Algorithms & Model

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May 2025

Algorithm 1: Dynamic Consent Fatigue Estimation

Quantitative Assessment of Dynamic Consent Fatigue

In any healthcare settings that is experiencing regular consent request, may evaluate Consent Fatigue (C) by utilizing the systematic approach offered by the dynamic consent model. This concept distinguishes between dynamic and non-dynamic events, where the dynamic events indicated by frequent, urgent, or highly contrasted consent requests, on the other hand, non-dynamic events are more general in nature.

The consent related events are expressed by a set $E = \{e_1, e_2, ..., e_m\}$, each involving response of the patient. The model evaluates each event using ten primary factors $F = \{f_1, f_2, ..., f_{10}\}$. These include frequency f_1, urgency f_2, outcome severity f_3, patient capacity f_4, and human-centered variables under f_5. Specifically, f_5 incorporates nine sub-factors $H = \{h_1, ..., h_9\}$ such as age (h_1), literacy (h_4), and mental health (h_9).

Every trigger e_j is imperilled to an impact evaluation utilizing a fatigue weight function. $X_j(f_i)$, which quantifies the contribution of each element to fatigue. The dynamic classification profoundly depends on variability in f_2, f_4, and the key human sub-factors h_1, h_6, h_9.

The algorithm compute specific fatigue per trigger (C_{e_j}) and sums them to generate the Total Consent Fatigue C, given by:

$$C = \sum_{j=1}^{m} \sum_{i=1}^{10} X_j(f_i)$$

This model adjusts to real-time scenarios by utilizing predefined or machine-learned models to dynamically allocate weights. Utilizing several contributing factors consent fatigue can be quantified, facilitating adaptive, personalized consent procedures designed with the aim to reduce cognitive overload and enhance patient experience in decision-making.

Algorithm 1: Dynamic Consent Fatigue Estimation

Input:

- Event $E = \{e_1, e_2, \ldots, e_m\}$: a set of consent triggers.
- Set of fatigue-influencing factors $F = \{f_1, f_2, \ldots, f_{10}\}$.
- Human sub-factors $H = \{h_1, h_2, \ldots, h_9\}$ under factor f_5.
- A fatigue weight function $X_j(f_i)$ representing the quantified impact of factor f_i on trigger e_j.

Output: Total Consent Fatigue C

Mathematical Representation:

$$C = \sum_{j=1}^{m} \sum_{i=1}^{10} X_j(f_i)$$

Where:

- C: Total Consent Fatigue for event set E
- C_{e_j}: Consent fatigue for individual trigger e_j
- $X_j(f_i)$: Quantified impact of factor f_i on trigger e_j
- Factors include request frequency, urgency, outcome severity, patient capacity
- Human sub-factors (e.g., age, literacy, cultural background) are modeled within f_5

Steps:

1. **Normalize Input Factors:**
   Initialize total consent fatigue: $C = 0$
2. **For each consent trigger $e_j \in E$:**
   - Initialize $C_{e_j} = 0$ (Consent fatigue for trigger e_j)
3. **For each factor $f_i \in F$:**
   - Evaluate $X_j(f_i)$, the quantified impact of f_i on e_j
   - If $f_i = f_5$ (Human Factors), include sub-factors $h_k \in H$ in the calculation
   - Incorporate dynamic factor weighting based on:
     - High variability in f_2 (Time-Critical Nature)
     - f_4 (Patient Capacity)
     - Sub-factors: h_1 (Age), h_6 (Language/Cultural Background), and h_9 (Cognitive/Mental Health State)
   - Use predefined or machine-learned models to compute $X_j(f_i)$
   - Accumulate: $C_{e_j} \leftarrow C_{e_j} + X_j(f_i)$
4. **Accumulate into Total Fatigue:**
   $C \leftarrow C + C_{e_j}$

Dynamic vs Non-Dynamic Trigger Classification

A trigger e_j is classified as *dynamic* if it exhibits high variability in:

- f_2: Time-Critical Nature, f_4: Patient Capacity to Consent, f_5: Human Factors: especially sub-factors:
  - h_1: Age, h_6: Language / Cultural Background, h_9: Cognitive / Mental Health State

Otherwise, the trigger is treated as *non-dynamic*.

