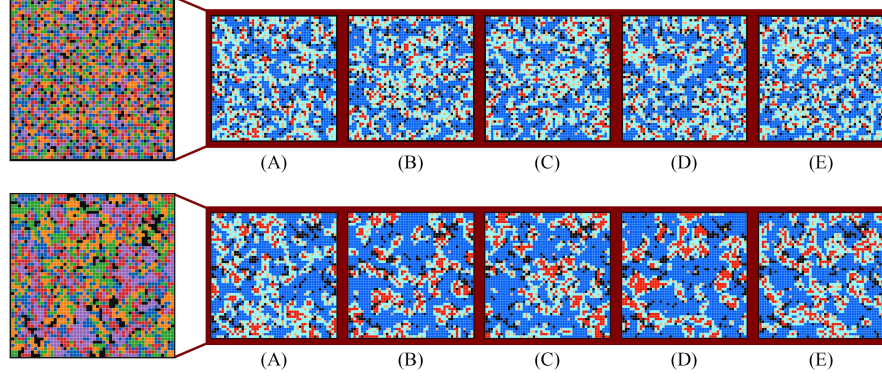


Fig. 3 Ones matrix correlated HDPSM ($T_G = 0.50$) pre-simulation (top) and post simulation (bottom) with cluster maps per agent type. Colors based on Table 1

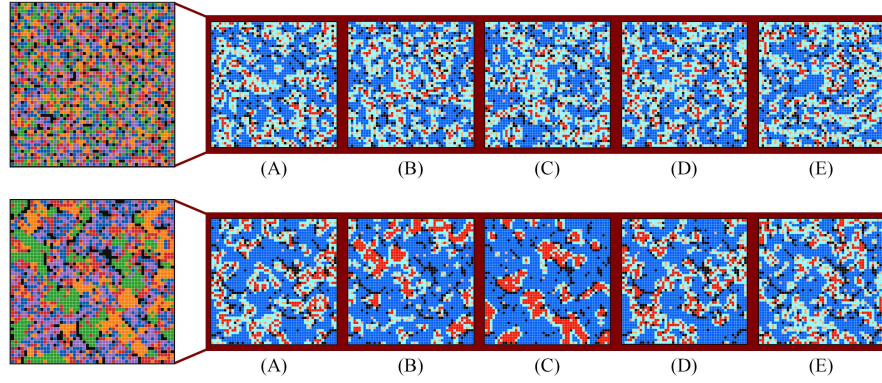


Fig. 4 Mount matrix correlated HDPSM ($T_G = 0.50$) pre-simulation (top) and post simulation (bottom) with cluster maps per agent type. Colors based on Table 1

A repeated-measures ANOVA analysis was done for each of the simulation runs' pre-post values of classifier percentages. The results indicated a significant effect ($p < .001$) of classifier type on percentage change across all four-different matrix types (and two threshold conditions). The effect sizes ranged from large (partial $\eta^2 = 0.78$) to extremely large (partial $\eta^2 = 0.913$), that indicated high levels of the variance in the outcome being attributed to the Moran's I classifier. Pairwise comparisons with

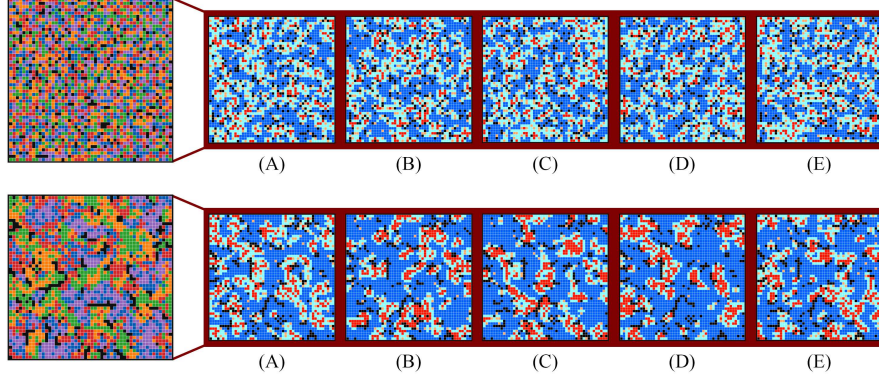


Fig. 5 van der Linden matrix correlated HDPSM ($T_G = 0.50$) pre-simulation (top) and post simulation (bottom) with cluster maps per agent type. Colors based on Table 1

