Advances in Human Factors of Transportation, Vol. 186, 2025, 117–124
https://doi.org/10.54941/ahfe1006500

Improving Operational Safety by Leveraging the Structured Exploration of Complex Adaptation Framework

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ABSTRACT

Traditional safety management often overlooks the nuances of human adaptation in complex socio-technical systems, from which derives a wealth of unexploited tacit knowledge. To demonstrate the usefulness of analyzing daily operation, this paper proposes an application of the Structured Exploration of Complex Adaptations (SECA) framework to proactively identify weak signals in everyday operations. Specifically, the framework consists in semi-structured interviews analyzed using the Grounded Theory (GT) method, supported by Large Language Models (LLMs), enabling deeper insights into everyday operations.

Keywords: Resilience engineering, Safety management, Knowledge management, Complex adaptive systems, Human adaptations, Systems performance variability

INTRODUCTION

High risk industries, such as aviation, invest heavily in investigating unwanted events, driving continuous improvement in the context of the regulatory framework provided by international and national authorities. While well-established reporting systems successfully support traditional root cause analyses, they often fall short in capturing the nuances of human adaptation within complex socio-technical systems.

This paper describes the SECA (Structured Exploration of Complex Adaptations), as a novel method inspired by Resilience Engineering and knowledge management principles (Patriarca et al., 2022a). The SECA method aims to capture and analyze data directly from the operators' narratives, enabling the identification of recurring patterns in everyday operations that could indicate potential areas of improvements in operational safety.

Evolution of Safety Thinking

If we consider the evolution of safety thinking, there are two major paradigms that have guided safety management systems, Safety I and Safety II (EUROCONTROL, 2013). While these labels are often effective at communicating a sort of evolutive reasoning, they can be as well misinterpreted. Indeed, we can think of a contrast between linear event-based (accident, incident) analyses; and complex systemic ones (based on everyday performance variability).

Traditional aviation safety approaches have for a long time followed a linear orientation, with the goal of preventing things from *going wrong*, primarily through a reactive approach. It concentrates on identifying and eliminating hazards and errors after incidents have occurred. This involves looking into the chain of events in order to find the culprit in incidents and accidents, usually tracing back the main cause in the form of "human error". This approach follows on a "causality credo" which entailed that by understanding the root cause of incidents and accidents, they can be prevented from occurring again. It entails the need for a strict adherence to regulations, procedures and standards as a mean to prevent errors and accidents, with no appetite for performance variability (EUROCONTROL, 2014).

In contrast, systemic safety management emerged as a need to respond to the ever-growing complexities of aviation in which a pure linear approach would no longer suffice to account for the variabilities in potential contributing factors. This entailed the development of a more pro-active approach to safety that emphasized the need to understand everyday operations to ensure things *go right* consistently. As a result, systemic safety management acknowledges the ability of the individual and organizations to adapt to constantly changing conditions and unforeseen challenges, considering humans as an asset in the system. Performance variability becomes in this case desirable, if appropriately monitored and managed.

In essence, to continue to remain safe there is a clear need to regard two approaches on a complementary basis, with Safety I continuing to react to unwanted events, while Safety II would allow to explore everyday operations, recognizing and valuing human adaptability and resilience.

New methods are therefore needed to enable this conceptual thinking to be strategically implemented within high-risk industries.

On this basis SECA originates in the second streams of safety management and development. It was built as a method for capturing and codifying knowledge dynamically and continuously with the ultimate purpose of unearthing weak signals. The aim of SECA is to support analysts to go beyond a linear decomposition of events, promoting the idea that organisations can capture and codify knowledge dynamically without the need for actual incidents or accidents to take place. It provides a basis for extracting and connecting pieces of information that might otherwise remain unused, searching for patterns of systemic factors.

BACKGROUND

SECA has been developed in order to enable organizations to pro-actively focus on identifying weak signals before having them contribute to any adverse events. A weak signal is regarded as a "*a seemingly random or disconnected piece of information that at first appears to be background* *noise but can be recognized as part of a significant pattern by viewing it through a different frame or connecting it with other pieces of information.*" (Schoemaker and Day, 2009).

Based on the Systems Thinking principles (EUROCONTROL, 2014), the SECA method encompasses the idea that everything is interconnected and that one part of the system cannot be understood if looked at in silo.

