System Dynamics Model for Proportionality Assessment in Military Operations

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Abstract: This research introduces a System Dynamics (SD) model for proportionality assessment in military operations. This is done under a broader perspective adopted for the collateral damage component considering two cases, as follows. In the first case only collateral physical effects are considered and in the second case a combination of physical and psychological collateral effects are considered. Furthermore, the model comprises feedback loops by linking civilian injury, death, damage to objects, and military advantage to a proportionality assessment stock. With this scope, Monte Carlo simulations over 100 time steps are conducted and revealed that incorporating psychological damage reduces the share of proportional assessments by 7 percentage points and slows the accumulation of proportional judgments. At the same time, the sensitivity analysis shows a steeper decline in proportional outcomes when psychological impacts are included. In addition, further statistical tests are conducted and from a comprehensive evaluation it can be seen that the model provides a robust and interpretable tool for exploring how different collateral-damage considerations shape proportionality decisions and can inform military rules of engagement and policy debates.

Keywords: Military operations, Proportionality, Artificial intelligence, System dynamics

1. Introduction

motto: *"War is the realm of uncertainty; three quarters of the factors on which action in war is based are wrapped in a fog of greater or lesser uncertainty." (Carl von Clausewitz)*

Advances in artificial intelligence (AI) and computational modelling over the past two decades have expanded the way how decision-support systems are built (Duan, Edwards & Dwivedi, 2019; Gupta et al., 2022). Techniques such as machine learning, agent-based modelling, and computational modelling now underpin tools that can process vast, heterogeneous data streams, uncover hidden feedback loops, and generate what-if scenarios in real time (Abar et al., 2017). In domains ranging from healthcare to urban planning, these computational approaches have enabled various stakeholders to anticipate emergent behaviours, test policy interventions in silico, and improve resilience against unforeseen shocks (Van Dam, Nikolic & Lukszo, 2012; Cools & Maathuis et al., 2025; Emami, Lorenzoni & Turchetti, 2024).

In critical societal domains where decisions carry profound ethical, legal, and humanitarian consequences, the integration of AI and computational models is particularly vital. The military context exemplifies this need: operational decisions often hinge on rapidly evolving intelligence, complex interdependencies, and stringent legal constraints (Spoor & De Werd, 2023; Kanellopoulos & Ioannidis, 2024). Such systems have the potential to transparently incorporate rules of engagement, simulate collateral-damage trade-offs, and quantify uncertainty become force multipliers for commanders and policymakers (Maathuis, 2024b; Davis, Kulick & Egner, 2025). By translating doctrine into executable models, AI-enabled tools can both enhance situational awareness and ensure adherence to international humanitarian law (Deeks, 2020; Ohja, 2024).

A central element of targeting processes in military operations is the proportionality assessment, a legal and ethical judgment that balances the anticipated military advantage of an attack against the expected harm to civilians and civilian objects (Cohen & Zlotogorski, 2021; Lekea, Lekeas & Topalnakos, 2023). The proportionality assessment comprises two core components: collateral damage, encompassing civilian injury, death, and property destruction, and military advantage, representing the operation's strategic or tactical gain. Under international humanitarian law, an attack is permissible only if the projected military advantage is not outweighed by collateral harm (Solis, 2021; Solf, 2023; Maathuis & Chockalingam, 2023; Daniele, 2024). This judgement must be made swiftly and under uncertainty, highlighting the need for computational aids that can codify and apply proportionality criteria consistently.

Although several theoretical frameworks and modelling efforts have explored proportionality assessment, ranging from formal logic formulations to probabilistic risk analyses, there remains a gap in understanding its dynamics across space and time. Existing approaches often treat proportionality as a static threshold decision rather than as an evolving process subject to feedbacks, delays, and varying operational tempos. Spatial heterogeneity (e.g., population distributions, infrastructure layouts) and temporal factors (e.g., campaign phases, resource depletion) can profoundly influence proportionality judgements yet are rarely captured in a dynamic model (Maathuis et al., 2025). To address these challenges, this research proposes a System Dynamics (SD) model that frames proportionality assessment as a stock-and-flow process, integrating expert-based rules for collateral damage and military advantage into cumulative proportional and disproportionate stocks (Radzicki & Taylor, 2008). The model explicitly contrasts two cases: Case 1, where collateral damage accounts only for physical harm, and Case 2, where psychological injury is also included. By embedding the full set of 54 scenario combinations into a continuous simulation environment, the SD model allows tracing how aggregate proportionality judgments evolve under different parameterizations.

