



Humans and Risk: Insights from Fossil Fuels, Nuclear, Medical, Aerospace, and AI

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Human Factors & Safety



Aviation



Space



Fossil Fuels



Medical



Nuclear

Alphonse Chapanis – WWII B17s

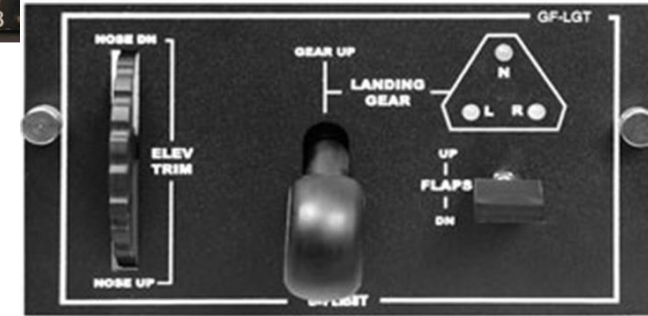


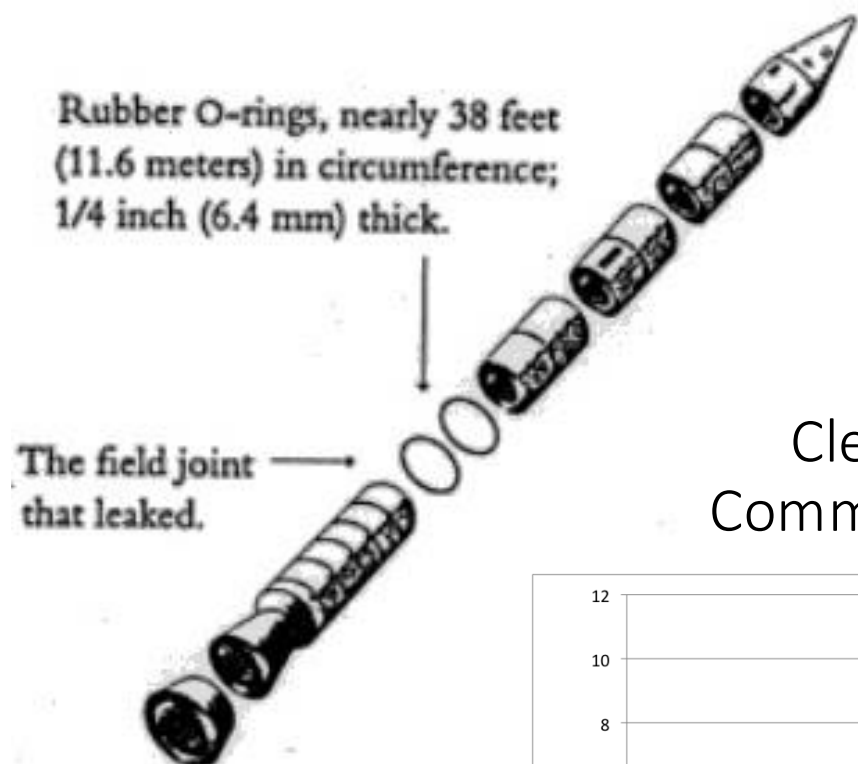
Image source: <https://documentaryheaven.com/crash-of-flight-111/>



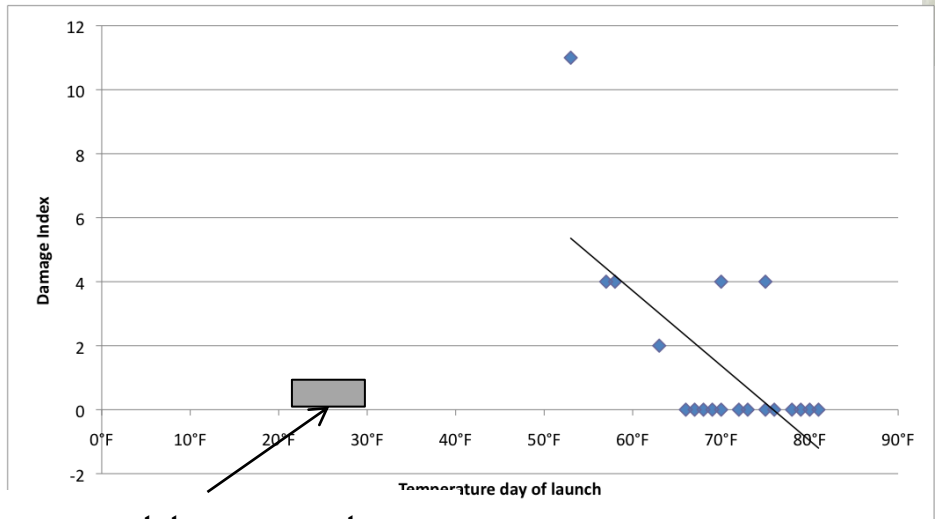
Swissair MD-11 New York to Geneva 1988

- Co-pilot suggested ignoring checklist and landing swiftly in the minutes before crash
- Pilot wanted to follow standard procedure
Wall Street Journal reported

Challenger Disaster



Clearer Method of Communicating Problem



Forecast temperature for launch

Engineers' Communication of Problem

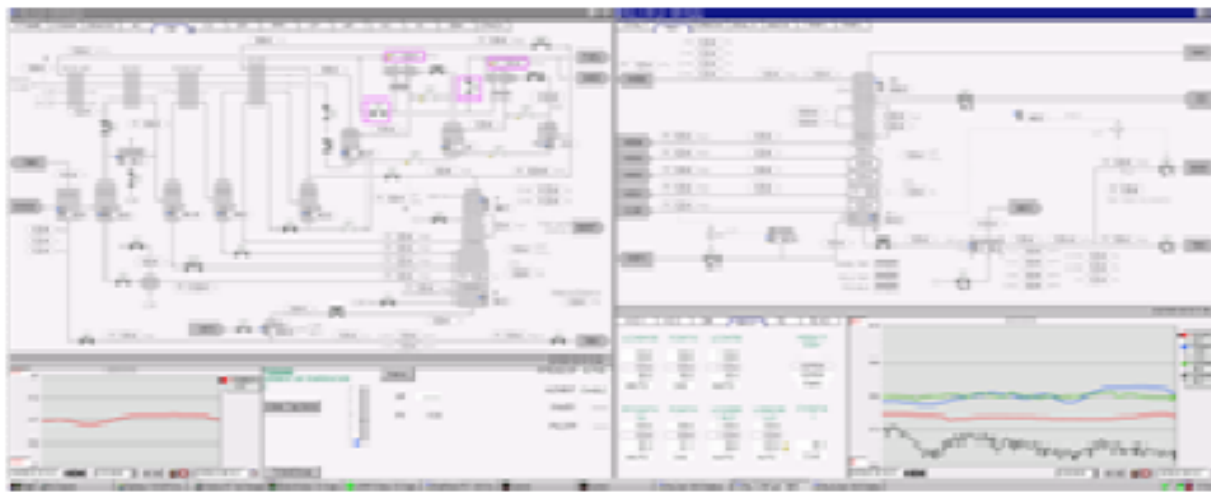
HISTORY OF O-RING TEMPERATURES (DEGREES - F)

