Project Factors: A Digital Classification System to Assess Project Failures

Approach, Insights, and Next Steps

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Background & Questions at the intersection of OCE and DT

NASA's Office of the Chief Engineer (OCE) portfolio includes engineering, project, and knowledge management policy, guidance, standards, training, lessons learned, and best practices.

Digital Transformation (DT) is about harnessing digital technologies to transform NASA's work, workforce, and workplace.

DT notionally mitigates risk in increasingly complex systems.

QUESTIONS

Is there digital evidence to supplement Subject Matter Expertise (SME) for making DT system-level investments (to avoid mishaps)?

How can we capture digital evidence from failure investigations of the factors that lead to mishaps?

How to avoid or mitigate some of the challenges that are inherent with traditional (mishap investigation) processes when we use digital classifications, potentially exacerbating existing weaknesses while adding new ones?

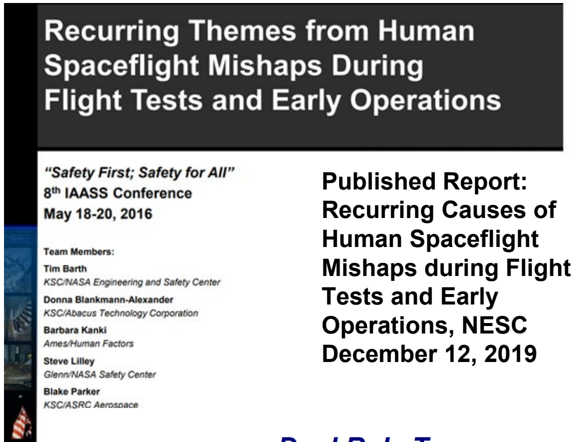
…, thus was born something we call Project Factors

- Recognizing that NASA's engineering capability is accumulated in our people (workforce), processes (work), and infrastructure (workplace).
  - Knowledge transfer and new insights require dedicated research
  - Our digital databases do not typically address organizational questions like "what (nuanced) factors lead to failure or success?," especially during the development process to enable insights across projects, organizations and lifecycles.
  - We lack digital evidence to objectively prioritize system-level, multi-disciplinary engineering capability investments
  - Lessons Learned, Mishap Investigation Board Reports, and project problem reports are locked in text formats
- Project Factors is a body of work to address these document/personnel-based limitations thru digital classification
- Project Factors demonstrates an ability to study across projects to identify common factors leading to failure, risk emergence and actionable outcomes
  - Leverages prior work, reflects upon semantics, and provides a test ontology
  - May provide objective evidence to support high leverage system-level investments in digital information management, automation, analytics, machine learning, model-based digital twins, etc.
  - Enables ability to evolve and mature data analytics across this spectrum:
    - Descriptive → Diagnostic → Predictive → Cross-Functionally Prescriptive
  - May help justify a priority shift from solving technical/physical problems to addressing new challenges for increasingly complex sociotechnical systems

Revisit the Motivation

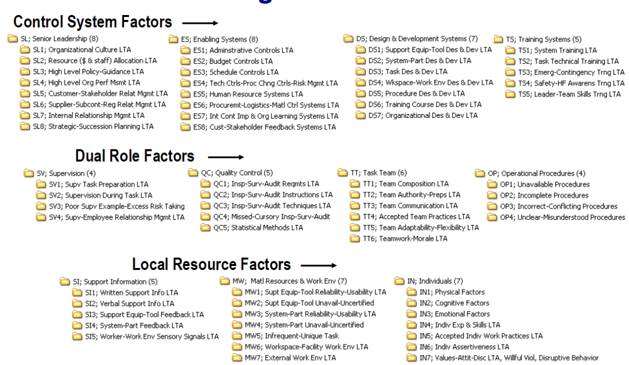
- Failure classification schemes, potentially:
  - Capture human insight digitally, by providing a common method for describing failures and their impacts
  - Enable trending and analyses throughout the project lifecycle
  - Potentially improve assessment consistency across projects
  - Potentially provides early warning
- Expect patterns to emerge, with opportunity to estimate a return on system-level investments greater than any one project would assume by themselves
- Create and supplement SME insights with digital data, trends over time, and patterns across organizations, projects, disciplines, and domains.

