OPEN ACCESS
IOP Publishing | ISECAEP
Journal of Reliability Science and Engineering
J. Reliab. Sci. Eng. **2** (2026) 023001 (30pp)
https://doi.org/10.1088/3050-2454/ae6512

Perspective

Reliability is a new science: we are on the right way

Xiao-Yang Li[1], **Shi-Shun Chen**[1], **Waichon Lio**[1] **and Rui Kang**[1,2,*]

[1] *School of Reliability and Systems Engineering, Beihang University, Beijing, People's Republic of China*
[2] *Smart Aviation Center, Hangzhou International Innovation Institute of Beihang University, Beihang University, Hangzhou, Zhejiang 311115, People's Republic of China*
E-mail: *leexy@buaa.edu.cn*, *css1107@buaa.edu.cn*, *liaowj18@buaa.edu.cn* and *kangrui@buaa.edu.cn*

Abstract

Reliability has long been treated as an engineering practice supported by testing, statistics and standards, yet its status as a scientific discipline remains unsettled. From the perspective of the philosophy of scientific truth, a science is characterized by a dual structure that unifies empirical truth and mathematical truth under an axiomatic system. The empirical truth is established through universally repeatable controlled experiments, and the mathematical truth is expressed through isomorphic symbolic representations. Building on this criterion, this paper examines whether reliability can be regarded as a science in the strict sense of scientific truth. We first clarify the scientific object of reliability by proposing a new definition: reliability is defined as the repeatability of system function across time and space. This definition shifts reliability from an experience-based engineering concern to a more explicitly defined theoretical object. On this basis, a coherent framework of reliability science is constructed. Reliability principles are organized as an axiomatic system centered on margin, degradation and uncertainty; reliability experiments are formulated as controlled and repeatable processes designed to verify the chance-causal relations implied by these axioms, with a hierarchical structure ranging from controlled observation to controlled experiment; and a corresponding mathematical framework is developed to express reliability laws through distance, relation and change. This scientific structure further reveals the shortcomings of current mathematical tools in dealing with time-evolving uncertainty, leading to the natural development of an axiomatic extension, called Biandong Statistics, which arises as a derivative outcome of the proposed framework. The validity of this framework is further illustrated by its applicability across engineering, living and social systems, demonstrating that reliability is a general system-level property wherever meaningful system functions exist. By integrating axioms, experiments, mathematical representation, and cross-domain applicability into a unified structure, this work provides a philosophical and structural basis for understanding reliability as a coherent scientific discipline, in which empirical and mathematical components jointly realize the dual structure of scientific truth and outlines the overall disciplinary landscape of reliability science.

Keywords: reliability science, belief reliability, scientific truth, axiomatic systems, controlled experiments, biandong statistics

* Author to whom any correspondence should be addressed.

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1. Introduction

The concept of reliability in engineering emerged gradually as manufacturing methods evolved from craftsmanship to mechanized mass production. In early industrial practice, product performance was ensured mainly by overdesign and meticulous workmanship. While effective for small-scale production, this approach could not meet the requirements of large-scale, standardized manufacturing. The introduction of interchangeable parts in the late nineteenth and early twentieth centuries marked a turning point [1–3]. Interchangeability required consistent manufacturing accuracy, which in turn led to the development of statistical quality control. Sampling inspection and probability-based analysis became essential tools to manage process variability. A notable example came from firearm manufacturing, where the need for precise interchangeability promoted the creation of tolerance systems and formal inspection procedures. These methods were effective in reducing variability at the point of production, but they focused exclusively on conformity to specification rather than long-term functional performance.

During the Second World War, quality control techniques were widely applied to military production [4]. However, operational experience revealed a different class of problems. Even components produced under strict quality control exhibited wide variation in failure times during service. In complex military equipment, such as airborne electronics, some units failed after short use while others operated much longer under the same conditions. This inconsistency indicated that product quality at delivery was insufficient to ensure dependable performance throughout the service life. The challenge shifted from preventing defects at production to ensuring sustained operational performance, which required new concepts and analytical methods.

At this stage, probabilistic models were incorporated into reliability analysis. Lusser introduced a formula expressing system reliability as the product of the reliabilities of its independent components [5]. Originally developed for missile hit probability, the Lusser product formula demonstrated that system reliability decreases rapidly as the number of components increases, unless each component's reliability is exceptionally high. This insight provided a quantitative link between component-level performance and system-level outcomes, and it highlighted the limitations of quality control when applied to complex systems.

Recognizing the strategic importance of this issue, the United States department of defense formed the advisory group on the reliability of electronic equipment (AGREE) in 1957. The AGREE report defined reliability as the probability that a system performs its intended function without failure for a specified period under stated conditions, clearly distinguishing it from product quality [6]. More importantly, it established that reliability must be addressed during the design phase rather than being treated as a post-production concern. The report also presented a complete framework for reliability engineering, including the definition of reliability metrics, the allocation of reliability requirements across subsystems, the use of prediction methods, the implementation of structured testing and evaluation procedures, the assessment of economic trade-offs, and the inclusion of reliability-related clauses in procurement contracts [4, 7]. The AGREE framework became the foundation for a series of detailed technical standards, such as MIL-STD-781 for reliability testing [8], MIL-STD-217 for reliability prediction [9], and MIL-STD-338 for maintainability analysis [10]. Over time, these standards were transformed into the MIL-HDBK series of handbooks, reflecting a shift from mandatory compliance to authoritative reference. This historical progression, which began with the pursuit of manufacturing consistency, advanced through the probabilistic treatment of system performance, and culminated in a structured and

comprehensive approach to reliability, marked the formal establishment of reliability engineering as an independent and systematic discipline.

The codification of reliability engineering through the AGREE report and subsequent standards built a comprehensive set of methods for reliability management in the design stage. However, their scope remained essentially engineering oriented. They offered structured procedures and empirical tools but did not constitute a unified scientific theory of reliability. In practice, their predictive accuracy depended heavily on historical data, idealized statistical models and simplifying assumptions about failure processes. As systems became more complex, operated under more varied conditions and incorporated new technologies such as advanced electronics and software, these assumptions often proved inadequate. The limitations of the engineering framework naturally prompted efforts to explore whether reliability could be grounded in a formal scientific discipline with universal principles and experimentally verifiable laws.

The search for a scientific foundation is often traced to Gnedenko [11], one of the earliest scholars to treat reliability as a subject of theoretical science rather than purely engineering practice. In his formulation, a reliability problem is defined within a formal 'reliability space' in which three elements, namely the system states, the time domain and a probability measure, are jointly specified. This construction parallels the axiomatization of probability theory by Kolmogorov and provides a logically self-consistent basis for describing system behavior under uncertainty. By abstracting away from specific hardware, Gnedenko's framework made it possible to treat different systems within a unified mathematical structure. However, his approach remained fundamentally statistical. It characterized reliability in terms of probabilistic distributions of time to failure, without explicitly linking these probabilities to the underlying physical mechanisms.