MOTOR	MBT	AMB	O-RING	WIND
DM-4	68	36	47	10 MPH
DM-2	76	45	52	10 MPH
QM-3	72.5	40	48	10 MPH
QM-4	76	48	51	10 MPH
SRM-15	52	64	53	10 MPH
SRM-22	77	78	75	10 MPH
SRM-25	55	26	29 27	10 MPH 25 MPH

Zero Gravity Behaviors in ISS

- Best optical window ever installed in any human space vehicle
 - Astronauts want to use it
 - In zero gravity need handle to stay by window
 - There was something by window that had affordance of a handle
- It was a pressure hose
 - Crew members used it to stabilize themselves while taking pictures out of the window
 - This bent the pressure hose and was cause of air leak





Interface Designed Using Human Factors Methods



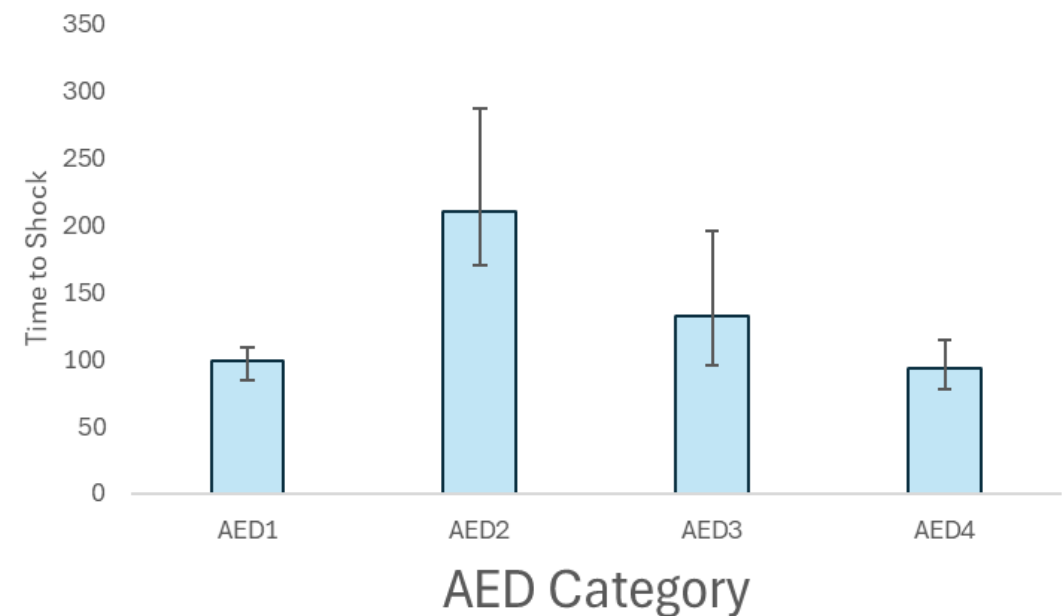
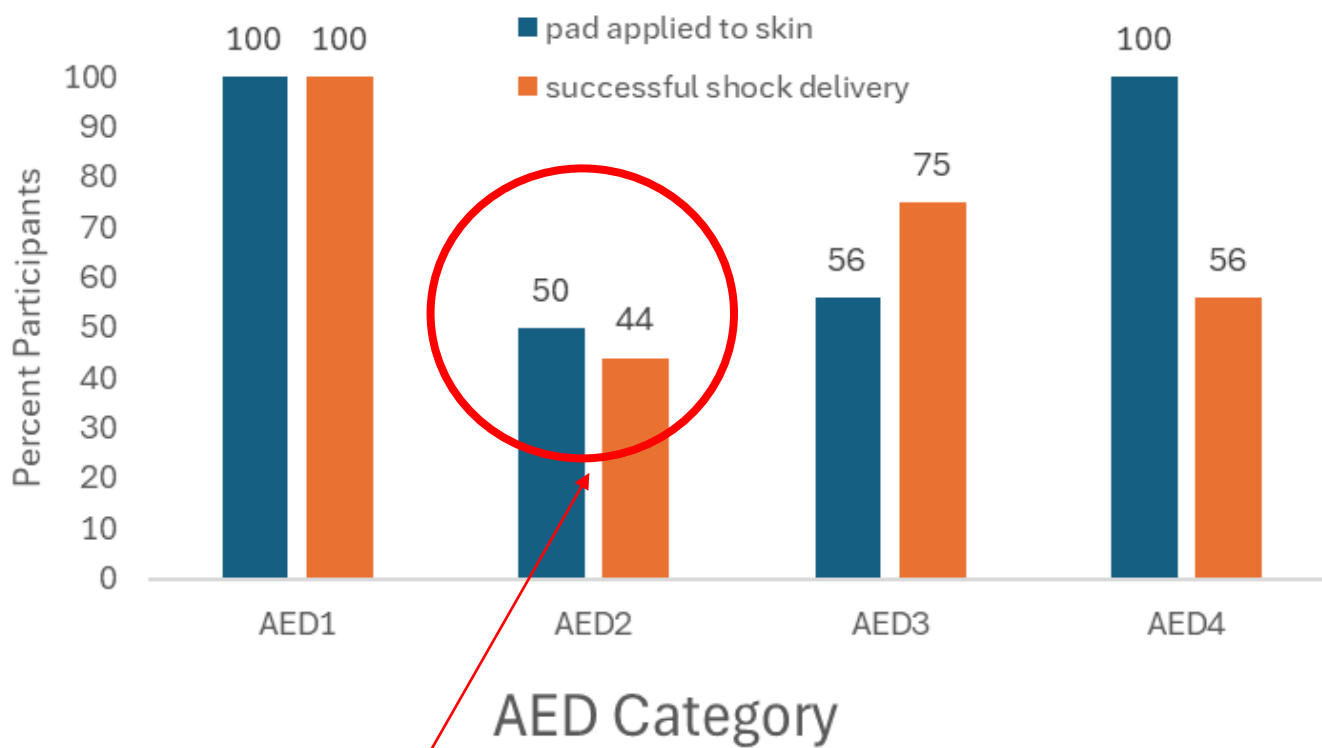
Traditional Interface

Control operations in Chemical Plant

With different interface design, workers

- completed scenarios 7.5 min faster (41% improvement)
- successfully dealt with failures in 96% of the cases (26% improvement)
- recognized failure before 1st process alarm in 48% of cases (38% improvement)

