When Less is More: Optimizing Prescription ALERTS under Fatigue

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Research Motivation

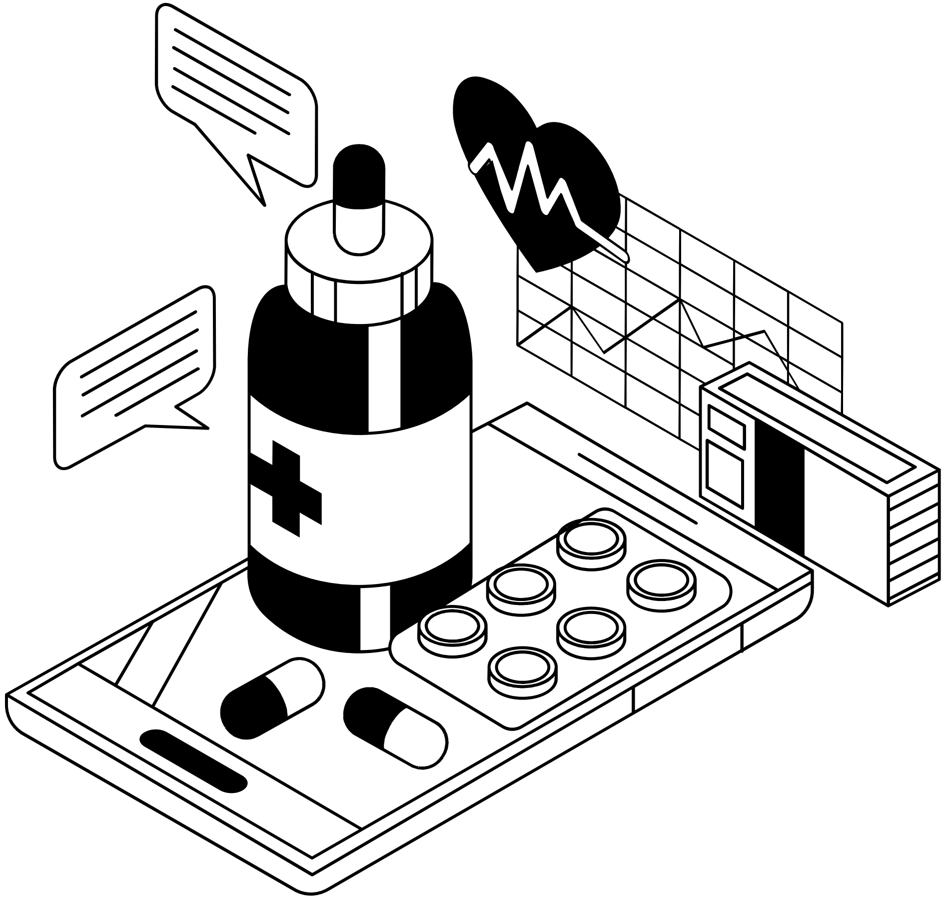
Literature Review

Model Framework & Structure

Special Case in the Real World

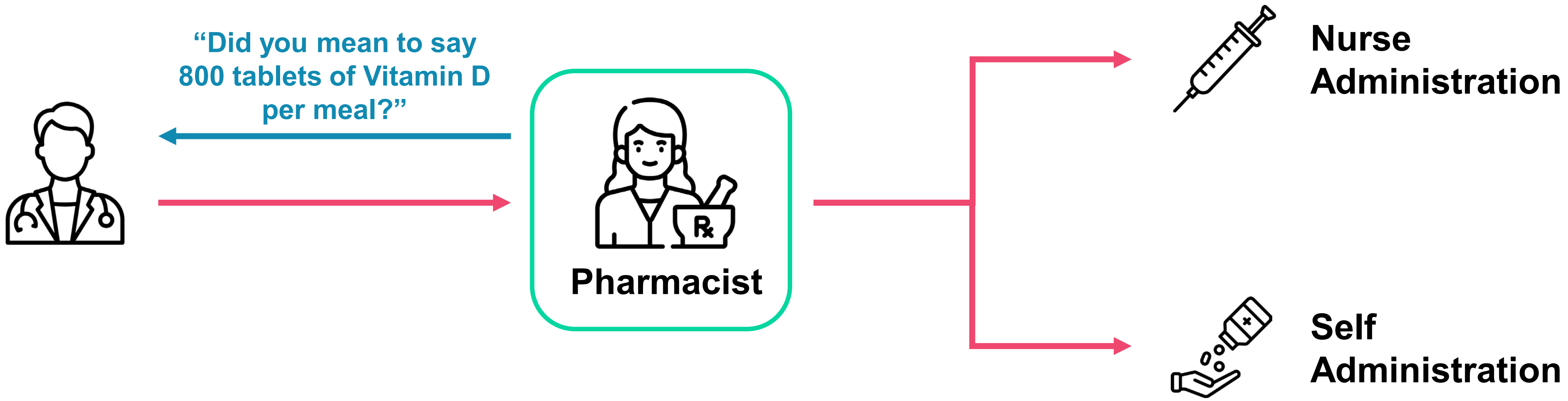
Case Study

Conclusion



Research Motivation

Overview of the Prescription Workflow



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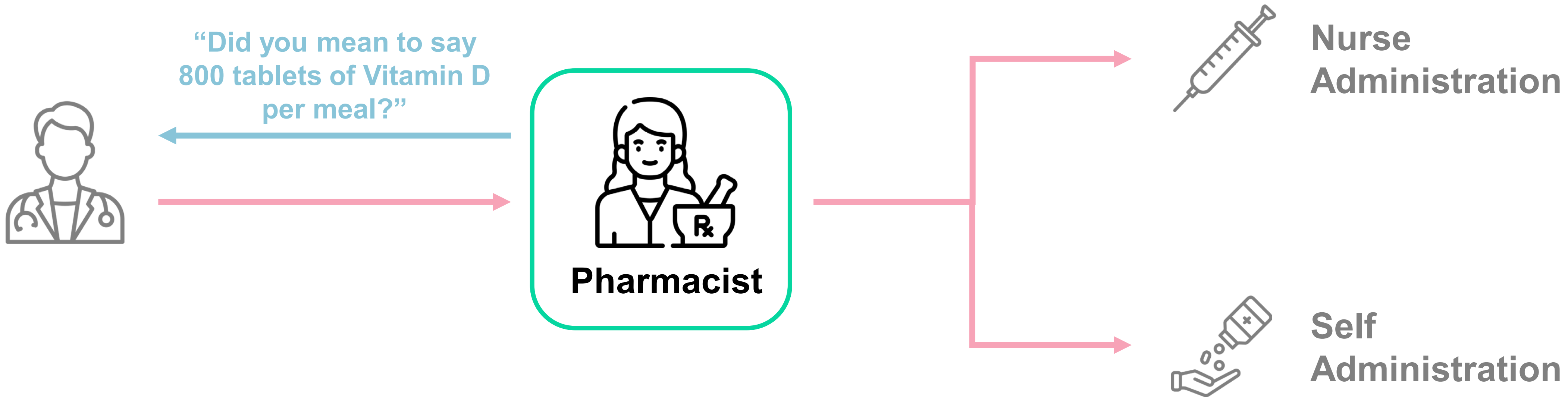


Pharmacists act as the **last line of defence**

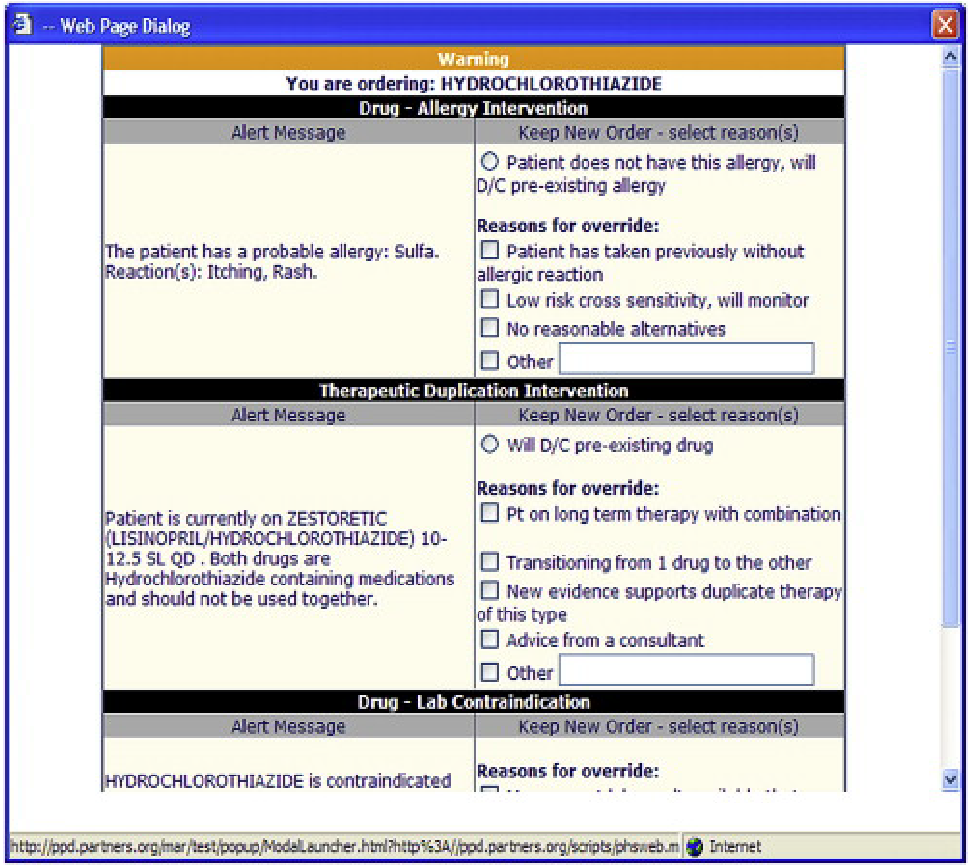
3%
Prescription Error Rate

(Naseralallah et al. 2020)

