A New Approach: Utilization-Driven Management for Infusion Pumps

Connor Roberts
Opal HTM

Ekundayo Shittu, PhD
The George Washington University

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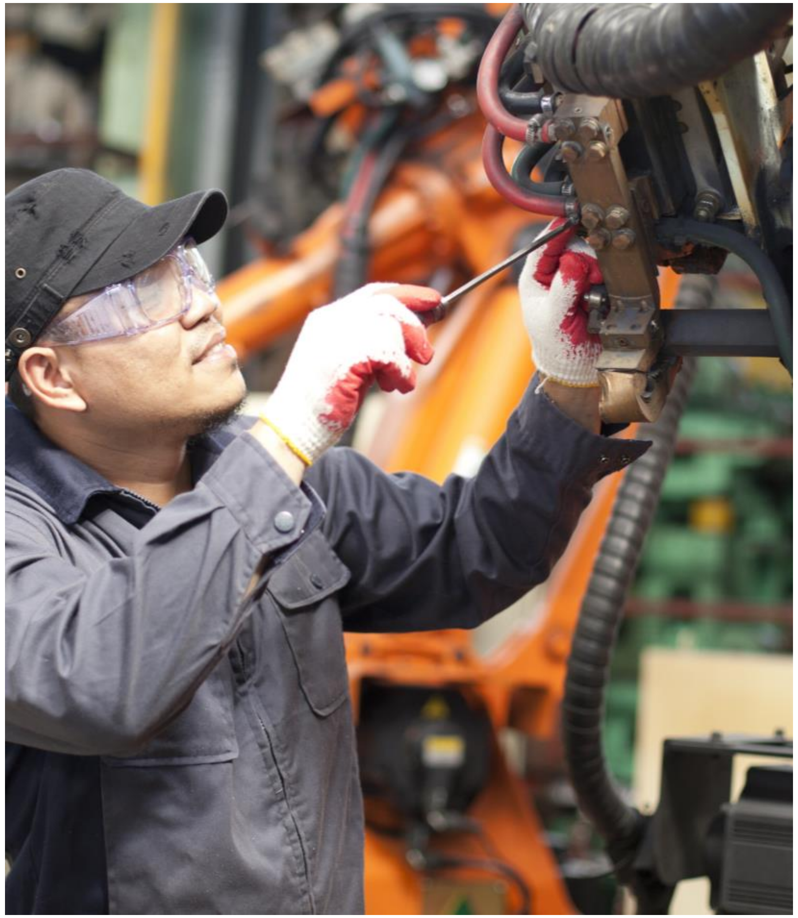
Utilization-driven maintenance – is it feasible?



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Utilization-driven maintenance – is it feasible?

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Emerging Opportunity

- Data-driven alternative equipment maintenance (AEM) programs have gained traction over the past decade[1]
  - **Reduced service costs** and **improved patient safety**

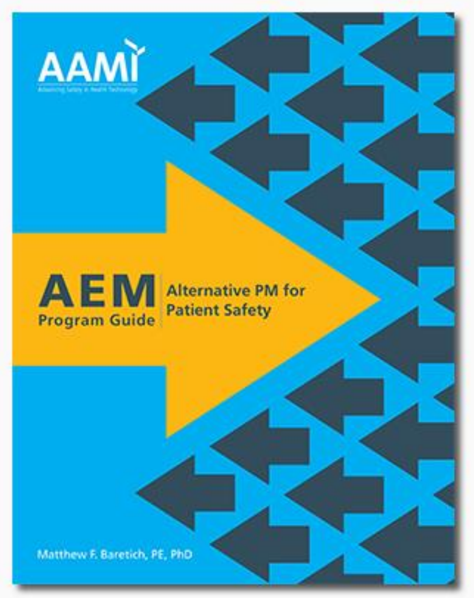


image: AAMI

- Connected medical devices offer new sources of data[2]
  - Device utilization may be a powerful input for AEM

- Infusion devices are an ideal candidate for investigation
  - Long-established, widely-used class of networked devices
  - Damaged infusion pumps were ranked **#3 in ECRI's Top 10 Healthcare Hazards** of 2022[3]

image: flaticon.com

Research Overview

➢ We conducted a study analyzing the impact of utilization on maintenance for infusion devices

- 2020 AAMI Foundation Mary K. Logan Research Award
- Collaboration between **The George Washington University**, **Opal HTM**, **UCSF Health**, and **Bainbridge Health**

Findings:

➢ **Utilization does impact maintenance,** but in a counterintuitive way

➢ There exists an **optimal utilization range** wherein devices are most reliable

➢ This **relationship can be quantified and leveraged** to support HTM decision-making

About Us

Connor Roberts

Founder & CEO

connor.roberts@opalhtm.com

Opal HTM

Background in electrical engineering and healthcare logistics research. Founded Opal HTM with the mission of advancing HTM through research and development.

- **MS**, Engineering Management, The George Washington University
- **BS**, Electrical Engineering and Economics, The George Washington University

Ekundayo Shittu

Associate Professor

eshittu@gwu.edu

THE GEORGE WASHINGTON UNIVERSITY

WASHINGTON, DC

Experienced researcher specializing in data analytics, supply-chain logistics, and decision making under uncertainty. Funded by NSF, DoE, AAMI, and others.

- **PhD**, Industrial Engineering & Operations Research, University of Massachusetts, Amherst
- **MS**, Industrial Engineering, American University in Cairo, Egypt
- **BEng**, Electrical Engineering, University of Ilorin, Nigeria

Learning Objectives

We will cover how to:

- Obtain utilization data for infusion devices
- Apply survival analysis to extract deep insights from maintenance records
- Characterize the impact of device utilization on repair frequency
  - Using both basic and advanced analysis techniques
- Leverage these insights to improve device safety and maintenance efficiency

Data & Methodology

Data Collection

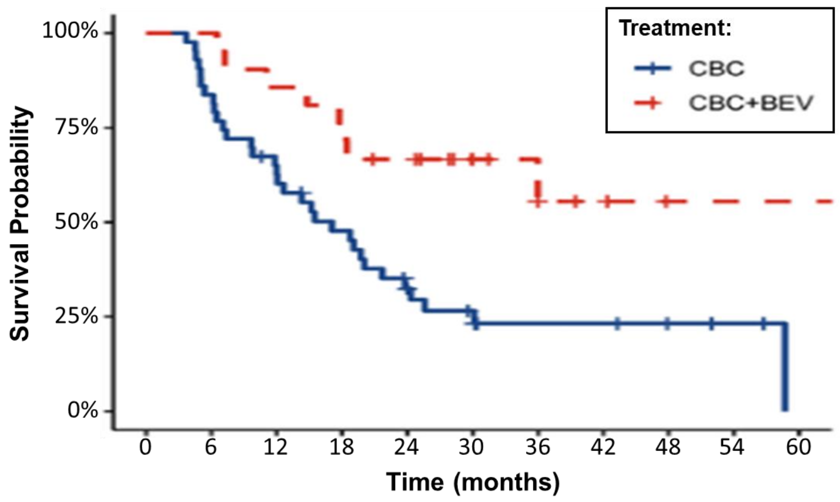
- 5,761 devices in study
  - 3,990 channels and 1,771 control units
- Infusion logs
  - 6 years; 66.7 million events
  - **Actions:** infusion started, stopped, alarmed, etc.
  - **Attributes:** timestamp, infusion rate, drug infused, programmed duration
- Maintenance records
  - 17 years; 119,425 work orders
  - **Actions:** inspection, corrective maintenance, manufacturer recall, device installation, etc.
  - **Attributes:** request date, completion date, part description, labor report, etc.

image: bd.com

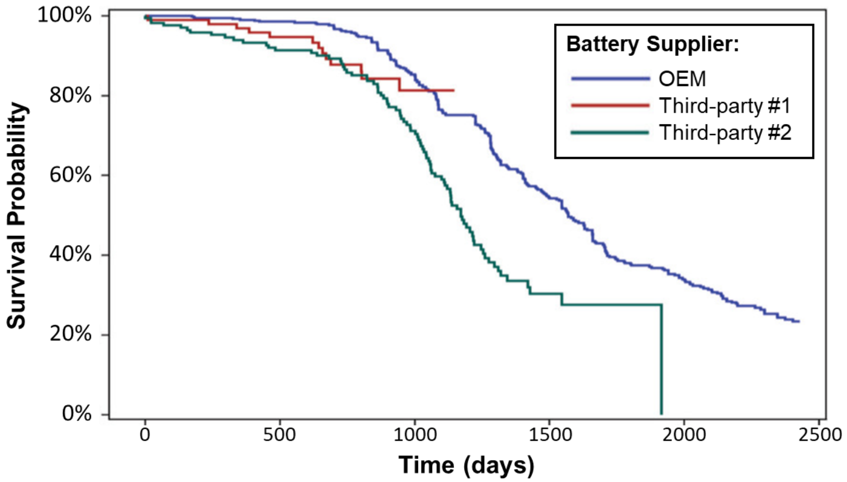
Survival Analysis: A Powerful Tool for HTM

- Survival analysis is a branch of statistics for analyzing *time-to-event* processes
  - Used in medicine, economics, reliability engineering[4]
  - Maximally extracts information from partial (i.e., censored) data
- Well suited for AEM formulation
  - Deeper insights than MTBF
  - Shows how reliability changes over time
  - Can compare the impact of different factors
- Readily employed using Python or R
  - Can also be incorporated into CMMS

Example 1 (Medicine): Chemotherapy efficacy study [5]

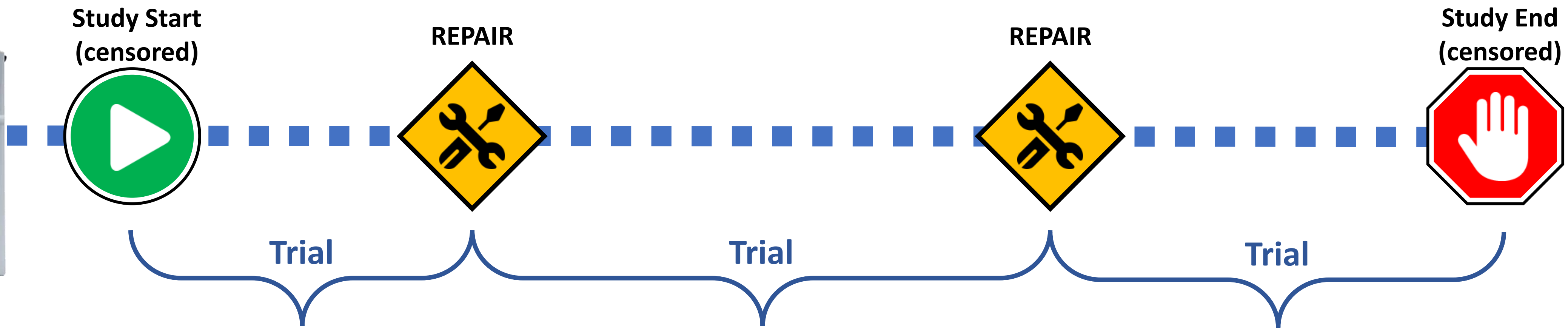


Example 2 (HTM): Infusion pump battery comparison[6]



Data Preparation

Maintenance logs can be treated as a collection of reliability trials, each with a duration and event (repair).