Economic benefit estimated at
\$1,090,000 CAD per year



Medical

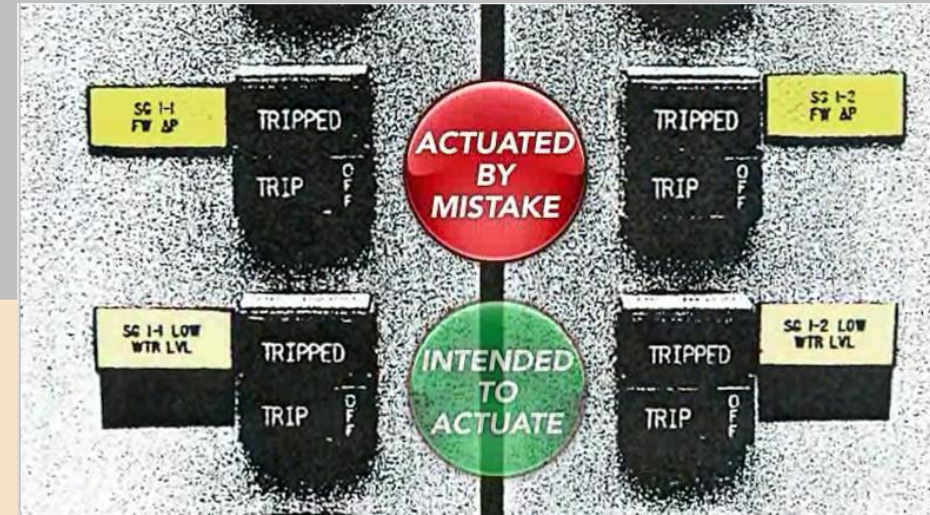
Completed these despite clearly inferior interaction design

Davis Bessie Loss of Feedwater

June 9, 1985

Initiating Event

Main Feed pump #1 tripped because of capacitor failure
Isolation valve closed and then tripped on high pressure

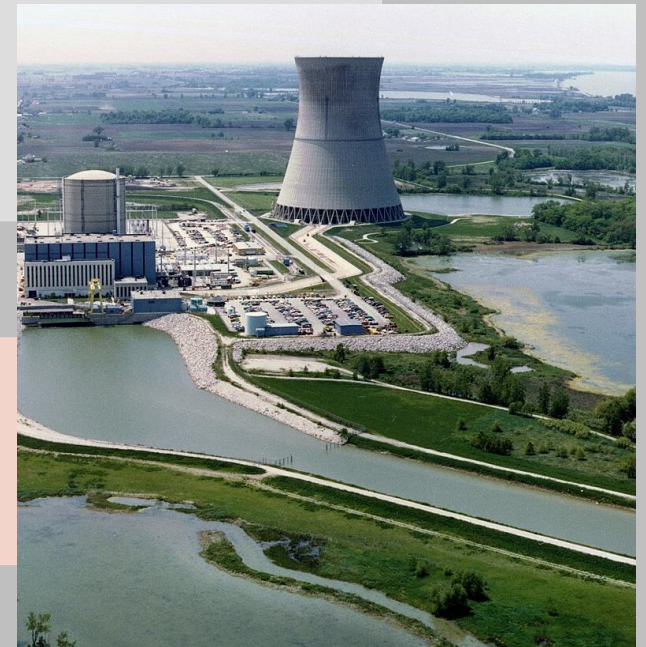


In Control Room – *exacerbation of event*

Unclear layout of auxiliary feedwater displays & controls
This caused isolation of the auxiliary feed water

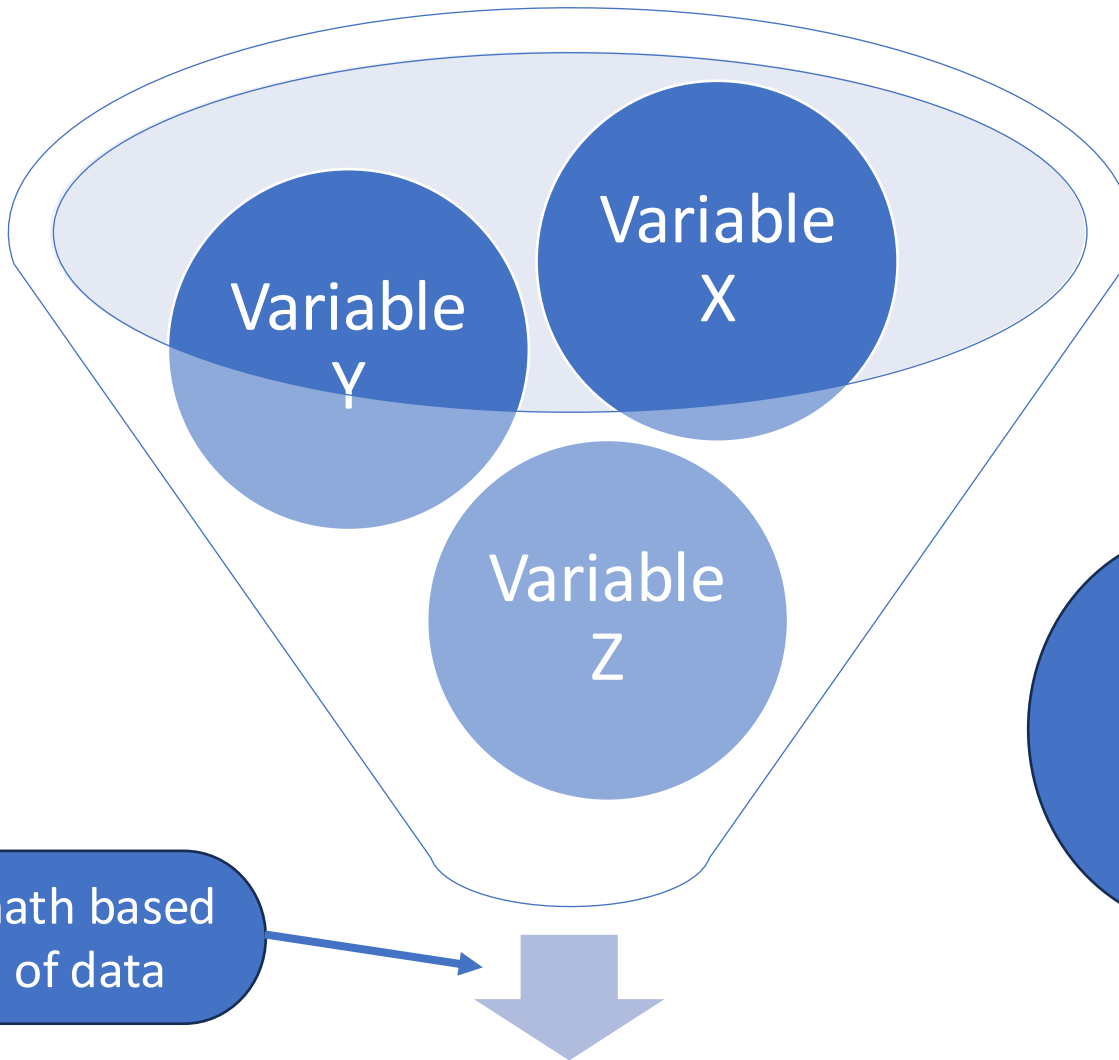
In Secondary – *resolution of event*

Communication method for operator not close to turbine
Lack of training regarding system operation
No display of the turbine's RPM



