Learning from experience in the context of autonomous ships:

An opportunity for a step change in generating safety knowledge?

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Research Objective

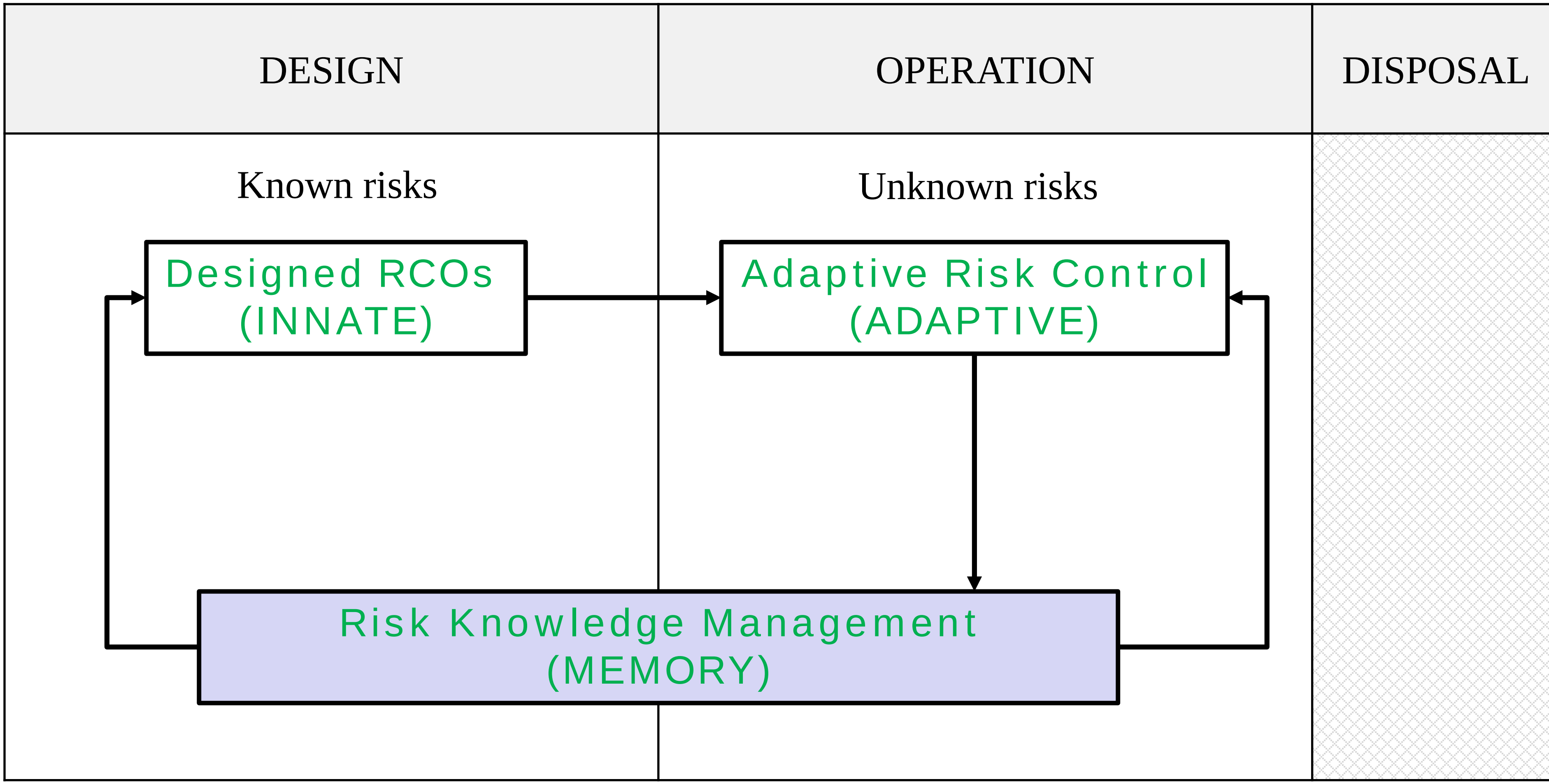
How can we turn operational information into knowledge that feeds back into design?

With the introduction of autonomous ships, can we afford to learn reactively?

Research Objective

Life-Cycle Risk Framework

Distributed risk management based on biological immunity mechanisms



(see also Ventikos and Louzis, 2018; 2019)

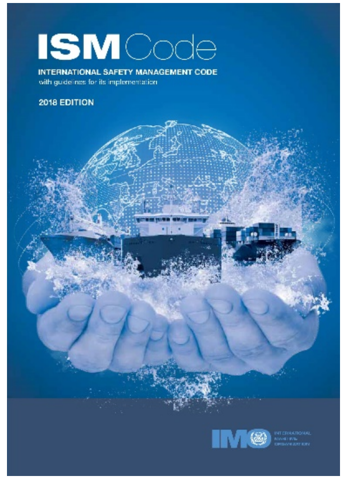
Learning is the capability to avoid the recurrence of incidents and improve safety by taking measures based on the **knowledge extracted from experience**.