Later studies attempted to establish reliability measures on the basis of material and functional degradation mechanisms, generally referred to as reliability physics or the physics of failure. Feinberg [12] represents a prominent example of this trend. Although the term 'reliability science' was not explicitly stated, he interpreted failure mechanisms and accelerated testing within the framework of irreversible thermodynamics. By modeling degradation mechanisms such as fatigue, wear, oxidation, and chemical reactions through entropy generation, his approach connected measurable physical quantities to service life and provided a theoretical basis for accelerated testing under elevated stress. This brought physical interpretability to reliability indicators, yet the analysis ultimately returned to probability metrics, such as the hazard-rate and the bathtub curve, and thus remained essentially statistical in nature. The same orientation is evident in other reliability physics methods. In 1968, engineers at Bell Laboratories found that the Arrhenius equation, originally formulated to describe the dependence of chemical reaction rates on temperature, could be applied to evaluate the lifetime of plated wire memories [13]. Since the model shows that higher temperatures accelerate reaction rates and thus shorten device life, it provided a clear rationale for conducting accelerated life tests and opened the way for the systematic use of acceleration models in reliability engineering. Other examples include the Eyring model [14], which incorporates multiple stress factors such as temperature and humidity, and the Coffin-Manson relation for thermal fatigue [15]. Although these models are grounded in physical reasoning, in engineering applications they are used primarily to extrapolate time-to-failure distributions from high-stress laboratory conditions to expected field performance. Their focus is therefore on estimating service life under given conditions rather than on identifying reliability laws that are universal in scope and verifiable through controlled and repeatable experiments.

Rocchi [16] followed another approach by introducing concepts from statistical mechanics into reliability theory. He proposed a Boltzmann-like entropy formalism to describe the evolution of system degradation over time, with particular attention to explaining the empirical bathtub curve of hazard rate behavior. In his interpretation, the three phases of the bathtub curve, which are infant mortality, constant failure rate and wear-out, can be viewed as analogous to thermodynamic phases governed by entropy changes. This analogy offered a narrative link between physical degradation and statistical hazard functions. However, the bathtub curve itself cannot be regarded as a universal scientific law because its shape is inferred from aggregated field data, is sensitive to the mix of underlying failure modes, and cannot be reproduced in a consistent manner under controlled and repeatable laboratory conditions across different systems.

As early scientific explorations of reliability accumulated yet remained fragmented and limited in scope, the academic community began to ask whether reliability could be defined not only as an engineering practice but as a scientific discipline with its own principles and laws. This question came into sharp focus at the 10th international conference on mathematical methods in Reliability in Grenoble in 2017. The organizers convened a dedicated panel session titled 'Is reliability a new science?', chaired by Singpurwalla. His lead article in the subsequent special issue of applied stochastic models in business and industry provided the intellectual anchor for the discussion and synthesized its key themes [17]. In this article, he traced the question back to Gnedenko's foundational contributions [11], framed the definitional and methodological challenges facing the field, and set out the philosophical and practical stakes of recognizing reliability as a science. The special issue compiled six further contributions addressing definitions, philosophy, and methodology [18–23]. Among these contributions, Anderson-Cook [18] examined definitions and concluded that reliability can meet common criteria for science while also sharing features with engineering. Lawless [19] placed reliability closer to engineering but emphasized the central role of statistics for learning and action. Natvig [20] argued that the label matters less than the field's societal importance. Rykov [21] revisited Gnedenko's view and saw reliability as a path to hard knowledge rather than a mature science. In a rejoinder, Singpurwalla and Lai [22] synthesized these positions and emphasized reliability's role as a framework for decision-making under uncertainty, drawing on Bayesian inference as a unifying principle. He also highlighted the philosophical analysis by Zhang *et al* [23], which proposed that science embodies a unity of truth and value, where 'truth' refers to the verifiable fact of failure and 'value' to the imperative of prediction and prevention. Besides, Zhang *et al* [23] further proposed that reliability possesses its own historical, theoretical and practical discourses. Historically, it has evolved from implicit concern with failures to an explicit paradigm addressing their mechanisms and prevention. Theoretically, they formalized reliability through three core equations describing performance, performance margin and a reliability metric, thereby linking loss of function to underlying causes and quantifying reliability. Practically, they described reliability as a complete methodological system for coping with failures and their uncertainties, one that has progressed from experience-based avoidance, to semi-quantitative methods, and ultimately toward an envisioned phase of fully quantitative control.

The above debate on whether reliability is a science has focused mainly on macroscopic systems grounded in classical physics and engineering logic. At the microscopic scale, where quantum effects prevail, degradation mechanisms and reliability measures can differ fundamentally. Recent work by Sun and his group extends reliability science into this quantum domain. Cui *et al* [24] defined a trajectory-based metric through the evolution of probability amplitudes in Hilbert space, which was derived directly from the equations of quantum mechanics. This

captures the deviation of a device's actual trajectory from its ideal one, accounting for coherence and interference, and is fully rooted in quantum dynamics rather than macroscopic failure data. Du *et al* [25] further elaborated on the conceptual transition from classical to quantum reliability. They discussed how consistent histories, a foundational concept in quantum theory, provided a natural probabilistic framework for describing the operational lifetime of quantum devices. Embedded in quantum formalism, their model establishes quantum reliability as a distinct branch of reliability science, applicable to emerging quantum technologies and governed by microphysical laws. These studies do not replace macroscopic perspectives but complement them, showing that reliability can be defined from first principles across physical scales. This cross-scale definability strengthens the claim that reliability is not merely an applied methodology but a candidate for a universal science.

Overall, various research directions have sought to advance the scientific development of reliability from distinct perspectives. These include axiomatic formulations grounded in statistical theory, physics-of-failure models based on degradation mechanisms, and cross-scale characterizations informed by fundamental physical theories such as statistical and quantum mechanics. However, these approaches remain fragmented and isolated in scope. Some emphasize mathematical formalisms, others focus on physical mechanisms, while some concentrate on object-level modeling. What is still lacking is a systematic theoretical framework that can simultaneously address what the scientific object of reliability is, what its fundamental principles are, how repeatable experimental verification should be conducted, and how isomorphic mathematical representations should be constructed. For example, in frontier studies such as quantum reliability, although deeper physical descriptions have been introduced, the work remains primarily at the object or model level and does not resolve the problem of constructing an overall scientific form of reliability. Therefore, the central challenge of current reliability science research is not the absence of specific models, but the lack of an integrated and structured organization of reliability as an independent science.