Algorithm 2: Probability of Consent Fatigue

Probabilistic Estimation of Consent Fatigue Risk

The dynamic permission model quantifies stressors into a probability by assessing contextual and patient-specific elements to enable adaptive permission techniques and customized techniques in time-sensitive or cognitively demanding scenarios.

Every single consent event $E = \{e_1, e_2, ..., e_n\}$ involves one or more consent triggers. These are assessed utilizing ten primary factorsf_1 to f_{10}, such as frequency(f_1), urgency (f_2), patient capacity (f_4), and human-centered factors (f_5), which include sub-factors h_1 to h_9 for example, age, education level, and cognitive state.

Initially, all inputs are standardized within a [0,1] range to guarantee comparability. For every trigger e_j, a weighted risk score R_{e_j} is calculated using the following equation:

$$R_{e_j} = \sum_{i=1}^{10} w_i \cdot X_j(f_i)$$

where $X_j(f_i)$ presents the impact score of factor f_i on trigger e_j, and w_i is its weight or sensitivity. The sigmoid function has been used to convert the risk score to a probability.

$$P_{e_j} = \frac{1}{1 + e^{-R_{e_j}}}$$

For events involving more than one trigger, fatigue can be aggregated as an average probability:

$$P_{\text{fatigue}}(E) = \frac{1}{n} \sum_{j=1}^{n} P_{e_j}$$

The final probability $P_{\text{fatigue}} \in [0, 1]$ signifies the probability of a patient confronting consent fatigue, permitting systems to modify the frequency and format of successive consent exchanges.

Algorithm 2: Probability of Consent Fatigue

Input:

- Consent trigger e_j or full event $E = \{e_1, e_2, \ldots, e_n\}$
- Factors f_1 to f_{10} and human sub-factors h_1 to h_9
- Trained probabilistic model or scoring rules

Output: Final probability $P_{\text{fatigue}} \in [0, 1]$, representing the likelihood of consent fatigue.

Steps:

1. **Normalize Input Factors:**
   Normalize or scale each factor f_i and relevant sub-factors into the range $[0, 1]$ or convert to standard scores.

2. **Compute Weighted Risk Score for Each Trigger e_j:**
   Let:

$$R_{e_j} = \sum_{i=1}^{10} w_i \cdot X_j(f_i)$$

   where:

   - $X_j(f_i)$: Impact of factor f_i on e_j (from the original model)
   - w_i: Weight or sensitivity of that factor toward causing fatigue (learned or set empirically)

3. **Map Risk Score to Probability (e.g., using Sigmoid Function):**

$$P_{e_j} = \frac{1}{1 + e^{-R_{e_j}}}$$

   This gives the probability that consent fatigue will occur for trigger e_j.

4. **Aggregate Across All Triggers:**
   For event E, compute:

   - **Average probability:**

$$P_{\text{fatigue}}(E) = \frac{1}{n} \sum_{j=1}^{n} P_{e_j}$$

   - Or apply other strategies such as maximum value, weighted average, or thresholding depending on the use case.

Threshold Calculation

- τ_C: Threshold for cumulative consent fatigue (total score C)
- τ_P: Threshold for immediate fatigue risk (probability P_{fatigue})

Interpretation Layer

- If $C > \tau_C$: High cumulative burden
- If $P_{\text{fatigue}} > \tau_P$: High immediate risk of fatigue
- Adjust strategy: bundle, delay, simplify, or automate consent interactions

Dynamic Consent Fatigue Management Model (DCFM)

The proposed framework integrates CF estimation and risk prediction into a unified, intelligent system for adaptive consent delivery. It is structured into three layers. Layer 1 implements Algorithm 1, which calculates the cumulative fatigue score and quantifies the contribution of individual influencing factors. Layer 2 utilizes Algorithm 2 to compute the risk score and derive the probability of CF through a sigmoid transformation. Layer 3, the threshold interpretation layer, assesses the outputs against predefined benchmarks. Specifically, when the predicted fatigue probability P_{fatigue} exceeds the threshold τ_P, it indicates a high risk of fatigue, prompting adaptive consent strategies.