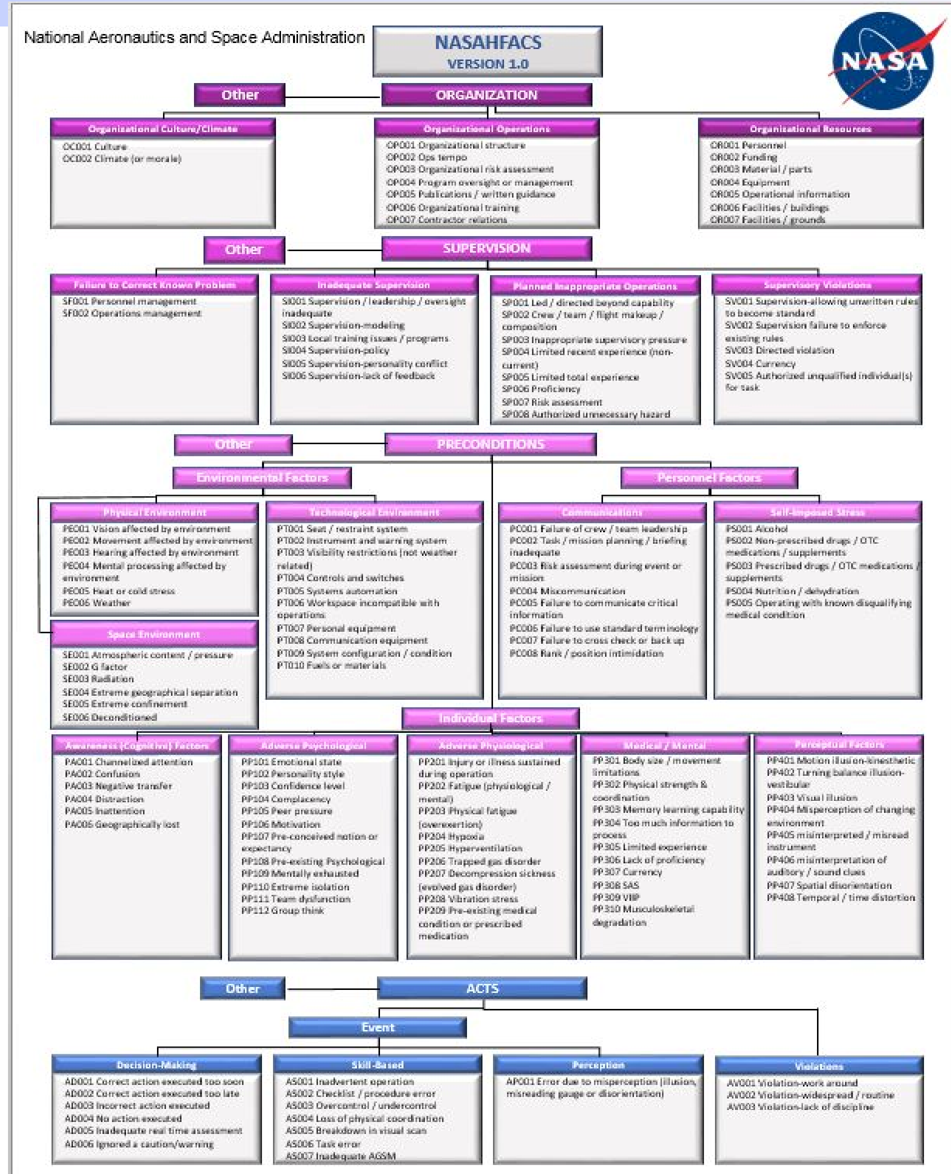
Informed by Prior NASA efforts to look across projects



Published Report: Recurring Causes of Human Spaceflight Mishaps during Flight Tests and Early Operations, NESC December 12, 2019