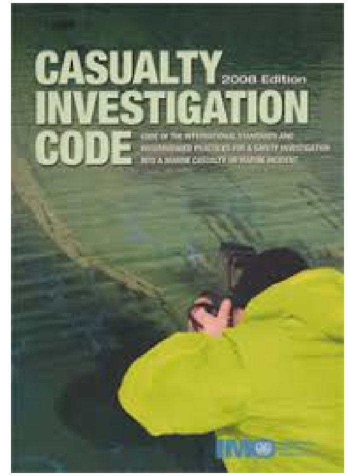
(Jacobsson et al., 2011)

Learning from experience – Practice

Shipping companies

- incidents and casualties (**reactive**)
- near-misses (**proactive**)





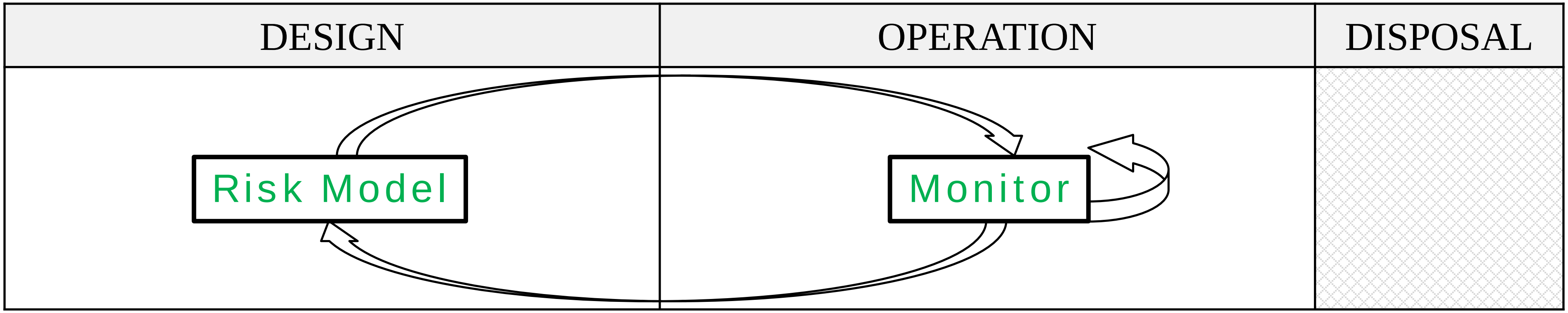
Flag States

- investigate major accidents (**reactive**)
- provide recommendations to the IMO

CHAIN stage (Lindberg et al., 2010)	Limitations
1) Reporting	Under-reporting: • Incidents (Psarros et al., 2010; Hassel et al., 2011), Near-misses (Storgard et al., 2012) • Data confidentiality - shipping companies and P&I Clubs (Pomeroy and Earthy, 2016)
2) Selection	High-consequence, low-frequency accidents
3) Investigation	"What-You-Look-For-Is-What-You-Find" principle (Hollnagel, 2008)
4) Dissemination 5) Recommendations 6) Learning effectiv.	Recommendations: • Limited generalizability. • Compliance with ineffective procedures – work-as-done is not improved