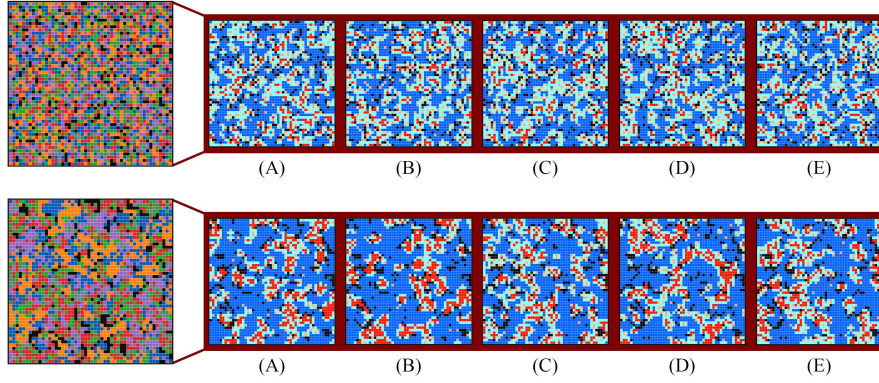


Fig. 6 Choi matrix correlated HDPSM ($T_G = 0.50$) pre-simulation (top) and post simulation (bottom) with cluster maps per agent type. Colors based on Table 1

Bonferroni adjustment also revealed significant differences between all classifier pairs, across all eight conditions ($p < .001$).

Finally, the research explored the effect of choice of intercorrelation matrix to construct personality equations and its effect in spatial correlation by conducting separate repeated-measures ANOVA on all eight pairs of chosen matrix and thresholds. According to [10], the strength of correlation between FFM traits is weakest in Ones matrix (mean $\bar{\rho} = 0.152$), moderate in Mount et. al. matrix (mean $\bar{\rho} = 0.290$), and highest in van der Linden et. al. matrix (mean $\bar{\rho} = 0.439$). The results of this research showed that the highest change in HH and LL clusters was when the van der Linden's matrix was used as the underlying structure for personality as well as van der Linden matrix having the highest effect size (Table 2). The simulation was consistent across both threshold values with the Mount matrix having a higher effect size than the Ones matrix. The classifier effects remained very large across all three chosen personality matrices (for both threshold values), which provided significant evidence of the results being robust to choice of matrix. As an added note, constructing a synthetic

matrix (Choi matrix) provided the highest effect sizes (partial $\eta_{33}^2 = .913$ and partial $\eta_{50}^2 = .906$) thus indicating the effectiveness of using synthetic intercorrelation matrices when doing traits based simulation for spatial autocorrelation, such as Schelling’s Segregation Model.

Table 2 Comparison of within-subjects effect sizes (Greenhouse-Geisser) based on chosen intercorrelation matrix

Matrix (Threshold)	F	p-value	Partial η^2
Ones (0.33)	51.795	< .001	.787
Mount (0.33)	42.655	< .001	.753
van der Linden (0.33)	109.751	< .001	.887
Choi ¹ (0.33)	147.105	< .001	.913
Ones (0.50)	79.882	< .001	.851
Mount (0.50)	50.656	< .001	.783
van der Linden (0.50)	123.640	< .001	.898
Choi ¹ (0.50)	135.229	< .001	.906

¹Choi is a synthetic matrix proposed in [10]

4.2 Non-Correlated vs. Correlated Personality Vectors

In contrast with [1] that used non-correlated personality values, the distribution of classifier values also saw visually notable increases in HL and LH classifiers, which indicated towards an underlying alteration when intercorrelated personality data was introduced. Given the limited number of simulation runs, an exploratory MANOVA analysis was conducted on one of the all dominant traits active ($T_G = 0.33$) post-simulation cluster distributions and one of the van der Linden matrix ($T_G = 0.33$) post-simulation distributions. The purpose for this comparison was to asses the effect of the introduction of a correlation-based mechanism on spatial cluster patterns, and if substantial pursue it in the future. The results of the MANOVA and descriptive analysis should be interpreted as preliminary change indicators rather than conclusive evidence of causal effects.

The results displayed significant multivariate effect ($F(3, 6) = 1.31$; $p = 0.003$; partial $\eta^2 = .891$) and indicated towards substantial clustering differences when using correlated versus uncorrelated personality data. Univariate testing revealed significant effects for HH ($F(1, 8) = 21.77$, $p = .002$, partial $\eta^2 = .731$), HL ($F(1, 8) = 21.77$, $p = .002$, partial $\eta^2 = .731$), LH ($F(1, 8) = 40.35$, $p < .001$, partial $\eta^2 = .835$), and LL ($F(1, 8) = 42.23$, $p < .001$, partial $\eta^2 = .841$).

The analysis of descriptive statistics revealed a decrease in HH (4.71%) and LL (14.63%) homogeneous clusters, whereas HL (4.71%) and LH (13.83%) outliers saw an increase. This indicated that the spatial organization of the simulated system did get altered towards a more heterogeneous clustering composition. On further visual inspection, increasing the acceptance threshold for the intercorrelation matrix based agent (T_G) i.e. a more selective agent results in a more tightly packed cluster similar to a non-matrix based agent with low acceptance threshold i.e. a more tolerant agent.