50K+
Annual Deaths due to Prescription Error

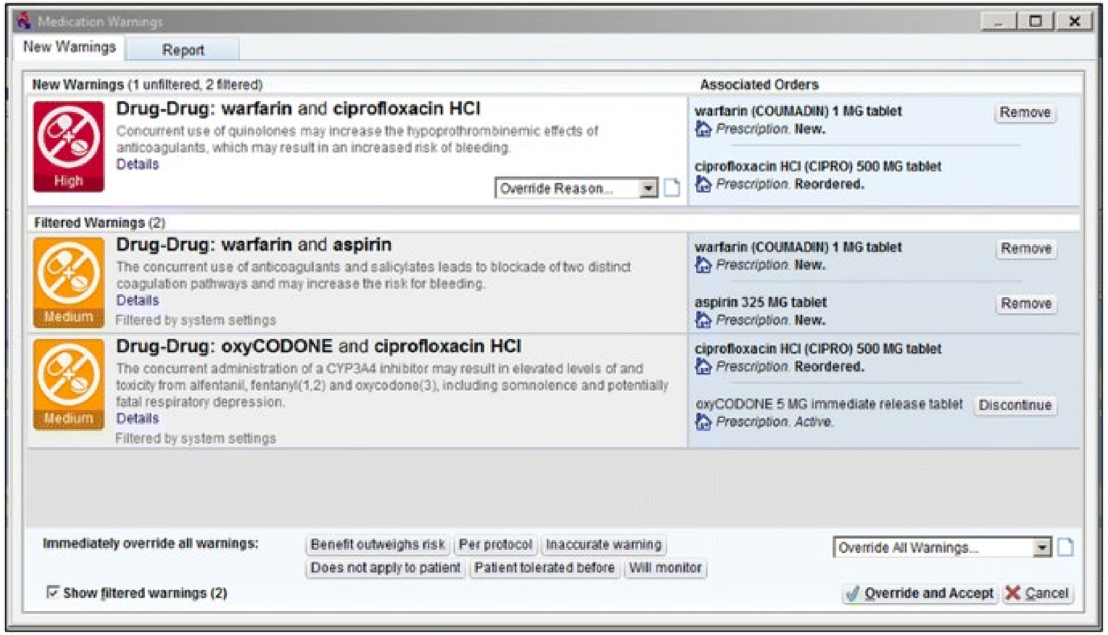
(AHRQ 2015)

Computer Provider Order Entry (CPOE) Systems



Ⓐ Tier 1 (most severe)

Ⓑ Tiers 2 (moderate) and 3 (least severe)



Error Reduction by 50%+

How much of a good thing is TOO much?

7-15

Average # of Alerts per Prescription

100-1000

Average # of Alerts per Shift

90%+

Time Spent Dealing with Alerts

96%

Override

*"A hospitalized teenager received **38x** overdose of antibiotic because clinician advised to 'ignore all alerts'."*
-AHRQ Patient Network

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GOAL: Understand optimal alerting strategy under fatigue.

Research Question

How to optimize CPOE alerts to balance between providing essential alerts and minimizing unnecessary interruptions?

Literature Review

Literature Review

Behavioral Dimension

- **Fatigue ↓ compliance in clinicians**
- **Repeated interruptions → lower responsiveness**
  - Nanji et al. 2014
  - Dai et al. 2015
  - Ancker et al. 2017
  - Schwartz et al. 2021
  - Joseph et al. 2021
  - Bavafa and Jonasson 2024
- **Probability of a favorable parole among judges: 65% → ~0%**
  - Danziger et al. 2011

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Clinical Approaches

- **Tiering/context filters; adjust severity/frequency**
- **Rule-based threshold tuning can reduce burden (often manual/static)**
  - Cash 2009
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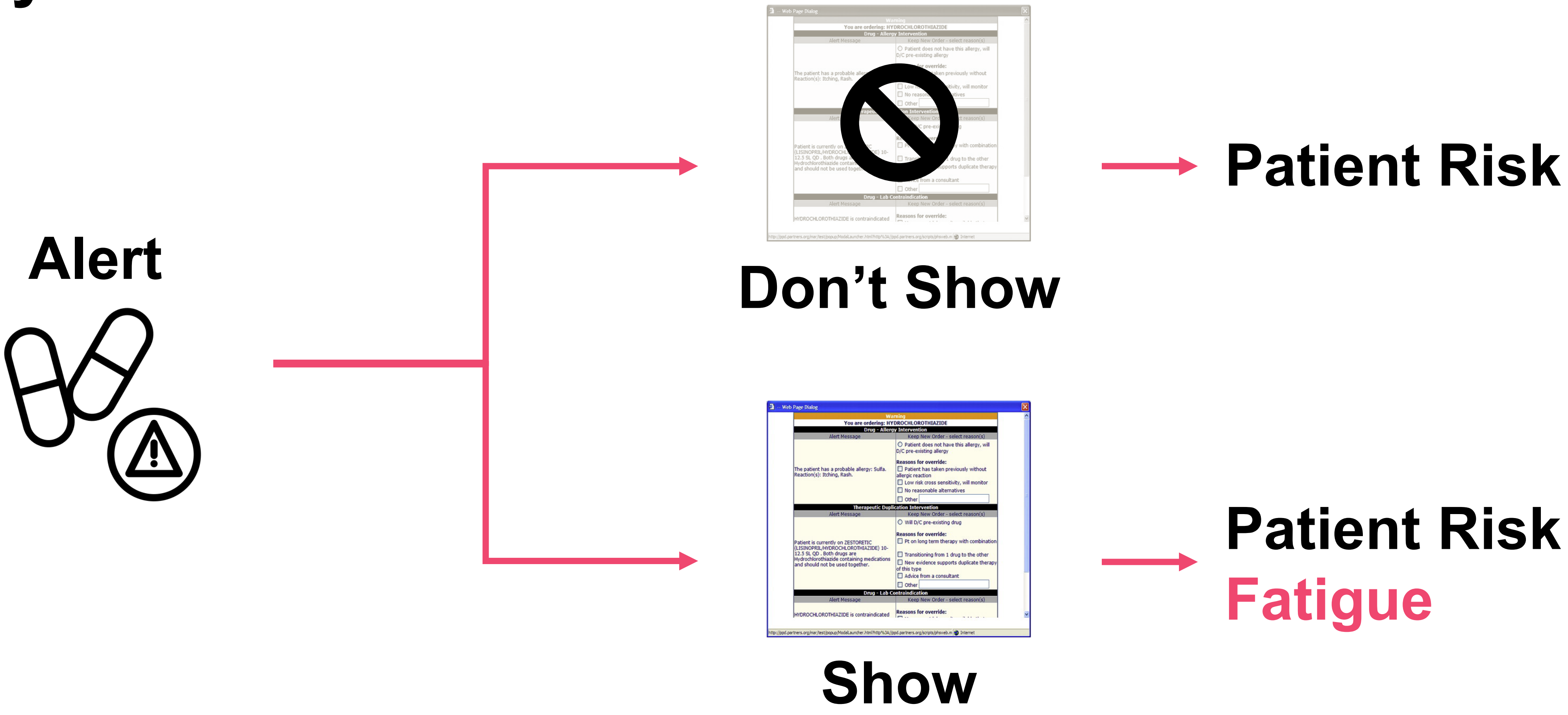
Machine Learning / Statistical Approaches

- **Predict/suppress low-value alerts (overrides/outcomes)**
- **Personalize relevance (patient/clinician-specific models)**
  - Malone et al. 2023
  - Chen et al. 2024
  - Martell 2019; Poly et al. 2020
  - Graafsma et al. 2024

Model Framework & Structure

Why is this difficult?



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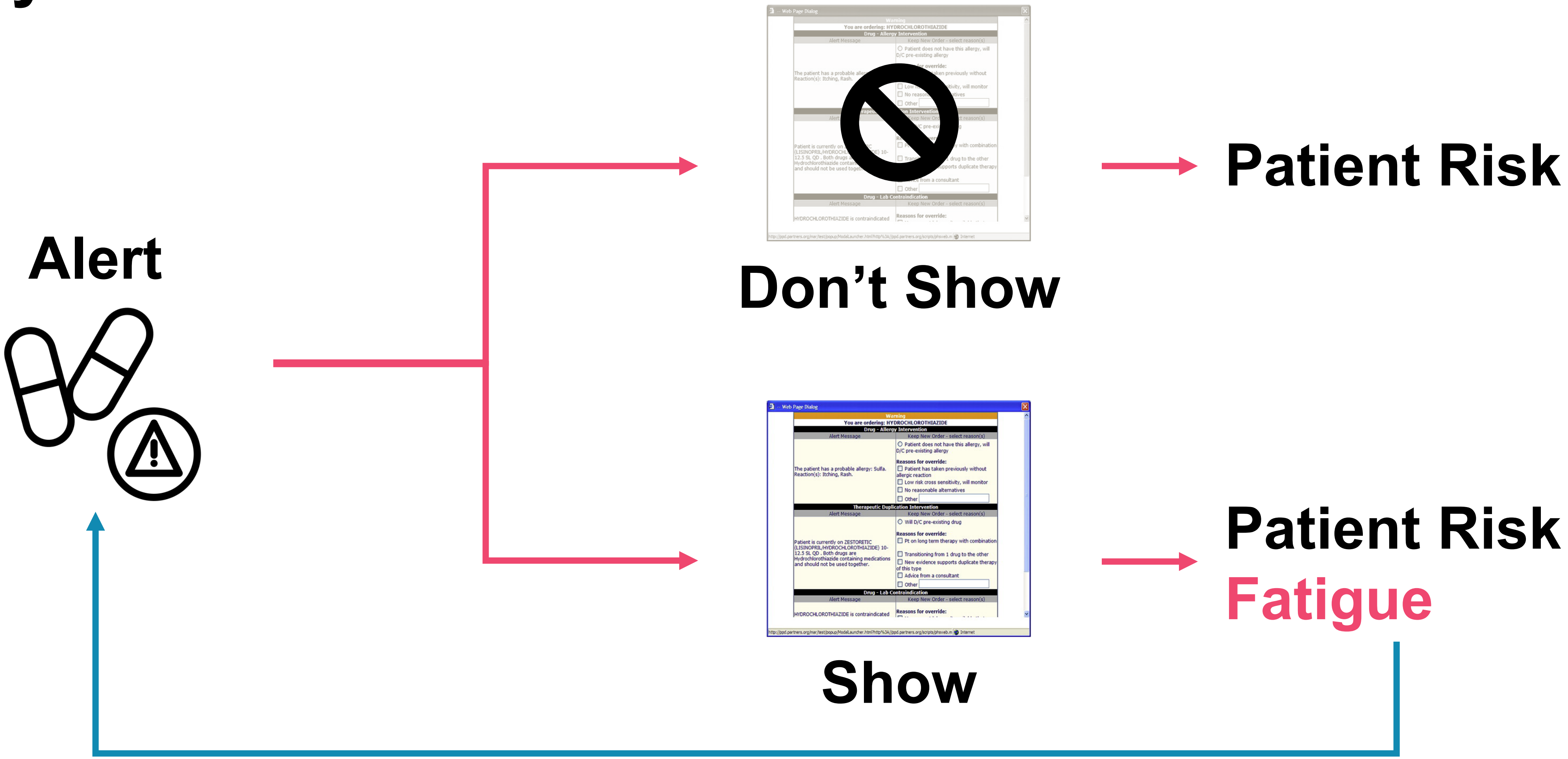
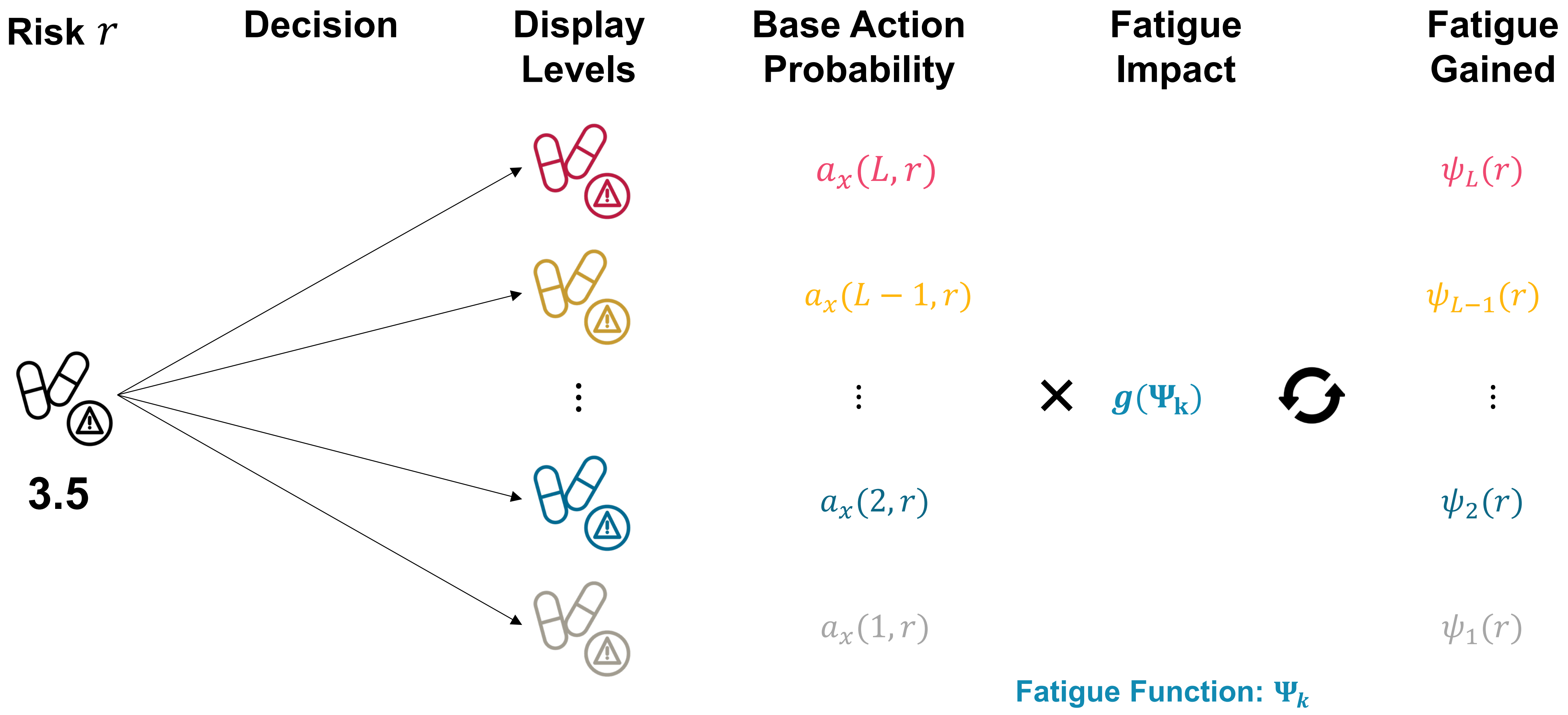