Dual Role Taxonomy of Contributing Factors and Causes





Office of Safety and Mission Assurance Published Report: *An Accident Precursor Analyses Process Tailored for NASA Space Systems,* Frank Groen, Michael Stamatelatos, Homayoon Dezfuli and Gaspare Maggio, January 2010, and Handbook NASA/SP-2011-3423

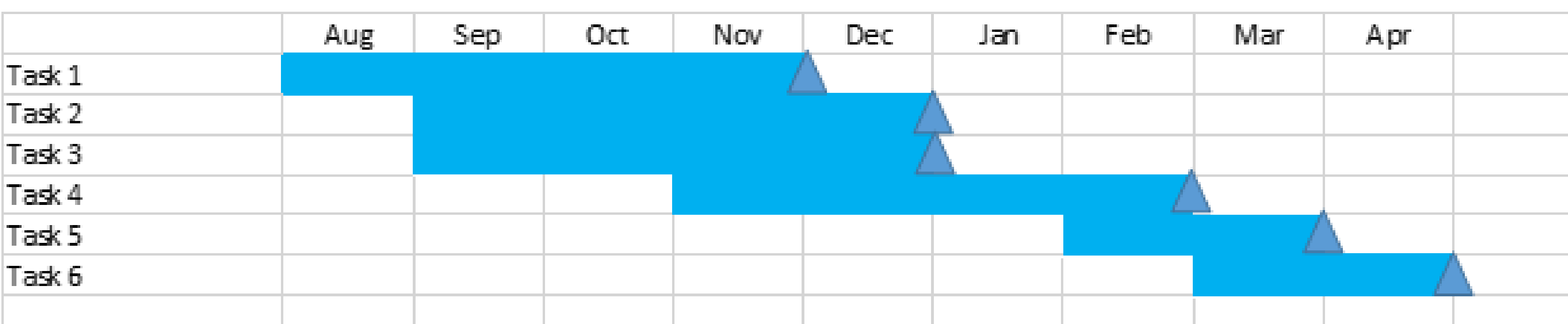
Influenced by critical observations from Human Factors community

- Appreciating nuance of human behavior, impacts of agentive language and human contributions to success
  - **Agentive Language in Accident Investigation: Why Language Matters in Learning from Events,** Crista Vesel, ACS Chem. Health Saf. 2020, 27, pp 34-39., and related NESC Academy online discussion: **The Power and Pitfalls of Language in Accident Investigation (https://nescacademy.nasa.gov)**
    - "Language has a strong influence on the assignment of causality…may create an artificial stopping point for inquiry, which can affect the ability of an organization to learn from events and create a safer working environment"
  - ***Human Performance Contributions to Safety in Commercial Aviation***, Jon B. Holbrook, Michael J. Stewart, Brian E. Smith, Lawrence J. Prinzel, Bryan L. Matthews, Ilya Avrekh, Colleen T. Cardoza, Oliver C. Ammann, Viraj Adduru, Cynthia H. Null/NESC
    - "failure to fully consider the human contributions to successful system performance in civil aviation represents a significant and largely unrecognized risk"
  - ***Human Error, pre-Print, Null, Cynthia H. (2018) Chapter 2.2 Human Error***. In Sgobba, T., Kanki, B., Clervoy, J-F., & Sandal, G.M. (Eds.) Space Safety and Human Performance. Butterworth-Heinemann, Oxford, England
    - "Years of taking an approach to safety that focused on protecting systems from their operators did not increase safety."
  - ***Project Factors Team discussion and guest speakers included***
    - ***People's Role in Operations***, Presentation Nov. 5, 2020, Immanuel Barshi, "When we characterize safety only in terms of errors and failures, we ignore the vast majority of human impacts on the system"
    - Jon Holbrook discussion on human error and real-world impact on mishap reporting
      - Complex systems are not linear, and single events are rarely causal, therefore these models can oversimplify operational situations and fail to accurately describe how success and failure occur in complex systems. At best, this limits the lessons that are learned; at worst, this leads to learning wrong lessons.
      - NASA extensive approach to documenting anomalies and lessons learned. However, the approach was perceived as so onerous that this created pressures to determine that an anomaly didn't reach the criteria for triggering the documentation process. In addition, personnel often couldn't see how (or if) captured lessons learned were being translated into actionable results.
  - Formative Takeaway: While the above appears generally applicable to operational environments, like cockpits, we understand that studying "failures" is still relatively fallow ground for the system of people and processes we use during our pre-operational development phases. Additionally, while critical for awareness, some of the warnings about agentive language have less impact when the focus is on processes or distributed teams.