Learning from experience – Advancements

Life-Cycle Risk Management

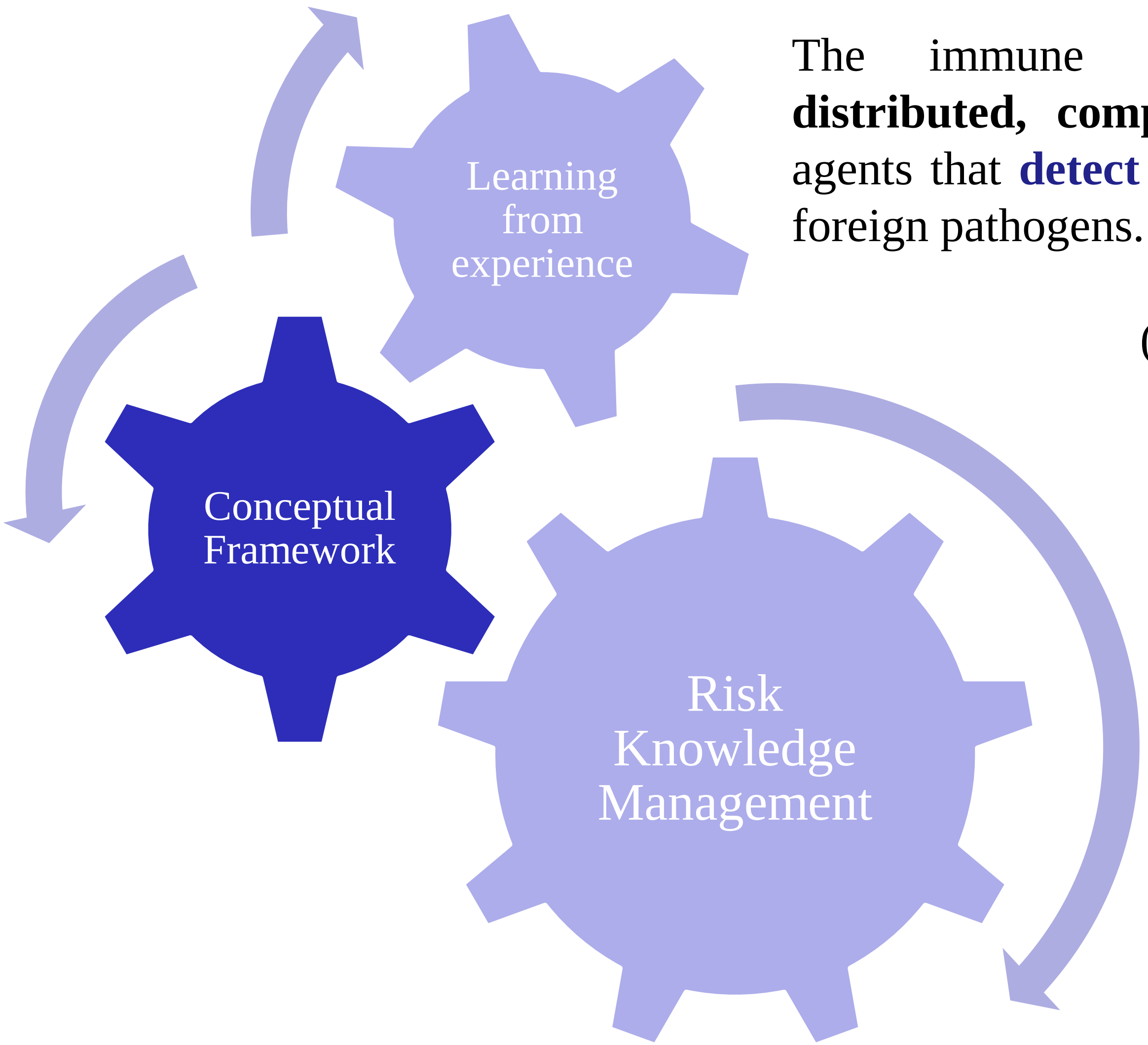


(see also Lee, 2007; Vassalos and Papanikolaou, 2015; Kang et al., 2013)

Learning for Autonomous ships – complex and digitalized systems

- Total reliance on experience for learning will probably prove ineffective, requiring **more reliance on proactive risk analysis** (Leveson, 2011)

- **Complexity conceals the root causes** and gives rise to **new types of incidents** that have never been experienced before (Pomeroy and Earthy, 2016)



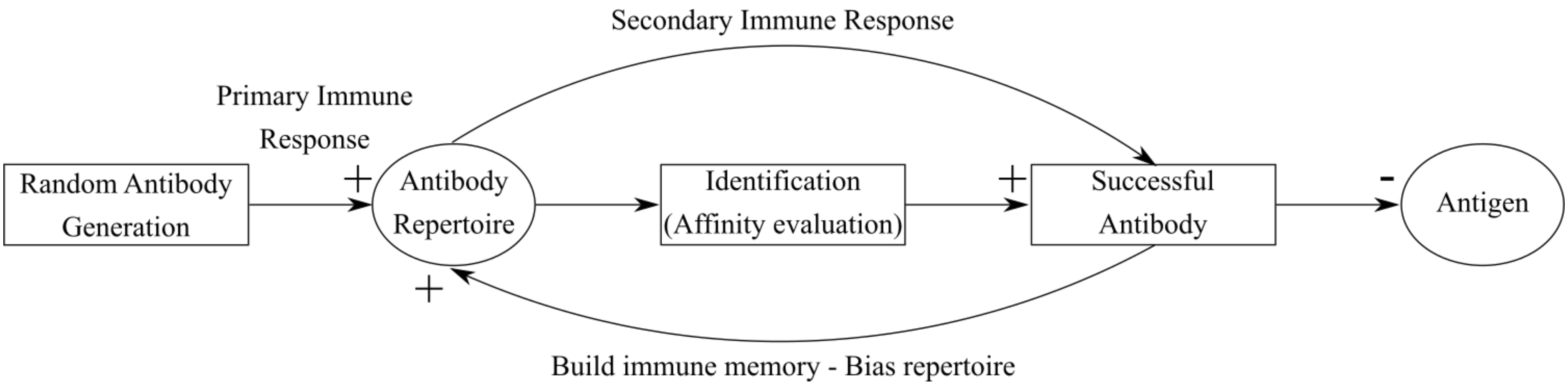
The immune system is a **distributed, complex system** of agents that **detect** and **respond** to foreign pathogens.