Embi and Leonard (2012),
Ancker et al. (2017)

Modeling Framework



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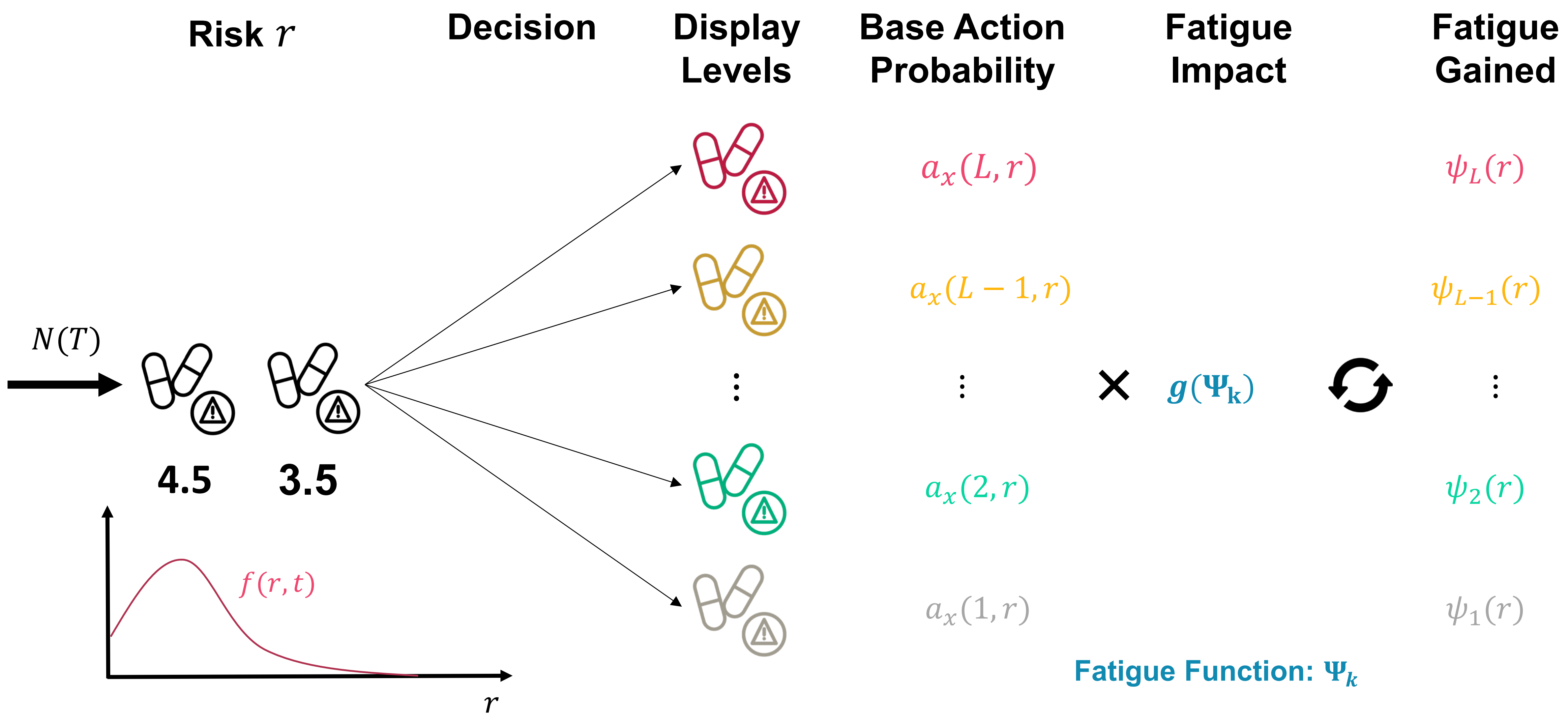
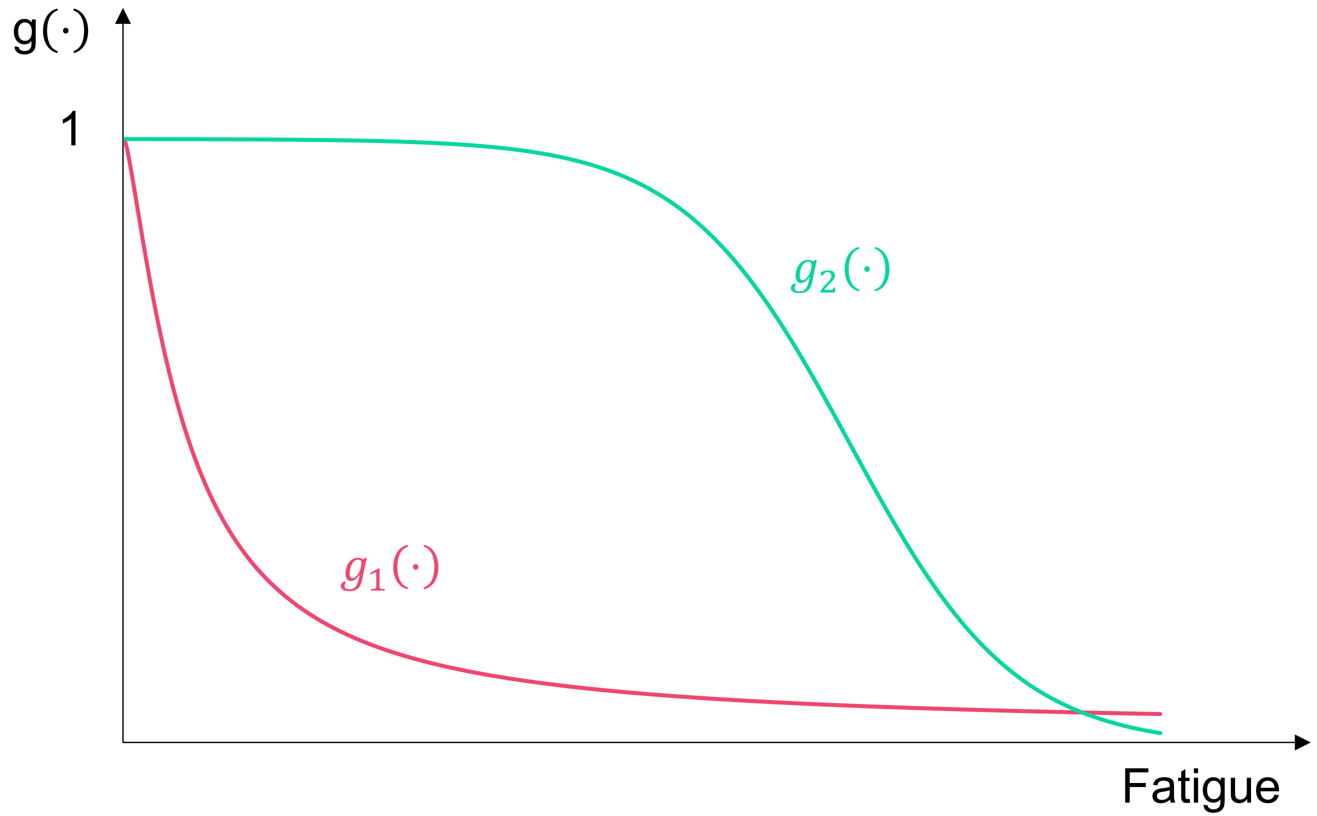


