A Rapid Prediction and Response System (RPARS) to Facilitate Guided Self-Regulation During Pandemics

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Abstract. It has become imperative to disrupt viral transmission by proactively guiding individual behavior in a targeted approach. While broad population-oriented technologies such as digital contact-tracing and vaccine passport apps have been tried, advanced privacy-preserving approaches are needed to ingest user information in real-time, and better adapt to changing epidemiological circumstances. In response, this paper: 1) briefly discusses guided self-regulation as a possible means of disrupting viral transmission via the use of digital technology, 2) outlines a prototype Rapid Prediction and Response System designed to facilitate guided self-regulation in an advanced privacy-preserving approach, 3) describes the significance of the prototype system to research and practice, and 4) presents a high-level evaluation plan.

Keywords: Guided Self-Regulation, Privacy Preservation, Agent-based Simulation, Viral Transmission, Digital Technology, Public Health, Pandemics.

1 Facilitating Guided Self-Regulation During Pandemics

Deadly viruses spread quickly in communities, even when pharmaceutical [1] and population-level [2] interventions are in place. It is therefore necessary to develop targeted methods to disrupt viral transmission by guiding individual behavior. In doing so, we must develop forward-looking methods to continually process personal risk information in secure and privacy-preserving approaches. The notion of guided self-regulation extends the theoretical foundation of behavioral self-regulation [3–5], and consists of three technology-enabled behavioral sub-processes intended to disrupt viral transmission events: *self-detection*, *self-prevention*, and *self-tracing* [6]. *Self-detection* consists of routines to continuously monitor personal symptoms and health changes towards predicting whether a viral load is present. *Self-prevention* consists of routines to improve individual behavioral adherence performance towards reducing primary transmission events. *Self-tracing* consists of routines to track shared viral exposures towards reducing secondary transmission events [6]. Digital technologies may be leveraged to facilitate guided self-regulation by providing individuals with personalized epidemiological information, predicting individual transmission risk, and delivering targeted guidance, while still preserving individual privacy [7–9]. For example, in the context of a university setting, virus transmission may be contained by informing and guiding student behaviors on and off campus.

2 Rapid Prediction and Response System Architecture

The Rapid Prediction and Response System (RPARS), a prototype under development at Rotterdam School of Management - Erasmus University, is designed to facilitate guided self-regulation during pandemics. The broad purpose of the system is to first predict risk of viral transmission in communities, and then proactively guide individual behavior to disrupt transmission events. To do so, it dynamically integrates personal information derived from *real-world behavioral contexts* with information derived from *simulated-world epidemiological networks* within a privacy-preserving framework. The RPARS architecture consists of three interacting mechanisms: 1) A *Dynamic Messaging Mechanism*, which facilitates individual guided self-regulation sub-processes: *self-detection*, *self-prevention*, and *self-tracing*. 2) A *Dynamic Risk Assessment Mechanism*, which generates risk information derived from simulated epidemiological networks approximating *social patterns*, *infection spread*, and *disease progression* within focal communities. 3) A *Privacy-Preserving Integration Mechanism*, which dynamically integrates information between system components via distributed *contextualization*, *translation*, and *matching* processes. A conceptual representation of the RPARS architecture is shown in Figure 1.