(Hofmeyr, 2001)

Conceptual Framework

Mechanisms of the adaptive immune system

- Learning (**primary immune response**)
- Retention and future re-use of information (**secondary immune response**)



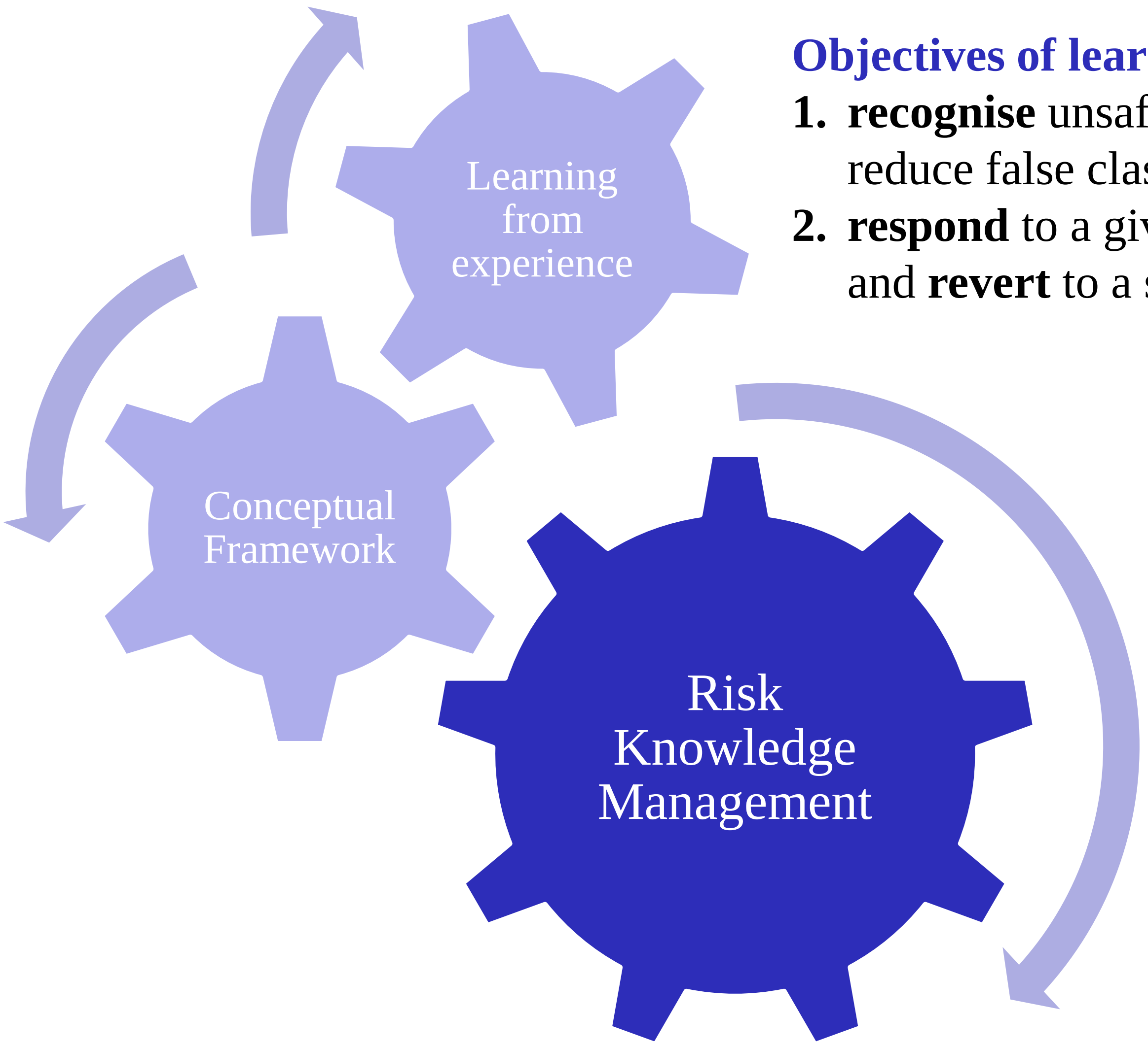
- Immune memory is a high-level behaviour (Smith, 1999)
  - **Associative**: acts on similar pathogens
  - **Robust**: effective even if some “memory cells” are lost
- Learning and memory is a way to **bias the antibody repertoire** from a random structure to one that is **more specific** to the threats the organism has encountered (Perelson and Weisbuch, 1997)

Conceptual Framework

Basic concepts and analogies

Immune System	System	Description
Self	Safe state	State where **the system operates safely** (acceptable risk)
Nonself	Unsafe state	State where **the system operates with an increased likelihood of adverse consequences** (unacceptable risk)
Antibody	State Detector	Classifier that distinguishes between safe/unsafe (self/nonself)
Immune response	Risk Control Options (RCOs)	Strategies: • eliminate safety threats • revert the system to the safe state