It is undeniable that a series of historical developments, theoretical explorations, and philosophical discussions collectively suggest that reliability has gradually evolved from an engineering methodology into an emerging discipline with clear scientific potential [26]. Accordingly, this work aims to construct an independent scientific form of reliability from the perspective of the philosophy of truth. The main contributions of this paper are as follows:

- Reliability is redefined in a scientific sense, thereby clarifying the scientific object of reliability research.
- Based on existing reliability principles and related studies, an overall framework of reliability science with an iterative expanding structure of 'principles-experiments-mathematics' is constructed.
- The expandability and universality of reliability experiments are systematically analyzed and justified from an epistemological perspective.
- An axiomatic conception of a new mathematical theory, termed biandong statistics, is proposed to characterize the measure structure of uncertainty evolving with time.

The rest of this paper is organized as follows. Section 2 discusses the philosophical foundations of reliability science. Section 3 develops the dual structure of scientific truth in reliability, including reliability science principles, reliability experiments, reliability mathematical frameworks, and the demonstration that reliability is a science. Section 4 presents applications across engineering, living and social systems and discusses lifecycle guidance. Section 5 provides the disciplinary big picture and outlook.

2. The philosophical foundations of reliability science

2.1. Philosophical reflection

The problem of reliability did not arise only with the advent of modern engineering. From a longer historical perspective, experiential concerns related to reliability already existed when humans first began to use tools. Whether a tool would be available at a critical moment, whether it could maintain its intended function through repeated use, and whether it would remain stable under different conditions constitute the earliest judgments of reliability at the level of personal truth. At this stage, reliability was not an explicitly named object of inquiry, but rather an experiential confidence embedded in practical activity.

Viewed from the continuity of technological practice, human concern for reliability gradually emerged alongside the use of tools and systems. During the era of handicraft production, however, this concern remained largely confined to the individual level. The stability of a tool's performance primarily affected the efficiency and safety of a single user, and the consequences of instability were limited to the domain of personal experience.

The Industrial revolution fundamentally altered this structure. With the emergence of mechanized production and mass manufacturing, instability in system performance was no longer an occasional phenomenon within individual experience, but began to appear repeatedly in the form of batches of similar products. At this point, the reliability problem was elevated systematically from personal truth to social truth. Products of the same type exposed similar failure modes at different times and in the hands of different users, so that reliability was no longer a subjective judgment of whether a product worked well, but a concrete problem that required collective recognition and response.

As industrial systems continued to develop, humanity's capacity to transform the world expanded, and the objects involved in reliability extended from individual products to complex systems and engineering infrastructures composed of many subsystems. At this stage, the consequences of system failure were no longer limited to the interruption of local functions, but could trigger cascading effects that influenced broader structures of social operation. Accordingly, reliability as a problem of social truth was continuously amplified, and its importance became increasingly prominent with the growth of system scale and complexity. It was through this historical process that reliability was gradually detached from immediate personal judgment and objectified as a technical problem. This transformation gave rise to a professional practice centered on engineering methods, namely reliability engineering. Through testing, statistical analysis and standardization, engineering approaches provided effective means to cope with large-scale system failures. This stage should not be regarded as a substitute for reliability science, but rather as its necessary historical precursor.

However, as engineering objects and application contexts continued to change, the limitations of relying solely on engineering methods became increasingly evident. Reliability assessment depended heavily on existing failure data, making it difficult to support forward-looking design decisions. In addition, engineering models were often constructed for specific objects and operating scenarios, which constrained their explanatory power and limited their adaptability. More importantly, such approaches failed to address a more fundamental question: why are people still able, and indeed still required, to form stable confidence in system performance under conditions where change and uncertainty are ubiquitous?

It is precisely these internal tensions that drive a further inquiry: can reliability transcend the level of empirical engineering practice and rise to a science with a clearly defined object of study, a coherent system of principles, and a sound methodological foundation? This question marks the transition of the reliability problem from the experiential domains of personal and social truth toward the

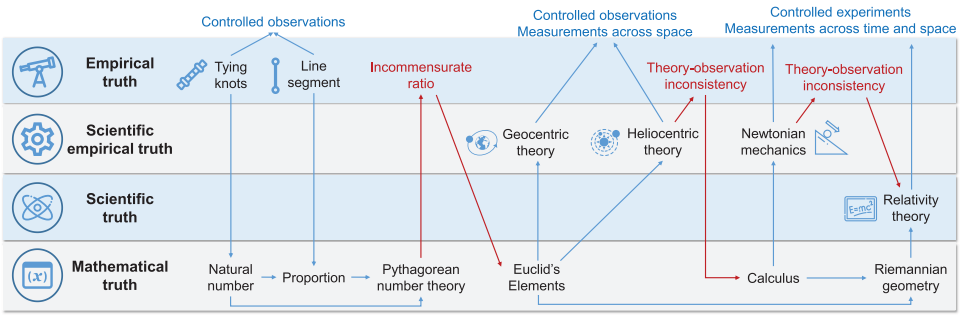


Figure 1. History of science.

theoretical domain of scientific truth. Building on earlier philosophical analysis, this study presents a scientific redefinition of reliability:

Reliability is the repeatability of system function across time and space.
This definition points to the presence of scientific laws in reliability. The key challenges are to determine what these laws are, how they can be discovered and represented, and how they can be used to guide our interventions in the world. These are the questions explored in the following section.

2.2. How a discipline becomes a science

To address the question raised in the previous section, we first discuss how a discipline can be regarded as a science. The status of a discipline as a science cannot be judged only by its technical tools or by the usefulness of its results. Building on Jin's philosophy of truth, science may be understood as a bridge that links empirical truth with mathematical truth [27]. Scientific progress is not a simple accumulation of observations but a dynamic interaction among three essential elements: controlled and repeatable experiments, symbolic representation and axiomatic systems [28, 29]. Controlled experiments ensure that claims remain verifiable within the empirical world. Symbolic representation, most often in mathematical form, provides abstraction and logical extension across contexts. Axiomatic systems integrate both into a coherent structure, allowing knowledge to be both demonstrable and generalizable [30]. These features distinguish science from practical techniques, empirical summaries or philosophical speculation.

The history of science demonstrates this interplay in successive stages, as illustrated in figure 1. In early human practice, knot-tying represented the first controlled act of recording quantities, and the abstraction of numbers created a symbolic bridge from experience to representation. In ancient Greece, mathematics reached axiomatic form through Euclid's *Elements*. The scientific bridge was gradually shaped when such formal systems were reconnected with empirical observation in astronomy. Kepler's laws of planetary motion, Galileo's telescopic discoveries, and Newton's synthesis of celestial and terrestrial mechanics in the *Principia* exemplify how observation and mathematical formulation were united into a consistent explanatory framework.