Duration: >120 days
Repairs: Left IUI Connector

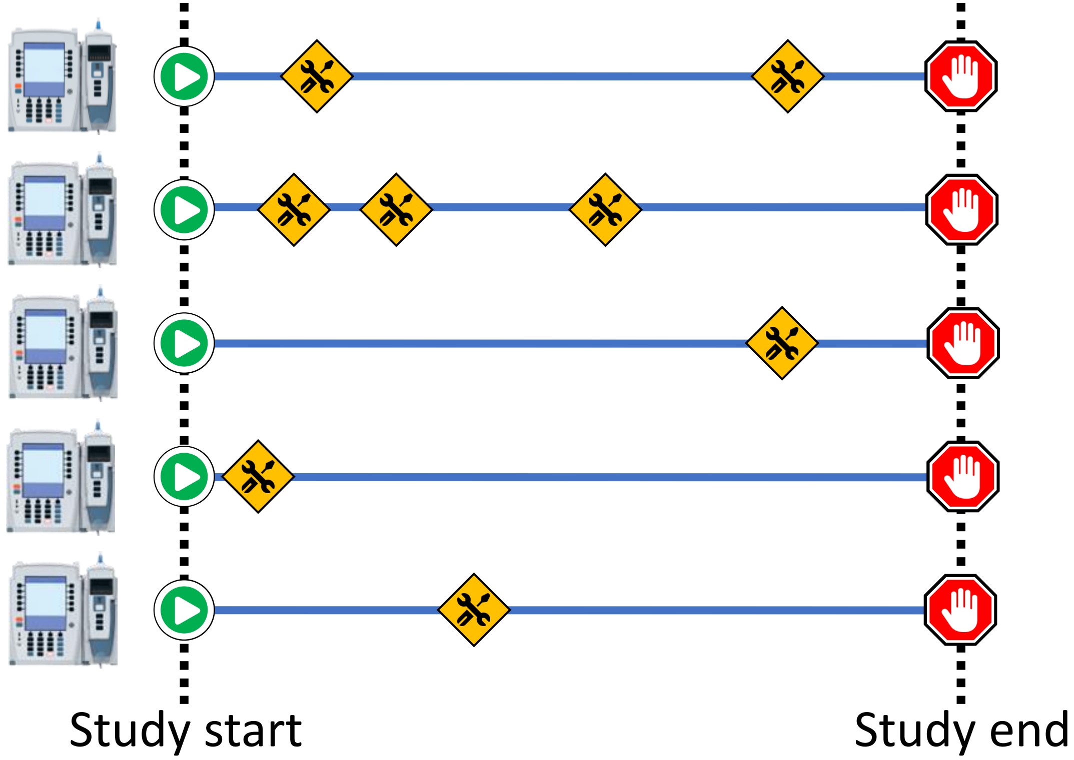
Duration: 450 days
Repairs: Bezel Assembly, Latch Assembly

Duration: >300 days
Repairs: n/a

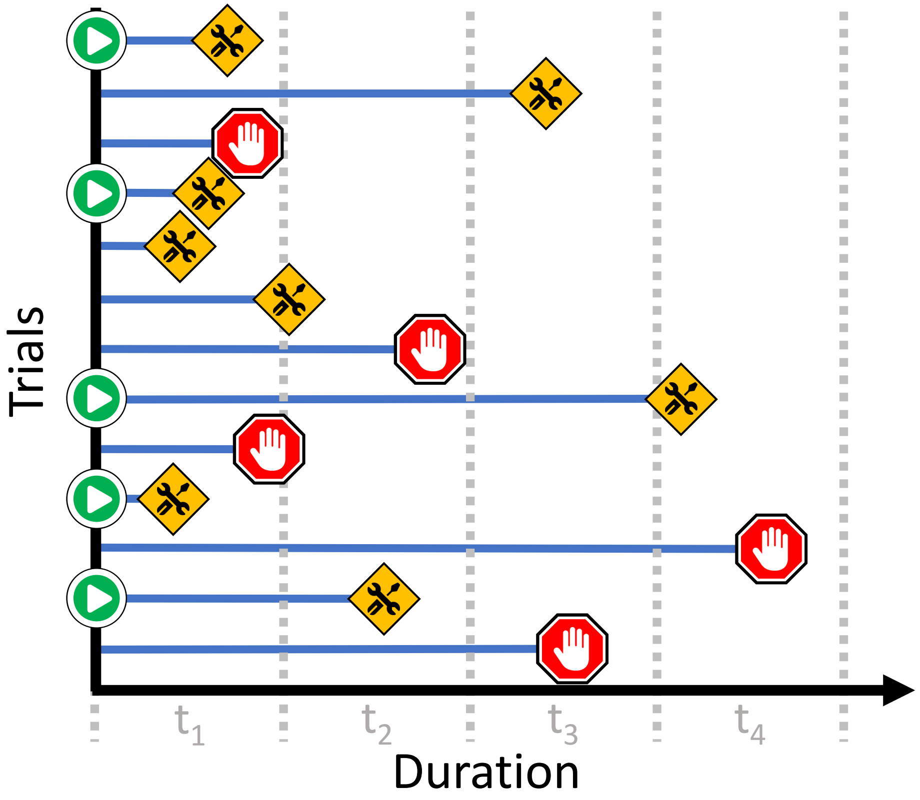
Data Preparation

Maintenance logs can be treated as a collection of reliability trials, each with a duration and event (repair).

CMMS Records



Time-to-Event Data



Key Reliability Estimators

Repair Probability

What is the chance of repair over time?

$$Repair\ Probability = 1 - \prod_{i:\, t_i \leq t} \frac{n_i - r_i}{n_i}$$

Repair Occurrence

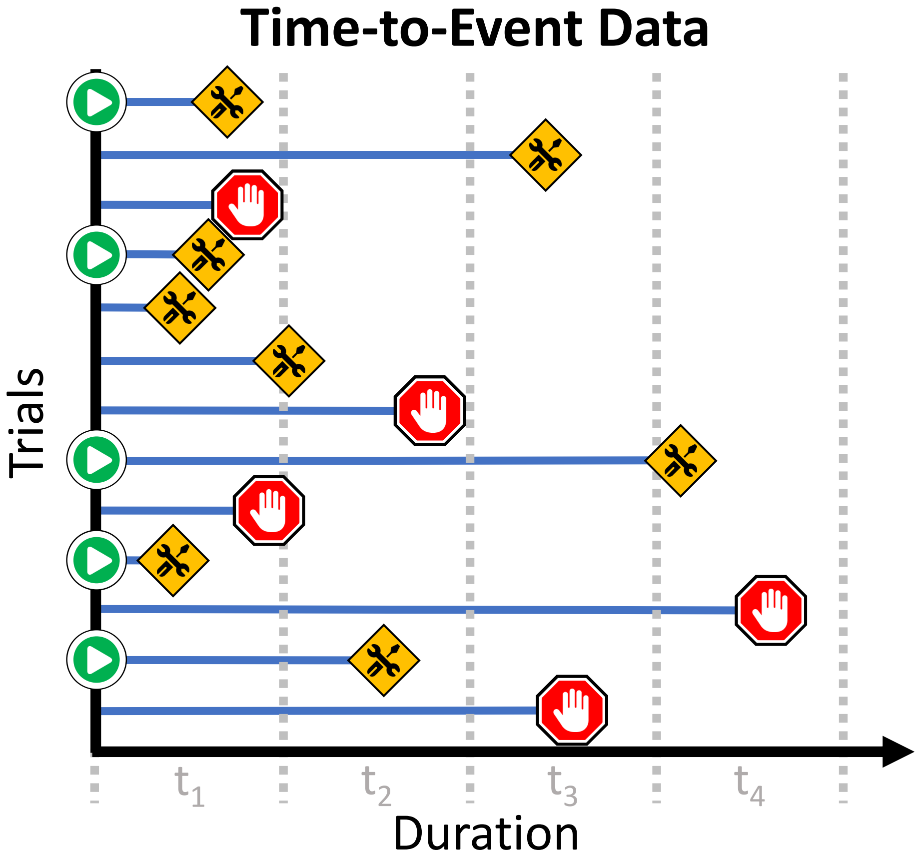
How many repairs are expected over time?