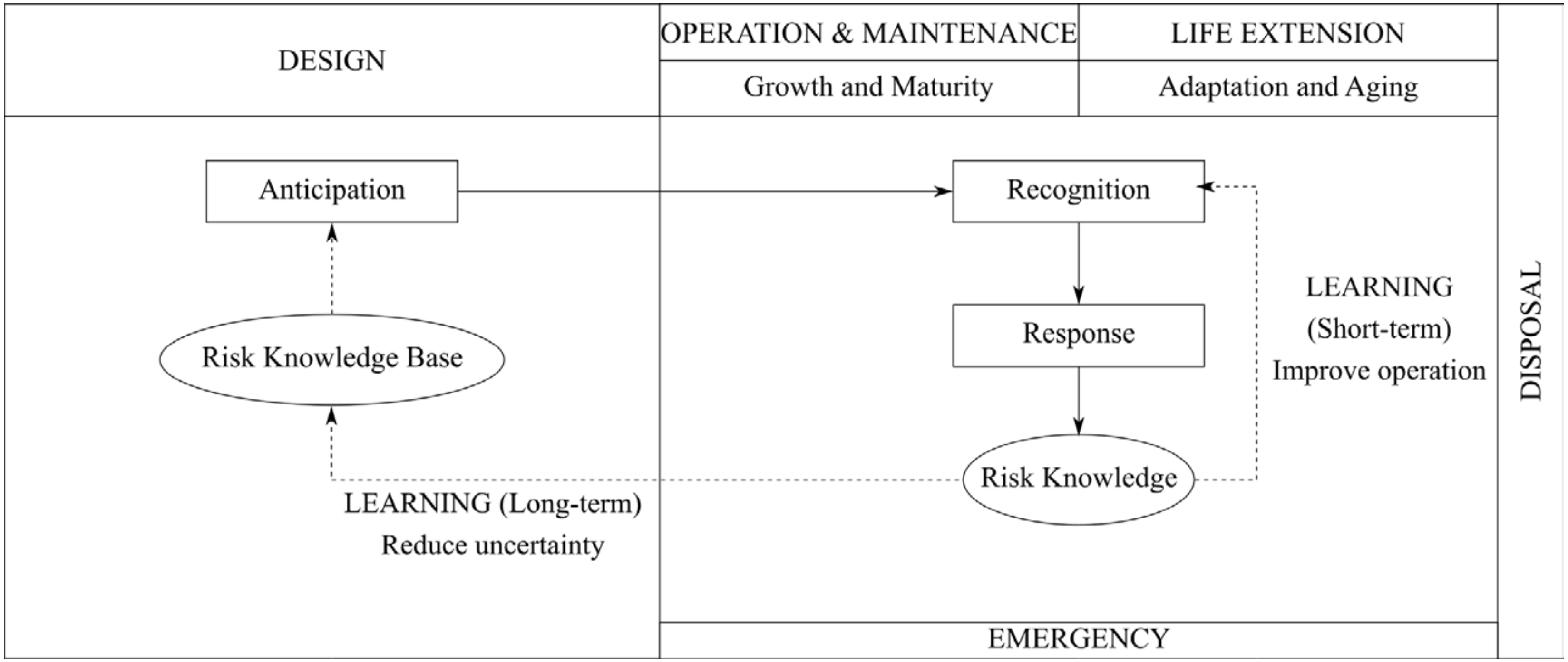
System state := set of **safety indicators** with values in defined ranges that remain **constant or steady** for a specified time window (INCOSE, 2015)



Objectives of learning

1. **recognise** unsafe states and reduce false classification,
2. **respond** to a given unsafe state and **revert** to a safe state.

