Using Agent-Based Simulation to Accurately Model Human Processes

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ABSTRACT

In human processes, like the Integrated Disability Evaluation System (IDES), the variability in execution of thousands of interpersonal encounters will limit the systemic predictive capability of traditional modeling methods such as regression. To combat this limitation, we developed an agent-based model that replicates every step in the IDES process and simulates the associated human actions. In effect, our model simulates a digital twin of every human involved in the process. Analysis of model outputs shows that performance metrics of individual agents in the simulation are similar to their real-world counterparts, and that aggregate system performance is highly accurate. The success of this simulation model allows for increased confidence in the predictive accuracy of what-if analysis conducted on human processes, where process changes may be modeled to inform policy recommendations.

ABOUT THE AUTHORS

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INTRODUCTION

The Integrated Disability Evaluation System (IDES) combines the Department of Defense (DoD) and Department of Veterans Affairs (VA) disability systems. Integrating these systems improves the accuracy and consistency of disability determinations and the timeliness of providing both DoD and VA disability benefits to eligible Service members (DoD Warrior Care, 2019). Service member data is collected by government representatives throughout the IDES using the Veterans Tracking Application (VTA). The types of data collected include demographic and system progress information, which are used to assess IDES performance through metrics such as system timeliness and inventory.

Booz Allen Hamilton provides predictive analytic support to the IDES, so that policy directors can be informed of the potential systemic effects that policy changes can cause. Through exploratory data analysis and subject matter expert interviews, Booz Allen Hamilton realized that the variability caused by the human nature of the system was difficult to quantify using traditional statistical methods such as regression. Due to the human variability, we decided that an agent-based simulation would be the best approach to understand and replicate the system.

METHODS

Agent-based simulation is a computational modeling technique that simulates the actions and interactions of autonomous entities (agents) to assess their effect on the system as a whole (Moshref-Javadi, 2019). This technique is particularly effective in the simulation of human systems, as agent-based models can capture emergent phenomena –a whole that is greater than the sum of its parts – which frequently escapes data collection (Bonabeau, 2002). The massive quantity of individual decisions required in the IDES was key in the decision to implement agent-based simulation.

We utilized AnyLogic, a multi-method modeling software, to build its agent-based model with the goal of replicating the IDES. We began by mapping out the IDES process step-by-step and identifying the agents that perform actions at each step. Then, we conducted subject matter expert interviews to determine the timeliness and frequency of potential agent actions and collected information on the business rules restricting these actions. Next, we created agent profiles for all service members whom entered the IDES in 2018 (VTA data) and calibrated our model. Finally, we performed an evaluation of our results at the overall process and stage-by-stage levels.

Mapping the IDES Process

At a high-level overview, the IDES consists of 4 main phases, which contain a total of 11 core process stages and 5 Service member initiated actions (see Figure 1)(DoD Warrior Care, 2019).