$$Cumulative\ Repairs\ per\ Device = \sum_{i:\, t_i \leq t} \frac{r_i}{n_i}$$

n_i : number of devices at risk at time t_i

r_i : number of repairs at time t_i

images: flaticon.com



Analysis – Part I

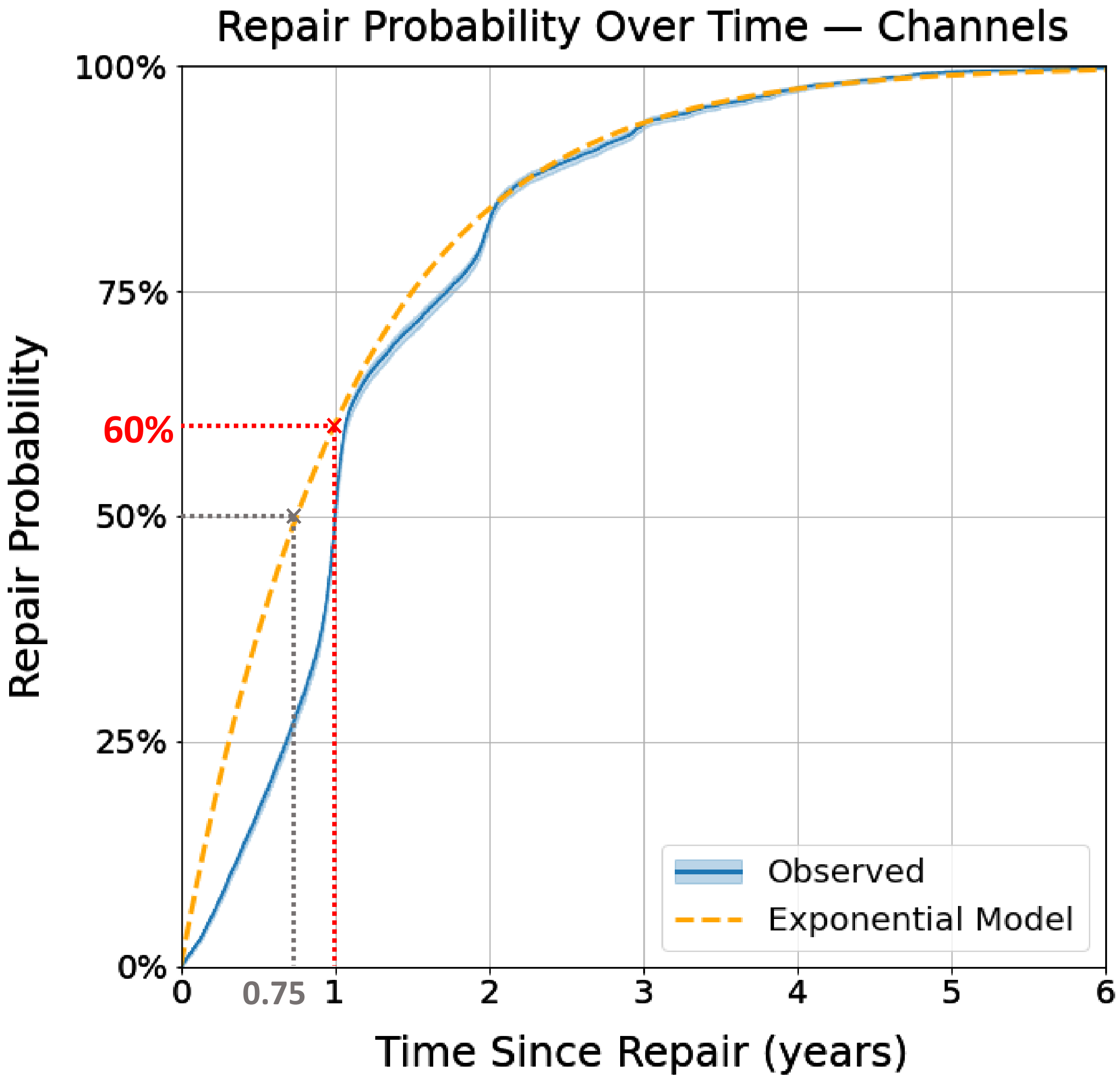
Reliability characteristics of channels

Repair Probability

Repair Probability

What is the chance of repair over time?

- High repair probability after only one year
- Repair probability jumps at one-year increments
  - Distortion due to annual PM
  - Can be overcome by fitting a statistical model
- Exponential model demonstrates likely actual breakdown process
  - Repair probability: 60% within one year
  - Median time between repairs: 0.75 years (275 days)

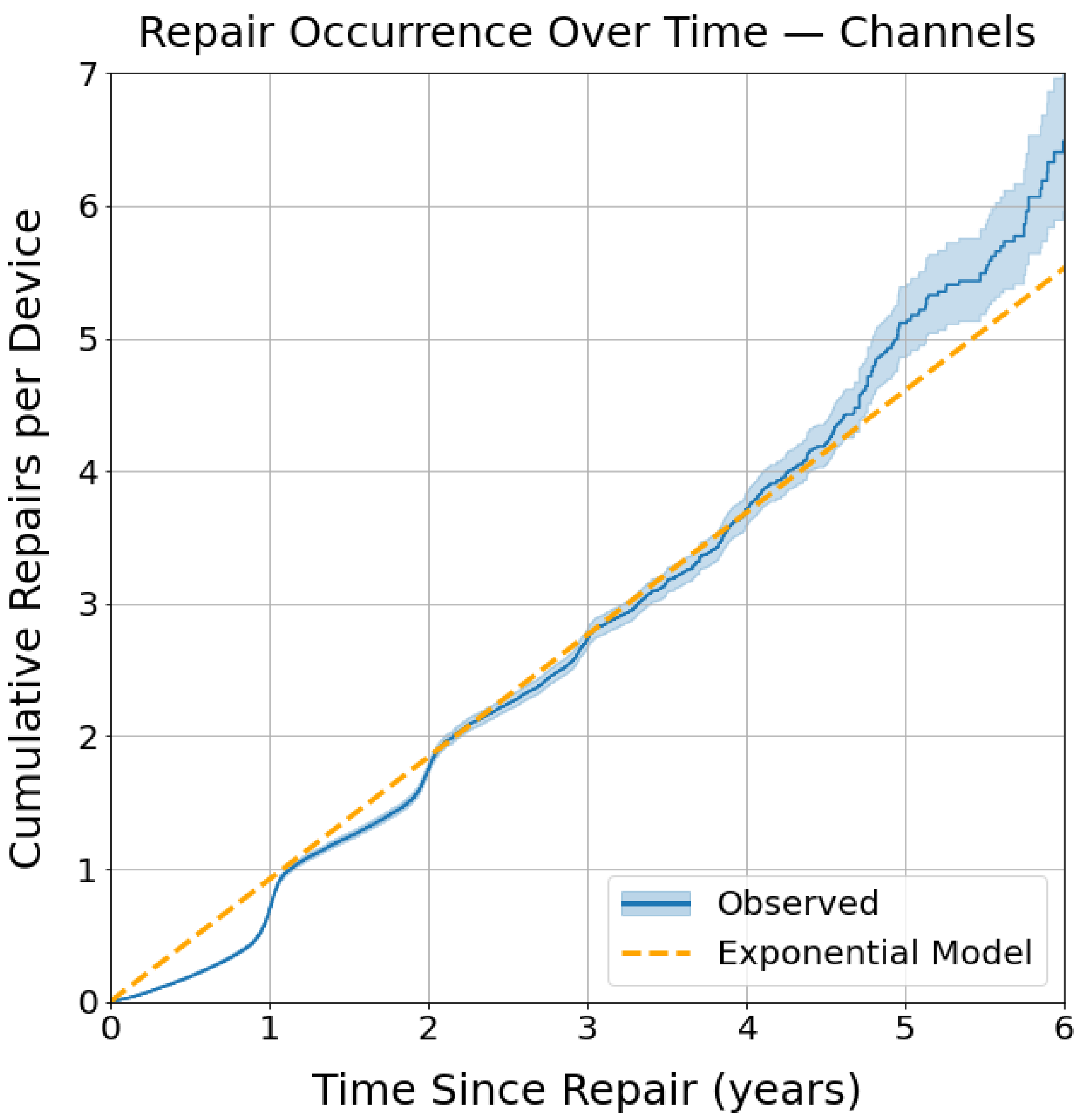


Repair Occurrence

Repair Occurrence

How many repairs are expected over time?

- Shape of curve provides insight into the breakdown process
  - Concave = early failures (quality issue)
  - Convex = wear out
  - Linear = constant, random failures
- Repair rate is roughly *constant* over the long run: 0.92 repairs per year, per device
  - Can inform parts/labor forecasting
- Some convexity after fourth year, may indicate slight wear out

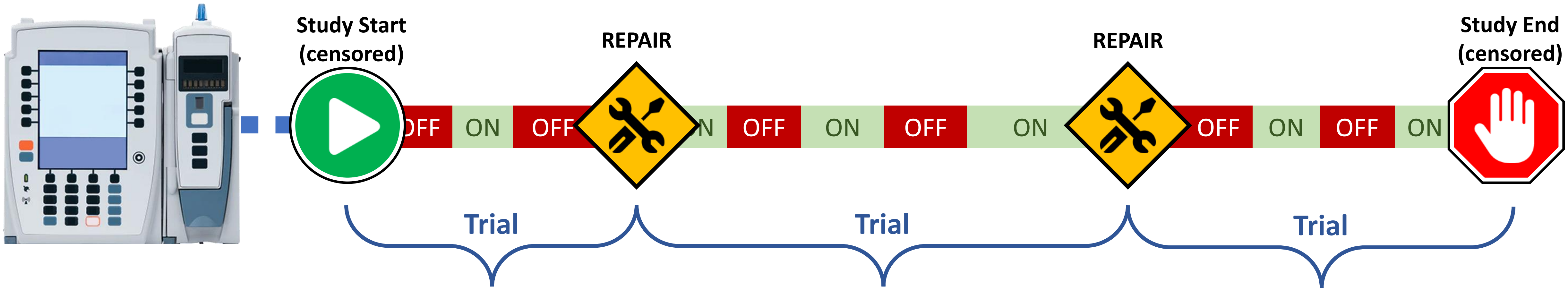


Analysis – Part II

Basic analysis of utilization impact

Incorporating Utilization Data

Infusion logs are combined with maintenance records to create a history of device utilization and repairs over the duration of the study.