Overall, the preliminary investigation suggested that the introduction of a correlation matrix did preserve the underlying spatial pattern and also redistributed the classifier cells among the Local Moran’s I categories. This helped in producing different spatial clusters pattern when compared to the non-correlated simulation, increasing the heterogeneity of the clusters. When compared to classical Schelling’s Model and Multi Agent Schelling models, this essentially meant more visual heterogeneous composition (based on property such as color of agent), but the preservation of the clustering behavior on a spatial arrangement level.

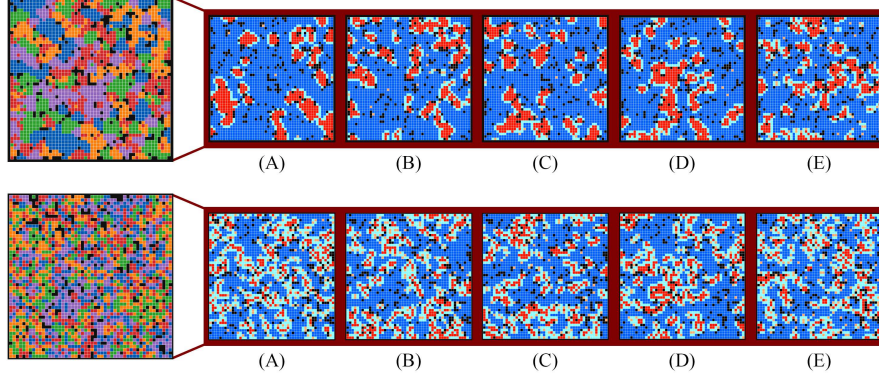


Fig. 7 Comparison between post-simulation spatial clusters of non-correlated (top) vs. van der Linden correlated (bottom) personality vector ($T_G = 0.33$)

5 Conclusion

This research presented an extension to its predecessor research’s [1] HDPSM (high dimensional personality-based Schelling Model) agent by utilizing an FFM intercorrelation matrix for generating personality vectors, rather than randomized values. The results of the simulation for this research provided significant statistical significance regarding clustering of agents possessing similar personality vectors. The results also corroborated prior findings by having the van der Linden matrix have the highest effect sizes (previously known to have the highest FFM correlation values among the three), when compared against the Ones and Mount matrices. All effect sizes were relatively high, thus supporting the robustness of the results with respect to the choice of matrix. Finally, this research was also able to utilize a synthetic matrix based on the guidelines by [10] which proved to have an even higher effect size than the van der Linden matrix, thus suggesting that validity of the construction guidelines for synthetic intercorrelation matrices when considering meta-analysed multivariate analysis.

6 Limitations & Future Work

This research does have certain limitations that should be addressed in future iterations. First, the compositional structure of classifier percentages. The results were

based on aggregation through difference, which may obscure meaningful information regarding the quality of the the underlying scores. Als, the HH, HL, LH, and LL scores are sum to a fixed total so increase in one will result in decrease in another. This dependence of the classifier measures should be considered when interpreting the difference scores. Second, the intercorrelation matrices and synthetic matrix generation are borrowed from the field of organizational psychology, which may not always be relevant when considering criteria-based personality beyond that of an employee. In the same line, matrices other than the ones mentioned in this research could produce different dynamics. Third, when considering certain randomization techniques (such as Box-Muller), the values were clamped to a range to eliminate negative personality factor values, which could introduce a departure from normally distributed values near the boundaries. This was also evident from moderate deviations in tests of normality. Finally, the limited number of simulation runs might impact the repeated-measures ANOVA, thus a larger dataset will provide with greater confidence in the generalization of these findings.

This research aims to further contribute towards the larger ecosystem of the Multi-Agent Needs and Traitspace Intelligence System (MANTIS) by augmenting the HDPSM agent with the concept of meta-analysed intercorrelation matrices to personality driven agent based simulation. Traits are not isolated silos of functions that humans can have accurate control over and representation of. The human personality is always an interplay of complex underpinnings of values, traits, facets, needs, and the interaction with each other. The researchers propose to utilize this core of HDPSM for exploring topics such as effect of utilizing various similarity calculation techniques (such as the Mahalanobis Distance), utilizing non-dominant CPVM (i.e. all values of CPVM are equal), utilizing FFM matrices beyond the field of organizational psychology, sensitivity analysis of unequal agent type distribution and thresholds, and using torroidal-worldspace for agent’s movement and hope that this framework can be utilized to look at exisiting literature under the new lens of digital simulation.

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