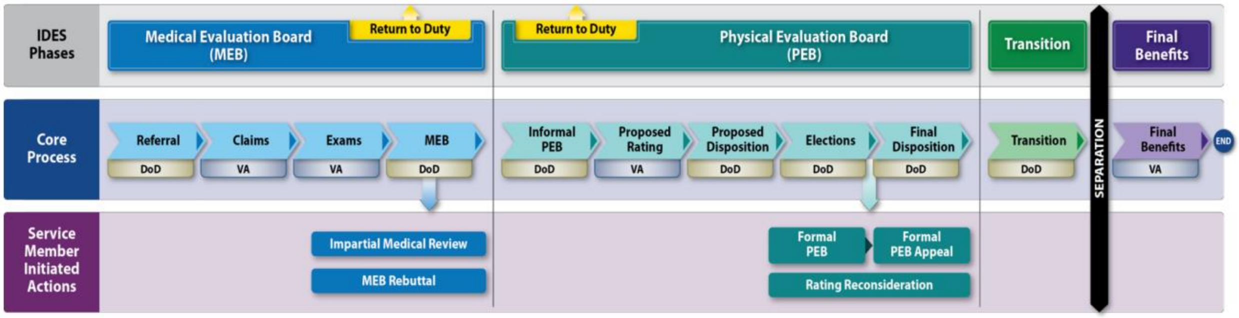

Figure 1: High-Level IDES Overview

Each of the core process stages and Service member initiated actions requires a series of interactions between IDES government employees and Service members to be considered complete. For modeling purposes, we focused on digitally re-creating these interactions by identifying the agents (Service members and employees) involved and estimating the timeliness of each interaction. Additionally, we identified the correct sequence of the interactions and all potential outcomes of each interaction.

Modeling each interaction of agents in the IDES process was paramount in our development process, as it allowed increased confidence in the predictive accuracy of what-if policy analysis.

Subject Matter Expert Interviews

Due to the extensive and complex nature of the IDES process, subject matter expert (SME) interviews were required to validate our digital representation of process interactions and help formulate assumptions for simulation. Specifically, we interviewed every type of DoD and VA personnel that work on the IDES process and ensured that our understanding of each interaction was an accurate representation of their actual work function. Some key systemic assumptions presented to SMEs can be seen in Table 1.

Table 1: Systemic assumptions presented to SMEs

Assumptions
All Service members go through the same IDES process, specific to their service
A Service member may only be in one stage at a time
All interactions include a maximum of 1 Service member and 1 personnel
Queueing operates as first in first out (FIFO)
Service members may only interact with personnel at their assigned Medical Treatment Facilities (MTFs) and Physical Evaluation Board (PEB) sites
Service members enter the IDES according to VTA data
Service members elect for Service member initiated actions at the rate represented by VTA data
Service members are returned to duty at the PEB sites at the rate represented by VTA data

These interviews were important in model development, as only SMEs who are familiar with the process are in a position to judge whether important decision points and underlying theory are appropriately integrated into the structure of the model (Kuntz et. al, 2013).

Creating Agent Profiles

Once our digital representation of the IDES process interactions was validated by SMEs, we created agent profiles for every Service member and personnel present during the simulation period. These agent profiles allow us to analyze and evaluate each interaction in our simulation. Information included in the DoD and VA personnel agent profiles can be seen in Table 2.

Table 2: DoD and VA Personnel Agent Profile

Characteristic	Description
Location	The MTF or PEB site where this person can interact with Service members
Job Profile	The job title of this person
Organization	The organization that this person works for
Function	The interactions that this person can perform

Information included in the Service member profile can be seen in Table 3.

Table 3: Service Member Agent Profile

Characteristic	Description
Location	The MTFs and PEB sites where this person can interact with DoD and VA personnel
Service	The military service of this person
Referral Date	The day which this person enters IDES
Condition Profile	The profile of condition(s) for which this person in referred to the IDES
Current Stage	The current stage of the IDES process that this person is undergoing
Previous stages	The path of stages in IDES that this person has already completed
Current Task	The current interaction that this Service member is undergoing, where it is happening, and with which personnel
Leave	Whether or not the Service member is on leave, and how much leave they have taken

Residual Calibration

Due to the large number of hand-offs between personnel in the IDES process, there is a significant amount of processing time that is not explained or is external to the digital representation of the system. We call this residual time. Some examples of this residual time are: appointment scheduling, official document requests, shipping of documents and packages, and Service member election consideration time. Residual time in the simulation model is measured as an average over the simulation period as defined in Equation 1.

$$Residual\ Time = \frac{\sum_{i=1}^{n} V_t}{n} - \frac{\sum_{i=1}^{n} M_t}{n} \tag{1}$$

Where V_t is the VTA timeliness value and M_t is the model timeliness value for each month in the simulation period. An example visualization of stage-by-stage residual time can be seen in Figure 2.