Building on this foundation, a comprehensive evaluation of the SD model through Monte Carlo simulations is conducted, one-way and two-way sensitivity analyses, and statistical hypothesis tests. Through this approach it is demonstrated how the inclusion of psychological harm systematically shifts proportionality outcomes toward more conservative disproportionate judgments, slows the accrual of proportional rulings, and heightens sensitivity to key inputs such as injury severity, death probability, and object damage. These results reflect the model's capacity to support robust what-if exploration and inform rules-of-engagement calibration.

The main contributions of this research are threefold: (1) the development of a transparent, rule-based SD model that operationalizes proportionality assessment for two collateral-damage cases; (2) a comprehensive evaluation methodology that incorporating dynamic simulation, sensitivity sweeps, and statistical validation in order to quantify the impact of psychological harm on proportionality judgements; and (3) the demonstration of actionable policy insights revealing how spatial-temporal dynamics and feedback structures can guide adaptive rules of engagement and decision-support tool design for modern military operations.

The outline of this article is structured as follows. The second section discusses the background of this research together with relevant related studies. The third section presents the methodological approach taken to achieve the aim of this research. The fourth section provides an overview of the design and implementation aspects of the model proposed. The fifth section discusses the results obtained from the comprehensive evaluation process conducted in this article. Conclusively, in the sixth section concluding remarks and future research perspectives are tackled.

2. Research Background

SD is a modelling framework for understanding and modelling the behaviour of complex systems over time using stocks, flows, feedback loops, and time delays (Azar, 2012; Bala, Arshad & Noh, 2017). At its core, SD distinguishes between stocks, which are the accumulations or "states" of a system such as population levels, inventory, or cumulative judgments and flows, which are the rates at which stocks increase or decrease (Duggan, 2016). Feedback loops, both reinforcing and balancing, capture the causal interdependencies that generate non-linear, often counterintuitive dynamics. (Richardson, 1981; Roos, 2024). By formalizing these elements into differential or difference equations within a simulation environment, SD enables researchers and decision-makers to trace how changes in one part of a system ripple through the whole, producing growth, decay, oscillations, or equilibrium states. Importantly, SD emphasizes the endogenous structure of systems by stressing that observed patterns arise more from the system's architecture than from isolated external events (Richardson, 2011; Naderi et al., 2025).

The role of SD spans disciplinary boundaries, providing a unifying language to analyse socio-technical, economic, environmental, and organizational phenomena (Moradkhani,, 2023). In military contexts, SD can reflect how doctrines, force posture, collateral damage considerations, and public perceptions interact over the course of a campaign or crisis (Bakken & Gilljam, 2003; Koivisto, J., Ritala, R., & Vilkko, 2022). By explicitly modelling the feedback between, for example, civilian harm and political support, or between resource depletion and operational tempo, SD helps identify leverage points where modest policy adjustments yield outsized effects. Its implications extend to policy design: rather than reacting to surface-level symptoms, commanders and planners can anticipate policy resistance, unintended side-effects, and traps caused by reinforcing cycles. SD's capacity to surface these systemic risks makes it an indispensable tool for strategic foresight and what-if scenario testing (Kohler, 2021; Kunc, 2024).

SD modelers start by capturing design aspects and building causal loop diagrams to map out perceived key relationships and potential feedback loops. These qualitative maps are then translated into quantitative stock-and-flow models, parameterized with empirical data or expert judgments. In this process, simulation experiments can range from baseline runs to extensive sensitivity sweeps across uncertain parameters in order reveal the robustness of proposed interventions under varying conditions (Ford & Flynn, 2005; Maathuis & Chockalingam, 2023b; Norton et al., 2025). Further, the results are visualized in time-series plots, phase diagrams, or sensitivity heatmaps, facilitating collaborative discussion and consensus-building. In peacekeeping, logistics, and humanitarian missions alike, SD models have been employed to balance competing objectives such as maximizing mission success while minimizing collateral damage by revealing the dynamic trade-offs that static analyses often overlook (Besiou Stapleton & Van Wassenhove, 2011; Costa et al., 2015; Lopez, 2023).

In public health, SD models tackle the dynamics of chronic disease progression and healthcare delivery, guiding policy on hospital capacity and vaccination strategies (Gozluklu & Sterman, 2000). Moreover, urban studies apply SD to capture land-use change and traffic congestion feedbacks, informing sustainable transportation planning (Haghshenas, Vaziri & Gholamialam, 2015; Fontoura & Ribeiro, 2021). In environmental applications include carbon–climate interactions and resource-management policy evaluation, SD modelling helps clarifying how emission controls propagate through biogeochemical cycles (Yu et al., 2024). In economics and business, SD underpins supply-chain coordination models that diagnose the notorious “bullwhip” effect in inventory control (Abdulkadir, 2023), and it was further used in forecasting macroeconomic growth under varying fiscal regimes (Davis & Gómez-Ramírez, 2022).