Project Factors Approach

- Establish product focused, finite team engagement
  - RESEARCH best practices for identifying project factors leading to failure
  - DEVELOP a digital classification system to assess project failures
  - POPULATE model with existing failure investigations and add new failures as they occur
  - ASSESS across failures and reassess investment opportunities

- Multi-disciplinary/org SMEs met during 2020/21 with specific tasks including:
  - Examined classification schemes for Project Management & Systems Engineering related failures
  - Developed a test classification scheme to apply on NASA cases (mishaps, close calls, lessons, etc.)
  - Empirically exercised the classification scheme – An Initial Demonstration
  - Assessed for common factors across projects with intent to identify investment opportunities, completed but not statistically significant



Research Methodology[1]

Research Questions

- How consistent are failure classification schemes within disciplines?
- How different are failure classification schemes between disciplines?
- What trends exist in failure classification schemes?
- What within the body of knowledge about classifications is critical to understand before custom innovations should be considered?

Search Term Examples	
Failure	Types of success
Success	Project failure
Failure categorization	Factors
Failure classification	Criteria
Project categorization	System failure
Types of failure	Engineering failure
Causes of failure	Studying failure

1) Identify Research Questions to Guide Search

- *RQ1: Are there quantifiable differences in perceived causes of failure for projects based on discipline?*
- *RQ2: Are perceived causes of failure consistent within each discipline?*
- *RQ3: Are there common perceived causes of failure in schemes from different disciplines?*

2) Search Google Scholar to Identify all Potentially Relevant Sources

Over 10,000 sources reviewed

- Multiple, evolving keywords used
- Not limited by publication date

3) Apply Inclusion Criteria to Obtain Final Dataset of Sources

Final 400 sources identified

- Published in English
- Not grey literature (i.e., no websites, pre-prints, whitepapers, or other non-peer-reviewed work)
- Relevant to project outcome (i.e., no medical literature)
- Contained a failure classification scheme

4) Extract Data for Analyses

Over 4,000 factors extracted

- Copy contents of scheme (perceived causes of failure) and definitions to database
- Extract characteristics of scheme and copy to database

5) Verification

- Inter-rater reliability for all extracted data
- Cross review of sources by two researchers

Literature Review → **Database Formation** → **Data Analysis** → **Scheme Formation** → **Assessment & Implementation**

[1] Pre-publication final draft, available upon request: "Advancing Progress in Project Failure Classification Research: Understanding Perceived Causes of Failure and Quantifying Disciplinary Differences Through Meta-analysis," to be submitted PMI's Project Management Journal, Casey Eaton, Amanda Banks, Bryan Mesmer, Kristin Weger, Robert Moreland