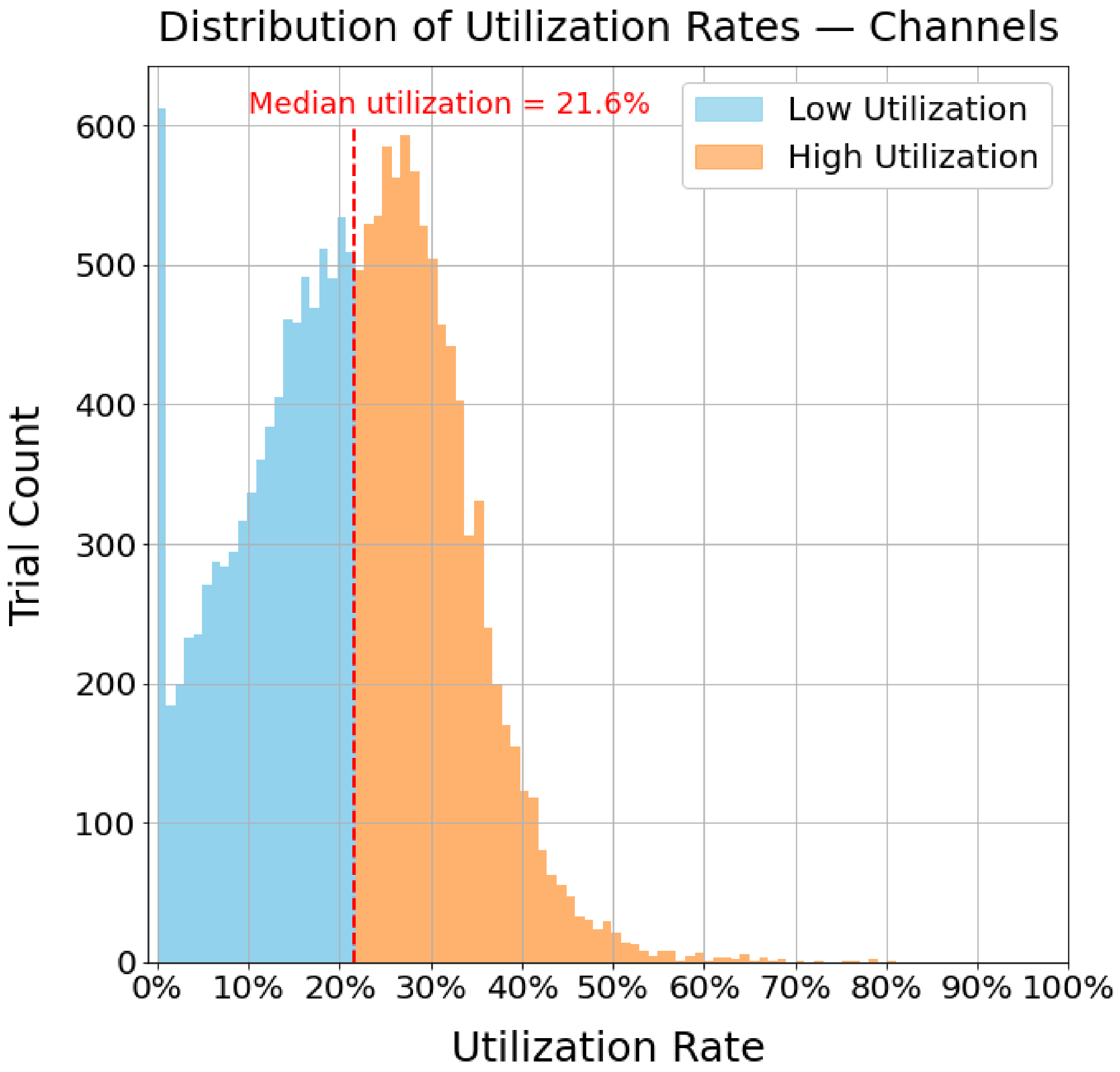
Duration:	>120 days
Repairs:	Left IUI Connector
Runtime:	605 hours
Utilization:	**21%**

Duration:	450 days
Repairs:	Bezel Assembly, Latch Assembly
Runtime:	3,240 hours
Utilization:	**30%**

Duration:	>300 days
Repairs:	n/a
Runtime:	864 hours
Utilization:	**12%**

Separating Trials by Utilization

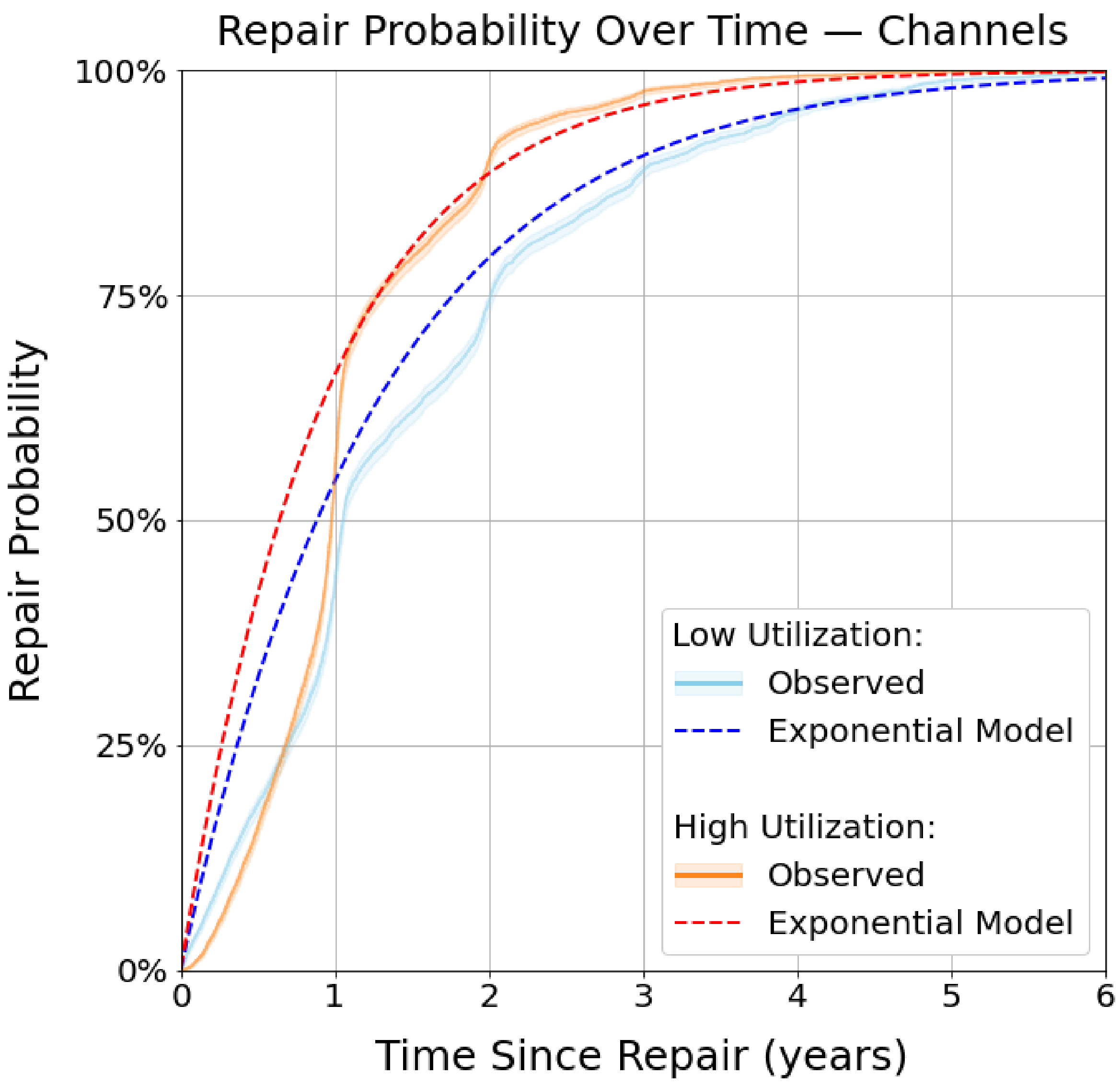
- Utilization % = $\frac{\text{Active Infusion Time}}{\text{Calendar Time}}$
- Median trial utilization: 21.6%
- Dataset can be divided into two groups based on device utilization
  - Low utilization: ≤ median
  - High utilization: > median
- To test the impact of utilization, we will compare the reliability of these two groups



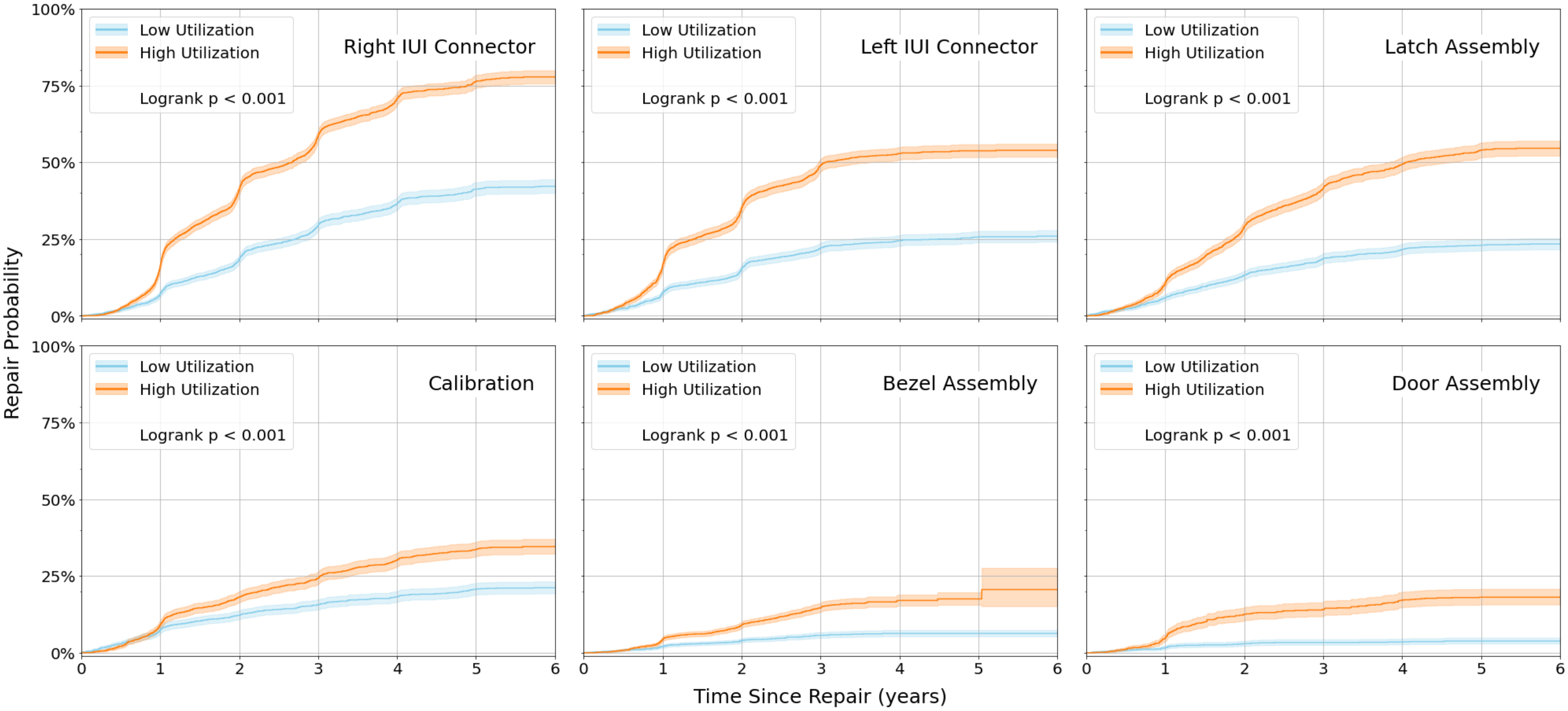
Repair Probability by Utilization

- High utilization devices demonstrate a greater repair probability over time
  - <u>Earlier, more frequent repairs</u>
  - Statistically significant: logrank test yields $p < 0.001$