Operator prevented escalation DESPITE these challenges

Predicting Things....
to Improve Safety



Lots of math based
on lots of data

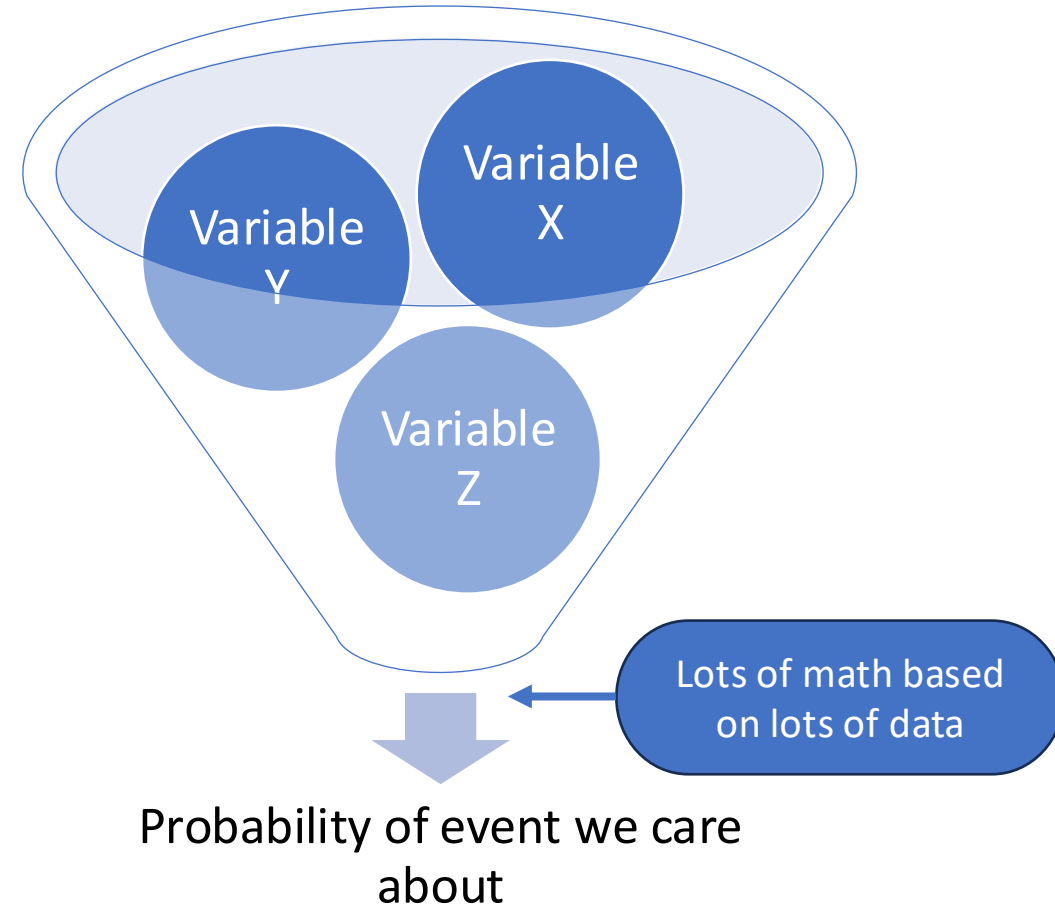
Probability of event we care
about

Higher *quality and quantity*
data improves predictions.

Questions I think about Regarding Humans & Safety

Are we

- including the appropriate predictors?
- trying to predict the right things?
- effectively integrating the different approaches?
- leveraging computational advances for “the math”?



Are we including the appropriate predictors?

- There are many HRA models and collectively they include performance shaping factors (PSF) from all aspects of human experience

- Organizational

Good Practices PSFs
(NUREG-1792)

*We are mostly including appropriate predictors and
even interactions between them, so
YES!!*

- Machine Design
 - Task
- Many investigations on interactions between the PSFs.

{still debate about accuracy of the models though}

Available Staffing

Human-System Interface

Environment

Accessibility/Operability of Equipment

Need for Special Tools

Communications

Special Fitness Needs

Consideration of "Realistic" Accident Sequence Diversions and Deviations

Are we trying to predict the right things?

- Human Errors (HRA)
 - Slips, trips, lapses, etc.
- Consequential event (PRA)
 - Nuclear:
 - Significant core damage frequency (CDF);
 - Large early release of fission products from containment (LERF)
 - Conditional containment failure probability

Basically, BAD THINGS



But what about predicting when humans “save the day”?



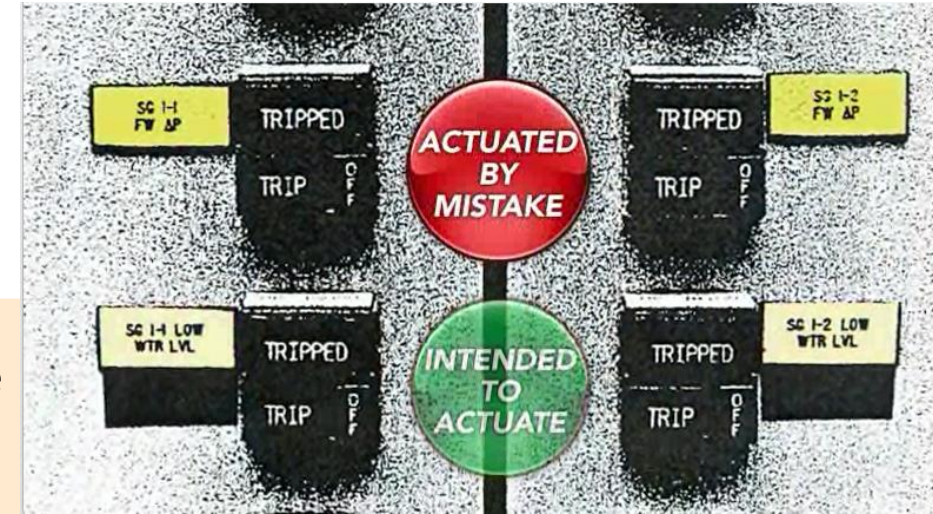
And what can increase the likelihood of this...

Davis Bessie Loss of Feedwater

June 9, 1985

Initiating Event

Main Feed pump #1 tripped because of capacitor failure
Isolation valve closed and then tripped on high pressure



*Operator prevented escalation DESPITE the challenges
What if interface had been designed better?
Faster resolution, fewer days with system down...?*

In Secondary – *resolution of event*

Communication method for operator not close to turbine
Lack of training regarding system operation
No display of the turbine's RPM