Within the military domain, SD models are used in logistics to optimize the placement and throughput of supply depots under contested conditions, enhancing force resilience against disruptions (Chang et al., 2017). In counterinsurgency campaign simulations employ SD to balance force-presence and civilian-impact trade-offs, revealing how local population support can shift over time (Mcguire, 2008). In the context of cyber defense, analysts have used SD to map attacker–defender escalation loops, optimizing investment in intrusion detection versus recovery capabilities (Williams et al., 2012; Canzani & Pickl, 2016). At the same time, SD are applied to assess terrorist threat response dynamics and evacuation protocols, improving interagency coordination under emergency scenarios (Esmaeili et al., 2025).

The proportionality-assessment SD model introduced in this research extends this rich lineage by constructing a rule-based, stock-and-flow representation of aggregated proportional versus disproportionate judgments, grounded in expert-elicited collateral-damage lookup tables. Unlike prior military SD models focused on resource flows or population dynamics, this research focuses on the legal and ethical decision criteria, enabling what-if exploration of injury, death, object damage, and psychological harm parameters which represents an existing gap in existing research and practitioner efforts.

3. Research Methodology

This research adopts the Design Science Research (DSR) methodology as framed by Kuechler & Vaishnavi (2012) and Peffers, Tuunanen & Niehaves (2018) applied in a responsible manner (Maathuis, 2024; Cools & Maathuis, 2025). By following the DSR methodology, a SD model is developed for conducting the proportionality assessment military in military operations by capturing the underlying feedback loops. This process starts with the identification and analysis of the context where this scope is defined, and from here identifying key variables, i.e., on the one side military advantage, and on the other side physical collateral injury, death, object damage. At the same time, two perspectives are considered for the collateral damage in order to not account (Case 1) and account (Case 2) psychological harm as being part of the collateral damage component. Then these relationships are translated into causal-loop diagrams and stock-and-flow structures, ensuring that reinforcing and balancing feedbacks (e.g., increased use of force leading to higher civilian harm, which in turn constrains operational aggressiveness) were faithfully represented. From here the SD model is implemented in accordance with the IHL (International Humanitarian Law) the SD model in a simulation environment to allow for dynamic “what-if” experimentation.

For demonstration and evaluation, a two use case simulation is executed. Case 1 abstracted collateral damage to purely physical effects, e.g., injuries, fatalities, and material destruction, while Case 2 augmented the SD structure with an additional feedback loop representing psychological harm as part of civilian impact. In each case, the model is calibrated against expert rule outputs (physical-only or enriched by psychosocial factors) and validated structural fidelity through extreme condition tests (e.g., zero advantage or zero civilian presence) and dimensional consistency checks. Furthermore, the behavioural validity was assessed by comparing the model’s time-series outputs such as cumulative civilian harm and operational utility against expected proportionality thresholds, ensuring that the SD model reproduced the expert-defined switch between proportional (P) and disproportional (DP) states under both scenarios .

Through sensitivity and scenario analyses, we quantified how variations in key parameters (e.g., the weight assigned to psychological harm and force-application rate) shifted the system’s equilibrium and tipping points.

From the structural robustness conducted against Monte Carlo–style perturbations of input distributions, the model demonstrates that the core causal archetypes remained stable across a wide range of plausible operational conditions.

4. Model Design

The SD model for proportionality assessment is built around four exogenous drivers, i.e., civilian injury severity (CD_injury), civilian death severity (CD_death), collateral damage on civilian objects (CD_object), and military advantage (MA). Each of these take discrete values (L/M/H i.e., Low/Medium/High or Y/N i.e., Yes/No) and are sampled every time step from configurable probability distributions. These inputs feed into a **rule lookup** block that implements the 54 scenario combinations (e.g. L–M–Y–L → DP).

At each time step t, the model executes the following operations:

- Step 1: Sampling by capturing the input elements from their distributions.
- Step 2: Rule evaluation through a lookup PA(t) = rule(injury, death, object, MA).
- Step 3: Flow computation where the new PA(t) = 1{PA(t)=P}, New DP(t)=1{PA(t)=DP}.
- Step 4: Stock update where the Cumulative P(t) = Cumulative P(t-1) + New P(t) and Cumulative DP(t) = Cumulative DP(t-1) + New DP(t).