	Low Utilization	High Utilization
Probability of repair within one year	**54%**	**66%**
Median time to repair	0.88 years (**323 days**)	0.64 years (**234 days**)

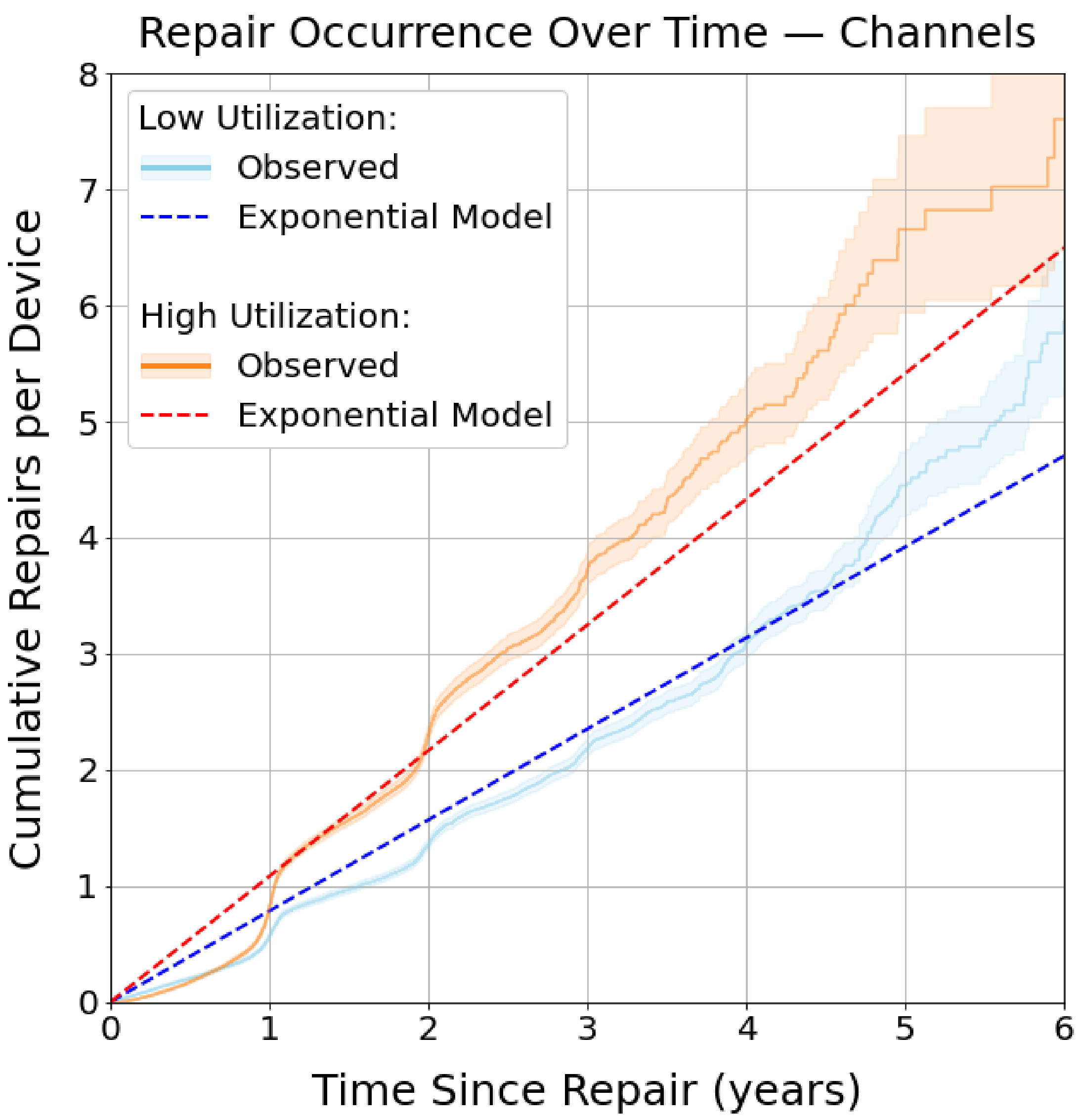


Probability of Common Repairs



Repair Occurrence by Utilization

- Repair rate is *relatively constant*, even for high-utilization devices
  - Utilization **increases the risk of random shocks**, rather than substantially accelerating physical wear
- Consistent with random damage driven by human error
  - Misuse, drops, fluid invasion
- Supports existing paradigm of scheduled condition inspections
  - <u>AEM Opportunity:</u> adjust PM intervals based on utilization



Analysis – Part III

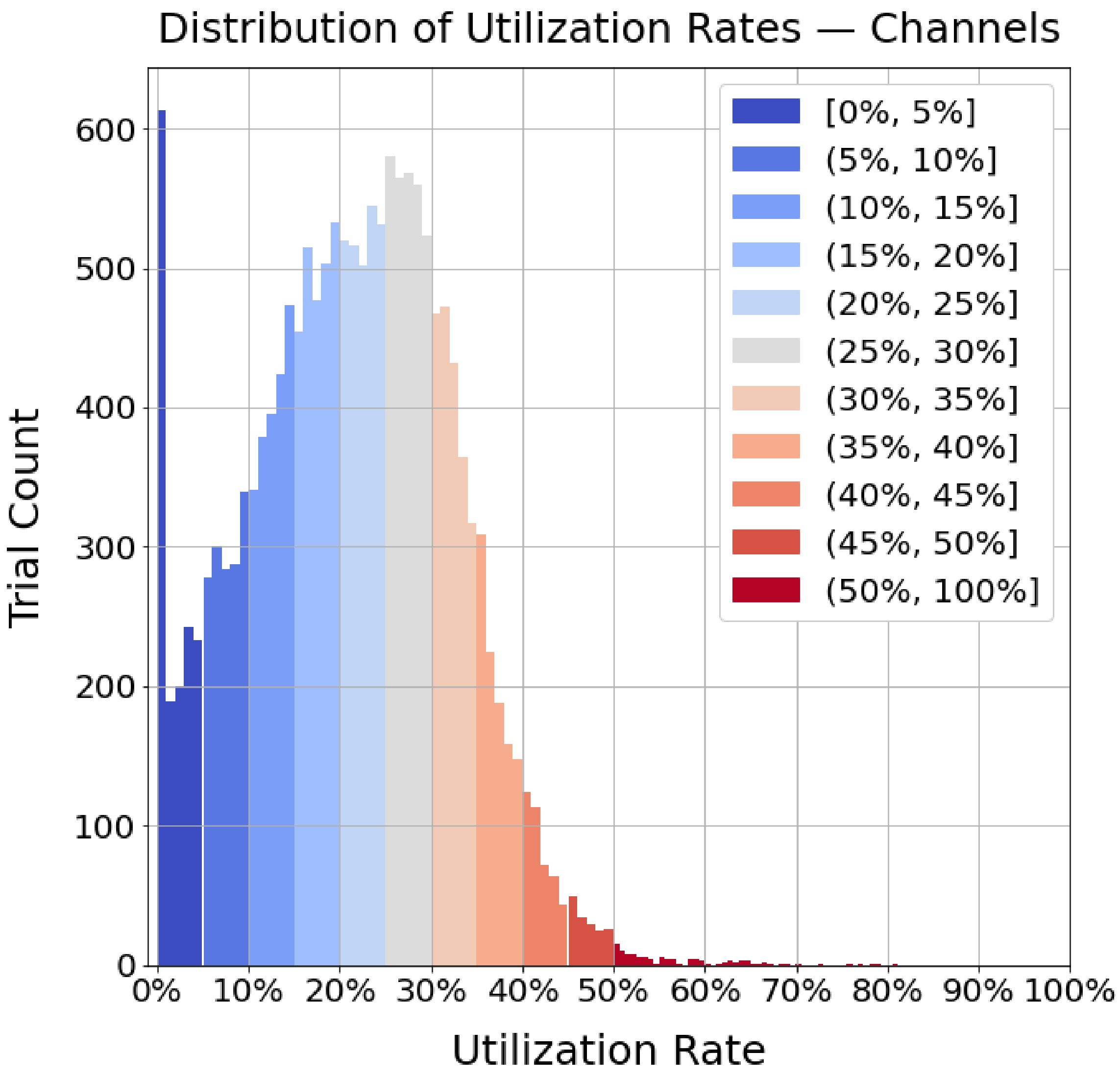
In-depth analysis of utilization impact

Digging Deeper

- To make this information actionable, we need to better understand the utilization-maintenance relationship