The Fatigue Linking Function

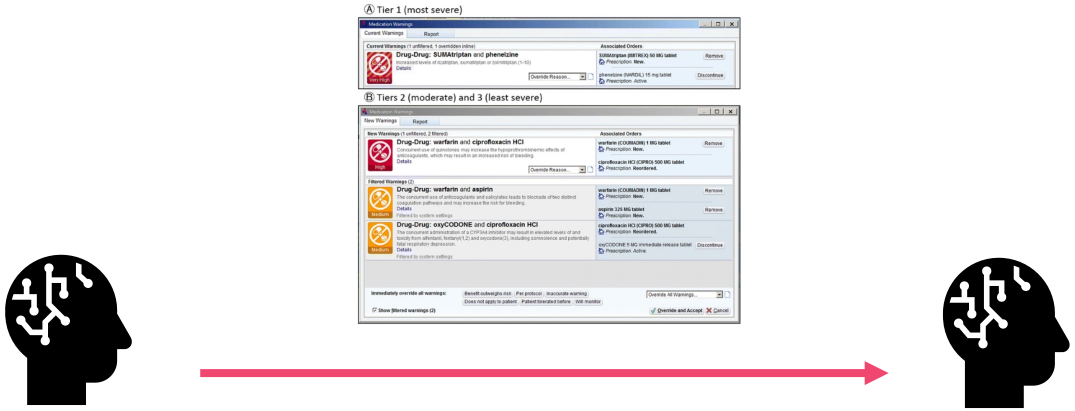


$g_1(\cdot)$: Pharmacist/clinician performance quickly deteriorates with fatigue, but maintains residual efficiency even under high fatigue

$g_2(\cdot)$: Pharmacist/clinician maintains high level of performance until fatigue is very high, and drops significantly

Fatigue Transition Dynamics

Ψ_k : Pharmacist's fatigue after processing k^{th} alert



Ψ_k Ψ_{k+1}

Display Levels

Assumption 1:

$U_{l,r}: [0,\infty) \rightarrow [0,\infty)$: Fatigue transition map

- Monotone
- Cumulative
- Identifiability

$$\Psi_{k+1} = U_{l+1,r+1}(\Psi_k)$$

Technical Result

Theorem 1

Under assumption 1, ∃ a strictly increasing transformation $\phi: [0, \infty) \to R$ and constants $\psi_{l,r} \geq 0$ such that defining the rescaled fatigue state $\widetilde{\Psi} = \phi(\Psi)$, the fatigue dynamic satisfies

$$\widetilde{\Psi}_{k+1} = \widetilde{\Psi}_k + \psi_{l_{k+1}, r_{k+1}}$$

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Translation

Any fatigue transition dynamics that satisfies Assumption 1 admits an equivalent representation in which fatigue transition is additive.

Dynamic Program

Decisions: $\pi_k(l|\Psi, r)$

Probability of a risk r alert
arriving at epoch k
will be shown at level l

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Objective:

$$\max_{\pi_1,\pi_2,\ldots} \mathbb{E}\left[\sum_{k=0}^{N(T)} \sum_{l=1}^{L} r_k \times \pi_k(l|\Psi_{k-1}, r_k) \times a_x(l, r_k).\, g(\Psi_{k-1}, r_k)\right]$$

Risk avoided
for K alerts

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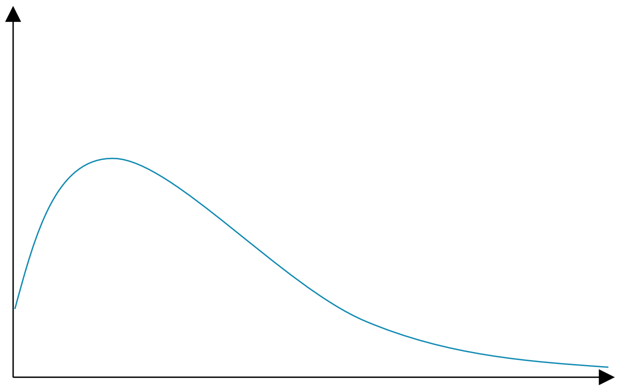

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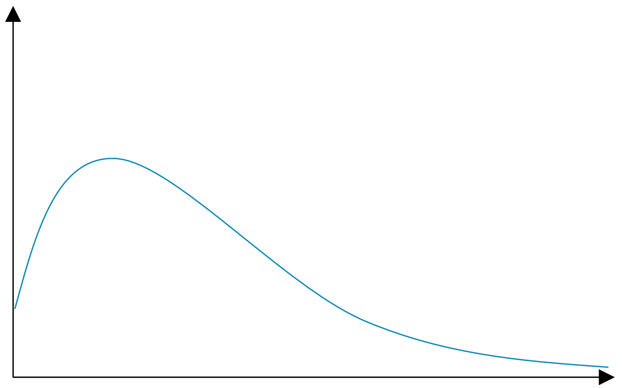

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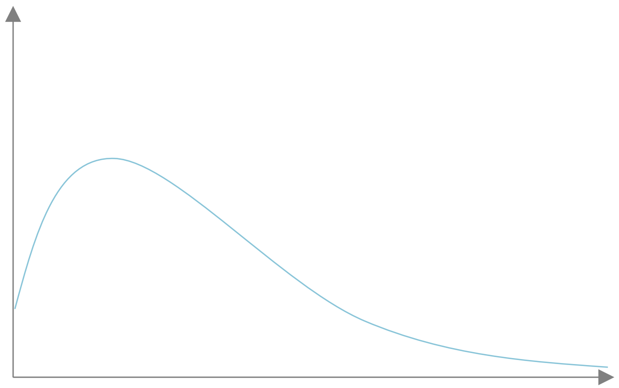
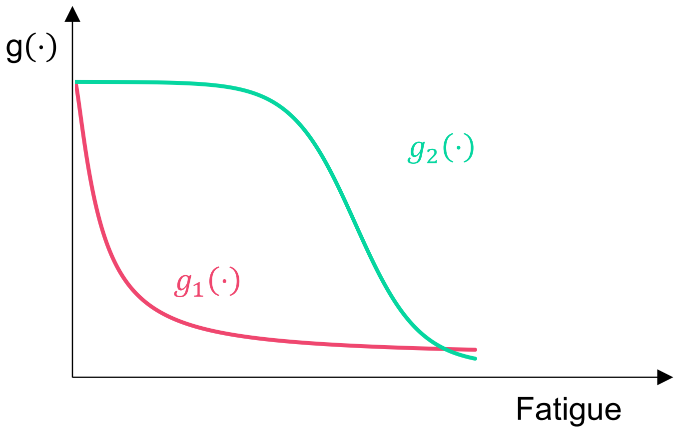
Risk avoided for K alerts





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Risk avoided for K alerts

Constraints: $l_k \sim \pi_k(.|\Psi_{k-1}, r_k) \qquad r_k \sim f(r, t_k)$

Fatigue depends on all past decisions

Dynamic Program

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Fatigue Dynamics:

$$\Psi_{k+1} = \Psi_k + \psi_{l_{k+1}, r_{k+1}} \qquad \Psi_1 = 0$$

Fluid Approximation

Decisions: $p_l(r,t)$

Probability of a risk r alert arriving at time t will be shown at level l

Objective:

$$\sum_{l=1}^{L}\int_0^{\infty}\int_0^{T} r \times \underbrace{\lambda(t)\, f(r,t) p_l(r,t)}_{\text{Instantaneous rate of risk } r \text{ level } l \text{ alerts}} \times \underbrace{a_x(l,r) g(\psi(t), r)}_{\text{Fatigue-impacted action probability}}\, dt\, dr$$

Risk avoided through alerts within time $[0, T]$

Constraints: $\psi(t) = \sum_{l=1}^{L}\int_0^{\infty}\int_0^{t} \psi_l(r)\, \lambda(s) f(r,s) p_l(r,s) ds\, dr$

Fatigue depends on all past decisions

Infinite-dimensional functional optimization problem

Technical Result

Theorem 2

Under the following assumptions, fluid-approximation is an asymptotically optimal approximation to the dynamic programming problem.

- Bounded Mean Risk and Arrival
- Bunded Fatigue
- Lipschitz Fatigue: $\exists L_g < \infty$ s.t. $\forall r, \Psi, \Psi', |g(\Psi, r) - g(\Psi', r)| \leq L_g |\Psi - \Psi'|$

Special Case in the Real World

A Special Case: Alert or Not?

Two Levels

Alert No Alert

Stationary Risk Distribution

$$f(r,t) = f(r)$$

Exponential Linking Function

$$g(\Psi, r) = \eta(r)\exp(-\beta\ \Psi)$$

"Rate of attention decrement"

Mackworth (1948), Warm et al. (2008)

A Special Case: Alert or Not?

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Alert

No Alert

Stationary Risk Distribution

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Exponential Linking Function

$$g(\Psi, r) = \eta(r)\exp(-\beta\ \Psi)$$

Fatigue rate

Mackworth (1948), Warm et al. (2008)

Theorem

Define: $H(y) = \int_0^{\infty} \left(r\, a_x(r) - y\, \psi(r)\right)^+ f(r) dr\,,$ $\qquad G(y) = \int_0^y \frac{1}{H(x)}\, dx$

Screening index: $S(r) = \frac{r\, a_x(r)}{\psi(r)}$

Show an alert iff $S(r) \geq G^{-1}(\beta(T - t))$

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Baseline Expected Risk Avoidance

Fatigued Induced

A Special Case: Alert or Not?