In this process, a level variable encapsulates each input's probability mass function, allowing the run of sensitivity experiments by altering injury or death likelihoods. Because all interactions are discrete and rule-based, the model remains highly interpretable and directly traceable through elicited lookup tables. Although the base model has no endogenous feedback from PA stocks back to inputs, its causal loop diagram (CLD) clarifies potential extensions. Four reinforcing feedbacks (R1–R4) link each collateral-damage dimension positively to the PA decision node, i.e., higher injury, death, object damage, or military advantage push PA toward DP, and these feed into the accumulating PA stocks.

To compare the two modelling specifications where in Case 1 only psychical damage is considered in the collateral damage component and in Case 2 both psychical and psychological harm is considered in the collateral damage component, the only structural change is replacing CD_injury_no_psycho with CD_injury_with_psycho. Here it is important to mention that all other stocks, flows, and sampling mechanisms remain identical. Furthermore, from a simulation conducted over 100 time steps it can be seen that Case 2 produces 7 percentage points more DP outcomes (44.4 % vs. 37.0 %) than Case 1 under uniform input distributions.

5. Evaluation

From the evaluation conducted, out of 54 possible scenario combinations, Case 1 (physical damage only) yields 34 P and 20 DP, whereas Case 2 (including psychological harm) yields 30 P and 24 DP. This is visualized in Figure 1 in the 7.4% drop in proportional outcomes when psychological harm is accounted for.

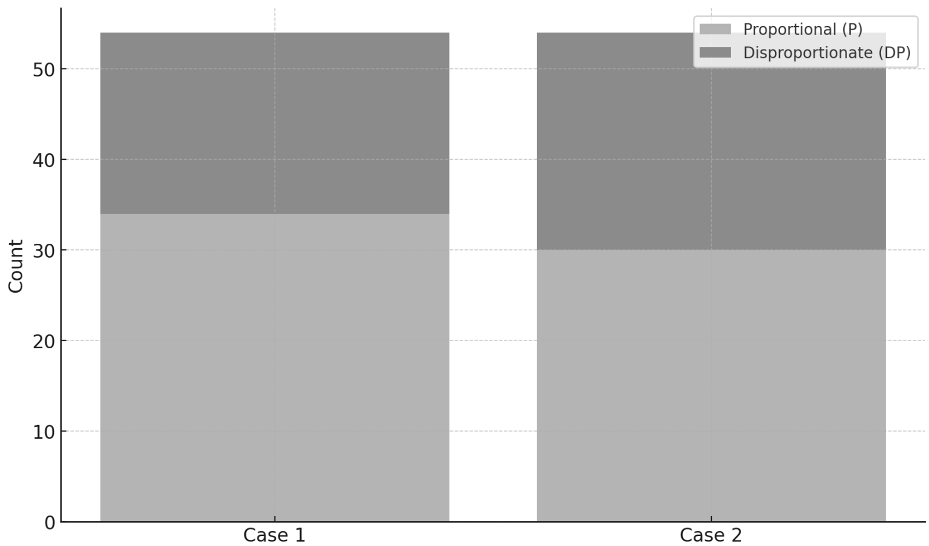

Figure 1: Evaluation for both cases

To observe how judgments accumulate over successive engagements, two discrete time stock and flow stocks are implemented: Cumulative P and Cumulative DP with flows driven by the instantaneous PA decision each step. Under uniform scenario sampling, the time series shown in Figure 2 lets seeing that Case 1's cumulative P stock rising approximately linearly to ~34 by step 54, then plateauing, while Case 2 grows more slowly, plateauing around 30 by the same step. This divergence illustrates how Case 2's inclusion of psychological damage systematically reduces the rate at which proportional judgments accrue.