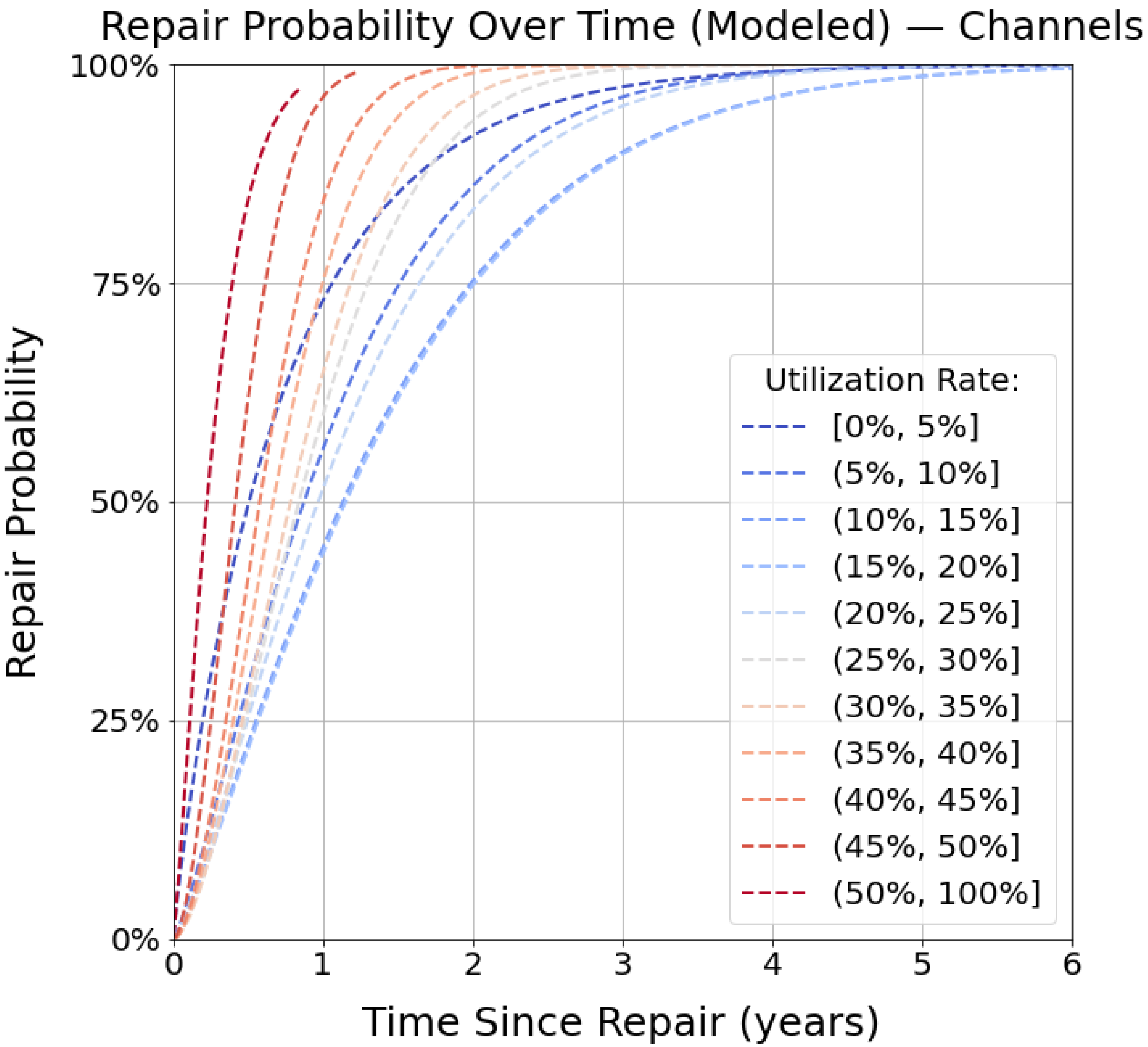
- First: Increase granularity of analysis
  - Separate dataset into additional utilization groups and compare repair probability

- Later: Apply regression analysis
  - Derive equation describing impact of utilization on repair frequency



Repair Probability, Stratified by Utilization

- Higher utilization devices generally have a greater repair probability
  - Earlier, more frequent repairs
  - But there are exceptions!
- For clarity, we will consider where in time each curve reaches 60% repair probability
  - Corresponds to existing risk threshold of annual PM (from slide 15)

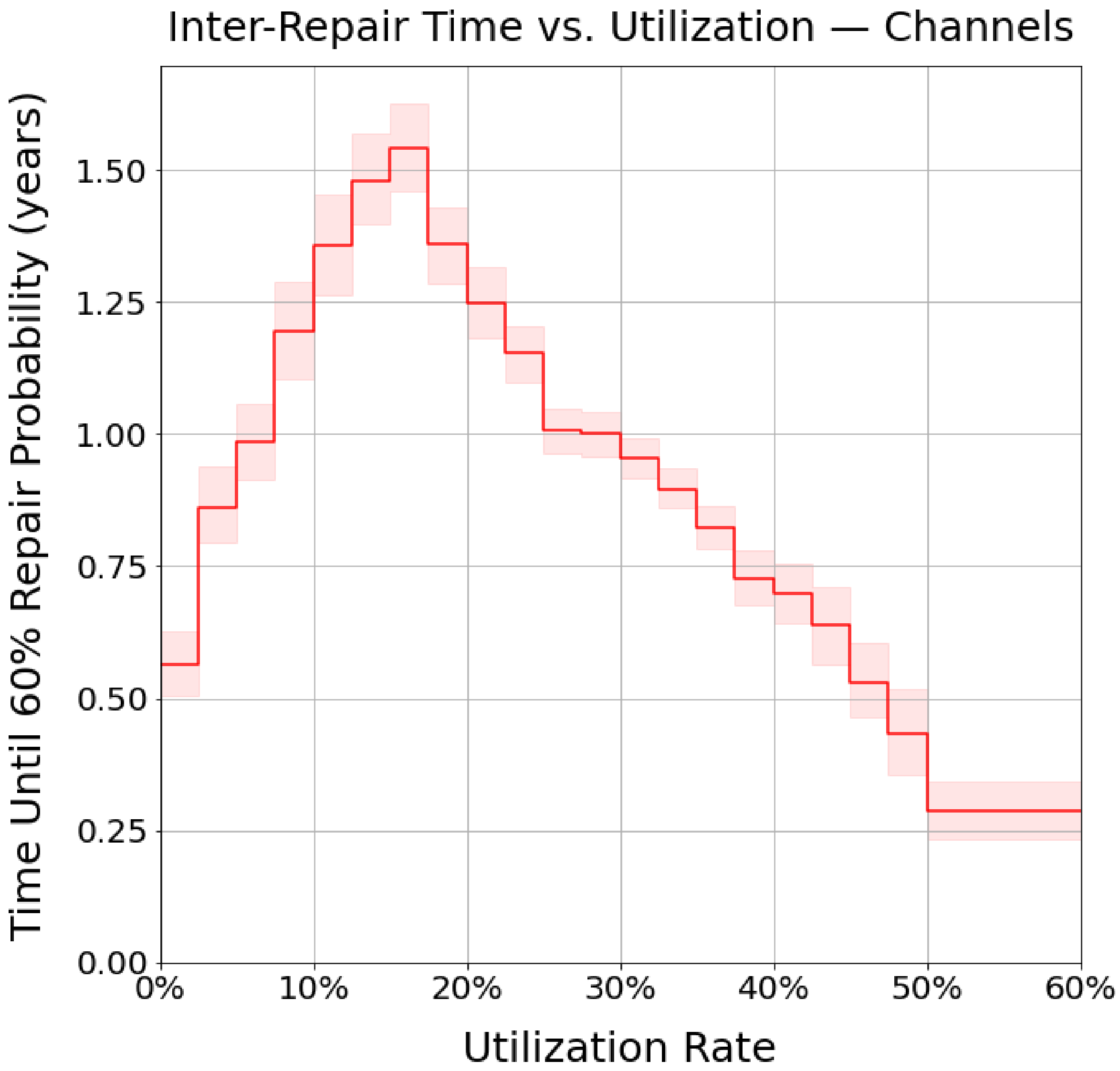


Utilization Impact on Repair Timing

- Channels with 10% to 20% utilization have the greatest time between repairs

- Higher levels of utilization are associated with greater repair frequency

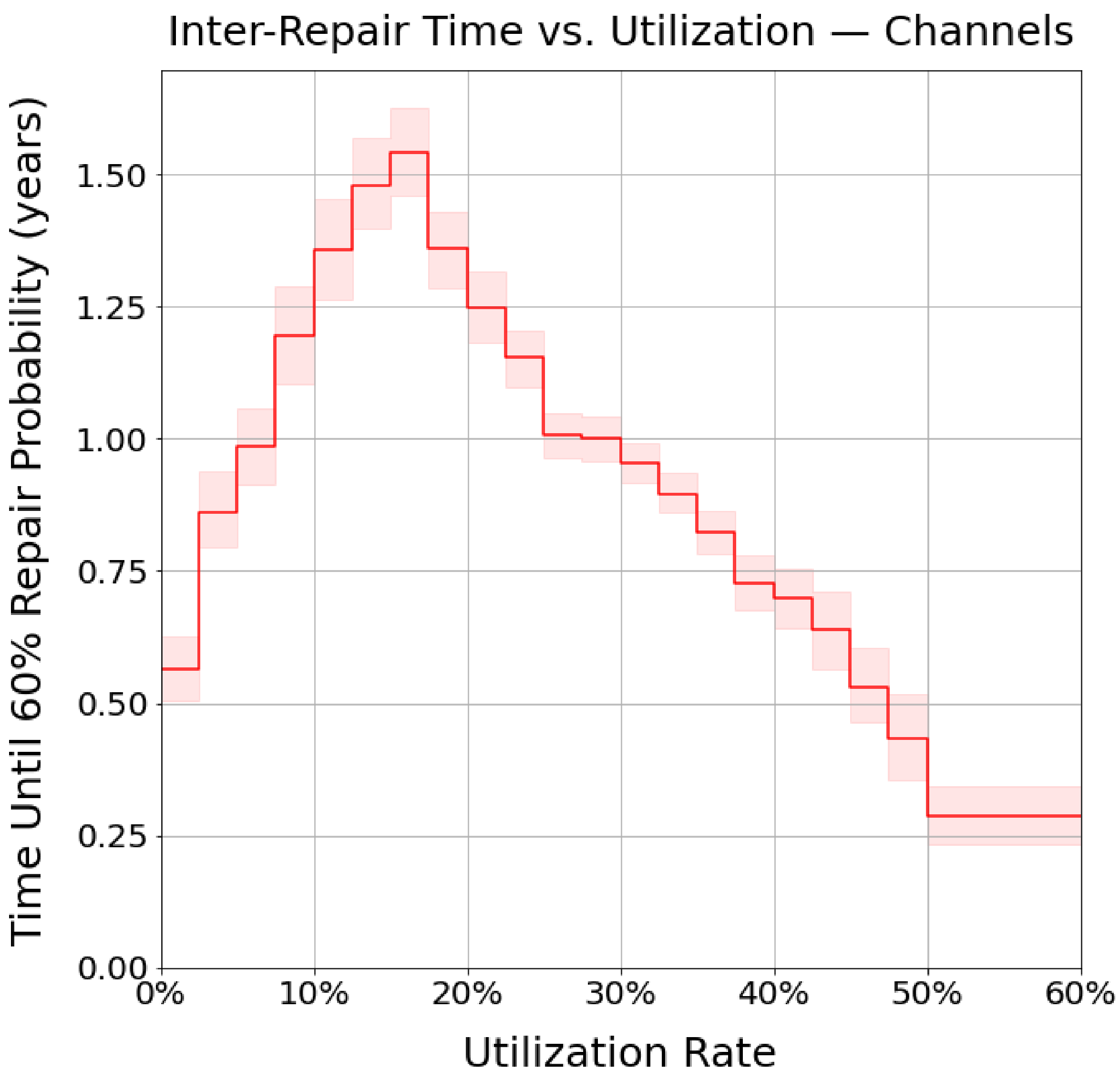
- However, very low utilization is also associated with earlier repairs