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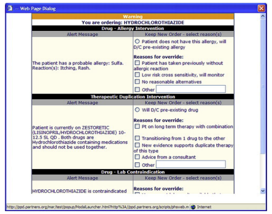
Baseline Expected Risk Avoidance

Threshold y

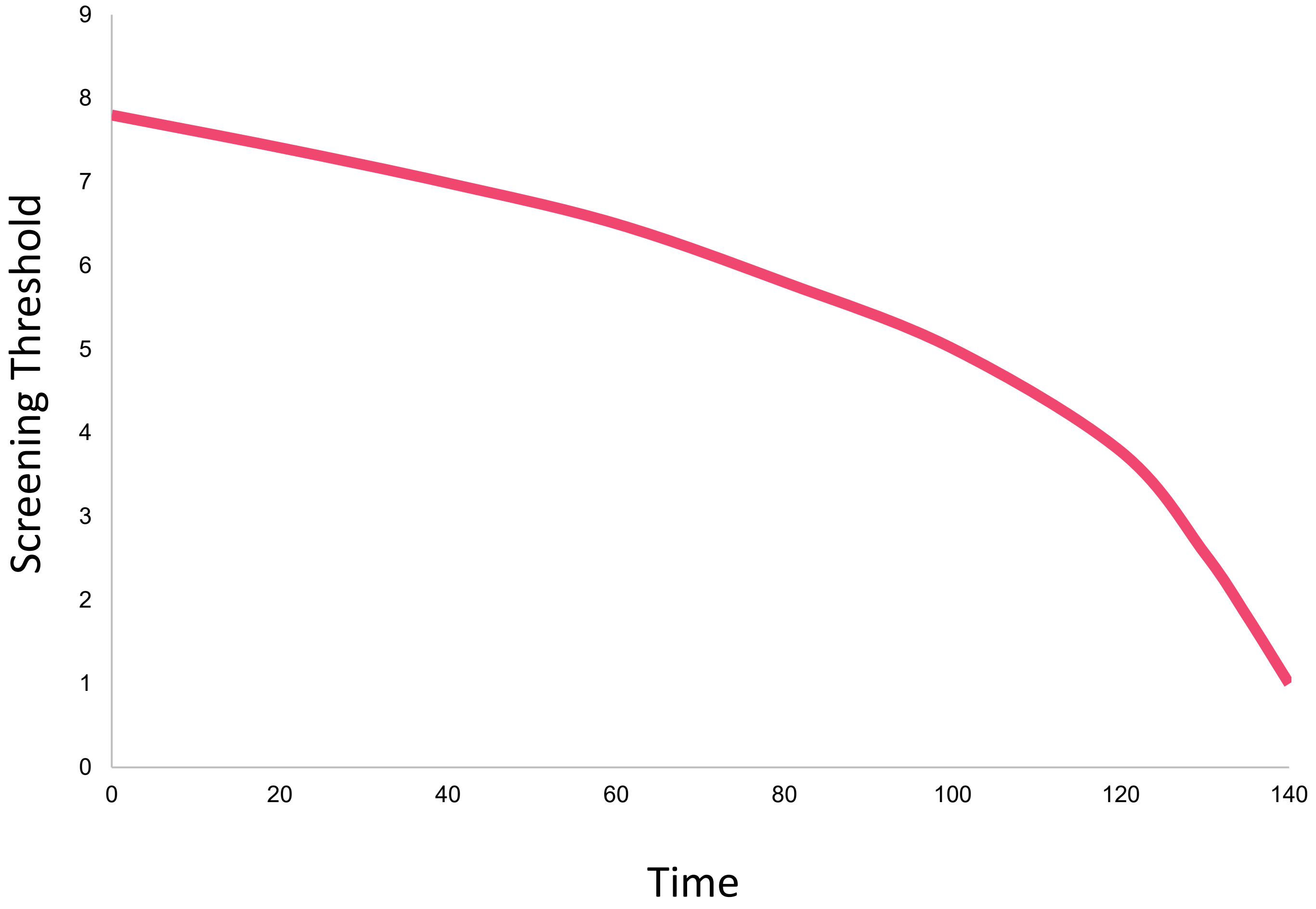
Fatigued Induced

Illustration of Screening Threshold



$S(r)$

G^{-1}



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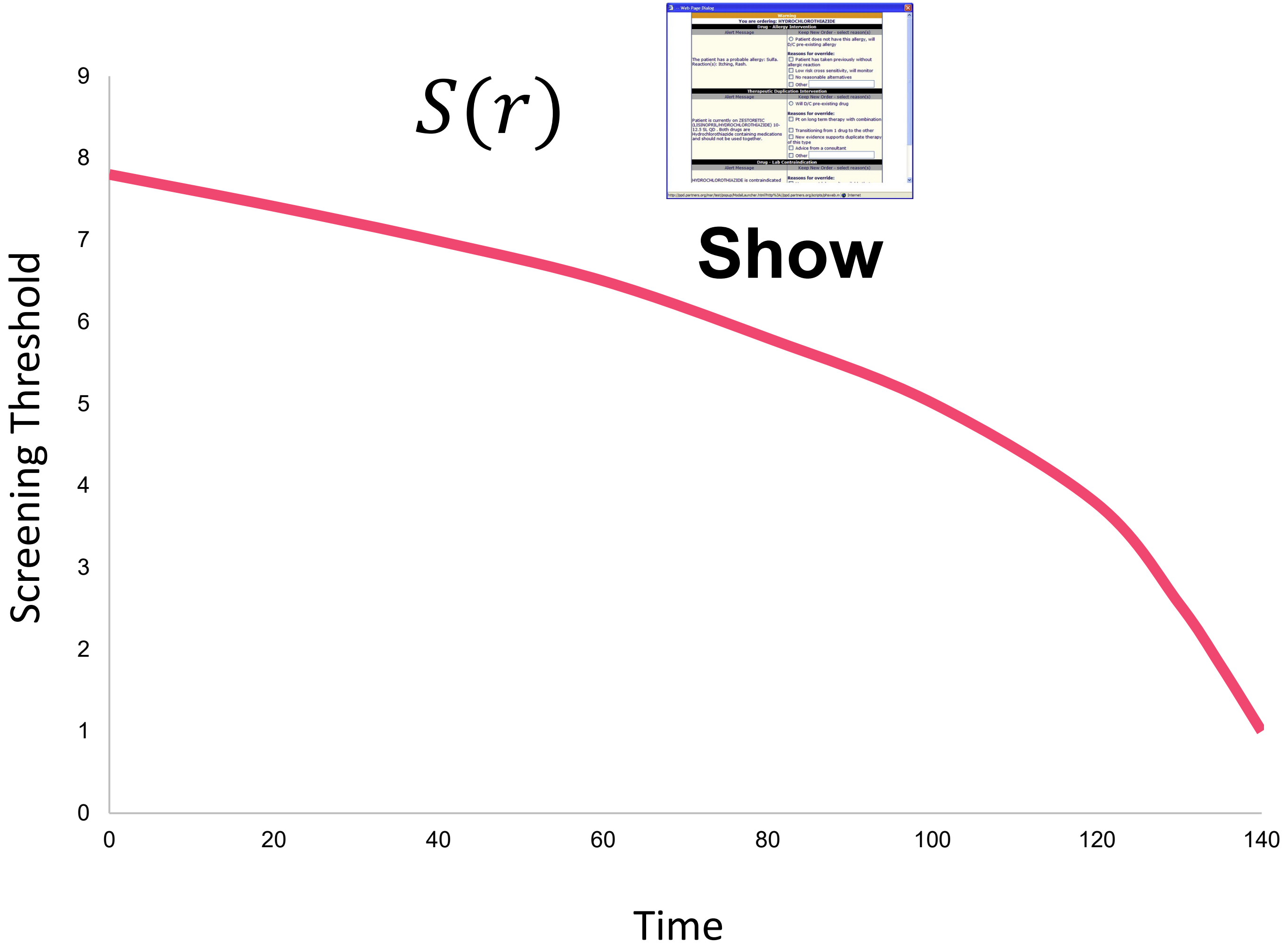

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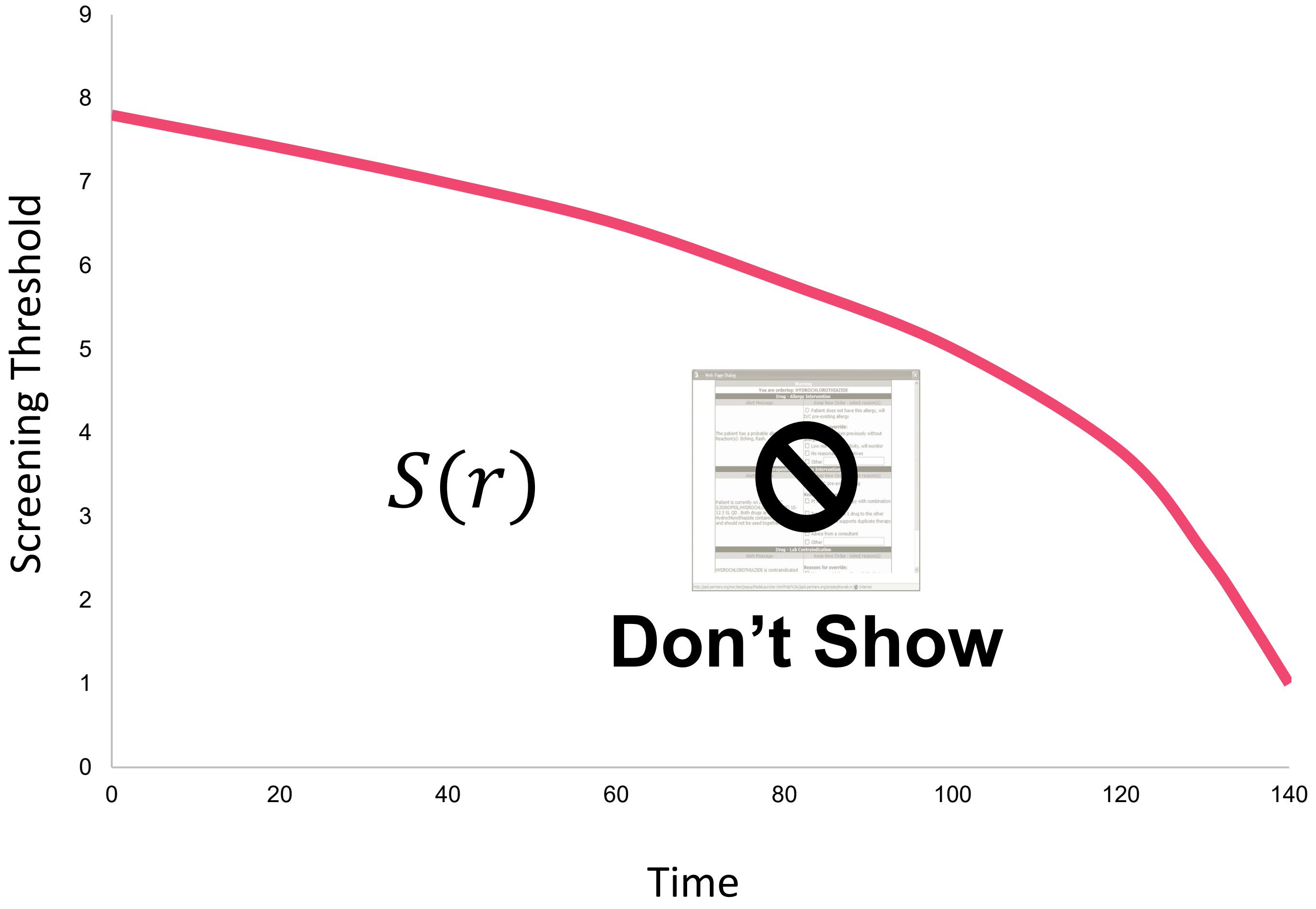