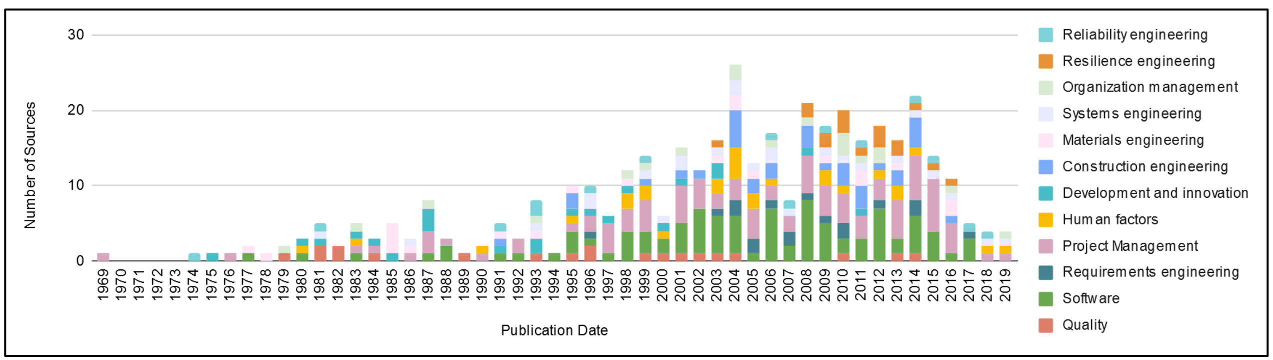
Database Formulation

Literature Review → **Database Formation** → Data Analysis → Scheme Formation → Assessment & Implementation

- **The database of classification schemes includes two types of data: scheme characteristics and factors.**
  - **The 4513 factors were grouped into 77 high level codes that contain similar factors.**
- **Inter-rater reliability for two coders indicated substantial agreement for coding the scheme characteristics (κ= 0.72), the discipline (κ = 0.81), and the factors (κ = 0.80).**

Portion of Codes for the Factors and Definitions

Code	Definition
People (PPL)	Individuals or stakeholders involved in or affected by the project.
Commitment & Completion (CMT)	Dedication or lack of dedication to finishing the project or tasks as well as completing the project or tasks.
Communication (COM)	Transfer of information, including the act, quality, or process of communication, or errors in communication such as misunderstandings.
Feedback (FBK)	Form of communication in which information about performance or status is transferred, such as a lack of feedback, frequent or accurate feedback.
Culture & Climate (CUL)	Atmosphere and customs in an organization or team, such as attitudes regarding the work environment or motivation to change or improve.

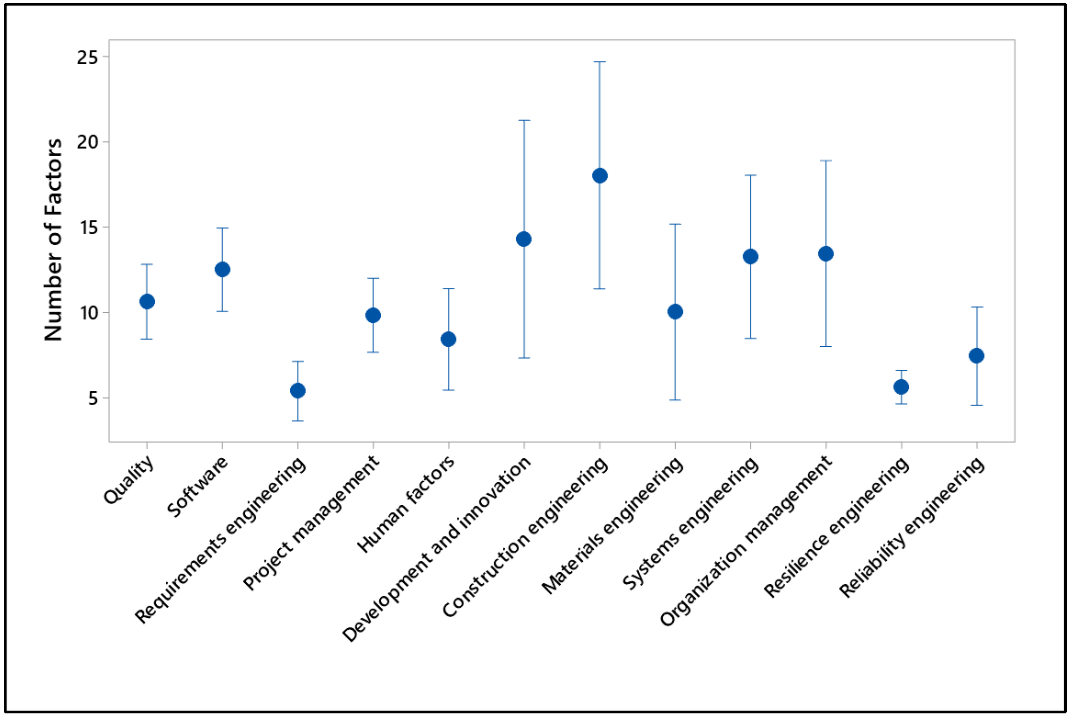


Sources of Schemes by Discipline and Publication Year

Data Analysis

Literature Review → Database Formation → **Data Analysis** → Scheme Formation → Assessment & Implementation

What numerical scheme characteristics are different depending on the discipline?