US Airways Flight 1549
New York City



Qantas Flight 72, Perth

Safety Snapshot: Split-second Decision Saved the Day (and more) in Perth

by John Craft in Things With Wings

Mar 18, 2014

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Tweet

Comments



Qantas Flight 72, Perth



Qantas Flight 32, Changi, Singapore

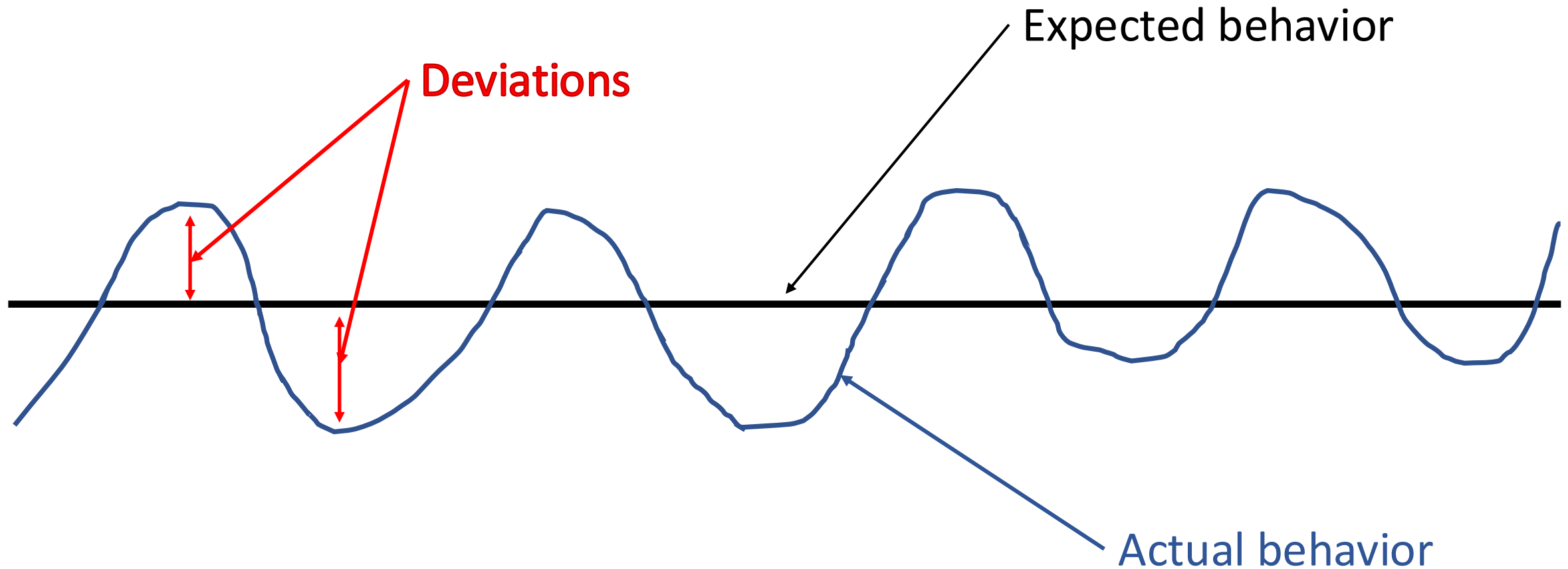


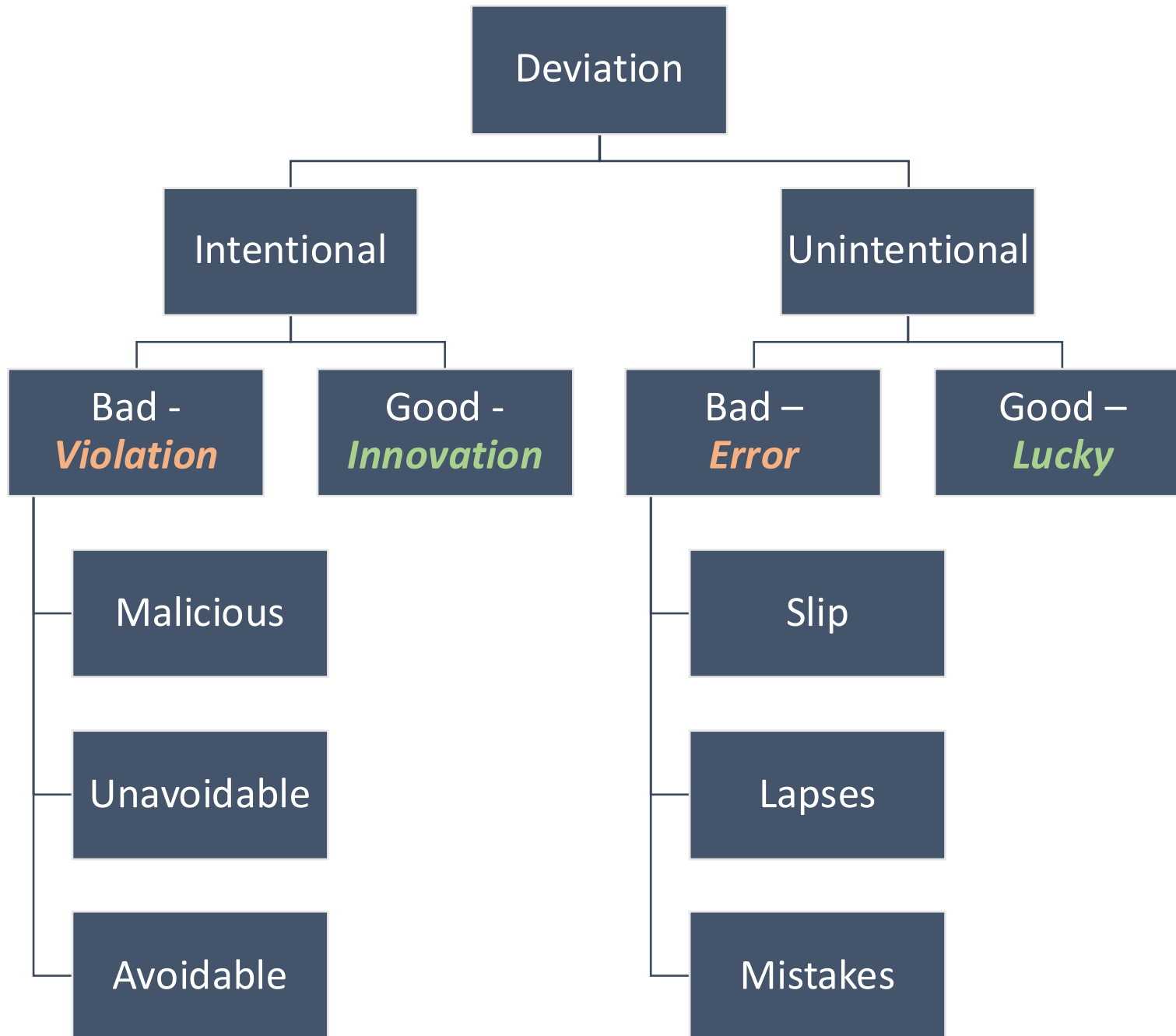
British Airways Flight 38, London

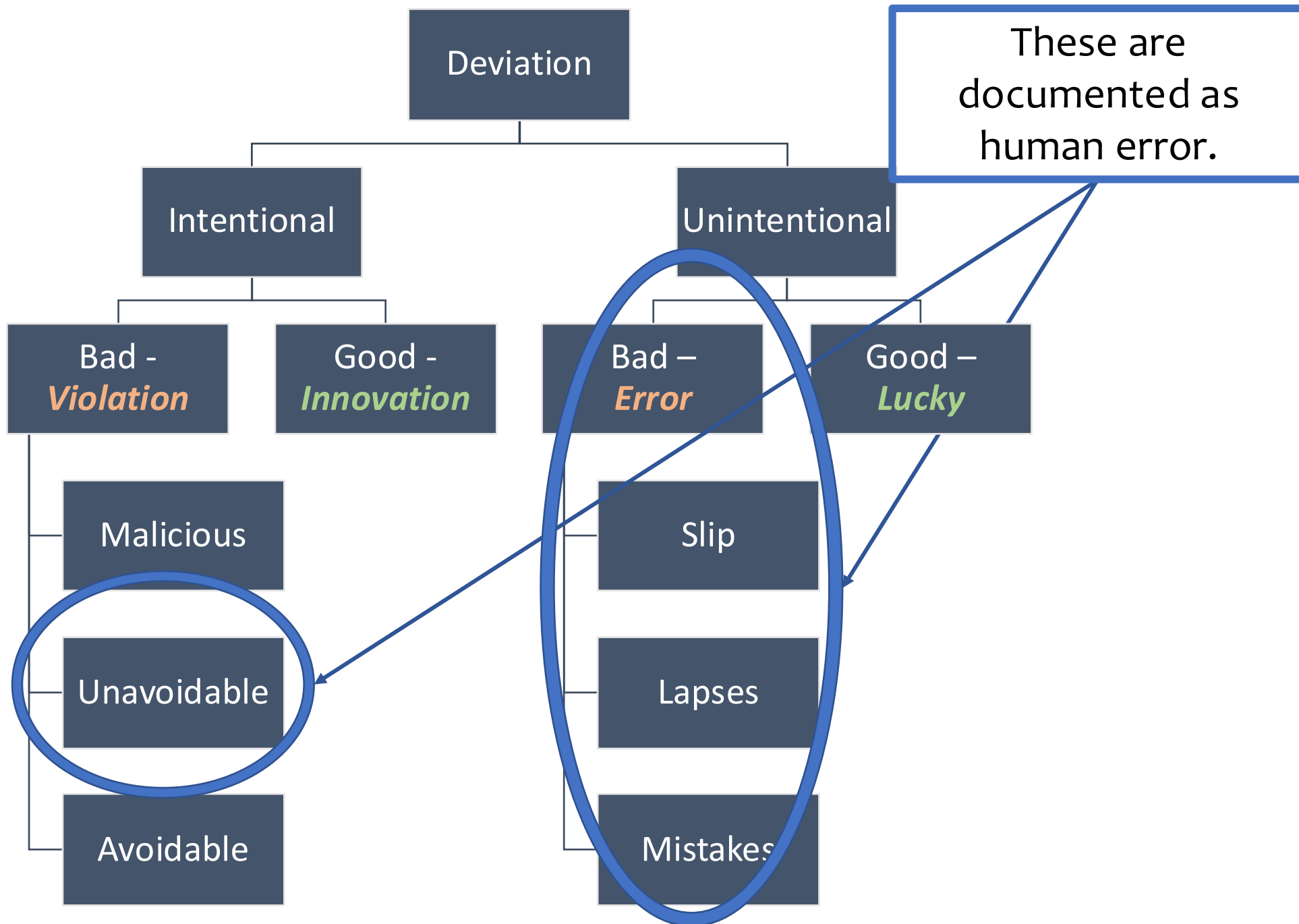
EASA	EMERGENCY AIRWORTHINESS DIRECTIVE
	AD No.: 2014.0266.E
	Date: 09 December 2014
	Note: This Emergency Airworthiness Directive (EAD) is issued by EASA, acting in accordance with Regulation (EC) No 216/2008 on behalf of the European Commission. In Member States and of the European third countries that participate in the activities of EASA under Article 90 of the Regulation.