Furthermore, SECA allows for a systematic exploration of normal operations that would help uncover "trade-offs" and "pressures" at individual, team and/or organizational level. This would create the opportunity for bridging the gap between "work as done" versus "work as imagined" or "work as prescribed" and other work proxies for that matter (Shorrock, 2020). This kind of understanding should be seen as essential for building resilient organizations and for fostering a positive safety culture, as it reveals how individuals and teams are able to adapt daily. In essence, by identifying weak signals organizations can learn not just from failures, but also from the more subtle indicators present in daily operations.

From Data to Wisdom

Although there is much to learn from undesired events such as incidents or accidents, they are not an exclusive source of data (Shorrock, 2020). Making sense of everyday operations may allow to create usable knowledge, too. This learning approach involves connecting pieces of information that would otherwise have gone unnoticed and remained buried in daily successful operations.

This concept is formally associated with the Data-Information-Knowledge-Wisdom (DIKW) framework, in which each stage builds upon and enhances the previous one.

In brief, data is raw, unorganized bits with little relevance if they do not appear in a specific context. To move from data to information, non-relevant pieces of data need to be excluded, while the others need to be structured and contextualized, allowing them to become information, conveying information about *what*, *when*, *where*. At this point, connecting information produces knowledge by revealing relationships and enabling goal-oriented use. Finally, knowledge transforms into wisdom, when systems thinking principles and local context are integrated, enabling decision-making processes proactive actions for the future.

Tacit-Explicit Knowledge Conversions

The DIKW cycle demands for a relative, dynamic, and humanistic dimension, differentiating between explicit and tacit knowledge.

Specifically, explicit knowledge is structured, objective, and easily documented, often found in books and written in records. Accordingly, it can be easily identified, articulated, shared and analyzed. Tacit knowledge, on the other hand, is more personal and subjective, derived from individual experiences, intuitions and insights that are difficult to extract and codify.

A key challenge for safety analysts lies in making tacit knowledge explicit, with the aim of capturing the nuances of everyday operations to achieve system safety or more generically, performance enhancements. Specifically, knowledge conversion occurs through the interaction between tacit and explicit knowledge, increasing their quality and/or quantity (Nonaka et al., 2000).

However, although implicit and explicit knowledge are complementary to each other, it is important to emphasize that the conversion can be chaotic, leading to partial information that either expands or narrows details to be studied jointly. A SECI cycle is what allows a continuous iterative knowledge conversion passing through the so-called Socialization (tacit-tacit), Externalization (tacit-explicit), Combination (explicit-explicit), Internalization (explicit-tacit) stage. We suggest SECI to be at the core of learning from successful everyday operations.

METHOD

The following sections detail the SECA interview structure. SECA utilizes semi-structured interviews with frontline personnel in order to capture narratives of everyday operations. These interviews explore the context of the event, the individual's responses, any pressures faced, or conflicts encountered. Further on, using a semi-automated process, leveraging Large Language Models (LLMs) and human analysts, allows for the data analysis to take place in order to identify recurring patterns in everyday operations, revealing potential areas for improvement in operational safety.

SECA Interview Structure

The concept of weak signals, promoted by Resilience Engineering (Patriarca et al., 2018) and further supported by knowledge management principles (Nonaka et al., 2014), represents the theoretical foundation encouraging the essential analysis of adaptations and trade-offs. These notions are condensed in the SECA framework, which aims to interpret knowledge as a social phenomenon, from which to retrieve meaningful insights to enhance the safety of operations. Specifically, broadening the perspective, SECA aims to learn from everyday operations going beyond root cause analysis and a linear decomposition of a specific work domain.

To achieve the desired result, SECA relies on interviews conducted with frontline personnels who are asked to recount any event that is deemed interesting for various reasons. In this regard, in line with the purpose of the SECA framework, it is critical to specify that the event narrated must not have had any negative outcome deemed necessary to be reported according to the organization bureaucratized systems. This dimension, referred to by "Context", is supported by three more dimensions, accounting for a total of 11 questions. In particular, the "Responses" dimension allows interviewees to explain how they behaved in that specific instance, whether they adhered to the rules, and how their colleagues would have reacted in the same situation (both *"less experienced"* as well as *"more experienced"* colleagues). The "Pressures" dimension, instead, supports individuals to externalize eventual pressures from either the blunt-end or front-end and the reasons that led to that tense situation. Last, but not least, the "Conflicts" dimension provides insights into the goal conflicts and trade-offs that interviewees faced at critical decision-making moments (Patriarca et al., 2022b).