- **Confidence intervals were calculated for numerical scheme characteristics to determine if the characteristics depended on the discipline.**
  - **The number of factors in a scheme differs based on the discipline.**
  - **Publication date was also found to be a statistically significant differentiator.**

Database Analysis → Scheme Characteristic Analysis → Numerical Scheme Characteristic Analysis

Data Analysis

Literature Review → Database Formation → **Data Analysis** → Scheme Formation → Assessment & Implementation

What categorical scheme characteristics are different depending on discipline?

Discipline	Failure	Success	Both Failure and Success
Development and innovation	9.09%	54.55%	36.36%
Project Management	21.98%	69.23%	8.79%
Resilience engineering	23.53%	70.59%	5.88%
Quality	25.00%	75.00%	0%
Requirements engineering	52.94%	23.53%	23.53%
Software	56.99%	31.18%	11.83%
Construction engineering	57.58%	27.27%	15.15%
Organization management	63.16%	31.58%	5.26%
Human factors	74.07%	11.11%	14.81%
Systems engineering	88.00%	4.00%	8.00%
Reliability engineering	93.33%	6.67%	0%
Materials engineering	100.00%	0%	0%
Grand Total	**50.25%**	**38.75%**	**11.00%**

- **The focus of a scheme on failure or success depends on the discipline.**
- **Six characteristics were statistically significantly different depending on the discipline.**

Category	Pearson Chi-Square Value	Contingency Coefficient	DF	Significance Level	Cramer's V
Publication Type	149.53	0.522	77	p<0.0005	0.231
Cause or Result Focus	40.16	0.302	11	p<0.0005	0.317
Empirical or Qualitative	57.41	0.354	22	p<0.0005	0.268
Classification Method	132.4	0.499	66	p<0.0005	0.235
Success or Failure	142.15	0.512	22	p<0.0005	0.422
Structure	21.89	0.228	11	0.025	0.234
Life Cycle	22.02	0.228	22	0.458	0.166

Database Analysis → Scheme Characteristic Analysis → Categorical Scheme Characteristic Analysis

Data Analysis

Literature Review → Database Formation → **Data Analysis** → Scheme Formation → Assessment & Implementation

How similar are the top level coded factors within and between disciplines?

- **Within a discipline:**
  - **Failure investigations using different schemes would likely come to different results since the factors are different.**
- **Between different disciplines:**
  - **Different schemes have very different rankings for factors, indicating that the factors in the schemes differ depending on discipline.**
  - **Even the highest level codes show significant differences between disciplines.**

Code	Quality	Software	Requirements engineering	Project management	Human factors	Development and innovation	Construction engineering	Materials engineering	Systems engineering	Organization management	Resilience engineering	Reliability engineering	Total
People (PPL)	42.7%	36.8%	24.1%	41.4%	44.1%	32.3%	31.9%	12.7%	27.0%	47.0%	43.8%	8.6%	33.83%
Process (PRS)	33.3%	48.6%	70.1%	34.2%	40.8%	42.7%	42.4%	69.1%	55.6%	34.8%	32.6%	48.3%	47.41%
External Environment (EXT)	13.8%	7.2%	5.7%	13.4%	6.1%	10.4%	19.2%	12.7%	7.5%	12.9%	6.7%	24.1%	10.64%
Attributes (ATT)	8.3%	4.9%	0.0%	8.0%	4.1%	10.4%	4.2%	2.1%	3.3%	2.6%	15.7%	4.3%	5.87%
Other (OTH)	1.7%	2.4%	0.0%	3.0%	4.9%	4.3%	2.4%	3.4%	6.6%	2.6%	1.1%	14.7%	2.24%

Database Analysis → Factor Analysis

Findings from RESEARCH

Literature Review → Database Formation → Data Analysis → Scheme Formation → Assessment & Implementation

- Rigorous review of literature has produced a database of classification schemes with metadata that enables the development of a new NASA-specific scheme
- Demonstration of inter-rater reliability shows it is possible to achieve acceptable agreement between coders.
- A consistent scheme that considers factors important to different disciplines is necessary for consistent failure classification in multi-disciplinary projects.

