# Physics-Informed Neural Networks for Agent-Based Epidemiological Model Calibration

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During the COVID-19 pandemic, agent-based epidemiological models played a key role in modeling the spread of infectious disease and simulating proposed interventions to inform policy decisions in countries around the world. However, due to the complexity of human contact patterns and disease characteristics, these models rely on a large number of parameters that are difficult calibrate via traditional approaches. Using physics-informed neural networks in tandem with the SIR compartmentalized differential equation model, we create a framework that uses reported data to estimate disease spread and approximate corresponding disease parameters; we then use these parameters to calibrate agent-based model simulations that can evaluate potential policy interventions. Using both influenza and COVID-19 data, we demonstrate the framework's ability to produce accurate disease and parameter estimations despite noisy data. We then validate our approach using current state-of-the-art agent-based epidemiological models including OpenABM-Covid19, OpenCOVID, Covasim, and CovidSim. Further, we construct our own physical agent-based model, calibrated via our framework, to analyze the spread of airborne infectious diseases in school hallways. Our work creates a data-driven agent-based model calibration pipeline for future infectious disease intervention efforts.