Risk Knowledge Management



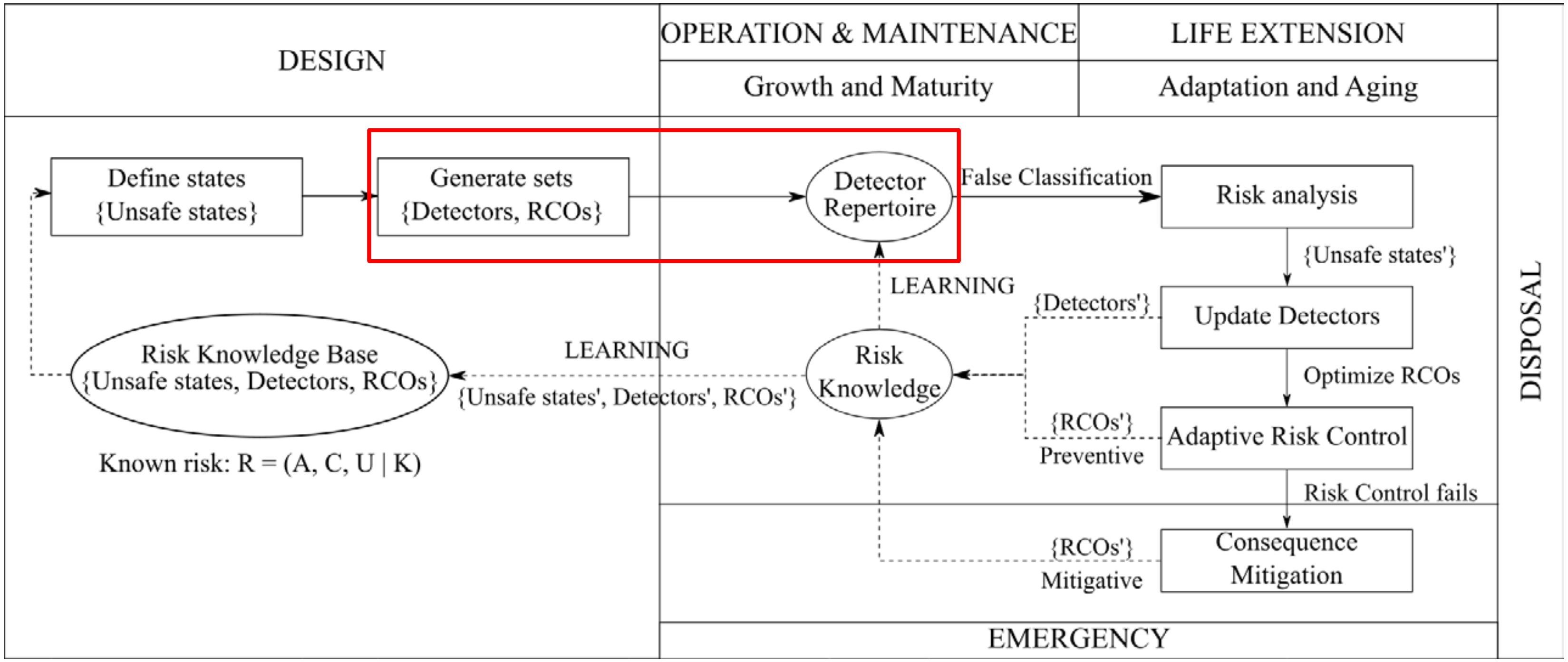
Improving recognition

Dynamically redefining what is considered unsafe by updating the detector set

Improving response

Recording successful risk control strategies for reverting to the safe state and correlating them to the specific unsafe state (**effectively recording a state transition**)

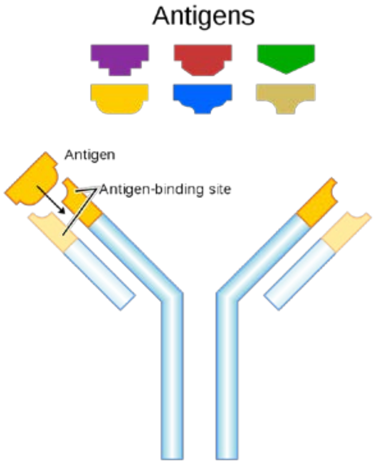
Risk Knowledge Management



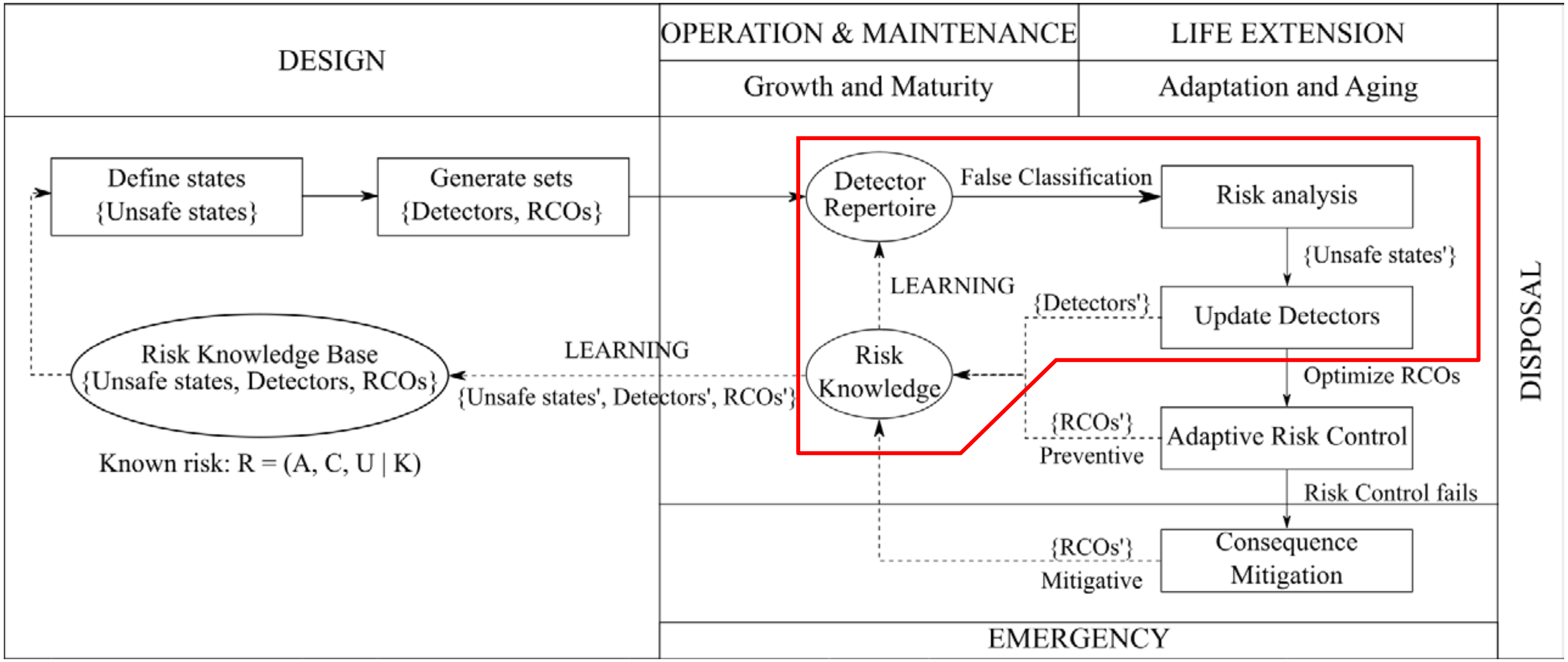
Detector Structure

$$\text{Detector} = \left\{ \begin{array}{c} \text{State} \\ \text{Safety Index given Risk} \\ \text{RCOs} \end{array} \right\}$$