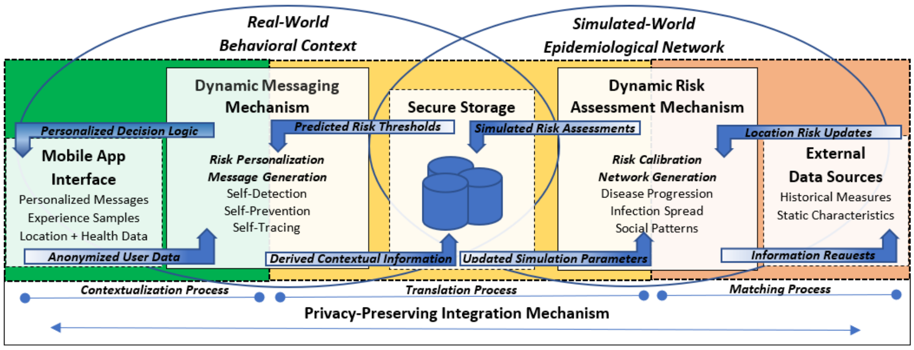

Fig. 1. Conceptual Representation of RPARS Architecture

2.1 Dynamic Messaging Mechanism

The *Dynamic Messaging Mechanism* guides individual self-regulation activities within real-world behavioral contexts through the delivery of personalized risk messages via the user’s mobile device. Displayed messages refresh when new epidemiological information emerges. For example, when a user’s health changes significantly, when entering crowded locations, or when viral variants emerge. This mechanism facilitates guided self-regulation within the three sub-processes outlined above. For example, for *self-detection*, health change information, combined with contextual information, is used to determine the propensity to contract a virus. For *self-prevention*, personalized risk messages inform users of recommended actions based on predicted transmission role (the likelihood of becoming a transmitter or receiver of viral particles), level of risk (the likelihood of participating in a transmission event), and personal risk tolerance. For *self-tracing*, contextual information is logged, together with user location and duration of exposure, to track exposure moments and identify community transmissions.

2.2 Dynamic Risk Assessment Mechanism

The *Dynamic Risk Assessment Mechanism* produces risk information derived from simulated-world epidemiological networks using an agent-based modeling framework adapted from [10]. The adapted framework simulates *social interactions*, *infection spread*, and *disease progression* in focal communities. Simulation parameters (e.g., initial infections, prevalence rate, area ventilation rate, daily traffic rate, testing policy, test accuracy, test capacity, contact tracing policy, distancing policy), are dynamically updated to proactively guide self-regulation activities in real-world behavioral contexts. The *Dynamic Risk Assessment Mechanism* re-generates simulated epidemiological networks based on contextual updates originating from the *Dynamic Messaging Mechanism*. To accomplish this, we integrate recent contextual information, activity levels, and other biometric information of active users, and fuse with measures derived from external location-based data sources and static location characteristics to simulate dynamic changes to social patterns. Assuming that system users are a representative sample of people at a location, location-level and population-level risk estimates are a weighted sum of the individual risk calibrated for users at different locations. Similarly, location risks are updated using the aggregate individual risk over time.

2.3 Privacy-Preserving Integration Mechanism

When collecting and processing personal information within and across interacting mechanisms, researchers must enforce strict measures to preserve individual privacy. Such measures include and are not restricted to: processing personal information lawfully and transparently, limiting data use to intended purposes only, ensuring accuracy of data, storing data no longer than necessary, protecting against unauthorized or unlawful processing, and demonstrating compliance with privacy laws [11]. Towards the objective of strictly adhering to these measures, we outline a *Privacy-Preserving Integration Mechanism* used to securely integrate information between real-world and simulated-world environments. Here we describe three integration processes: *contextualization*, *translation*, and *matching*.

The *contextualization* process interacts with the *Dynamic Messaging Mechanism*, and is contained in the user's mobile device. This process is facilitated through the execution of deployed decision logic, dynamically applied to personal data held in a secure data vault. Personal data, and processing of this data therefore remains locally on the device. When executed, pre-defined decision logic scripts associate changes in the user's behavioral context (e.g., changes in location, health, exposure) with relevant behavioral guidance rules. Through this process, personalized messages and prompts for information are displayed to the user. Decision rules may be updated by deploying new scripts from a server component. Such updates may occur when health regulations are adjusted, or new interventions are deployed. Personal data is retained on the user's mobile device for the time needed to trace exposure events. Access to the app interface, associated data, and displayed messages is protected with a password during user login.