Finally, it is important to specify that each question did not have any words limit, allowing the interviewee complete freedom to describe what they believed was truly relevant to the case under examination. From experience however, the interviewer usually restructures the content provided in the semi-structured format into the organized dimensions of the analysis.

Grounded Theory

Running SECA interviews generate textual data. For this purpose, considering the content of the questionnaires and the nature of contextual dependency of everyday operational performances in complex socio-technical systems (Johnson and Christensen, 2019), as well as its inherent connection to the adaptive nature of human behaviours (Hollnagel, 2012), the Grounded Theory (GT) was selected as the methodology for the analysis (Glaser and Strauss, 1967).

GT is a qualitative research methodology in social sciences aimed at developing theories grounded in real-world observations. Specifically, due to the interpretative nature of the analysis, GT requires inductively coding questionnaires to generate codes, which are intended as labels describing broader segments of data (Charmaz and Thornberg, 2021). Analyzing the obtained codes is expected to reveal recurring patterns linked to specific complex adaptations, which might otherwise go unnoticed.

It is then clear that GT is of interest for exploring dynamic processes over time, providing deeper insights into complex socio-technical systems. However, ensuring rigor and objectivity can be challenging due to its interpretive nature. Consequently, a customized semi-automated process was designed to conceptualize the SECA interviews on the basis of the GT concepts.

This section outlines the three steps composing the proposed semi-automated process, designed to unearth weak signals from input textual data. The process is defined semi-automated as it leverages Large Language Models (LLMs) to enhance output quality. However, human analysts remain actively involved, continuously overseeing LLMs to ensure finer granularity and greater relevance of the results.

Our Semi-Automatic Qualitative Coding Process

This step forms the core of the process and, in principle, could be performed with pen and paper. However, it would be time-consuming and, accordingly, impractical for large datasets. To address these limitations, LLMs are employed to team with the human analysts for reducing some burden on the qualitative investigation.

Identifying Codes From Data

The first part of the qualitative coding step focuses on identifying codes within textual data, i.e., words or sentence fragments that describe longer portion of text.

At this stage, LLMs can generate some brief descriptions for each identified code, enabling human analysists to easily assess their decisions.

Grouping Codes Into Categories

After identifying the codes, they are grouped into categories, with each category accompanied by a description. This step allows to obtain categories that, combined with each other, allow to unravel weak signals as recurring patterns.

At the end of this step, LLMs present the results in a human-readable table format, ensuring easy accessibility for human analysts.

Model Performance Assessment

After the qualitative coding step, human analysts evaluate the performance of LLMs in terms of accurateness of codes and categories and appropriateness of their descriptions. At this stage, human analysts have the freedom to adjust and/or supplement the LLMs' output to further enhance the quality of the results.

Identifying Weak Signals

The last step involves analysing the results to uncover subtle, often ambiguous indicators that, if left unaddressed, could lead to negative events in the future, i.e., weak signals.

Once new data is collected, the entire process starts over from the beginning.

EXEMPLARY RESULTS

The proposed approach is iterated on 50 SECA interviews gained from Air Traffic Control Officers (ATCOs). Some exemplary results are presented in this paragraph. For the sake of example, focusing on the i-th questionnaire, **Table 1** shows some exemplary codes and categories that have been identified.

Table 1: Exemplary codes and categories for a generic questionnaire.

Questionnaire Number	Dimension	Code	Category
i	Context	Teamwork	Collaboration
i	Context	Supporting teammates	Collaboration
i	Context	Adverse weather	Environmental factors
i	Context	Traffic complexity	Traffic condition
i	Responses	Experienced response	Expert judgements
…	…	…	…
i	Pressures	High management expectations	Organizational pressure
i	Pressure	No external pressure	External pressure
i	Conflicts	Balancing safety and efficiency	Operational trade-offs

As shown in **Table 1**, at least one code is identified for each dimension. Generally, since the "Context" dimension typically is the one wherein interviewee provide the most detailed responses, it often results in a larger number of codes. On the other hand, other dimensions tend to generate shorter responses, making fewer codes sufficient.

As for the categories, it is worth nothing that the first two exemplary codes (i.e., "Teamwork" and "Supporting teammates") are grouped under the same category (i.e., "Collaboration"). This represents the core of the SECA approach, as it enables human to quickly familiarize themselves with the event recounted in the questionnaire (climbing the first steps of the DIKW pyramid). More importantly, it plays a crucial role when analyzing relationships across multiple questionnaires.