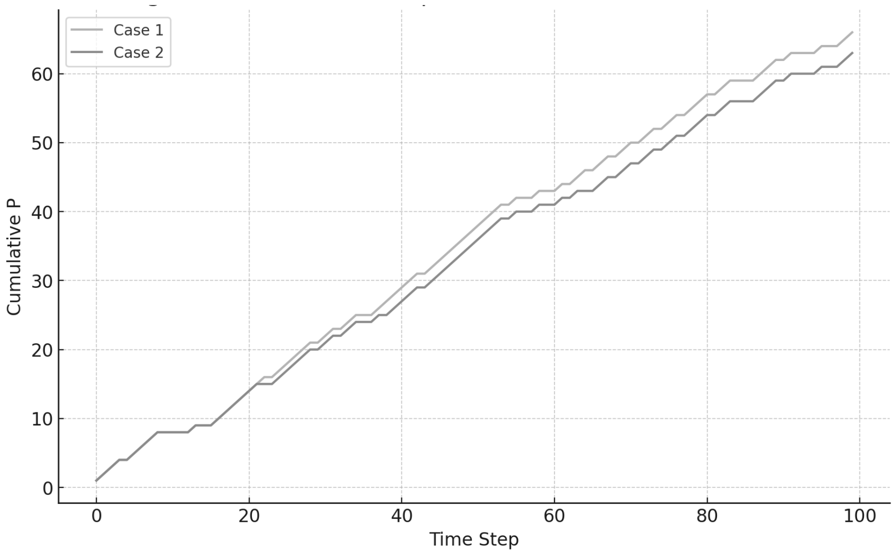

Figure 2: Cumulative proportionality assessments over time

Further, one's input probability is varied at a time (high-severity injury, high-severity death, and object damage likelihood) from 0 % to 100 %, holding other inputs uniform. To this end, Figure 3 plots the proportion of P judgments versus the probability of "High" injury: Case 1 declines from ~80 % to ~20 %, while Case 2 starts ~75 % and falls more steeply to ~15 %. Similar curves for death severity and object damage (not shown) confirm that psychological considerations amplify sensitivity, especially to object damage, shifting the curves downward by 3–5 percentage points on average.

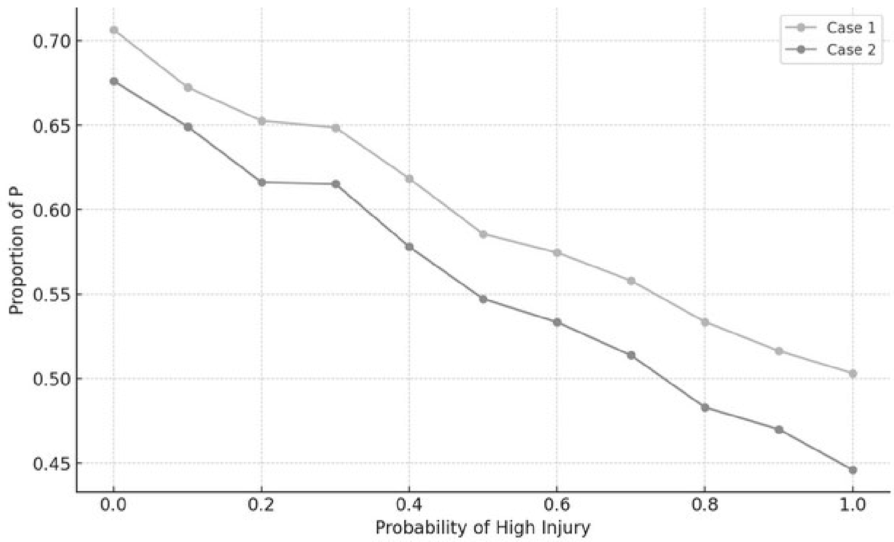

Figure 3: Sensitivity analysis to high injury

To explore interactions, a two-way are swept over p_H_injury and p_H_death, computing the difference in P proportions (Case 1 – Case 2) at each grid point. The resulting heatmap (Figure 4) reveals that the largest deltas (~5 pp) occur when both injury and death probabilities are high, indicating regions where psychological harm most strongly drives conservative (DP) outcomes. Moreover, from statistical two-proportion z-tests at each cell show that nearly 48 % of the grid cells exhibit a significant difference ($p < 0.05$), underscoring the robustness of this effect.

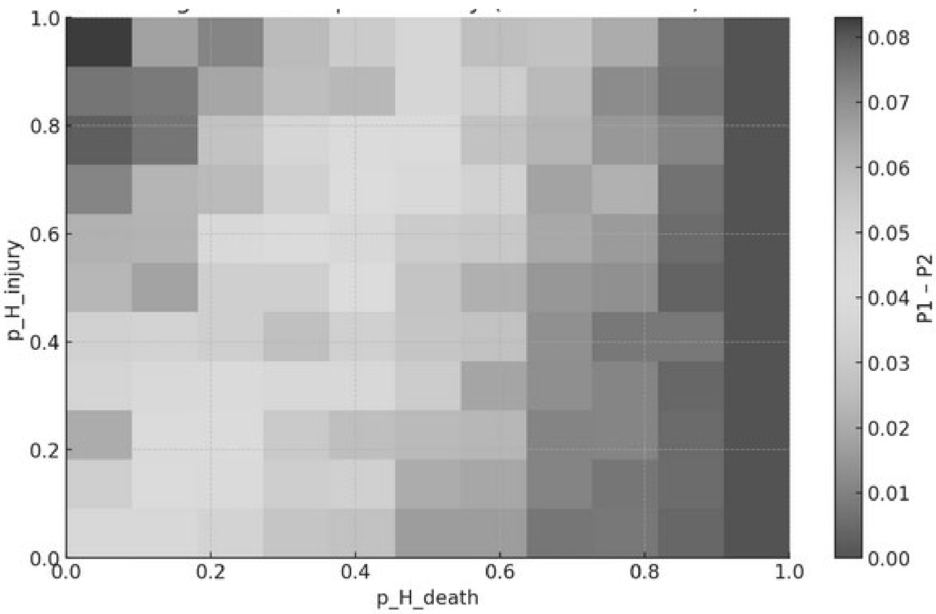

Figure 4: Delta Proportionality (Case1 and Case 2)