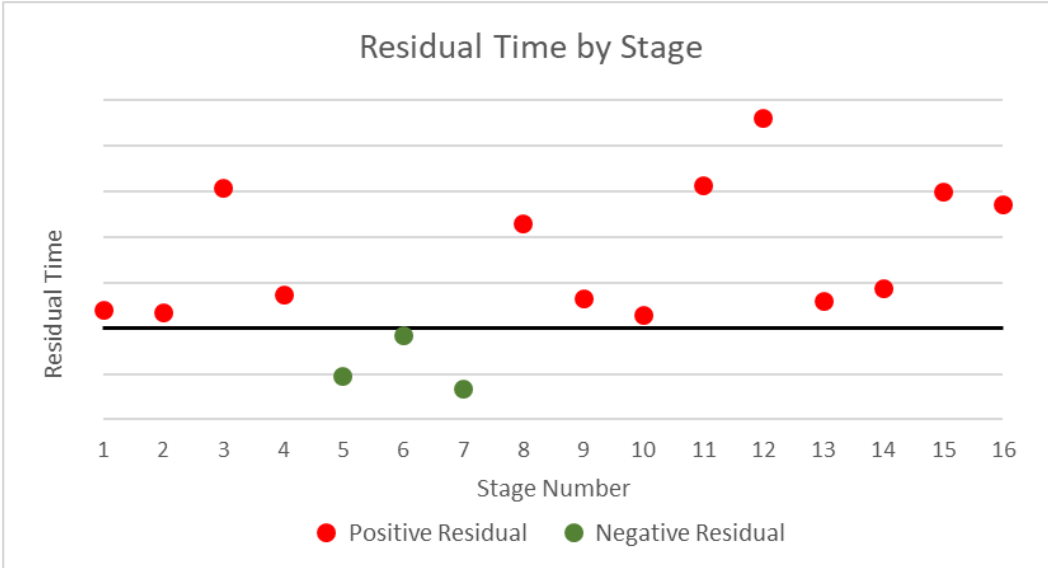

Figure 2: Residual Time by Stage

Once determining the residual time for each stage, we assigned each stage in our model a lognormal distribution of residual times, with parameters shown in Equation 2. Each time a Service member completes a stage, they will sample from the lognormal distribution of that stage and wait that amount of time before commencing the next stage.

$$\mu = \begin{cases} \mathbf{log}(Residual\ Time) & if\ Residual\ Time > 0 \\ -100 & if\ Residual\ Time \leq 0 \end{cases} \qquad (2)$$
$$\sigma = 0.15$$
$$\min = 0$$

We then ran our model in "calibration mode", iterating $\boldsymbol{\mu}$ each simulation run until all stages no longer require a change in $\boldsymbol{\mu}$**.** The requirements for changing $\boldsymbol{\mu}$ are seen in Equation 3.

$$\mu = \begin{cases} \mathbf{log}(RT_B) & if\ \dfrac{|RT_A - RT_B|}{RT_A} > 0.05 \\ \mu & if\ \dfrac{|RT_A - RT_B|}{RT_A} \leq 0.05 \end{cases} \qquad (3)$$

Where RT_A is the residual time of the previous simulation run for that stage and RT_B is the residual time of the current simulation run for that stage. After a simulation run in which $\boldsymbol{\mu}$ is unchanged for all stages, the model is considered calibrated and prediction validation can begin.

Evaluation Techniques

After calibrating our model, we ran a simulation of calendar year 2018 with an initial Service member agent population that mirrored the Service members in the IDES on January 1, 2018 according to VTA data. Upon completion of the simulation, we conducted evaluations of the results at the IDES process and stage-by-stage level to better understand the predictive capabilities of our model.