Training with data sets (known risks) to form
the detector repertoire for the operational phases



Risk Knowledge Management

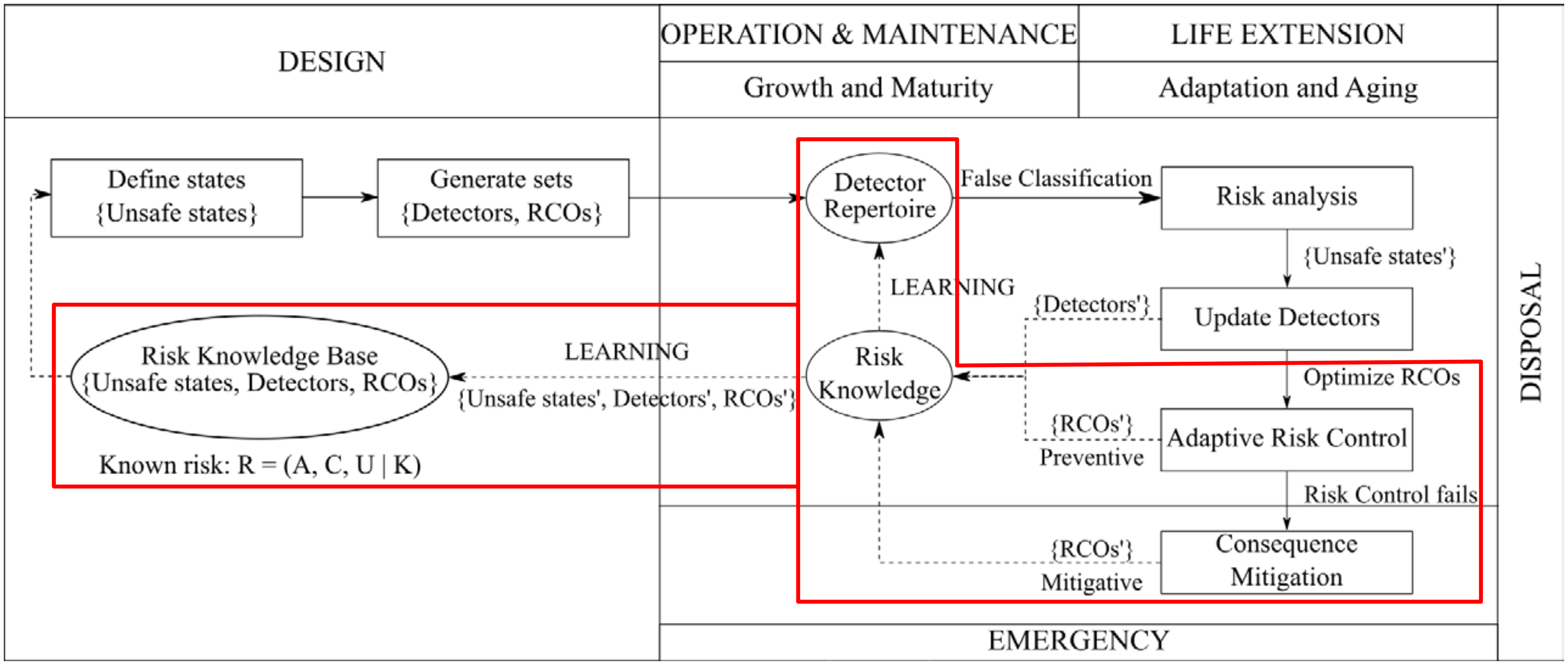


Identifying false classifications

- IF **Safety Index = Safe | Risk = Not Acceptable/High** → False classification

- Real-time risk analysis is resource intensive. Conduct only for **suspected false classifications** (e.g., boundary between self/nonself).

Risk Knowledge Management



Adaptive Risk Control

- IF False Classification → **Optimize different combinations of RCOs | State**
- IF Adaptive Risk Control fails → State = Emergency → **Optimize mitigation**

Updating Risk Knowledge

- $R' = (ST', C', U' < U \,| K' > K)$

Risk Knowledge Management – Example

Scenario

A ship is sailing at maximum service speed through an area where there is **low visibility due to dense fog and dense marine traffic**. The bridge team mainly depend on the on-board navigational equipment for verifying their position and the position of other vessels **without maintaining a proper lookout** for optical verification.

$$\text{State} = \left\{ \underbrace{\text{Visibility} = \text{Low},\ \text{Traffic} = \text{Dense},}_{\text{External conditions}} \underbrace{\text{Speed} = \text{High},\ \text{Situation awareness} = \text{Low}}_{\text{Internal conditions}} \right\}$$

$$\Downarrow$$

$$\text{Detector} = \{\text{State, Safety Index} = \text{Safe}|\text{Risk Level} = \text{Acceptable, RCOs} = \emptyset\}$$

$$\Downarrow$$

$$\text{Detector'} = \{\text{State, Safety Index} = \text{Unsafe}||\text{Risk} = \text{Unaccept., RCOs} = \text{Speed reduction}\}$$