Aggregating across all parameter sweeps, the mean difference in proportional judgments between Case 1 and Case 2 is ~3.1 percentage points, with a one-sample t-test strongly rejecting the null of zero difference ($t \approx 16.1$, $p \ll 10^{-30}$). Such statistically significant disparities, coupled with the systematic slowing of P accumulation and heightened sensitivity to collateral-damage inputs, highlight how incorporating psychological harm leads to more conservative proportionality assessments. These findings validate the SD model's utility in "what-if" exploration and reinforce the operational importance of non-physical harm in rules-of-engagement design.

Hence, transitioning from Case 1 (physical injury only) to Case 2 (physical + psychological injury) systematically shifts the proportionality profile toward more conservative judgments: the baseline count of proportional rulings falls by 7 percentage points, cumulative proportional assessments are made more slowly, and sensitivity curves to high-severity injury, death, and object damage uniformly lie below their Case 1 counterparts by 3-5 pp. Two-way parameter sweeps reveal the largest $\Delta P = P_1 - P_2$ (up to ~8 pp) when both injury and death probabilities are high, with nearly half of all grid cells exhibiting statistically significant differences ($p < 0.05$). Thus, incorporating psychological harm in the collateral damage component of the proportionality assessment not only increases the overall frequency of disproportionate outcomes, but also amplifies the model's responsiveness to variations in collateral-damage parameters, underscoring the critical role of non-physical suffering/harm in shaping robust, precautionary proportionality assessments.

6. Conclusions

In this research, a SD model for proportionality assessment in military operations was developed, evaluated, and proposed.. By encoding 54 collateral-damage scenarios into instantaneous proportionality assessment outcomes (P vs. DP), then aggregating these through cumulative stocks, this research demonstrates how the inclusion of psychological harm (Case 2) consistently reduces proportional rulings by roughly 7 percentage points, slows the accumulation of proportional judgments, and amplifies sensitivity to key input parameters. One-way and two-way sensitivity sweeps, coupled with statistical hypothesis tests, confirmed the robustness of these effects across a broad parameter space, while time-series and heatmap visualizations provided intuitive insights into the dynamic behaviour of this model. Together, these results reflect the model's utility as both an analytic lens on doctrinal trade-offs and a decision-support tool for military targeting decision-making support.

As future research perspectives, several paths are seen for extending this framework. First, introducing endogenous feedback, where rising Cumulative DP levels dynamically adjust future military advantage thresholds, approach that would capture adaptive policy resistance and command learning. Second, by integrating or extending this model with complementary methods (e.g., agent-based or cellular automata modules) could reveal how spatial heterogeneity and local interactions alter aggregate outcomes. Third, by considering calibration against historical engagement data and expert judgment elicitation exercises that would strengthen real-world validity. And fourthly, by expanding the collateral-damage taxonomy (e.g., including economic or cultural loss metrics), coupling with live operational data feeds, and embedding the model within interactive C2 dashboards could contribute to bringing this model toward operationalizing proportionality assessment in multi-domain operations settings.

Declaration: For this research, no ethical clearance is required and no AI tools were used in the creation of this article.

References

Abar, S., Theodoropoulos, G. K., Lemarinier, P., & O'Hare, G. M. (2017). Agent Based Modelling and Simulation tools: A review of the state-of-art software. *Computer Science Review*, *24*, 13-33.

Abdulkadir, R. (2023). *The Dynamics of Supply Chain Integration: Empirical Evidence from Public Health Supply Chains in Kaduna State, Nigeria* (Doctoral dissertation, Liverpool John Moores University (United Kingdom)).

Azar, A. T. (2012). System dynamics as a useful technique for complex systems. *International Journal of Industrial and Systems Engineering*, *10*(4), 377-410.

Bakken, B. T., & Gilljam, M. (2003). Training to improve decision making-system dynamics applied to higher-level military operations. *Journal of battlefield technology*, *6*(1), 33-42.

Bala, B. K., Arshad, F. M., & Noh, K. M. (2017). *System dynamics*. Singapore: Springer Singapore.

Besiou, M., Stapleton, O., & Van Wassenhove, L. N. (2011). System dynamics for humanitarian operations. *Journal of Humanitarian Logistics and Supply Chain Management*, *1*(1), 78-103.