IDES Process Predictions

We evaluated our model's IDES process level predictions in two separate ways. Our first evaluation technique was to calculate the accuracy in a variety of statistics that describe the distribution of Service member timeliness through the IDES – namely the mean, median, mode, standard deviation, interquartile range, spread, mild outlier low, and mild outlier high of the timeliness distribution. The second evaluation technique that we employed was to calculate the percent overlap of probability density functions of VTA and simulated Service member timeliness through the IDES. The formula for accuracy in this paper is defined in Equation 4.

$$\boldsymbol{Percent\ Accuracy} = \left(\mathbf{1} - \frac{\mathbf{1}}{\boldsymbol{n}}\sum_{\boldsymbol{i=1}}^{\boldsymbol{n}}\left|\frac{(\boldsymbol{R_i} - \boldsymbol{F_i})}{\boldsymbol{R_i}}\right|\right) * \mathbf{100\%} \tag{4}$$

Where R_i is the real (observed) value from VTA and F_i is the forecasted value from the simulation for each month in the simulation period. The formula for percent overlap of the VTA and simulated Service member timeliness probability density functions is defined in Equation 5 (Pastore & Calcagni, 2019).

$$\boldsymbol{Percent}\ Overlap\ (A, B) = \left(\int \mathbf{min}[f_A(x), f_B(x)]\, dx\right) * 100\% \tag{5}$$

Where $\boldsymbol{f_A(x)}$ and $\boldsymbol{f_B(x)}$ are the probability density functions of VTA and simulated Service member timeliness for the simulation period, respectively.

Stage-By-Stage Predictions

We evaluated our model's stage-by-stage level predictions by weighting the timeliness accuracy values for each stage, and subsequently taking the sum of weighted accuracies for all stages. The weighted accuracy of each stage is dependent on the number of Service members who go through that stage during the simulation period according to VTA data. The formula for weighted accuracy of a stage is defined in Equation 6.

$$Weighted\ \boldsymbol{Accuracy}\ (A) = Percent\ Accuracy * \frac{SM_A}{\sum_n SM_n} \tag{6}$$

Where, according to VTA data, SM_A is the number of Service members exiting a stage during the simulation period. The formula for stage-by-stage accuracy is the sum of all weighted accuracies, as defined in Equation 7.

$$Stage\ by\ Stage\ Accuracy = \sum_n Weighted\ Accuracy_n \tag{7}$$

RESULTS AND DISCUSSION

When evaluating our model's IDES process level predictions, we found that our Service member timeliness predictions were highly similar to historical values as indicated by the model accuracy values in Table 4. It should be noted that the range of model accuracy values in Table 4 are referencing a single simulation, and the minimum and maximum accuracy values by service.

Table 4: IDES Model Evaluation Timeliness Metrics and Accuracy (12-month simulation)

Statistic	Model Accuracy (Min-Max)
Mean	91-99%
Median	87-97%
Mode	84-100%
Standard Deviation	88-99%
Interquartile Range	84-100%
Spread	84-100%
Mild Outlier Low	87-95%
Mild Outlier High	89-98%

The high levels of accuracy in Table 4 are significant in the fact that they validate our ability to predict key aggregate performance metrics of the IDES process. This achievement increases confidence in future simulations by demonstrating our ability to replicate real-world systemic results from historical data.

Upon evaluation of our model's Service member timeliness distributions, we found that the percent overlap between simulation and VTA was 80-88% on a service-by-service basis. An example of our percent overlap analysis can be seen in Figure 3.