Research provides a credible starting point to engage additional SME's inside NASA

Initial Demonstration

GENESIS

MISHAP INVESTIGATION BOARD REPORT

VOLUME I

2. Inadequate Systems Engineering Process

- Root Cause 2.1: Inadequate requirements generation.
- Root Cause 2.2: Systems Engineering did not define detailed verification requirements for subsystems.
- Root Cause 2.3: Lack of documentation of changes made to verification methods.
- Root Cause 2.4: Systems Engineering verification process did not require consideration of a verifier's qualifications nor incorporate multiple verifiers.

GPM PSE box shaker close call
Mishap Classification: Close Call

ECFT-57 (Intermediate Cause)
Protection measures protect test equipment at the expense of the test a

Although the board has not found evidence that this is by design, the equip mechanisms tripped off by logic, that would always result in overtest, whe basic procedures can either avoid a shutdown completely, or result in a sof either the test equipment or the test article.

ECFT-37 (Intermediate Cause)
Test equipment is typically of greater value than hardware (when hard

This is a simple fact, but at GSFC, hardware is generally for space flight.

ECFT-38 (Root Cause)
Test equipment is not designed for space flight hardware.

Review of documentation and various forms of advertising indicates that s for this equipment. There is no indication of any special protections in pla other hardware, whereas the consequences of a problem are much different most other applications. At least two hard shutdown mechanisms impleme space flight hardware comprised the test article because of the impact of ov

ECFT-8 (Intermediate Cause)
A peak greater than overcurrent detection threshold was commanded.

The input is random, which would not exclude the presence of very high cu deviations over the mean. The time history shows a peak over ~1300 A.

ATLAS
Incident Classification: Close Call

NMIS Case Number: 15-100532

driven into the unit during the of the unit during the negative above the DC supply setting.

IC-3. There was no review o capacitors was discussed at t procedure
The separate review of the cir left an easy hole to miss key a

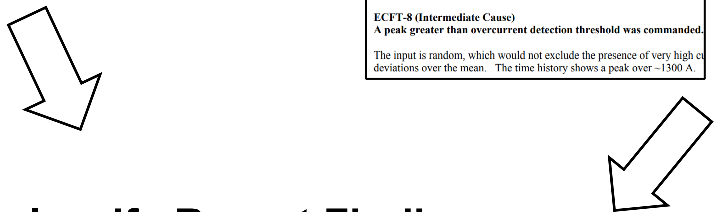
IC-4. Review by all relevant and the unintentional groun
There was a combination of fa EMI/EMC tests successfully f missing of key elements of th

Contributing Factor

CF-1. The predetermined se was unable to detect the incr input to the instrument coul
Interestingly enough, a time h several minutes, so it was clea test, knowing that something w

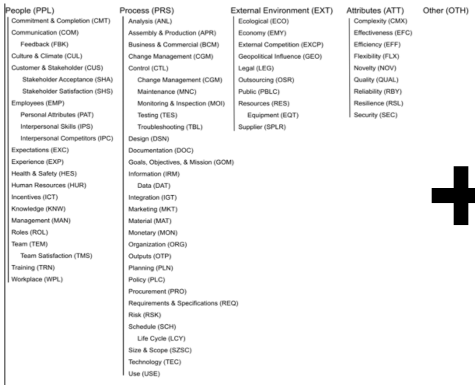
Root Causes

RC-1. There is no single res



Digitally classify Report Findings

Project Factor Ontology + System location



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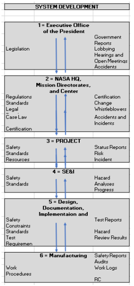