Canzani, E., & Pickl, S. (2016). Cyber epidemics: Modeling attacker-defender dynamics in critical infrastructure systems. In *Advances in Human Factors in Cybersecurity: Proceedings of the AHFE 2016 International Conference on Human Factors in Cybersecurity, July 27-31, 2016, Walt Disney World®, Florida, USA* (pp. 377-389). Cham: Springer International Publishing.

Chang, P. C., Fan, C. Y., & Huang, W. H. (2007, September). A system dynamics simulation approach for military supply chain management. In *Second International Conference on Innovative Computing, Informatio and Control (ICICIC 2007)* (pp. 422-422). IEEE.

Cohen, A., & Zlotogorski, D. (2021). *Proportionality in international humanitarian law: Consequences, precautions, and procedures*. Oxford University Press.

Cools, K., & Maathuis, C. (2024). Trust or Bust: Ensuring Trustworthiness in Autonomous Weapon Systems. In *MILCOM 2024-2024 IEEE Military Communications Conference (MILCOM)* (pp. 182-189). IEEE.

Cools, K., & Maathuis, C. (2025). FHATMO: Feedback Model for Human-AI Teaming in Military Operations. In *2025 International Conference on Military Technologies (ICMT)* (pp. 1-6). IEEE.

Costa, O., Santos, J., Martins, M., & Yoshizaki, H. (2015). A system dynamics analysis of humanitarian logistics coordination. In *Proceedings of the 34th international conference of the system dynamics society*.

Daniele, L. (2024). Incidentality of the civilian harm in international humanitarian law and its Contra Legem antonyms in recent discourses on the laws of war. *Journal of Conflict and Security Law*, *29*(1), 21-54.

Davis, P. K., Kulick, J., & Egner, M. (2005). *Implications of modern decision science for military decision-support systems*. Rand Corporation.

Davis, L. E., & Gómez-Ramírez, L. (2022). Teaching post-intermediate macroeconomics with a dynamic 3-equation model. *The Journal of economic educaTion*, *53*(4), 348-367.

Deeks, A. (2020). Coding the law of armed conflict: First steps. *Ashley Deeks, Coding the Law of Armed Conflict: First Steps, in THE LAW OF ARMED CONFLICT IN*, *2040*.

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. *International journal of information management*, *48*, 63-71.

Duggan, J. (2016). An introduction to system dynamics. In *System Dynamics Modeling with R* (pp. 1-24). Cham: Springer International Publishing.

Emami, S. G., Lorenzoni, V., & Turchetti, G. (2024). Towards resilient healthcare systems: a framework for crisis management. *International journal of environmental research and public health*, *21*(3), 286.

Esmaeili, R., Yazdi, M., Rismanchian, M., & Shakerian, M. (2025). Unveiling the dynamics of team cognition in emergency response teams. *Frontiers in Psychology*, *16*, 1534224.

Fontoura, W. B., & Ribeiro, G. M. (2021). System dynamics for sustainable transportation policies: A systematic literature review. *urbe. Revista Brasileira de Gestão Urbana*, *13*, e20200259.

Ford, A., & Flynn, H. (2005). Statistical screening of system dynamics models. *System Dynamics Review: The Journal of the System Dynamics Society*, *21*(4), 273-303.

Gozluklu, B., & Sterman, J. (2023). System dynamics to understand and improve the performance of complex projects. In *Research Handbook on Complex Project Organizing* (pp. 70-77). Edward Elgar Publishing.

Gupta, S., Modgil, S., Bhattacharyya, S., & Bose, I. (2022). Artificial intelligence for decision support systems in the field of operations research: review and future scope of research. *Annals of Operations Research*, *308*(1), 215-274.

Haghshenas, H., Vaziri, M., & Gholamialam, A. (2015). Evaluation of sustainable policy in urban transportation using system dynamics and world cities data: A case study in Isfahan. *Cities*, *45*, 104-115.

Kanellopoulos, A. N., & Ioannidis, A. (2024). Leveraging competitive intelligence in offensive cyber counterintelligence: An operational approach for the Shipping industry. *Security and Defence Quarterly*, *48*(4), 80-92.

Kohler, K. (2021). Strategic foresight: Knowledge, tools, and methods for the future. *CSS Risk and Resilience Reports*.

Koivisto, J., Ritala, R., & Vilkko, M. (2022). Conceptual model for capability planning in a military context–A systems thinking approach. *Systems Engineering*, *25*(5), 457-474.

Kuechler, W., & Vaishnavi, V. (2012). A framework for theory development in design science research: multiple perspectives. *Journal of the Association for Information systems*, *13*(6), 3.