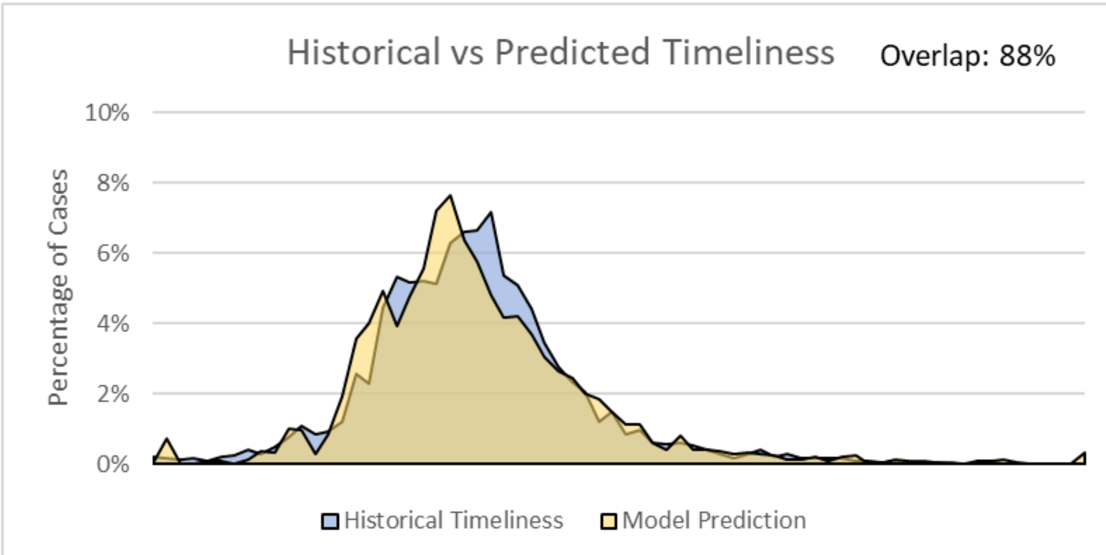

Figure 3: Predicted and Historical Timeliness Distributions (12-month simulation)

Due to the significant overlap of our simulation distribution with that of VTA, we can simply say that – in terms of IDES process timeliness - these Service member populations are similar (Pastore & Calcagni, 2019). The similarity of these populations is important in the application of our model, as it indicates that our simulated population will respond to policy or process changes in a manner near to the real population. Because of this, our model can be confidently used to perform what-if analyses regarding the impact of broad policy or process changing initiatives.

When evaluating our model's stage-by-stage level predictions, we found that our Service member timeliness predictions were generally highly accurate when compared to historical values, with an infrequent tail towards lower accuracy on a service-by-service basis as indicated by Table 5.

Table 5: Stage-By-Stage Model Evaluation Timeliness Accuracy (12-month simulation)

Min Accuracy	Max Accuracy	Average Accuracy
77%	97%	90%

The high levels of accuracy in Table 5 are significant in the fact that they validate our ability to predict Service member timeliness on a stage-by-stage basis. This achievement increases the scope of experiments for which our model may be used. Specifically, the high stage-by-stage accuracy allows for a more detailed evaluation of what-if analyses regarding policy or process changes by highlighting specific points in the IDES process that are most impacted in each scenario.

Due to the high accuracy of our simulation under multiple evaluation criteria, further exploration is recommended in using agent-based models to replicate and predict on large scale human processes. We believe that this technique will prove most valuable where what-if analysis on process change is desired.

REFERENCES

Dod Warrior Care. (2019). Integrated Disability Evaluation System (IDES). Retrieved from https://warriorcare.dodlive.mil/disability-evaluation/integrateddes/

Moshref-Javadi, M. (2019). Discrete Event and Agent-Based Modeling and Simulation. Retrieved from http://www.mit.edu/~moshref/Simulation.html

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences*, *99*(Supplement 3), 7280–7287. doi: 10.1073/pnas.082080899

DoD Warrior Care. (2019). The Integrated Disability Evaluation System (IDES). Retrieved from https://warriorcare.dodlive.mil/files/2019/05/IDES-New-Factsheet.pdf

Kuntz, K., Sainfort, F., Butler, M., Taylor, B., Kulasingam, S., Gregory, S., … Kane, R. L. (2013). *Decision and Simulation Modeling in Systematic Reviews* (p. 44). NCBI.

Pastore, M., & Calcagnì, A. (2019). Measuring Distribution Similarities Between Samples: A Distribution-Free Overlapping Index. *Frontiers in Psychology*, *10*. doi: 10.3389/fpsyg.2019.01089