This AD is issued in accordance with EU 2010/132, Part 21.A.05. In accordance with EC 2002/3002 Annex 1, Part 21.A.051, the continuing airworthiness of an aircraft shall be ensured by accomplishing any applicable ADs. Consequently, no person may operate an aircraft in which an AD applies, except in accordance with the requirements of that AD, unless otherwise specified by the Agency (EC 2010/132, Annex 1, Part 21.A.051). This AD is issued in accordance with the provisions of the EASA Regulation (EC 2002/3002) and the EASA Regulation (EC 2010/132).	

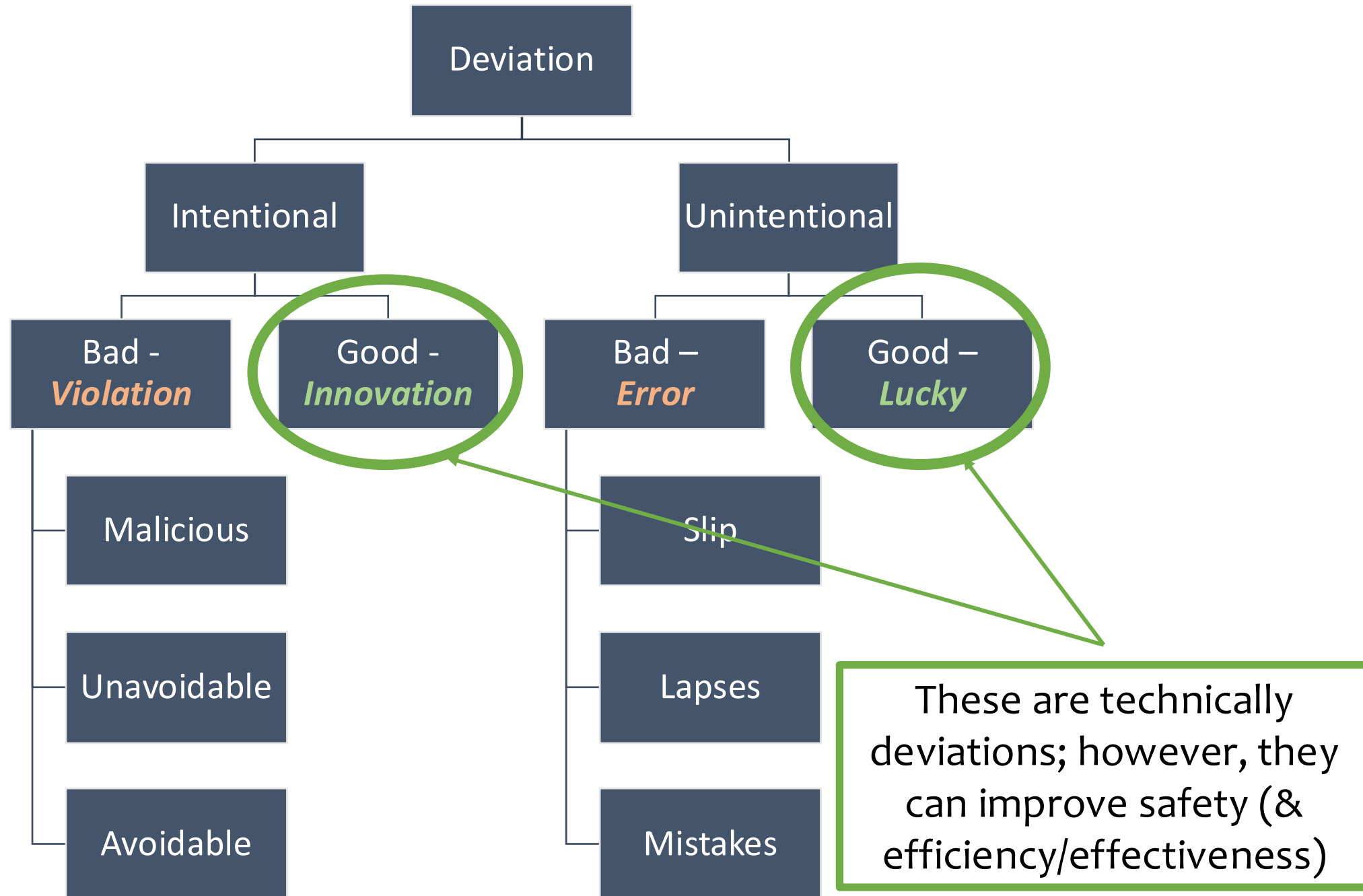
Lufthansa Flight 1829, Munich

Deviation









Focus now is on behavior
“below the line”

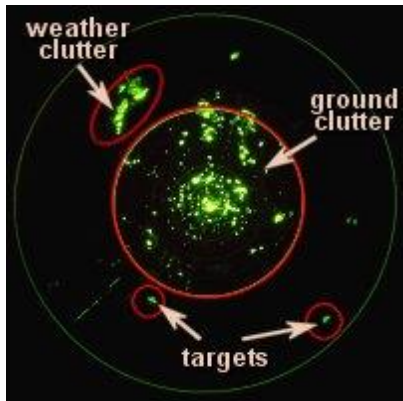
*What are we losing by not integrating the
innovations and needed support for the
“above the line” behaviors?*

I am still wondering if we are focusing
on all the right things...