However, until the early twentieth century, it remained at the level of *scientific empirical truth* rather than *scientific truth*. Newton's laws of motion and the law of universal gravitation were powerful symbolic expressions whose predictions matched controlled observations with high precision, yet their validity still depended on agreement with observations rather than on universally repeatable experimental foundations. The turning point came with the emergence of

relativity and quantum mechanics. Both theories established their axiomatic systems not merely from empirical agreement but from experiments that were controlled, repeatable and universally verifiable. The Michelson–Morley experiment [31] revealed the failure of classical assumptions about space and time; Einstein's relativity reformulated those axioms, and its predictions, such as the deflection of starlight, were confirmed under controlled conditions [32]. Quantum mechanics, developed in the same era, introduced axioms such as the uncertainty principle, which was mathematically expressed in symbolic form [33] and validated through precisely repeatable experiments [34, 35]. These revolutions marked a fundamental transition in the foundation of science, shifting from empirical truth defined by observational agreement to scientific truth grounded in axioms and universally repeatable controlled experiments. Through this transformation, the interplay between empirical and mathematical truth evolved into a higher synthesis.

From this perspective, three essential conditions must be met for a discipline to attain the status of science. First, it must possess an axiomatic system, that is, a set of fundamental principles capable of defining its theoretical structure. Second, these axioms must be symbolically expressible in mathematical forms, allowing empirical phenomena to be represented and predicted within a logically coherent framework. Third, the axioms must be verifiable through universally repeatable controlled experiments, ensuring that symbolic representation remains consistent with empirical truth. A discipline that lacks any of these three conditions may still yield valuable practical knowledge or technical applications, but it cannot be regarded as a true science. Science, in its mature form, evolves through the continuous interaction between axiomatic formalization and experimental verification, and it is this dynamic interplay that defines the process of scientific development.

Within this framework, the scientific status of reliability depends on whether it fulfills the above conditions of science. First, reliability must possess a coherent axiomatic system that defines its fundamental principles. Then, the axiomatic system should be dual structured. On one hand, the axiomatic system must be expressible in symbolic and mathematical form, enabling the laws of reliability to be represented, analyzed and extended beyond specific cases. On the other hand, the axioms must be verifiable through universally repeatable controlled experiments, ensuring that symbolic formulation corresponds to empirical truth. The challenge and promise of reliability science therefore lie in completing this dual structured axiomatic system, so that reliability can move from being an engineering practice to being recognized as a scientific discipline with both empirical grounding and axiomatic coherence.

3. Dual structure of the scientific truth in reliability

3.1. Reliability science principle

The first step in demonstrating that reliability qualifies as a science lies in establishing its axiomatic systems, also referred to as the *reliability science principles*. To clarify the essence of these principles, it is essential to revisit the scientific redefinition of reliability introduced in section 2.1: the repeatability of system function across time and space. A deeper understanding of this definition is best grounded in practice, in how reliability is experienced and expected in real-world systems. In engineering, reliability embodies the expectation that a system will maintain its intended function under varying conditions and over time. Whether one is operating an aircraft, transmitting data through a satellite link, or using a simple household appliance, the underlying demand is consistency of function when subjected to changing environments, aging and operational disturbances.

From this practical perspective, reliability can be defined as *the repeatability of system function across time and space*. This repeatability is not an abstract assumption but arises from controlled observations in engineering practice, such as monitoring failure times, measuring performance changes and analyzing how systems sustain their function in diverse environments. Reliability science, therefore, must explain not only whether a system performs but also how its performance maintains and why its behavior varies.

Since the repeatability of system function is regarded as the essence of reliability, the first step toward theoretical formulation is to express how the system function can be quantitatively assessed. This is accomplished through the concept of performance margin, which represents the measurable difference between system capability and functional requirement. A system is considered reliable when its performance exceeds the performance threshold of requirements, and unreliable when it falls short. This concept underlies the *Reliability Principle of Margin*, which is the first of the three axioms of reliability science [36]. The corresponding mathematical formal expression is given as:

$$M = m\left(P, P_{\mathrm{th}}\right), \tag{1}$$

where M is the performance margin, P is the measured performance, P_{th} is the performance threshold of requirements determined by user needs or standards, and $m(\cdot)$ is a margin function that quantifies the distance between P and P_{th}.

The reliability principle of margin captures the most direct causal law: system reliability depends on the balance between capability and requirement. It is in this sense that reliability connects naturally with management science, where system performance, user expectation and environmental constraint interact dynamically. The equilibrium among these elements determines not only the operational state of a system but also its perceived reliability within a broader socio-technical context.

Practice further shows that the performance margin does not remain fixed. Durability testing and field observations consistently demonstrate that performance degrades as systems are used. This degradation may take the form of wear, fatigue or corrosion, depending on the physical nature of the system. These empirical laws are consistent with the second law of thermodynamics, which states that entropy inevitably increases and that no system can maintain its original functional state indefinitely. The second principle, known as the *Reliability Principle of Degradation*, arises from the recognition that system performance is not static but evolves with irreversible time [36]. The corresponding mathematical formal expression is:

$$P = f_{\vec{t}}(\mathbf{X}, \mathbf{Y}), \tag{2}$$

where $\vec{t}$ denotes the irreversible time, $\boldsymbol{X}$ represents internal variables such as material properties or geometric parameters, $\boldsymbol{Y}$ represents external variables such as temperature, vibration or humidity, and $f_{\vec{t}}$ is the degradation function that integrates these influences.

Based on the reliability principle of degradation, reliability science is closely aligned with the principles of physics, especially thermodynamics and statistical mechanics, which describe the irreversible evolution of systems. At the same time, degradation mechanisms are governed by the specialized laws of different disciplines. Mechanical systems follow the principles of material mechanics and tribology; electronic systems follow the principles of circuit theory and semiconductor physics; control and software systems follow dynamic system theory and algorithmic stability. More generally, from the standpoint of systems science, the same logic applies across different levels of organization, from simple mechanical structures to complex socio-technical systems. This broad

correspondence demonstrates that reliability science is not isolated from the established disciplines but integrates their governing principles into a unified explanatory framework.

Even when degradation mechanisms are identified and quantified, repeatability is never purely deterministic. Under nominally identical conditions, failures occur at different times, and measured performances exhibit variation. This leads to the *Reliability Principle of Uncertainty*, which describes the inherent variability of systems and the limitations of human knowledge [36]. The corresponding mathematical formal expression is:

$$R = c\left\{m_{\vec{t}}\left(\tilde{P}, \tilde{P}_{\text{th}}\right) > 0\right\}, \tag{3}$$

where R is the reliability, defined as the possibility that the margin remains positive, $\tilde{P}$ is the performance considered as a random variable, $\tilde{P}_{\text{th}}$ is the performance threshold of requirements with uncertainty, $m_{\vec{t}}(\cdot)$ is the margin function accounting for degradation over time, and $c(\cdot)$ is a possibility measure such as probability measure or uncertain measure.