Layer 1: Consent Fatigue Estimation Module (Algorithm 1)
Input:

- Consent Event $E = \{e_1, \ldots, e_n\}$
- Factors f_1–f_{10}
- Human Sub-factors

Output:

- Fatigue Score C (cumulative burden)
- Factor impacts $X_j(f_i)$ per trigger — shared with Layer 2

Level 2: Fatigue Risk Prediction Module (Algorithm 2)

Input: Weighted sum of factor impacts from Layer 1

Core Function:

$$R_{e_j} = \sum_{i=1}^{10} w_i \cdot X_j(f_i)$$

$$P_{e_j} = \frac{1}{1 + e^{-R_{e_j}}}$$

Output: Probability of fatigue P_{fatigue}

Layer 3: Interpretation & Adaptive Decision Engine (Threshold Layer)
Inputs:

- C from Layer 1
- P_{fatigue} from Layer 2

Thresholds:

- τ_C: Burden threshold

- τ_P: Fatigue probability threshold

Output:

- Dynamic classification: Fatigue Level = {Low, Moderate, High}
- Consent adaptation strategy: Bundle, Delay, Simplify, Automate

Model Summary in Formula:

$$\begin{aligned}\text{DCFM Model} = f\left(E, \{f_i\}, \{h_j\}\right) &\rightarrow (C, P_{\text{fatigue}})\\ &\rightarrow \text{Adaptation Strategy}\end{aligned}$$

The model suggests four key strategies to reduce CF when risk exceeds a threshold: bundling (merge multiple consents), delaying (postpone non-urgent requests), simplifying (make language clearer), and automating (apply defaults for low-risk cases). These adaptations help maintain ethical standards while reducing cognitive load, supporting more sustainable and patient-centred consent processes in high-fatigue situations. This layered approach allows for continuous assessment and responsive management of CF in digital health or research environments.

The goal of DCFM model is to enhance consent by balancing medical accuracy with patient satisfaction, while reducing consent fatigue through intelligent, adaptive delivery methods.

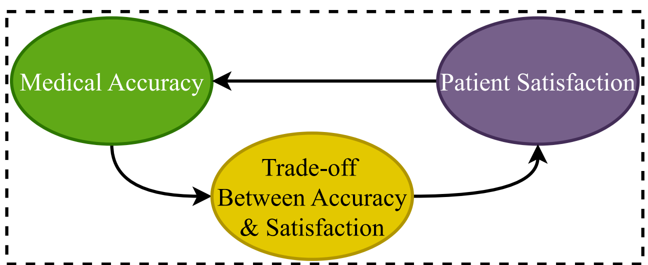

Figure 1: Goal of Dynamic Consent Model

These are the three components presented in Fig. 1 to achieve the goal of the DCFM model. These three components are codependent; optimizing one in isolation will consistently impact the others.

Formalized Optimization Goal:

$$\max\left[\alpha \cdot \text{Medical Validity} + \beta \cdot \text{Patient Satisfaction}\right]$$

$$\text{subject to: } C \leq \tau_C, \quad P_{\text{fatigue}} \leq \tau_P$$

Where:

- α, β: Tunable weights prioritizing medical versus patient-centered outcomes
- C: Cumulative fatigue score (from Algorithm 1)
- P_{fatigue}: Probability of fatigue (from Algorithm 2)
- τ_C, τ_P: Thresholds to ensure ethical and comfortable consent delivery