Sources of predictors

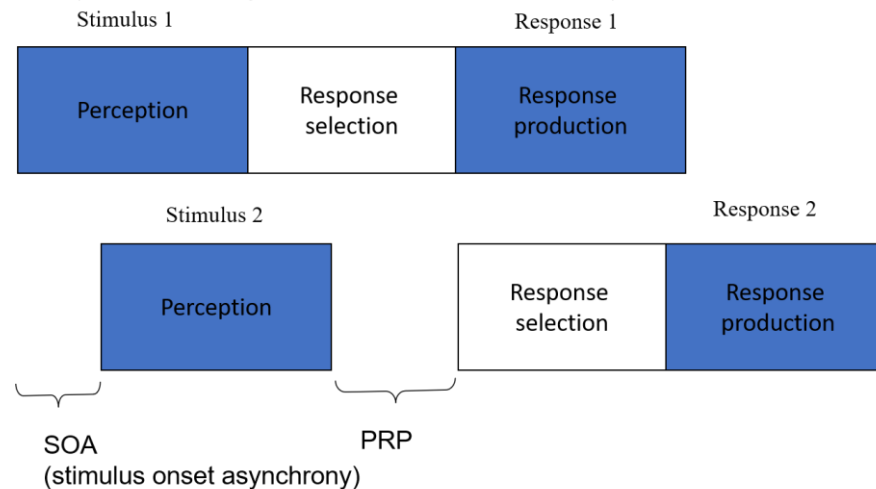
Cognitive Examples

Signal Detection

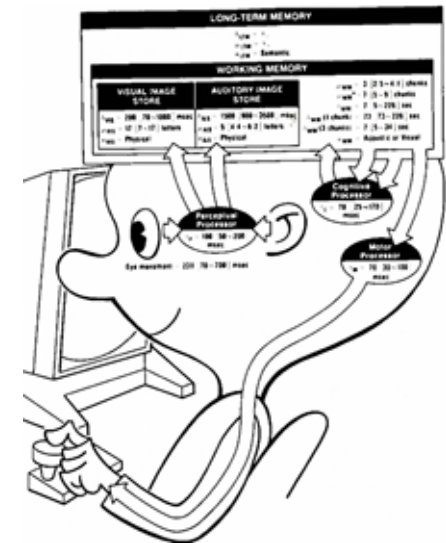


USS Vincennes

Psychological Refractory Period



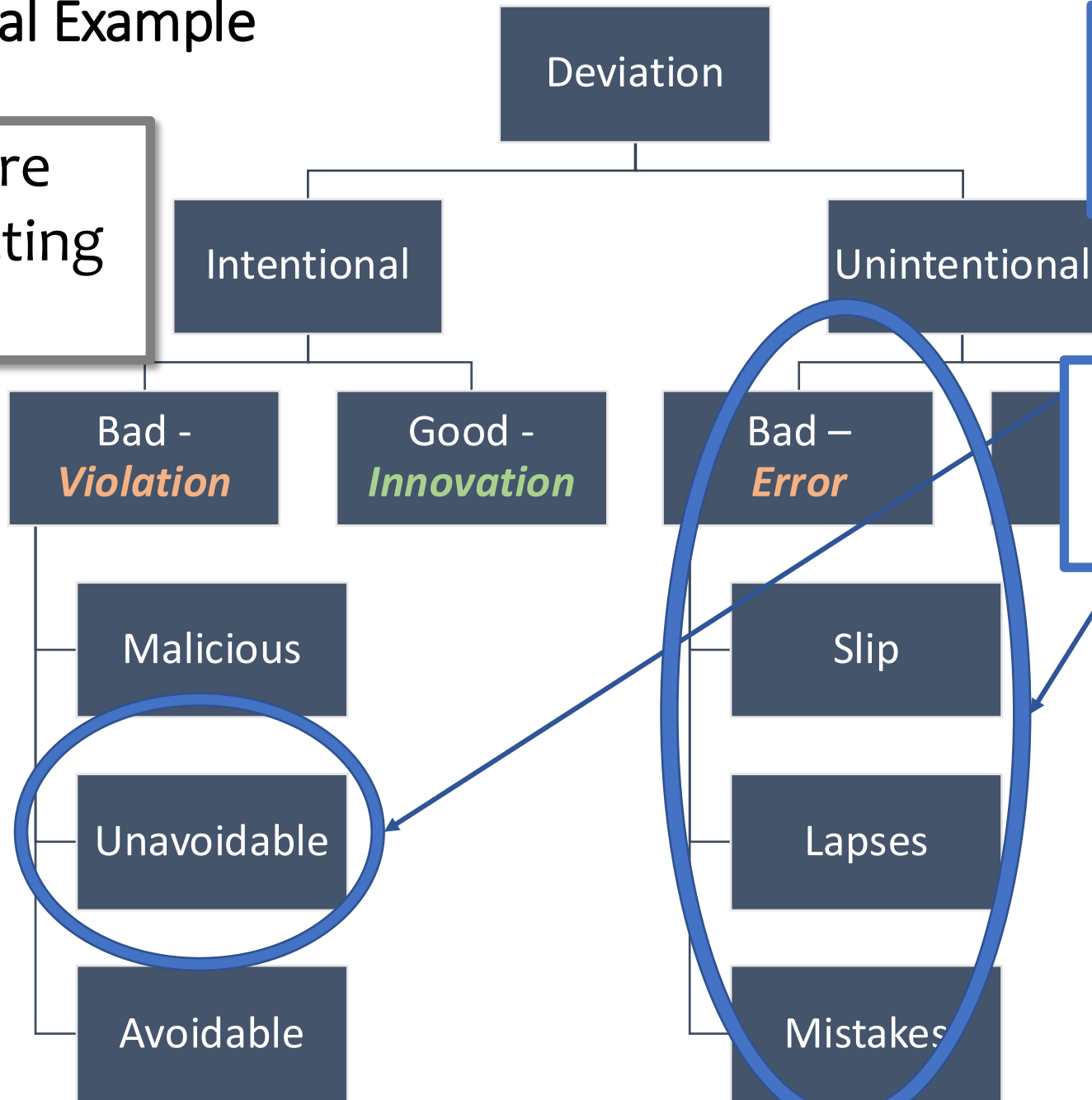
Computational Cognitive Modeling



Psychologists are really good at this...