Utilization Impact on Repair Timing

- Utilization level may be **both a cause and effect** of device breakdown/repair
  - High utilization → risk exposure → breakdown
  - Breakdown → user avoidance → low utilization
- In either case, utilization is an important signal as to device condition
- Application: Tiered PM schedule based on utilization

AEM Example	
Utilization	**PM Interval**
< 2.5% or > 35%	6 months
10 – 20%	18 months
All other	12 months



Survival Regression Analysis

- Quantify the influence of utilization on device reliability
- Consider (i.e., control for) other potentially contributing factors
- Accelerated failure time (AFT) regression
  - Estimates how variables *speed up* or *slow down* device breakdown[7]
  - Weibull AFT model is commonly employed in reliability engineering

Weibull AFT Model

$$R(t;x) = 1 - \exp\left(-\left(\frac{t}{\lambda(x)}\right)^{\rho}\right)$$

$$H(t;x) = \left(\frac{t}{\lambda(x)}\right)^{\rho}$$

$$\lambda(x) = \exp(\beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n)$$

$R(t;x)$: repair probability
$H(t;x)$: expected cumulative repairs
$\lambda(x)$: accelerated repair rate
ρ: shape parameter
$x_1, x_2, \ldots\ x_n$: independent variables
$\beta_0, \beta_1, \ldots\ \beta_n$: effects of independent variables (i.e., coefficients)

Regression Analysis Results

- Controlled for: device age, component age, hospital campus, cumulative runtime, and installation cohort
- Tested nonlinear functional forms
- **Result:** repair acceleration (λ) as a function of utilization (u):

$$\lambda(u) = \exp(2.11u - 6.70u^2 + 0.05\log(u))$$

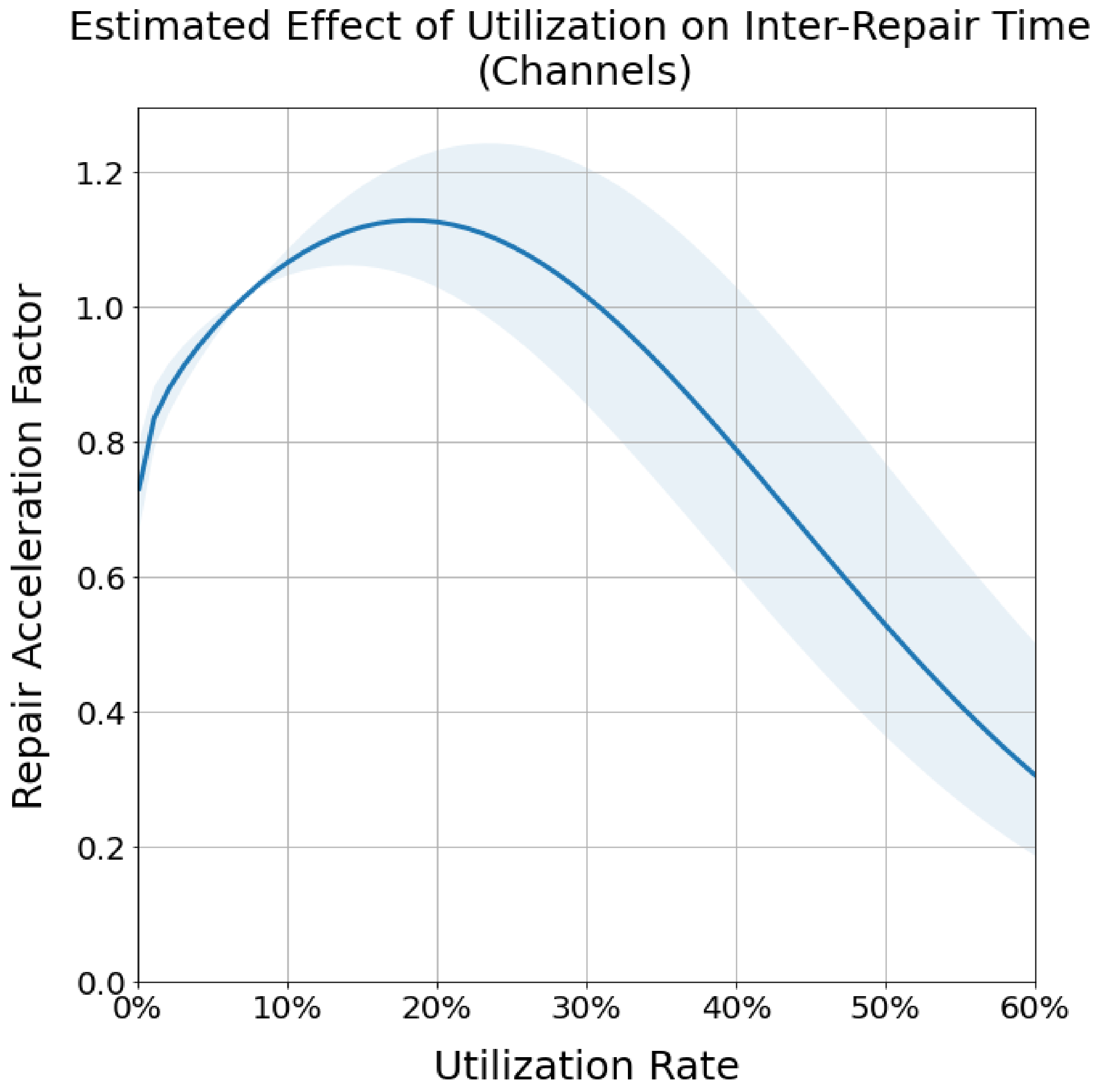
Variable	Unit	Coeff.	p-value
Utilization Rate	0.0 – 1.0	2.11	< 0.005
Utilization Rate^2	0.0 – 1.0	- 6.70	< 0.005
log(Utilization Rate)	0.0 – 1.0	0.05	< 0.005
Device Age	years	- 0.05	< 0.005
Device Cumulative Runtime	Run-years	- 0.18	< 0.005
Installed After 2012	True, False	- 0.35	< 0.005
Hospital Main Campus	True, False	- 0.33	< 0.005
Right IUI Connector Age	years	- 0.03	< 0.005
Left IUI Connector Age	years	- 0.01	< 0.005
Latch Assembly Age	years	- 0.01	< 0.005
Time Since Calibration	years	0.00	0.21
Bezel Assembly Age	years	- 0.02	< 0.005
Door Assembly Age	years	- 0.02	< 0.005

Regression Analysis Results

- **Result:** repair acceleration (λ) as a function of utilization (u):

$$\lambda(u) = \exp(2.11u - 6.70u^2 + 0.05\log(u))$$

- Resembles previous findings ✓
- <u>Applications:</u>
  - Prediction of time remaining until repair for each device
  - Dynamic PM schedules that account for differing device attributes/conditions