The *translation* process interacts with the *Dynamic Messaging* and *Dynamic Risk Assessment Mechanisms*, and is contained on a central server. This process consists of two sub-processes, which exchange information via an encrypted database. Data-access is divided between sub-processes to avoid direct communication. The first translation sub-process (i.e., upstream sub-process) receives contextual information derived from the real-world behavioral context and stores it for subsequent use in the *Dynamic Risk Assessment Mechanism*. Given user consent, anonymized contextual information is retrieved from app interfaces and is stored in the database. Within this sub-process, attributes are k-anonymized across individuals and locations and identifiable attributes are discarded. Data augmentation is carried to prevent reverse engineering to identify any unique source. The second translation sub-process (i.e., downstream sub-process) retrieves risk information from the *Dynamic Risk Assessment Mechanism* and translates it into a table for use in the *Dynamic Messaging Mechanism*. This table serves as a basis to delineate risk thresholds within decision logic scripts. Population-, location-, and subgroup-level risk measures are derived from the simulated epidemiological network and stored in associated database tables. Decision rule thresholds are generated from database queries, and are inserted into decision logic.

The *matching* process interacts with the *Dynamic Risk Assessment Mechanism*, and is contained on a central server. Real-world behavioral context attributes are matched with the closest entity in the simulation models. Mapping personal information from the upstream translation sub-process and generating risk assessments, and related guidance, is done using an inductive approach. That is, even for new users or sources with scarce information, the closest possible cluster of entities (i.e., users, groups, locations) in the simulation environment gives viable information about future course of actions and health status. The seamless interaction between dynamic messages and simulation models not only facilitates differential privacy, but also overcomes difficult analytical problems such as missing values or data veracity.

3 Significance of the Prototype

The prototype system outlined in this paper is both novel and practically relevant. By dynamically integrating information between real-world and simulated-world environments, the system provides a flexible living-lab research environment. The prototype system facilitates controlled field experiments, and enables real-time feature testing - thus allowing for rapid prototyping, development, and evaluation of specific use cases. The prototype may therefore be leveraged within broader research programs to inform development of the next-generation of technologies intended to disrupt viral transmission, or even to disrupt other health risks which become contagious within communities.

4 Evaluation of the Prototype

We develop and evaluate the prototype system following the Design Science Research paradigm [12, 13] in an iterative and progressive approach across multiple phases. During the first phase, we develop base functionality within the *Dynamic Messaging Mechanism* and *contextualization* process. We develop the app interface and server components, establish a secure connection to a wearable biometric device, and perform user testing. During the second phase, we develop the *translation* process, test translation functionality, and prepare integration requirements. During the third phase, we develop the *Dynamic Risk Assessment Mechanism*, define the matching process, and integrate external information sources. We integrate the *Dynamic Messaging* and *Dynamic Risk Assessment Mechanisms* via the *Privacy-Preserving Integration Mechanism*, and perform system testing.

During ongoing evaluation phases, we generate decision logic scripts from dynamic risk assessment models for validation in real-world behavioral contexts. The prediction performance of this model is trained and evaluated on limited ground-truth data. For example, we use a limited set of users with known location trajectory, intrapersonal attributes, and viral susceptibility history to generate risk scores, followed by evaluating the risk for a holdout sample. The efficacy of dynamic messaging on guided self-regulation is evaluated using field experiments. Users are assigned to groups to facilitate functional testing. We present users with guided self-regulation messages and examine user response via repeated experience sampling measures. Novel methodologies such as Micro-Randomized Trials (MRT) [14] are also being explored to analyze causal implications of guided messages. We continuously iterate between development of system functionality and user testing to optimize interventions and evaluate efficacy of the guided self-regulation approach. Throughout all phases, we involve users as co-evaluators, for example through experience sampling, and via auto-ethnographic data collection and analysis techniques (e.g., [15, 16]).

5 Discussion

This paper briefly discussed guided self-regulation as a possible means of disrupting viral transmission via the use of digital technology, outlined a prototype Rapid Prediction and Response System designed to facilitate guided self-regulation during pandemics, described the significance of the prototype to research and practice, and presented a high-level evaluation plan. The prototype outlined in this paper may be used to design and evaluate guided self-regulation interventions in the context of viral transmission. We also envision the possible adaptation of the developed mechanisms towards other guided self-regulation use cases. For example, to reduce the potential impact of emerging environmental health risks (such as air pollution, radiation exposure, or extreme climate events), or to disrupt the spread of harmful health behaviors (such as excessive smoking, alcohol consumption, or drug use). In developing and evaluating the prototype system, we hope to stimulate new forms of participatory design science research that directly involve users within iterative co-evaluation processes.

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