Kunc, M. (2024). Integrating system dynamics and scenarios: A framework based on personal experience. *Futures & Foresight Science*, *6*(1), e174.

Lekea, I., Lekeas, G., & Topalnakos, P. (2023). Exploring Enhanced Military Ethics and Legal Compliance through Automated Insights: An Experiment on Military Decision-making in Extremis. *Conatus-Journal of Philosophy*, *8*(2), 345-372.

Lopez, J. (2023). *Opportunities for System Dynamics Research in Operations Management for Public Policy* (Doctoral dissertation, Massachusetts Institute of Technology).

Maathuis, C., & Chockalingam, S. (2023). Modelling the influential factors embedded in the proportionality assessment in military operations. In *International Conference on Cyber Warfare and Security* (Vol. 18, No. 1, pp. 218-226). Academic

Maathuis, C., & Chockalingam, S. (2023b). Tackling uncertainty through probabilistic modelling of proportionality in military operations. In *ECCWS 2023 22nd European Conference on Cyber Warfare and Security* (No. 1).

Maathuis, C. (2024). Towards trustworthy AI-based military cyber operations. In *19th International Conference on Cyber Warfare and Security: ICCWS 2024*.

Maathuis, C. (2024b). Human-Centred AI in Military Cyber Operations. In *19th International Conference on Cyber Warfare and Security: ICCWS 2024*.

Maathuis, C., Cidota, M. A., Datcu, D., & Marin, L. (2025). Integrating Explainable Artificial Intelligence in Extended Reality Environments: A Systematic Survey. *Mathematics*, *13*(2), 290.

Mcguire, M. J. (2008). Modeling the effects of direct action operations on an insurgent population.

Moradkhani, N. (2023). *Study of a decision support approach in socio-technical systems management, based on the physical principles of point and solid mechanics* (Doctoral dissertation, Ecole des Mines d'Albi-Carmaux).

Naderi, M. M., Harris, M., Ghorbanichemazkati, E., Little, J. C., & Farid, A. M. (2025). Convergent Anthropocene Systems-of-Systems: Overcoming the Limitations of System Dynamics with Hetero-functional Graph Theory. *arXiv preprint arXiv:2505.21793*.

Norton, K. A., Bergman, D., Jain, H. V., & Jackson, T. (2025). Advances in surrogate modeling for biological agent-based simulations: Trends, challenges, and future prospects. *arXiv preprint arXiv:2504.11617*.

Ojha, Y. (2024). Artificial Intelligence in Armed Conflict: Perspectives from International Humanitarian Law. *Available at SSRN 5162209*.

Peffers, K., Tuunanen, T., & Niehaves, B. (2018). Design science research genres: introduction to the special issue on exemplars and criteria for applicable design science research.

Radzicki, M. J., & Taylor, R. A. (2008). Origin of system dynamics: Jay W. Forrester and the history of system dynamics. *US Department of Energy's introduction to system dynamics*.

Richardson, G. P. (1991). System dynamics: Simulation for policy analysis from a feedback perspective. In *Qualitative simulation modeling and analysis* (pp. 144-169). New York, NY: Springer New York.

Richardson, G. P. (2011). Reflections on the foundations of system dynamics. *System dynamics review*, *27*(3), 219-243.

Roos, M. (2024). Feedback, Circular Causality, and System Dynamics. In *Principles of Complexity Economics: Concepts, Methods and Applications* (pp. 253-338). Cham: Springer International Publishing.

Solis, G. D. (2021). *The law of armed conflict: international humanitarian law in war*. Cambridge University Press.

Solf, W. A. (2023). Protection of civilians against the effects of hostilities under customary international law and under protocol. In *The Conduct of Hostilities in International Humanitarian Law, Volume I* (pp. 3-21). Routledge.

Spoor, B., & de Werd, P. (2023). Complexity in military intelligence. *International Journal of Intelligence and CounterIntelligence*, *36*(4), 1122-1142.

Van Dam, K. H., Nikolic, I., & Lukszo, Z. (Eds.). (2012). *Agent-based modelling of socio-technical systems* (Vol. 9). Springer Science & Business Media.

Williams, C., Watson, T., Bryant, I., Mahrra, J., Miller, W. D., Fonash, P. M., ... & Peake, C. (2012). Resilient cyber ecosystems. *Crosstalk Journal of Defense Software Engineering*, *25*(5).

Yu, F., Yang, Y., Chen, L., Sheng, X., Yuan, X., Wang, Q., ... & Zuo, J. (2024). Assessment of system sustainability: a critical review of the combined application of system dynamics and life cycle assessment. *Energy, Ecology and Environment*, *9*(1), 58-67.