In practice, uncertainty arises from two fundamental sources. One is aleatory uncertainty, reflecting natural variability in materials, manufacturing and environments; the other is epistemic uncertainty, reflecting incomplete understanding of mechanisms or insufficient data for inference. Reliability science incorporates both forms by expressing reliability as the possibility that performance remains above the performance threshold of requirements over time. At a deeper level, it also connects the field with fundamental physics and epistemology. Quantum mechanics establishes the intrinsic existence of randomness in nature, while cognitive science and philosophy of knowledge recognize the unavoidable limits of human understanding. Reliability science, therefore, is built upon both the physical foundation of stochastic behavior and the epistemic foundation of reasoning under uncertainty.

3.2. Reliability experiment

A reliability experiment is a controlled experimental activity designed to verify the chance-causal relations among system performance margin, system performance, and performance requirement [37]. Its purpose is not to accumulate failure statistics, but to examine whether the causal structure implied by the reliability principles of margin, degradation, and uncertainty remains valid under controlled and repeatable conditions in real systems.

From the perspective of the philosophy of truth [27], any scientific experiment is structured around the relationship among the subject, the controlled process, and the observed object. The subject refers to the researcher who designs the experiment and interprets its results. The observed object is not merely a physical artifact, but a functional whole jointly constituted by the functioning system and the functional object to which it is oriented, such as users or objects. This whole serves as the physical carrier of system function and will hereinafter be referred to as the observed object. Reliability experiments are conducted with respect to this observed object. Under experimental conditions selected and maintained by the subject, it is examined whether the system function satisfies specified performance requirements, and the corresponding functional margin is quantitatively characterized.

Within this structure, reliability experiments embody the core attributes of scientific experiments emphasized in the philosophy of truth, namely repeatability, universality and controllability.

(1) **Repeatability:** When a subject selects a given set of control conditions and observes that the margin of the observed object is greater than zero (or exhibits a specific degradation pattern) under these conditions, the same margin (or process) result should be observable again in independent repeated tests.
(2) **Universality:** Under identical control conditions, different subjects are able to obtain consistent margin observation results, rather than results depending on individual experience or accidental phenomena.
(3) **Controllability:** The subject is able to freely select and stably maintain a set of observation conditions to acquire information about margin, performance and degradation, such as different load levels, working environments, operation modes or usage scenarios.

Notably, controllability does not require direct manipulation of all internal mechanisms of the observed object. In many cases, the system appears to the subject as a black box. When attention is focused on functional margin, the subject may vary external conditions and observe margin behavior without intervening in internal structure. Such activities constitute controlled observation rather than controlled experiment. In this context, controlled observation emphasizes that the observation process itself is fully controllable, so that the subject can deliberately select and maintain observation conditions to obtain reliable information about the system, as commonly seen in fields such as astrophysics. This controllability ensures that the process of acquiring information is repeatable in a general sense, allowing observations under the same conditions to be repeated consistently across trials. In the philosophy of truth, both controlled experiments and controlled observations are ways of understanding and investigating objects from the perspective of control. Controlled observations retain scientific significance because controllability is realized through the deliberate selection and repetition of observation conditions, and what the subject obtains is the scientific empirical truth of margin.

As control capability and system understanding improve, the scope of intervention expands. The subject becomes able to regulate internal variables such as material properties, geometric parameters, structural configurations, component interactions, and the pathways of energy and information flow, as well as usage-related factors. These two forms are therefore not opposed, but connected along a continuous spectrum defined by the degree of controllability and observability.

With further system decomposition, reliability experiments can extend to deeper levels of analysis. When attention shifts to material microstructures, thermal transport, electromagnetic behavior, chemical reactions or even quantum processes, the evolution of performance and margin becomes governed directly by fundamental physical laws. In this regime, reliability experiments increasingly resemble the universally repeatable controlled experiments of physics, with control targets extending from engineering parameters to fundamental physical quantities.

Accordingly, reliability experiments do not constitute a single experimental form, but a hierarchical system, as shown in figure 2. At higher levels, they take the form of controlled observations dominated by condition selection. At intermediate levels, they involve direct manipulation of internal variables. At deeper levels, they interface with fundamental physical experiments. This progressive transition from black-box observation to white-box experiment, and from engineering level to physical level, reflects the continuous deepening of reliability experiments.

In this way, reliability experiments as a whole satisfy the essential requirements of scientific empirical truth. Their objects are stably identifiable, their conditions are deliberately selectable, and their results are repeatable and

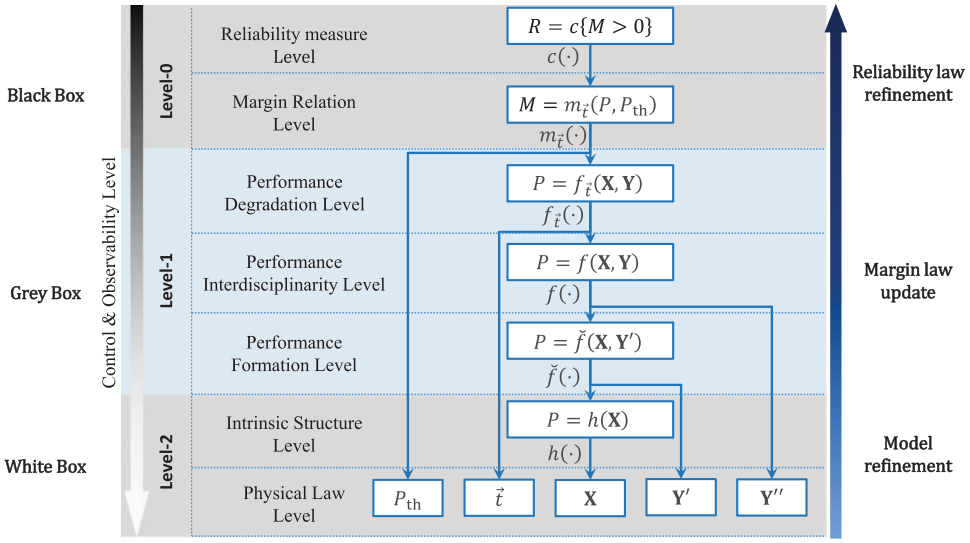


Figure 2. Hierarchical expansion of controlled experiments in reliability science.

consistent across subjects. Moreover, as controllability expands, the scientific empirical truth established by reliability experiments possesses an intrinsic pathway toward deeper scientific truth.

In the figure, $h(\mathbf{X})$ denotes the intrinsic structural relation of the functioning system; $P = \breve{f}(\mathrm{X}, \mathrm{Y}')$ denotes the performance generation function constructed under a specific disciplinary framework (functional relation); $P = f(\mathbf{X}, \mathbf{Y})$ denotes the interdisciplinary performance function integrating system internal and external factors; $\mathbf{Y}'$ represents operating conditions, and $\mathbf{Y}''$ represents the remaining external factors related to the system other than operating conditions, with $\mathbf{Y} = \mathbf{Y}' \oplus \mathbf{Y}''$, where $\oplus$ denotes the direct-sum operation. The figure illustrates that reliability experiments can evolve from controlled observation dominated by condition selection, to system-level controlled experiments with manipulable internal variables, and further toward physical-level controlled experiments governed by physical laws. The top level adopts $R = c\{M > 0\}$ and $M = m_{\vec{t}}(P, P_{\text{th}})$ to represent the margin criterion, the intermediate levels use $P = f_{\vec{t}}(\mathbf{X}, \mathbf{Y})$, $P = f(\mathbf{X}, \mathbf{Y})$ and $P = \breve{f}(\mathrm{X}, \mathrm{Y}')$ to describe performance generation relations, and the bottom level uses $P = h(\mathbf{X})$ to represent performance formation determined by intrinsic structure and physical mechanisms.