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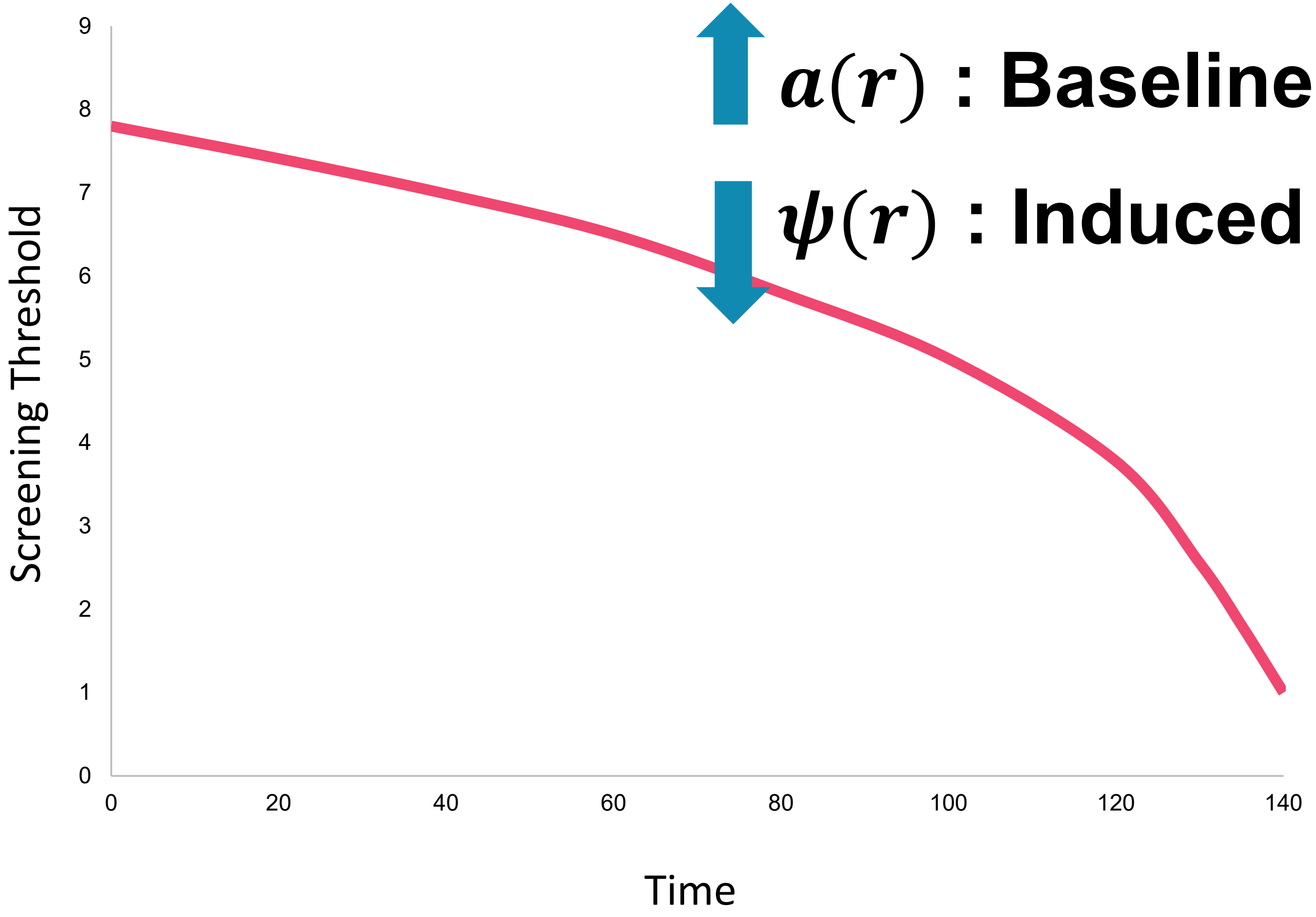
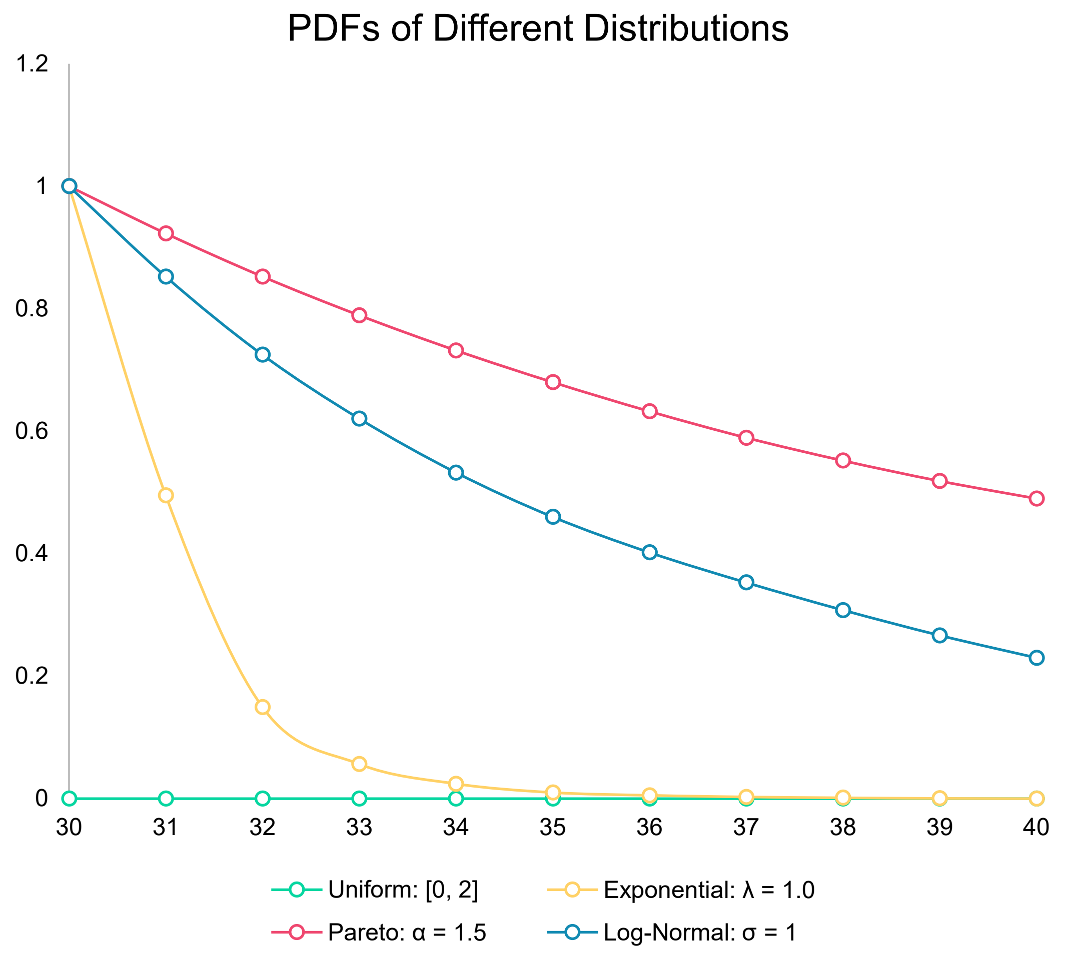
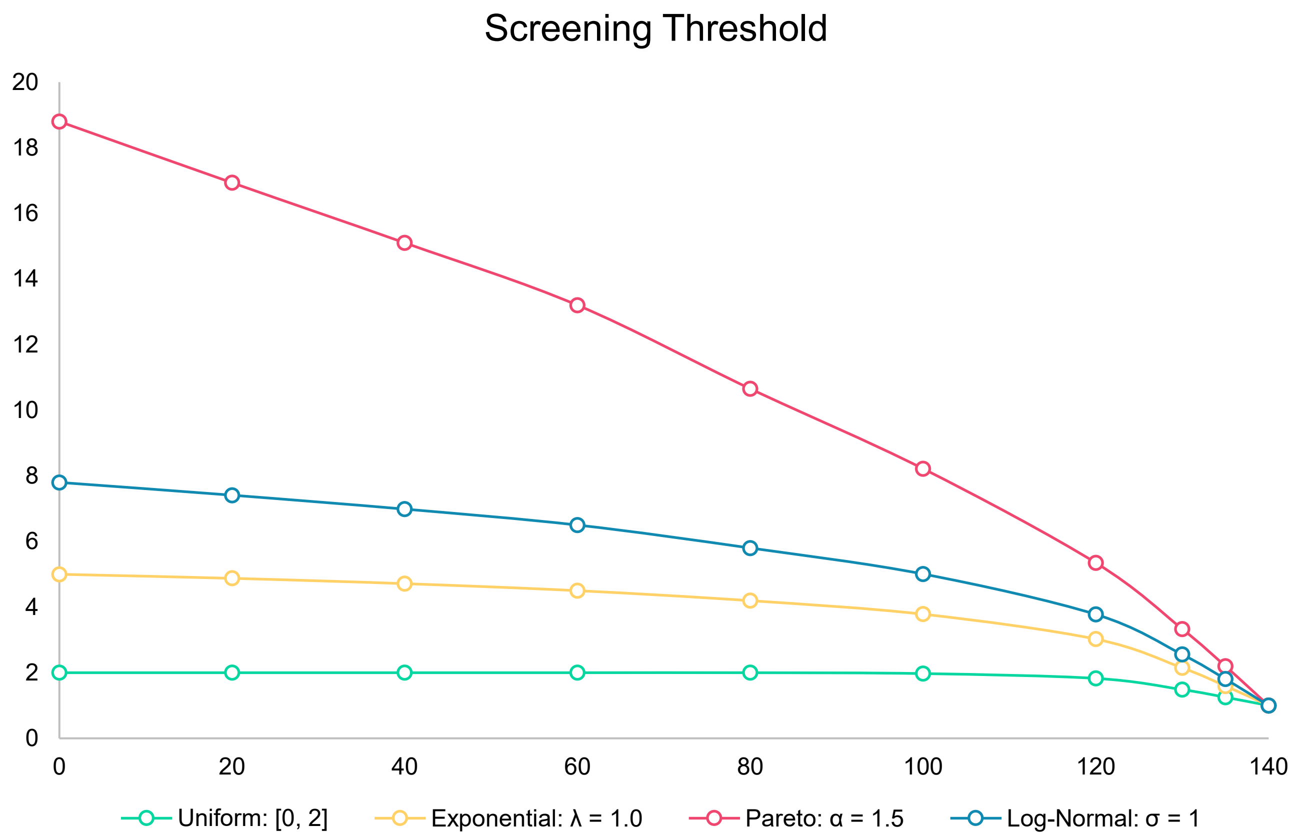