Psychosocial Example

Psychologists are good at predicting this as well.



If a negative consequence is presented for these

Creates a climate where workers avoid reporting issues.

I'm sure there are others, but let's start with these--

Human Reliability Analysis and
Computational Cognitive Modeling

*Are we integrating sources of
predictors?*

Types of modeling systems

Human reliability analysis

- Part of probabilistic risk assessment (PRA) that includes hardware and human reliability
- “A structured approach used to **identify potential human failure events** and to systematically estimate the probability of those events using data, models, or expert judgment” (ASME RA-Sb-2013)

Computational cognitive modeling

- Computational cognitive modeling to **simulate how the human mind works and user responses to inputs.**
- Used to test psychological theories as well as **predict user actions.**¹

¹Trafton, J. G., Harrison, A. M., & Hiatt, L. M. (2025). *Using cognitive models to generate data for machine learning models* (Report No. AD1334810). Naval Research Laboratory. <https://www.dmi-ida.org/knowledge-base-detail/Using-Cognitive-Models-to-Generate-Data>

Thoughts about integration

Creating new designs

- Cognitive models can support the creation of designs that reduce distractions¹
- This could inform the likelihood of human error

Simulations

- Cognitive model can be used to create simulations of scenarios with different types of reactors, interfaces, staffing models

Generation of data to inform human error rates

- Cognitive models can generate synthetic data of human behavior

¹Trafton, J. G., Harrison, A. M., & Hiatt, L. M. (2025). *Using cognitive models to generate data for machine learning models* (Report No. AD1334810). Naval Research Laboratory. <https://www.dmi-ida.org/knowledge-base-detail/Using-Cognitive-Models-to-Generate-Data>

Are we integrating sources of predictors?

- Short answer – No, we are not.
- Questions now
 - Should we? And if so, how?
- Answer is for better minds than mine.
 - But I do have thoughts about it.
- Start with the question:
 - Are we leveraging computational advances for “the math”?



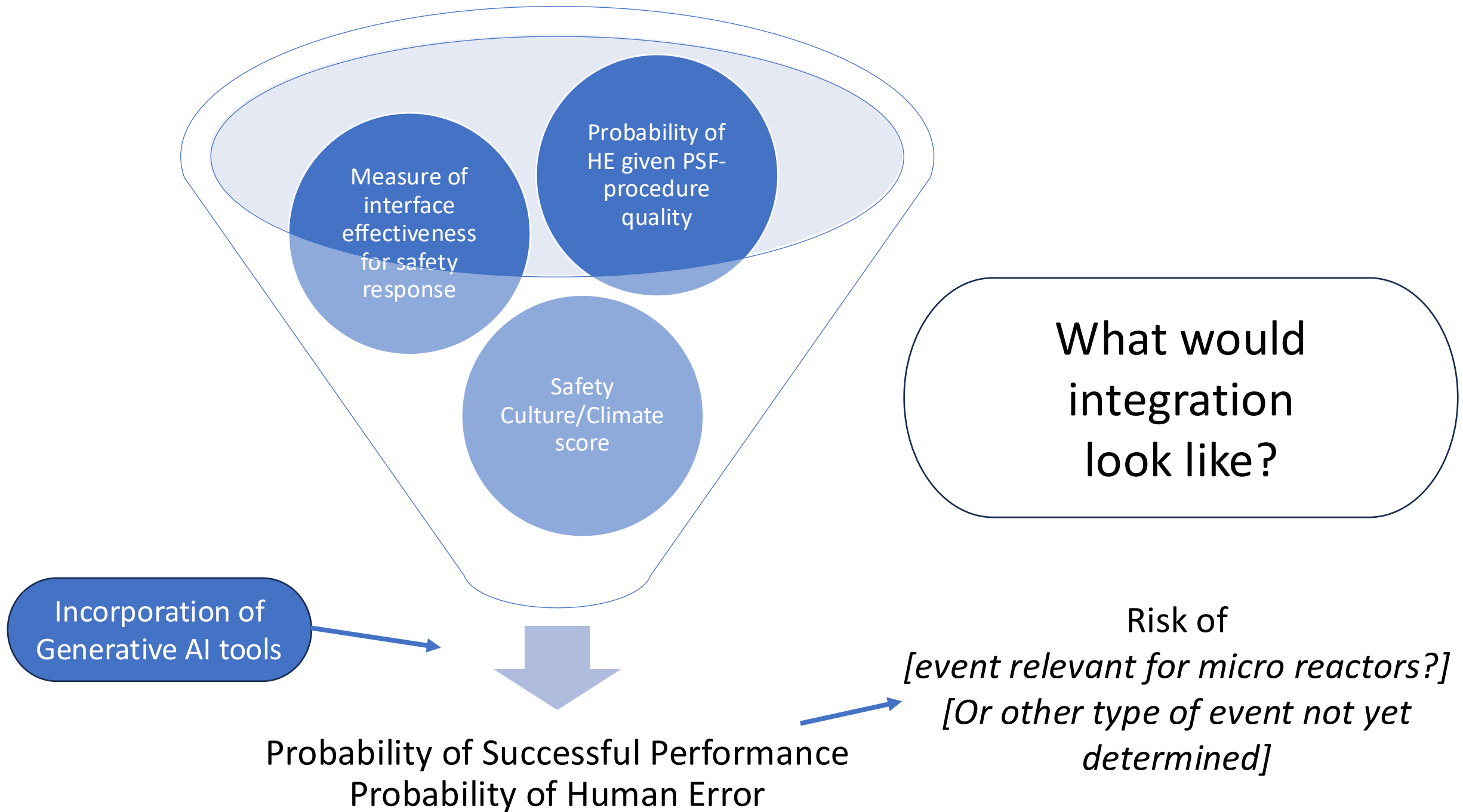
Are we leveraging computational advances for “the math”?

Types of AI

- Generative Adversarial Networks (GANs)
 - Neural network with a generator and discriminator
- Variational Autoencoders (VAEs)
 - Encodes input data into compressed format, decodes it into new output with a new variation
- Large Language Models

Can we or are we leveraging these to more easily:

- Isolate important variables
- Simulate scenarios that allows for answering "what if" questions
- Simplify variable using cognitive model's methods
- Quantify the role of each variable in a model
- Integrate alternative sources of predictors into existing PRA models



We can't wait for lessons learned

We need to learn how to effectively leverage these new tools to get ahead of potential issues so, we can help develop new solutions



Going back to Davis Bessie

Bad design contributed to human error and exacerbated the event

Bad design impeded humans' ability to mitigate the extent of the event

BUT they were able to do it anyway



It's not JUST about preventing human error; it's ALSO about supporting mitigation of the consequences

This changes the ultimate outcome of the PRA

Which may be different for reactors in the future

Let's think about the future

Current limitation of HRA

- Original data with only one type of reactor
- Limited ability to run/create models with specific interfaces

Can generative AI help?

- Generative Adversarial Networks (GANs)
- Variations Autoencoders (VAES)
- Large Language Models (LLMs)

Can advanced models help predict more than risk?

- Productivity
- Efficiency
- Fatigue

THANKS!

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