Analysis – Part IV

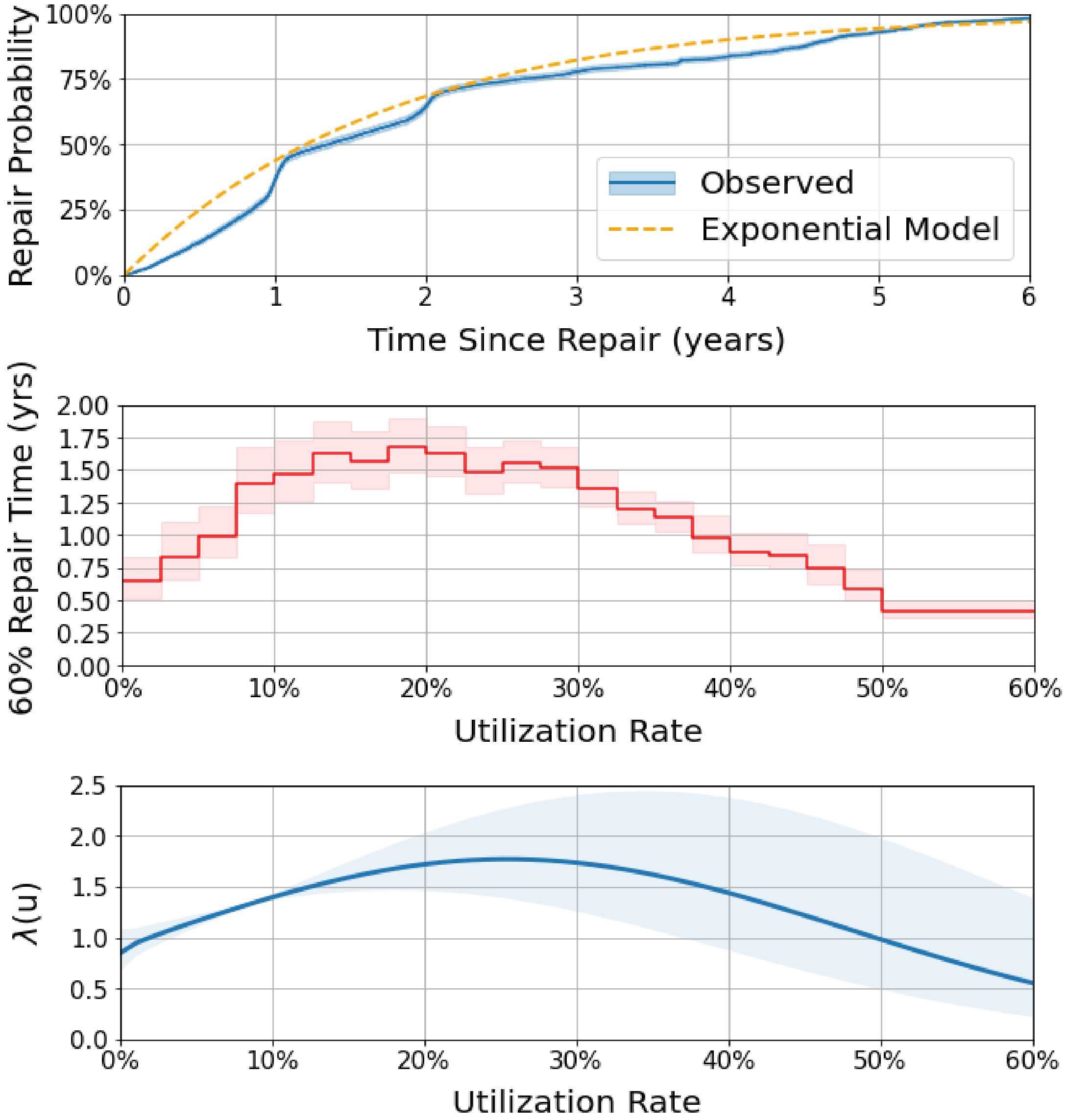
Characteristics of control units

Analysis of Control Units

- Utilization-maintenance relationship is similar to that observed for channels
  - Optimal utilization: 10% - 30%
  - Confirmed through AFT regression

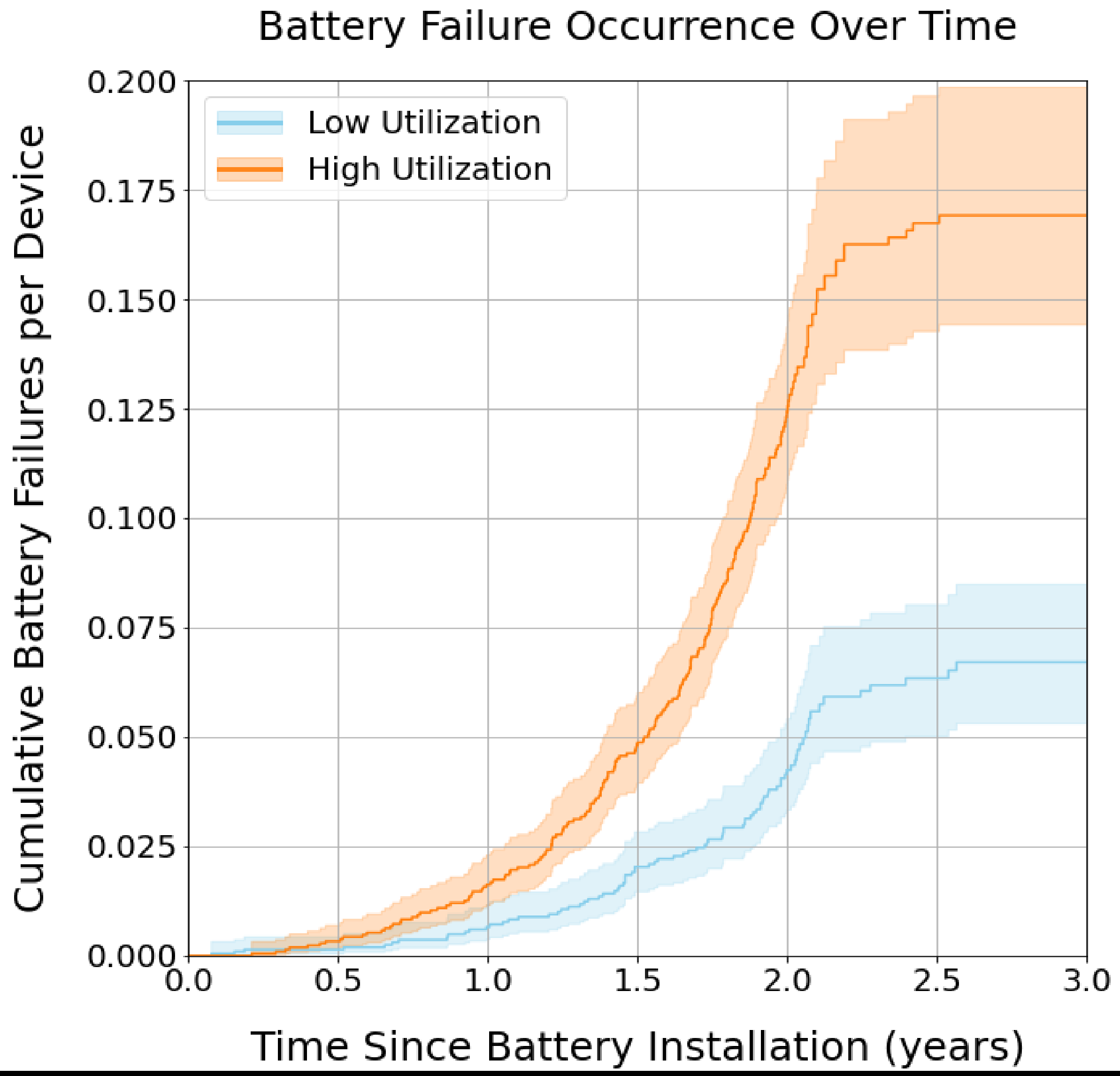
- Control units require repairs less frequently than channels

	All Control Units	Low Utilization	High Utilization
Probability of repair within one year	**44%**	**40%**	**48%**
Median time to repair	1.20 years **(439 days)**	1.36 years **(497 days)**	1.06 years **(390 days)**



Analysis of Battery Failures

- <u>Clear wear out pattern</u>
- Replacement schedule succeeds in maintaining low failure rate
- Battery failure is almost **<u>three times as likely</u>** in high utilization devices than low utilization devices after two years
  - 1-in-6 vs. 1-in-18 chance of failure
- Utilization-based replacement schedule could be highly effective



Discussion

Translating insight to action

Recap of Key Findings

Utilization has a quantifiable, statistically significant effect on repair frequency, even when controlling for other factors.

Peak reliability is observed around 15% utilization for channels and 20% for control units.

- Higher utilization drives increased risk exposure
- Very low utilization can be an early indicator that repair is needed

While device breakdown is primarily driven by random damage, batteries demonstrate a clear wear out pattern.

Potential Applications

- Utilization-informed annual inspections
  - Prioritize devices with very high or very low utilization
  - Replace certain components (e.g., batteries) based on total runtime
- Tiered PM schedule based on utilization, for example:
  - Heavily utilized devices inspected every 6 months (decreased patient risk)
  - Optimally utilized devices inspected every 18 months (improved HTM efficiency)
- Continuous utilization monitoring and response
  - Generate service calls for devices that clinicians appear to be avoiding
  - Load balance by removing high utilization devices from service until next inspection
- Dynamic, predictive maintenance programs

Future Research

- Topics for further investigation:
  - Methods and technology integrations for operationalizing these insights
  - Deeper look at why seldom used devices experience earlier repairs
  - Compare analysis across different hospitals and device types/makes/models
  - Incorporate machine learning techniques for predictive analytics
- We are preparing for follow-on projects:
  - Anticipating funding from National Science Foundation and National Institutes of Health
  - **We are recruiting hospital and technology collaborators!**

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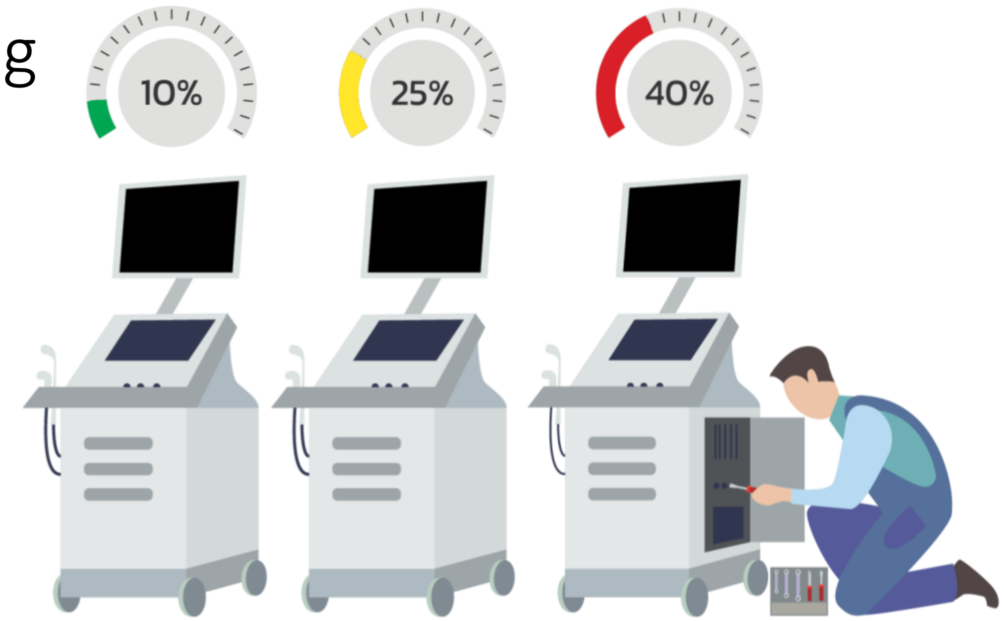
Final Thoughts

Utilization-based maintenance is feasible – and imminent!

- Equipment utilization data sources are proliferating
  - Infusion logs, RTLS, cybersecurity tools, new technologies

- Survival analysis is a powerful tool for unlocking actionable insights from maintenance records



- *You can help bring about this future!*

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eshittu@gwu.edu
connor.roberts@opalhtm.com