$a(r)$: **Baseline Acceptance**

$\psi(r)$: **Induced Fatigue**

Illustration of the Tail Risk Effect





Comparison with Baseline Policies

$\mathcal{P}^0$	**No Alert Strategy**
$\mathcal{P}^*$	**Optimal Strategy:** Decreasing Threshold Policy
$\mathcal{P}^A$	**All Alerts Policy:** Common default policy

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$$\frac{B_2^0}{B_2^*} = \frac{\mu_A}{\mu_\psi} \times \frac{1}{S_{max}}$$

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$\mathcal{P}^0$ **No Alert Strategy**

$\mathcal{P}^*$ **Optimal Strategy:** Decreasing Threshold Policy

$\mathcal{P}^A$ **All Alerts Policy:** Common default policy

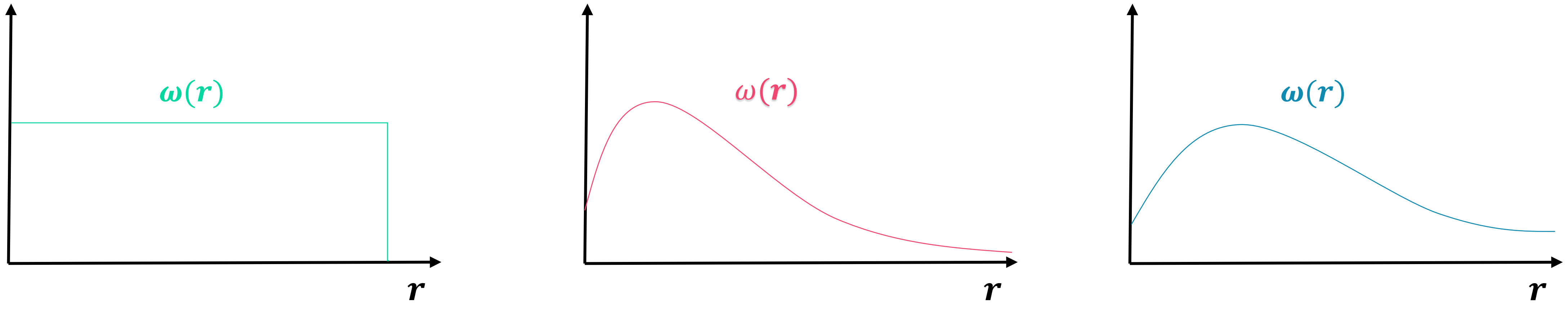
$\mathcal{P}^\dagger$ **Optimal *Fixed* Policy:** $r_1^*(t) = k$

The Effectiveness of Fixed Policies

Theorem

Normalized Expected Fatigue: $\omega(y) = \frac{1}{\mu\omega}\int_{S(r)=y}^{\infty} \psi(y) f(r)\, dr$

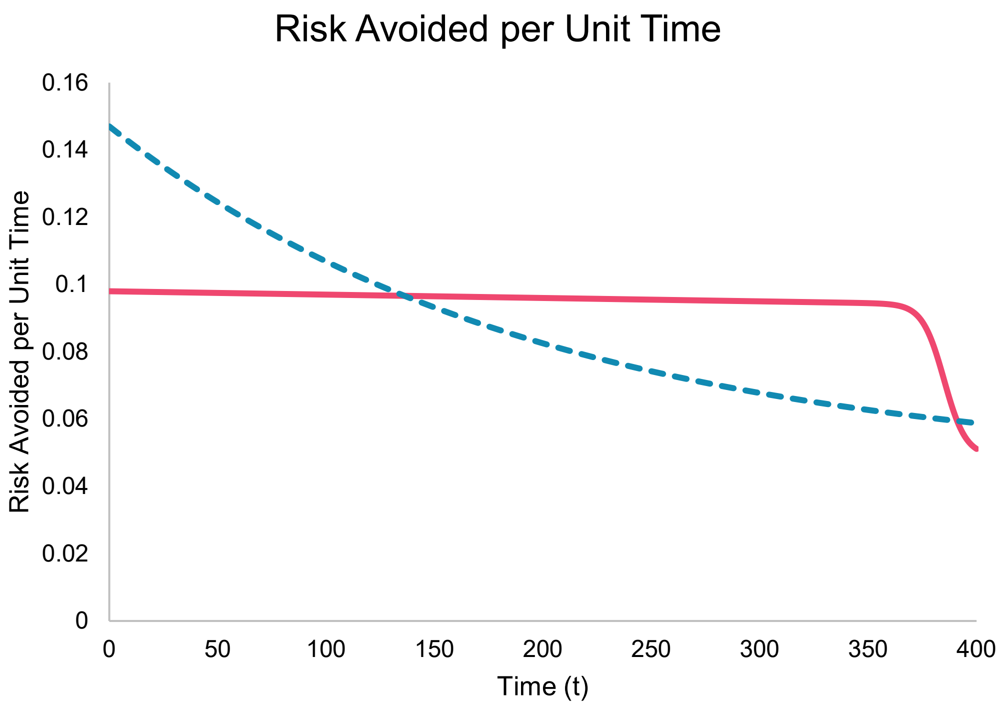
1. (Light-tailed $\omega(y)$) Tail of $\omega(y)$ belongs to the Weibull or Gumbel → $\lim_{T\to\infty} \frac{B_2^{Fix}(T)}{B_2^{*}(T)} = 1$
2. (heavy-tailed $\omega(y)$) Tail of $\omega(y)$ belongs to the Frechet → $\lim_{T\to\infty} \frac{B_2^{Fix}(T)}{B_2^{*}(T)} < 1$



Constant Optimal ✓ **Constant Optimal** ✓ **Constant Near-Optimal** ✓

Near-optimality of optimal fixed policy.

Optimal Fixed vs Optimal Policies



Optimal Solution: Decreasing

Fixed Solution: Constant

Optimal Solution: (Near) Constant

Fixed Solution: Decreasing

Tradeoff between alert vs risk fairness

Case Study

Real-world Data Calibration

University of Alberta Hospital

Pharmacist alert data from the University of Alberta Hospital System

Study Period
Jan 2021 – Dec 2024

Total Alerts
583,313

Avg Alerts / Shift
142

90th Percentile
> 449 Alerts / Shift

Override Rate
78%

Risk Estimation

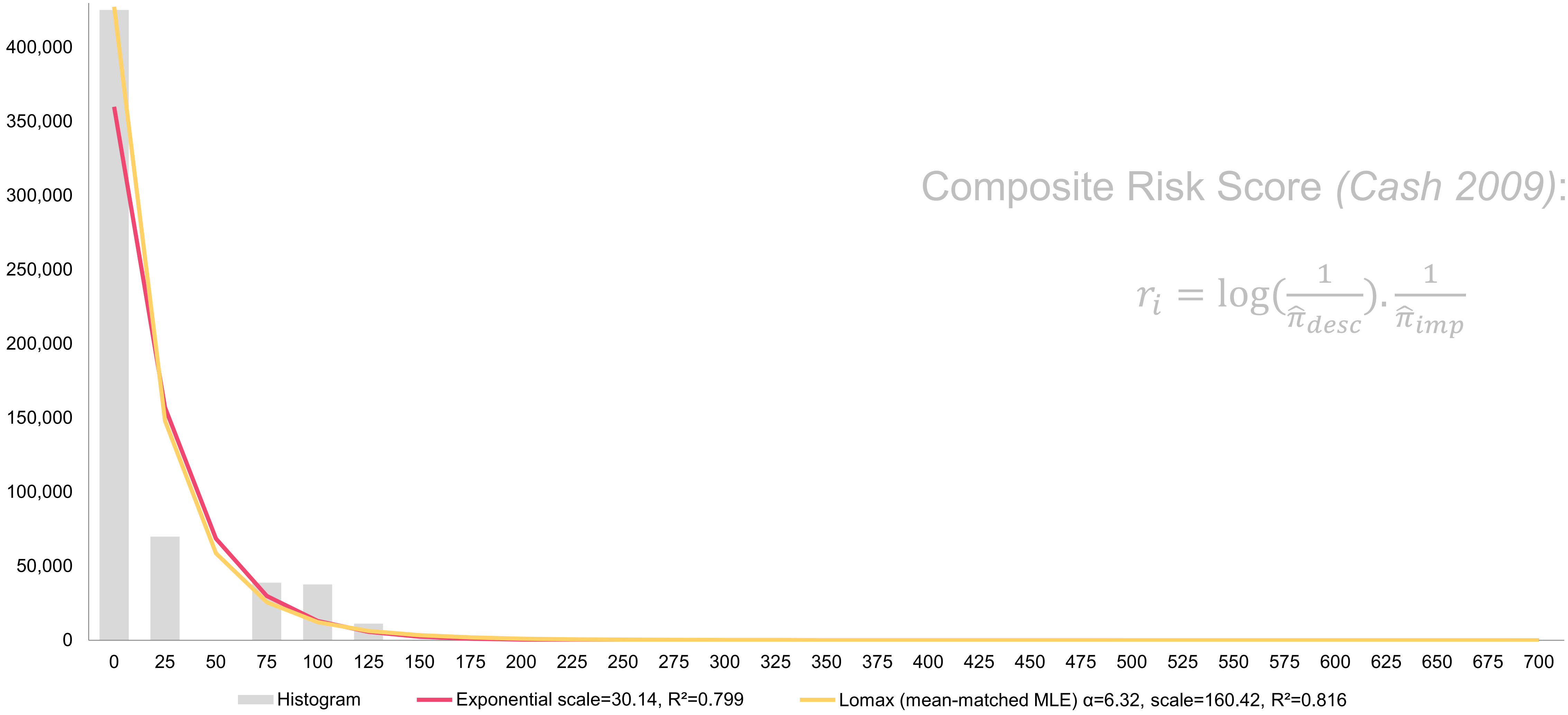
Alert Description	**Importance Level**
Moderate Interaction	**Low**
Severe Warning	**Medium**
Absolute Contraindication	**High**
Moderate Warning	**Very High**

Description → ***Templates***
Lowercasing, removing markup, digits, etc.