3.3. Reliability mathematical framework

The mathematical framework of reliability is grounded in the three reliability principles of margin, degradation and uncertainty. By representing these principles through the mathematical tools of distance, relation and change, it forms a precise symbolic system for expressing reliability laws. This framework provides a rigorous mathematical foundation needed for both experimental verification and engineering application.

Distance quantifies the deviation between a system's actual state and its reliable state, which is described by equation (1). While the term originates from classical geometry, its meaning here is fundamentally different. In Euclidean geometry, distance symbolizes the measured separation between two points in physical space, constrained by non-negativity, symmetry, and the triangle inequality. In the reliability mathematical framework, however, distance extends to a functional space defined by the boundary between reliability and failure. It no longer describes spatial separation but measures how system performance deviates from

the performance threshold of requirements. A positive distance indicates sufficient performance, a negative one indicates deficiency, and the absolute value reflects the degree of deviation from reliability. By allowing both positive and negative values, the reliability mathematical framework transforms the geometric notion of distance into a functional measure of performance sufficiency.

Relation is a central concept in the mathematical framework of reliability, characterizing system composition and performance degradation, which is described by equation (2). Its definition inherits the abstract meaning of relation in mathematics, yet it gains new significance in the context of reliability because the object of study is a system composed of interacting elements whose behaviors cannot be understood in isolation. Accordingly, the mathematical tools employed in this field naturally focus on representing interdependence, most of which are grounded in functional mathematics. These include analysis (e.g. mathematical analysis, real analysis, complex analysis, and functional analysis), algebra, geometry and category theory. The common goal of these branches is to transform the interactive laws among key system parameters into quantifiable and derivable functional relations. Analytical mathematics quantifies the rate of performance degradation as a function of internal and external variables, thereby providing a precise description of the continuous evolution of system performance. Algebra characterizes the structural organization of interactions through abstract symbolic systems (e.g. groups, rings and fields), which can represent coupling relations among components in a concise and consistent manner. Geometry captures positional and morphological associations among elements in space, using topological concepts to describe the invariance of spatial structures and to delineate the boundaries of the reliability domain more precisely. Taken together, these mathematical branches form a coherent structure in which analytical, algebraic and geometric representations jointly describe the quantitative, structural and spatial dimensions of system relations.

Change represents the culminating dimension of the reliability mathematical framework, describing how system performance evolves across time and space. Its essence lies in the dynamic process through which a system moves from a reliable to an unreliable state under the influence of irreversible evolution. Since the evolution of a system is governed by both aleatory uncertainty and epistemic uncertainty, deterministic models cannot capture the full complexity of its internal and external dynamics. Consequently, an accurate representation of this process must rely on axiomatic mathematical tools that can address uncertainty described by equation (3), most notably probability theory and uncertainty theory. The basic tools for describing performance degradation are stochastic processes and uncertain processes [38, 39]. In a probabilistic framework, classical theorems such as the law of large numbers and the central limit theorem must be satisfied, ensuring that outcomes converge to their expected values when the number of samples increases. However, when data are scarce or when the population itself changes over time and space, the empirical mean derived from observation can differ markedly from theoretical expectation. The formalism of probability theory nevertheless enforces convergence toward the expected value, which may drive predictions toward erroneous stability and lead to forecasts that are overly optimistic. Uncertainty theory provides a complementary yet opposite perspective. The uncertain process preserves properties such as distribution conservation and variance invariance, which guarantee stability under limited information. When data become abundant, however, these constraints cause the model to diverge, producing results that are overly conservative and often lacking predictive usefulness. The contrast between probability and uncertainty reveals a deeper structural limitation: both frameworks assume a static logical space in which measures remain invariant with respect to time. Yet in real systems governed by irreversible degradation process, both the underlying data

distribution and the epistemic interpretation of uncertainty change over time, making static measures inadequate for describing reliability.

To resolve this foundational gap, an extended axiomatic framework termed *Biandong Statistics* developed in reliability mathematics is introduced for the measure-theoretic transformation of uncertainty under degradation and epistemic evolution, within which the measure evolves with time and space. The term '*Biandong*' originates from Chinese, meaning 'change' or 'variation'. In this paper, we adopt this term to denote the axiomatic transformation of the underlying logic and constraint rules of the mathematical system, rather than merely describing temporal or parametric changes as in conventional dynamic or time-varying statistics. The essence of this framework lies in addressing a fundamental deficiency of traditional mathematics: by overemphasizing simplicity and closure of rules, classical axiomatic systems have created an unbridgeable gap between the symbolic world and the empirical world. Biandong statistics seeks to fix this gap by defining a new type of mathematical measure situated between probability measure and uncertain measure. Consider a nonempty set Γ and a σ-algebra $\mathcal{L}$ on Γ. The structure $(\Gamma,\ \mathcal{L})$ forms a measurable space, where each Λ in $\mathcal{L}$ represents an event. A biandong measure Bd is given on $\mathcal{L}$, satisfying the following axioms.

1) Normality axiom: $\mathrm{Bd}\{\Gamma\} = 1$ for the universal set Γ.
2) Duality axiom: $\mathrm{Bd}\{\Lambda\} + \mathrm{Bd}\{\Lambda^c\} = 1$ for any event Λ.
3) Subadditivity axiom: For every countable sequence of events $\Lambda_1,\ \Lambda_2, \ldots$, we have

$$\mathrm{Bd}\left\{\bigcup_{i=1}^{\infty}\Lambda_i\right\} \leqslant \sum_{i=1}^{\infty}\mathrm{Bd}\{\Lambda_i\}. \tag{4}$$

To calculate the Biandong measures of product events, the following product evolution axiom is proposed. Let $(\Gamma_k,\ \mathcal{L}_k,\ \mathrm{Bd}_k)$ be Biandong spaces for $k = 1,\ 2, \ldots$, the product evolution measure Bd is a Biandong measure satisfying

$$\mathrm{Bd}\left\{\prod_{k=1}^{\infty}\Lambda_k\right\} = \Phi(\beta)\prod_{k=1}^{\infty}\mathrm{Bd}_k\{\Lambda_k\} + \Psi(\beta)\wedge_{k=1}^{\infty}\mathrm{Bd}_k\{\Lambda_k\}, \tag{5}$$

where Λ_k are arbitrarily chosen events from $\mathcal{L}_k$, and $\Phi(\beta)$ and $\Psi(\beta)$ are evolving unit functions, which jointly determine how the measure transitions between probability measure and uncertain measure with respect to time and space. Notably, to maintain conciseness in the mathematical framework, the irreversible evolution in space and time is denoted uniformly by the symbol β. The evolving unit functions satisfy $0 \leqslant \Phi(\beta) \leqslant 1$, $0 \leqslant \Psi(\beta) \leqslant 1$, and $\Phi(\beta) + \Psi(\beta) = 1$ for any β. When $\Psi(\beta) \equiv 0$, the framework naturally reduces to classical probability, thereby recovering countable additivity. This construction transforms the traditional fixed set of axioms into an axiomatic class that evolves with time and space.