Learning outcome

- New detector is added to operational repertoire (**same ship – shared cognition with fleet**)
- New detector is generalized and added to Risk Knowledge Base (**other ships**)

Conclusions

Beyond the state of the art

Reactive learning	Bio-inspired approach
Identify root causes	Detect hazardous system states
Recommendations target specific conditions	• Learning product is **generalized** • Risk control is robust (look for **“similar” risks**)

Life-Cycle Risk Management approaches	Life-Cycle Risk Framework
Unclear methodological details on informational feedback loops	Risk Knowledge Management updates the whole risk picture (**detection, response**)
Classical risk modelling	• **Systems based** safety modelling • **Dynamic redefinition** of how unsafe states are described given risk knowledge

Conclusions

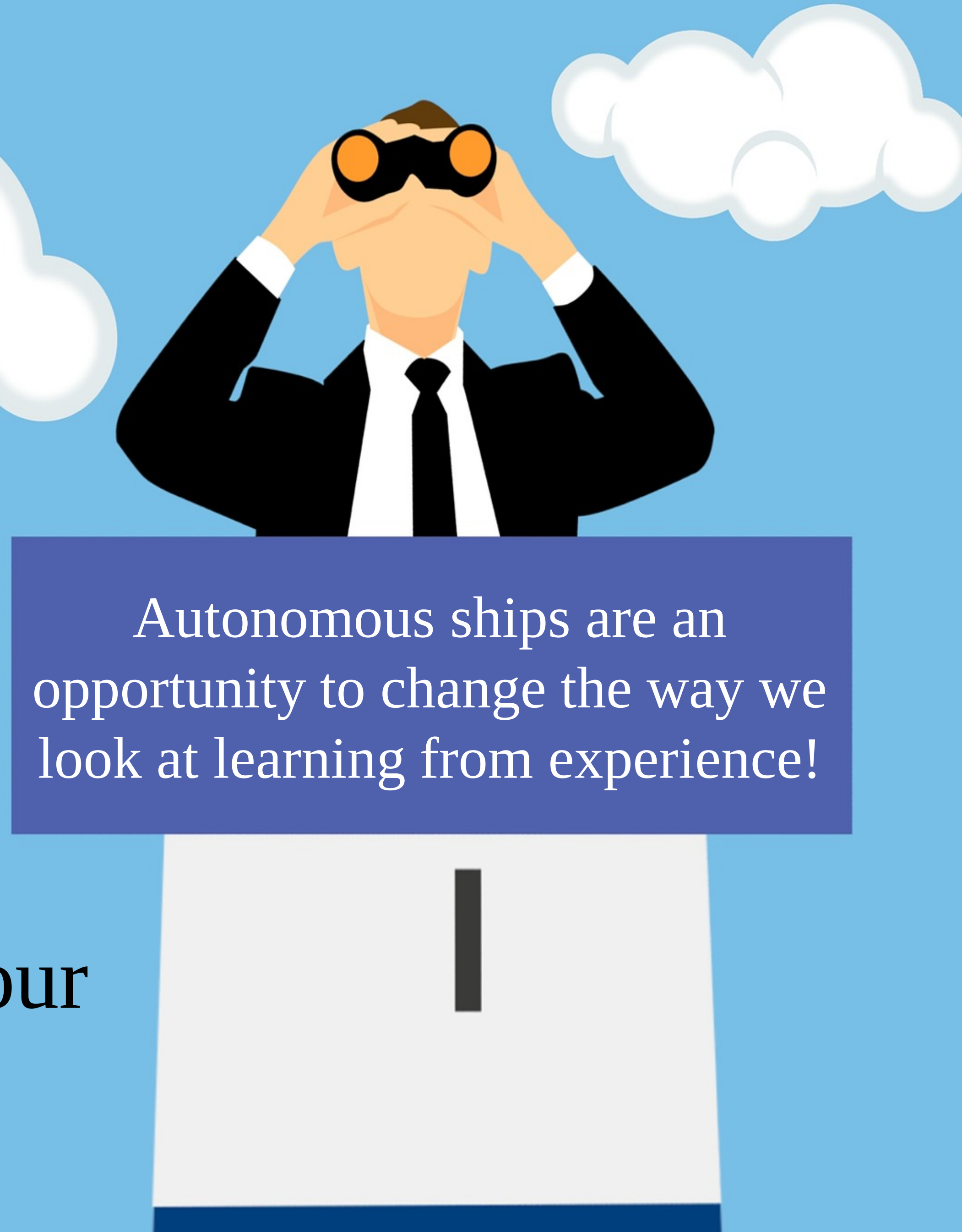
Learning is a **distributed life-cycle process**
The continuous improvement of the ability to **recognise unsafe states** of the system and to **respond** effectively and revert to a safe state.

Framework applicability

- Conventional ships - decision support to the crew
- Autonomous ships - automated decision making

Next steps of our research

- Generalizing risk knowledge (operation) into the risk knowledge base (design),
- Conducting real-time risk analysis during operation,
- Updating detectors through experience,
- Generating and optimizing RCOs during operation.



Thank you for your kind attention!