Composite Risk Score *(Cash 2009)*:

$$r_i = \log(\frac{1}{\hat{\pi}_{desc}}).\frac{1}{\hat{\pi}_{imp}}$$

Risk Estimation



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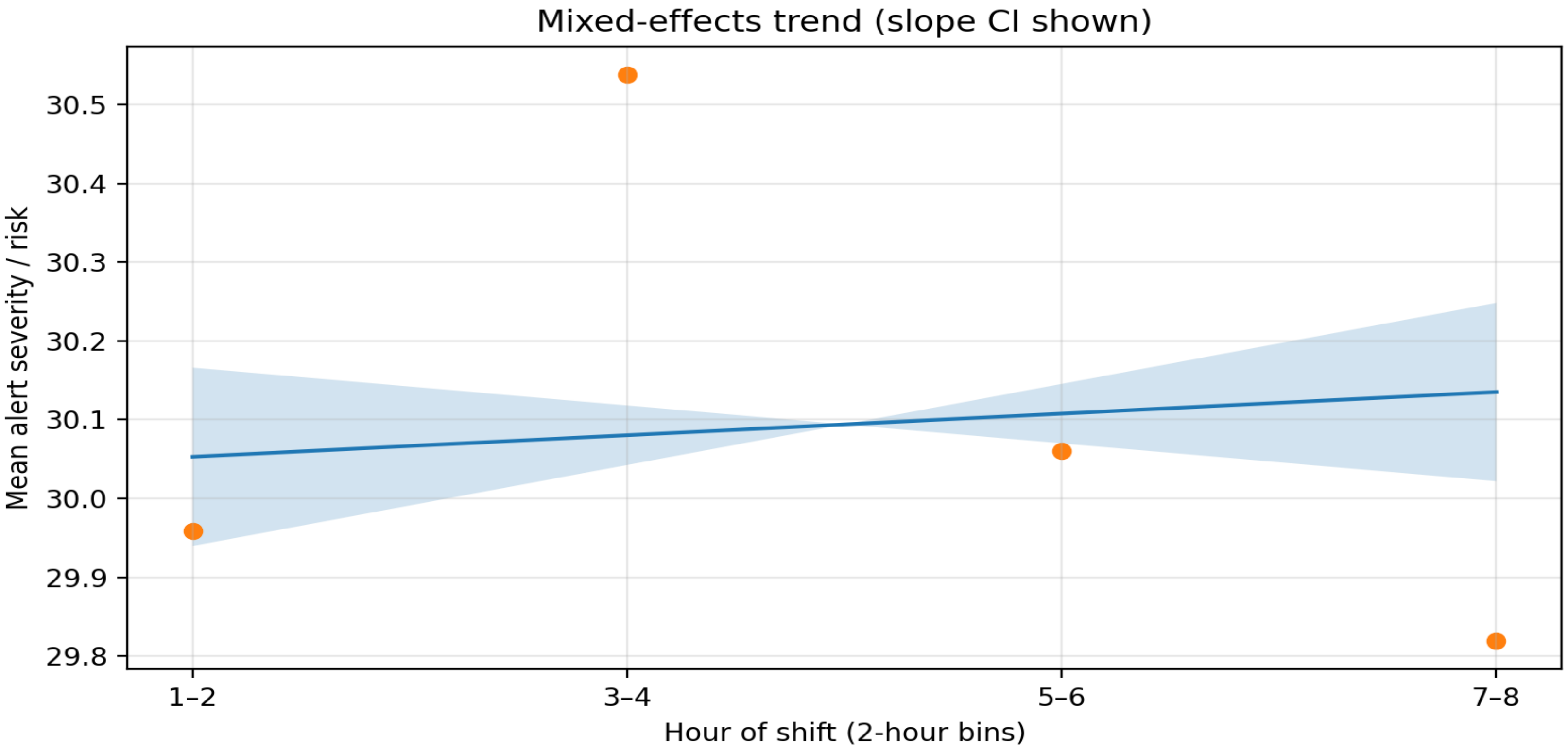
Risk Stationarity

Risk is stable across shift hours (no meaningful drift)



Behavioral Model

Exponential Decay:

Mackworth (1948), Warm et al. (2008)

$$P_i(\Psi, r, x) = \exp(-\hat{\eta}_i)$$

$$\hat{\eta}_i = Fatigue + Risk + Cumaltive\ Risk + Recovery + Exposure + Pharmacist + Shift$$

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Behavioral Model

5-fold CV AUC: 0.76

↓27% by 100 alerts

Stationary risk

Alert Fatigue

Term	Coef. Estimate	Feature Importance * $\times 1e-4$
Intercept	0.696318^{***} (0.063483)	NA
Alert index	$\boxed{0.003159^{***}\ (0.000133)}$	446
Alert Risk	-0.003197^{***} (0.000065)	68
Cumulative Alert index	-0.000043^{**} (0.000001)	9
Exposure before shift (learning)	-0.000189^{***} (0.000003)	32
Time between prescriptions (recovery)	0.0000007 (0.006239)	78
Shift Fixed Effect	Included not significant	<5
Pharmacist fixed effect	Included not significant	<5

** Feature importance is LOFO ΔNLL*

Policy Evaluation

Life-threatening alerts: *High-importance + contraindication*

Policy	Risk avoided (%)	Alerts shown	LT accepted (%)
Current	18.98	583,313	9.86
Fixed	25.62	389,717	53.31
Dynamic	26.20	415,923	55.10
Adaptive	27.95	429,668	57.72

Near-optimality of optimal fixed policy

Vs All Alerts	**Alerts**	**LT Reduction**
Optimal Dynamic\ Fixed Policies	~ -33%	~ +40%

2000-4000 lives saved

0.5 Billion in cost across the U.S.

Sensitivity Analysis

Misspecification	Policy	Parameter
Average Risk	Overestimation	$\hat{\lambda}_{exp} = 0.5\ \lambda_{exp}^{true}$
	Underestimation	$\hat{\lambda}_{exp} = 2\ \lambda_{exp}^{true}$
Risk Model	Model Mismatch	-
Fatigue	Overestimation	$\hat{\beta}^{glob} = 2\ \beta^{glob,\,true}$
	Underestimation	$\hat{\beta}^{glob} = 0.5\ \beta^{glob,\,true}$

<1% performance decay

No significant compromise of safety

Our proposed policies **still** perform significantly better

Reduce alerts by **50%**

Summary

Analytical Model A novel fluid approximation model for alert decision-making under operator fatigue

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Analytical Model — A novel fluid approximation model for alert decision-making under operator fatigue

Theoretical Results — Dynamic vs. Fixed: Alerting is not just a filter. It is a fair attention-allocation policy over time.

Impact — 2000-4000 lives **and** 0.5 billion in cost saved across the U.S.

Conclusion

Takeaway!

Healthcare staff have a limited ***Cognitive Budget***!

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Healthcare staff have a limited ***Cognitive Budget***!

Use it wisely by optimizing **human-AI interaction**

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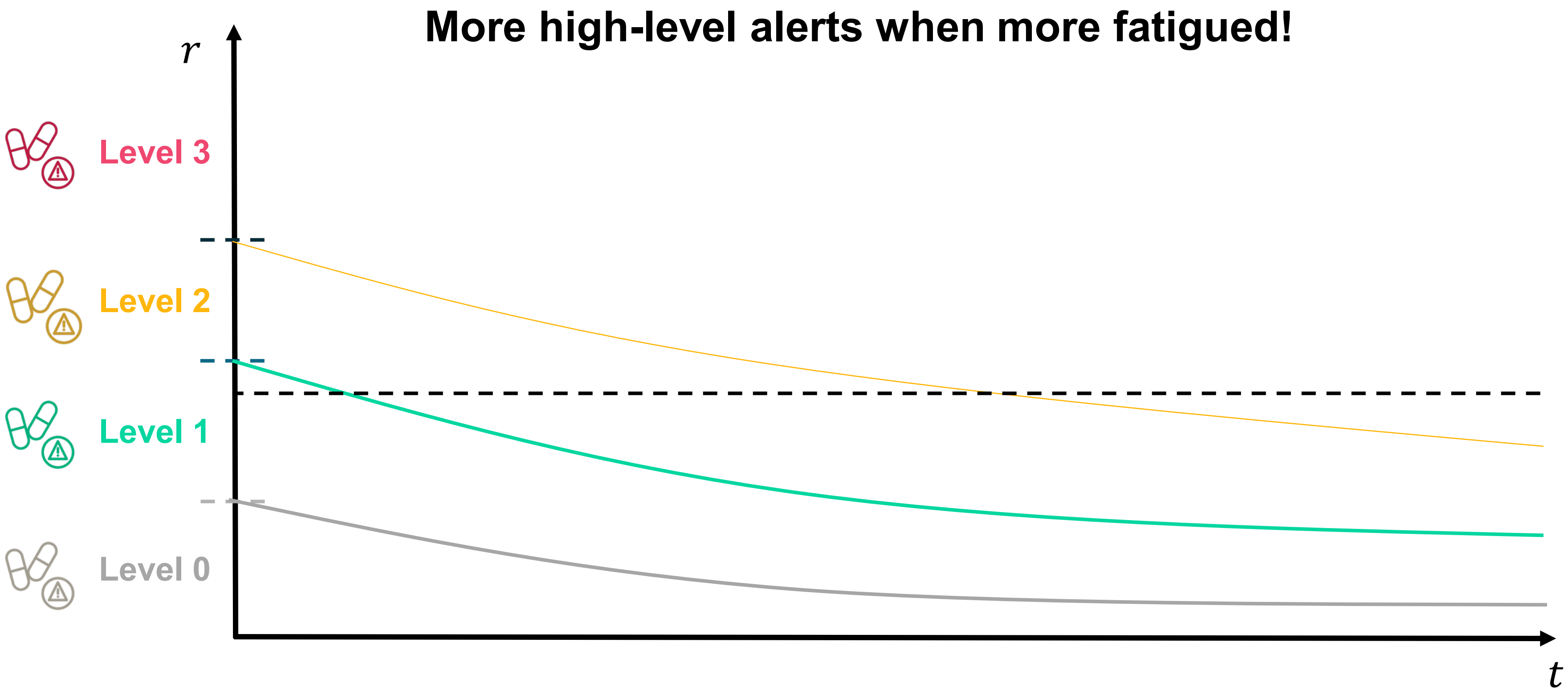
Thank You! Questions?

Structure of the Optimal Solution

Theorem

Under very mild conditions on the linking function $g(\cdot)$, the optimal solution to the alert fatigue problem always follows a threshold policy, in which the threshold decays over time.



Impact of Model Parameters

Corollary

The optimal risk threshold, $r_1^*(t)$, under Pareto, exponential and uniform risk distribution:

$$r_{1p}^*(t) = \lambda_p[(1 + \frac{\alpha\beta c}{\alpha - 1}(T - t))^{\frac{1}{\alpha}} - 1]$$

$$r_{1e}^*(t) = \frac{1}{\lambda_e}\ln(\beta c(T - t) + 1)$$

$$r_{1u}^*(t) = \frac{b\, \beta c\, (T - t)}{\beta c\, (T - t) + 2}$$

Mild Dependence on Costs (c, β) **Linear Dependence on Scale (b, λ_e, λ_p)**