After coding all the questionnaires, human analysts assessed the performances of the proposed semi-automated process, reporting that in about 90% of cases, codes and categories identified by the LLM were deemed satisfactory without requiring further refinement.

Finally, as a matter of example, the analysis allowed to identify a specific weak signal, i.e., a scenario where a combination of adverse weather and complex traffic leads to management pressure on ATCOs, who have to rely on their own experience to manage the situation effectively. If not carefully addressed, such situations could lead to undesired events in the future.

Same reasoning can be applied for all other questionnaires in the dataset.

CONCLUSION

To conclude, an effective exploitation of weak signals facilitated by methods like SECA represent a critical evolution in safety management systems, extending traditional incident-based analysis with normal performance investigations.

However, a successful SECA implementation requires ongoing commitment. This entails the need to allow a cultural shift to actively take place in an organisation, as well as to ensure robust data is collected before gaining wisdom.

Without doubt, by integrating the SECA approach in an organisation, a positive signal is sent top down from leadership emphasizing a commitment to continuous learning and demonstrating a genuine commitment to proactive safety management. This in turn is seen as having a beneficial impact on Just Culture and a more resilient Safety Culture.

As highlighted, effective scaling is not just about collecting more data but rather about making sense of it and using it to drive proactive and actionable safety improvements.

Leveraging data analytics and machine learning can uncover hidden patterns, highlighting potential weak signals that human analysts might miss otherwise or spent an ineffective amount of time extracting. Integrating these insights into a robust safety management system has the potential to ensure lessons learned are adequately shared and readily accessible across the organization.

ACKNOWLEDGMENT

We thank all the ATCOs, pilots, safety and human factors experts worldwide who have inspired, and contributed to the development and validation of the approach developed in this tool.

REFERENCES

Charmaz, K., Thornberg, R., 2021. The pursuit of quality in grounded theory. Qual. Res. Psychol. 18, 305–327. https://doi.org/10.1080/14780887.2020.1780357

EUROCONTROL, 2014. Systems Thinking for Safety: Ten Principles. A White Paper [WWW Document].

EUROCONTROL, 2013. From Safety I to Safety II: A White Paper [WWW Document]. URL: https://skybrary.aero/sites/default/files/bookshelf/2437.pdf.

Glaser, B. G., Strauss, A. L., 1967. The discovery of grounded theory: Strategies for qualitative research. Routledge, London, New York.

Hollnagel, E., 2012. FRAM: The Functional Resonance Analysis Method: Modelling Complex Socio-Technical Systems. Boca Raton, FL, USA: CRC Press. doi: 10.1201/9781315255071.

Johnson, R. B., Christensen, L. B., 2019. Educational research: quantitative, qualitative, and mixed approaches, 5. ed. ed. SAGE, Los Angeles, Calif.

Nonaka, I., Kodama, M., Hirose, A., Kohlbacher, F., 2014. Dynamic fractal organizations for promoting knowledge-based transformation – A new paradigm for organizational theory. Eur. Manag. J. 32, 137–146. https://doi.org/10.1016/j.emj.2013.02.003

Nonaka, I., Toyama, R., Konno, N., 2000. SECI, Ba and Leadership: A Uni®ed Model of Dynamic Knowledge Creation. Long Range Plann. 33.

Patriarca, R., Bergström, J., Di Gravio, G., Costantino, F., 2018. Resilience engineering: Current status of the research and future challenges. Saf. Sci. 102, 79–100. https://doi.org/10.1016/j.ssci.2017.10.005

Patriarca, R., Leonhardt, J., Licu, A., 2022a. Unearthing Weak Signals for safer and more efficient socio-technical systems. The Structured Exploration of Complex Adaptations (SECA) method.

Patriarca, R., Leonhardt, J., Licu, A., 2022b. Introducing the Structured Exploration of Complex Adaptations to learn from operations in an Air Navigation Service Provider, in: Book of Extended Abstracts for the 32nd European Safety and Reliability Conference. Presented at the 32nd European Safety and Reliability Conference, Research Publishing Services, pp. 33–40. https://doi.org/10.3850/978-981-18-5183-4_R01-05-315-cd

Schoemaker, P. J. H., Day, G. S., 2009. How to Make Sense of Weak Signals MIT Sloan Management Review.

Shorrock, S., 2020. Proxies for work-as-done: 1. Work-as-imagined [WWW Document]. Humanist. Syst. URL: https://humanisticsystems.com/2020/10/28/proxies-for-work-as-done-1-work-as-imagined/.