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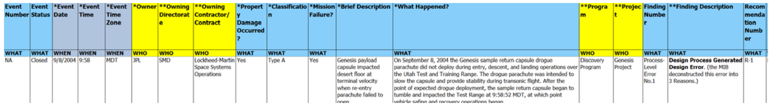
Join digital data with other (e.g., NMIS)



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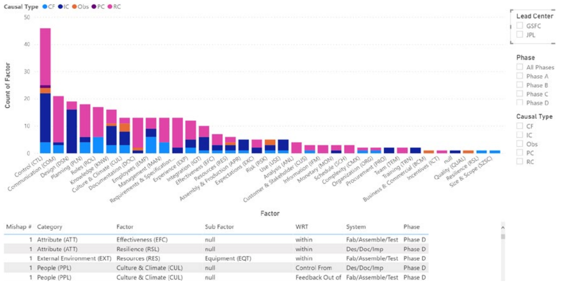
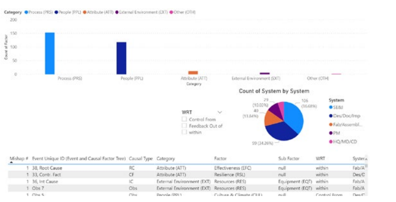


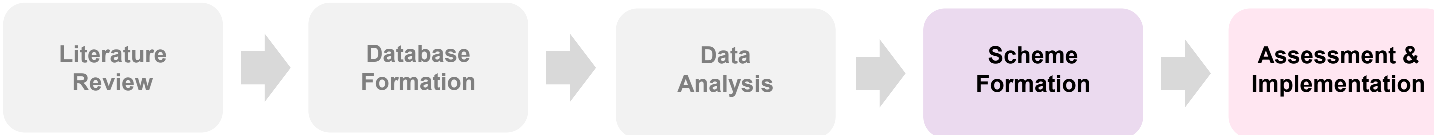


Big Picture Take-aways

Literature Review → Database Formation → Data Analysis → Scheme Formation → Assessment & Implementation

- A digital classification system can be developed for application across disciplines, but the classification activity requires intensive human-effort, and is subject to same weaknesses as traditional knowledge capture approaches (agentive language, cognitive bias, semantics, etc.)
- We demonstrated that we could capture digital evidence from failure investigations of the factors that lead to mishaps, with improving inter-rater reliability with training.
- While classifications appear as necessary for digital assessments, it is critical to address inherent problems with traditional mishap investigation processes with training and awareness that digital classifications potentially exacerbate existing weaknesses.
- There is limited digital evidence to supplement Subject Matter Expertise (SME) for making DT system-level investments (to avoid mishaps).
- There are many nuances and perspectives that can be addressed with classification. What is the role/focus of the classification system?
  - (a) broadly enable digital cross-project/discipline/org/time insights, vs
  - (b) a focus on factors and data that lead to actionable outcomes – perhaps with a changing focus, (much like NASA's Accident Precursor Analyses Process describes the necessity to focus on risk-significant evidence), vs

Next Steps



- Continue research to establish multidisciplinary failure classification scheme
  - UAH research
    - Determine dependencies and associations among factors.
    - Begin development of a multidisciplinary failure classification scheme that will identify and group important factors.
    - Evaluate the failure classification scheme using case studies.
  - Continue to Identify NASA content to apply classifications
- Reflect upon digital classification as a form of data interoperability
  - Should [future] digital classification efforts affect our case studies, mishap reports, lessons learned, etc. [now]?
  - Should [future] digital classification efforts affect our engineer’s documentation [now]?

Additional References

References included in our Pre-publication final draft, available upon request: “Advancing Progress in Project Failure Classification Research: Understanding Perceived Causes of Failure and Quantifying Disciplinary Differences Through Meta-analysis,” to be submitted PMI’s Project Management Journal, Casey Eaton, Amanda Banks, Bryan Mesmer, Kristin Weger, Robert Moreland

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