From a mathematical perspective, probability theory is a proper subset of Biandong statistics. This indicates that Biandong Statistics offers a theoretical framework that entirely includes classical probability theory, guaranteeing that its analytical performance will not be inferior to approaches relying solely on classical probability theory. Furthermore, the constraint of the product axiom in probability theory on event independence leads to an inherent bias in the reliability assessment of complex systems. Even if all components of a system have a high level of reliability, the overall reliability of the system only calculated by multiplication will be significantly underestimated, which is highly inconsistent with engineering practice. To overcome this problem, the specific

functional forms of $\Phi(\beta)$ and $\Psi(\beta)$ are determined by modeling the evolution process itself, allowing the measure to adapt to empirical conditions and to reflect both stochastic variation and epistemic constraint. Biandong statistics thus mediates between the optimistic tendency of probability theory and the conservative restraint of uncertainty theory. By embedding spatiotemporal dependence directly within the axioms, it provides a unified framework that is both mathematically rigorous and empirically consistent.

For illustration, consider an experimental campaign consisting of 100 controlled experiments. For the ith experiment, β is defined as $\beta = i/100$, where $i = 1, 2, \ldots, 100$, ensuring that $\beta \in [0, 1]$. At each experiment, a performance margin measurement m_i is obtained under specified spatiotemporal conditions. Suppose that at the ith experiment, the possibility of $m_i > 0$ is given by $99\% - 0.01\% \times (i-1)$. Under different measure-theoretic frameworks with $\Phi(\beta) = \beta$ and $\Psi(\beta) = 1 - \beta$, the reliability assessments are obtained as follows:

- At the 1st experiment ($\beta = 0.01$, 1 observation), we can obtain

$$\Pr\{m_1 > 0\} = \mathrm{M}\{m_1 > 0\} = \mathrm{Bd}\{m_1 > 0\} = 99\%.$$

- At the 20th experiment ($\beta = 0.2$, 20 observations), we can obtain

$$\Pr\{m_{20} > 0\} \approx 80.23\%,\ \mathrm{M}\{m_{20} > 0\} = 98.81\%,$$

$$\mathrm{Bd}\{m_{20} > 0\} = 0.8 \times 98.81\% + 0.2 \times 80.23\% = 95.09\%.$$

- At the 50th experiment ($\beta = 0.5$, 50 observations), we can obtain

$$\Pr\{m_{50} > 0\} \approx 53.45\%,\ \mathrm{M}\{m_{50} > 0\} = 98.51\%,\ \mathrm{Bd}\{m_{50} > 0\} = 75.98\%.$$

Here, Pr and M are probability measure and uncertain measure, respectively.

This example highlights a fundamental distinction among the three frameworks. Pr converges rapidly with increasing data, M remains conservative, while Bd provides a balance between these tendencies through the evolving unit functions $\Phi(\beta)$ and $\Psi(\beta)$, which is consistent with the three reliability principles and aligns better with practical intuition.

3.4. Reliability is a science

Jin's philosophy of truth [27] holds that the essence of science lies in forming a closed feedback loop between empirical truth and mathematical truth, with scientific truth serving as the bridge that connects them. The cornerstone of this bridge lies in the universal repeatability of controlled experiments and the symbolic connections of axiomatic systems. Reliability fits precisely with this framework: science principles, scientific experiments and mathematical framework jointly create a rigorous loop of scientific truth, as follows:

At the axiomatic level, the three reliability science principles introduced in section 3.1 form an axiomatic system, acting as the logical starting point for mathematical truth. They are not fragmented empirical summaries but abstract extractions of the system's inherent reliability. The reliability principle of margin characterizes the deviation between system performance and its performance threshold of requirements; the reliability principle of degradation reflects the universal law of time irreversibility; and the reliability principle of uncertainty tackles the shared issue of real-world variability and cognitive limitations. These three principles collectively establish a self-consistent axiomatic framework that maintains the alignment of mathematical truth with the essence of reliability, similar to frameworks in physics.

At the experimental level, section 3.2 demonstrates that reliability experiment is a controlled experiment whose central purpose is to verify the chance-causal relations among system performance, performance requirement, and performance margin. Under selectable and repeatable conditions, the subject can stably obtain observations of margin and its degradation evolution. Moreover, with increasing control capability, reliability experiments can evolve from controlled observation dominated by condition selection, to system-level controlled experiments with manipulable internal variables, and further toward physical-level controlled experiments governed by fundamental physical laws. This indicates that reliability research already possesses a universally repeatable controlled empirical structure, which should be understood as hierarchical and system-dependent, rather than as implying an identical degree of controllability across all domains. Whether evaluating performance margins and performance degradation of ion thrusters [40], coarse tracking systems [41] or cloud data centers [42], consistent results can be obtained across researchers.

At the symbolic level, section 3.3 shows that reliability science takes margin, degradation and uncertainty as its core principles, and represents them by mathematical objects such as distance, relations and change, respectively. On this basis, Biandong statistics is proposed to describe the measure structure of uncertainty evolving with time, thereby forming a self-consistent symbolic expression system. These mathematical expressions are not introduced as post hoc tools for fitting empirical data, but directly serve for the expression and deduction of reliability principles, and constitute the symbolic carriers of reliability laws. In this sense, reliability science also possesses the basic form of mathematical symbolic truth.

More importantly, the above controlled empirical structure and the mathematical symbolic structure are not isolated from each other. Reliability experiments aim to test the causal relations among margin, degradation and uncertainty, while mathematical expressions provide abstract representations of these relations. Experimental results can be used to validate, revise and further develop symbolic models, and the symbolic models in turn guide experimental design, variable selection and control strategies. This constitutes a spiral iterative process beginning with axioms, proceeding through mathematical deduction and experimental verification, followed by model revision and further experimental verification. Mathematical symbols enable the axiomatic system to be precisely aligned with empirical truth, while empirical truth provides the basis for validating and correcting mathematical predictions. Together, they constitute the scientific truth of reliability and continuously expand the cognitive structure of reliability science. This expansion process itself constitutes the development mechanism of reliability science, as illustrated in figure 3. Belief reliability theory [36] represents a concrete example of such reliability science, in which scientific principles, experimental validation, and mathematical symbols are systematically integrated into a unified theoretical framework.

From the perspective of the overall scientific system, reliability science has clear correspondences with other sciences, as illustrated in figure 4. Reliability science is neither basic physics nor a purely engineering technological discipline. It belongs to the domain of engineering sciences, while its theoretical foundations originate from basic sciences such as thermodynamics, statistical mechanics and quantum mechanics, which establish the fundamental laws governing the behavior of matter, energy and information. By integrating principles from different engineering disciplines at the system level, and centering on the core object of system-function repeatability, reliability science thus emerges and forms its own independent system of principles, experimental paradigms and symbolic structures. At the same time, reliability science is essentially different from

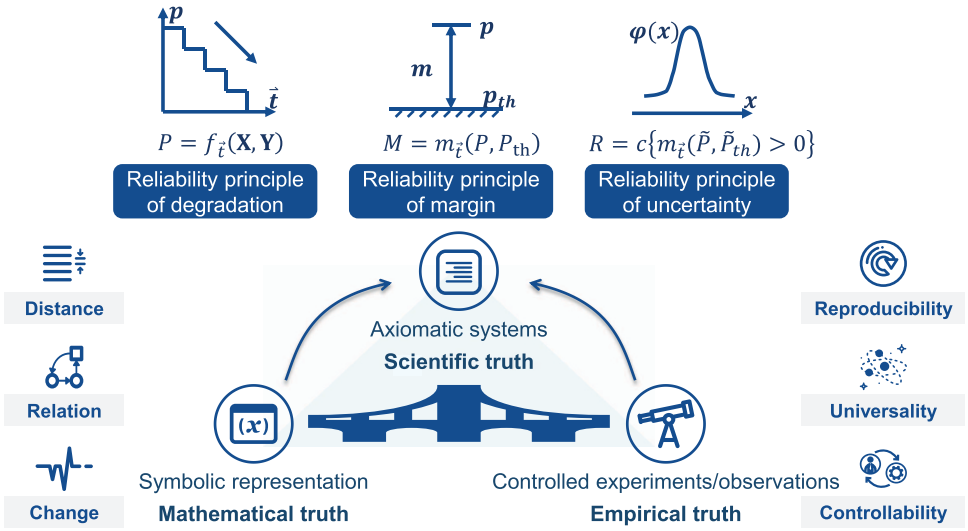


Figure 3. Dual structure of the scientific truth in reliability.

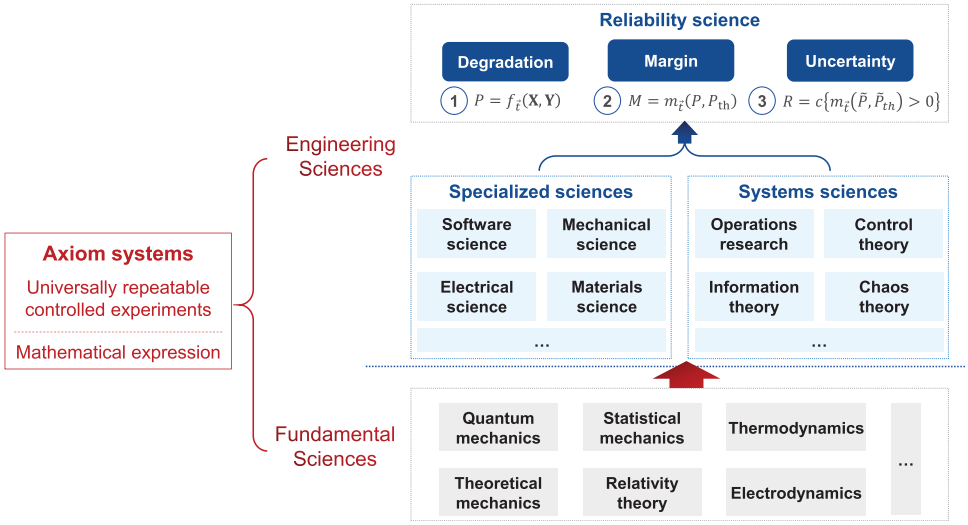


Figure 4. Relationship between reliability science and other sciences.

system science in terms of research perspective. System science focuses on what the world is composed of, complexity science explains how the world emerges through interactions, whereas reliability science concentrates on how the world maintains stable and dependable operation and avoids systemic failure. In essence, reliability science is formed through an emergent integration of other sciences.

Therefore, reliability is a new science. Its 'newness' does not lie in the appearance of a new research object, but in the fact that, for the first time, reliability is explicitly and systematically organized into an independent scientific form. This organization is achieved through the unified integration of axiomatic principles, an expandable system of universally repeatable controlled experiments, and a mathematical structure isomorphic to reliability principles. In this sense, reliability is no longer merely a technical index or a collection of methods used in engineering design, but a science with its own clearly defined theoretical object, experimental paradigm and mathematical language.

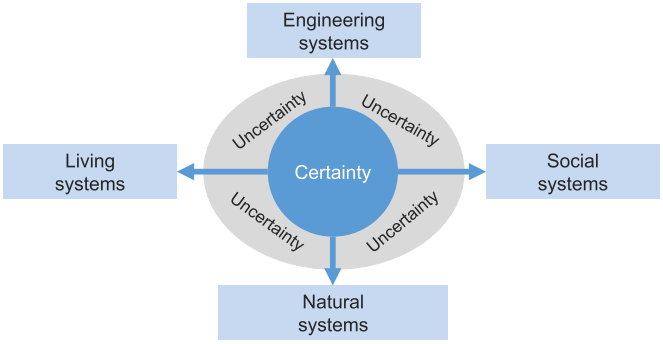


Figure 5. Application areas of reliability science.

4. Applications of reliability science

Reliability science demonstrates its maturity not only through its theoretical foundation but also through its wide range of applications, as shown in figure 5. The following survey highlights representative studies using the reliability science principles, covering areas from engineering systems to other complex systems, such as living systems or social systems.

4.1. Engineering systems

Engineering systems are human-made constructs developed to fulfill specific functional objectives. In essence, an engineering system represents a purposeful integration of components and relationships that together perform a defined function. As Qian described [43], a system is an organic whole composed of interacting elements that collectively realize a particular function. From this perspective, the foundation of any engineering system lies in its ability to perform a function.

Mechanical systems provide the most direct link between the principles of reliability science and their functionality. A representative example is the aircraft landing gear lock mechanism [44]. In this case, the locking function required the lock hook to reach and maintain a prescribed position during operation, and the rotation angle error of the lock hook under the locking state was therefore selected as the key performance indicator. The performance margin was defined as the distance between the allowable limit of this angle error and its actual value, so that a positive margin indicated successful locking. Based on the kinematic relationships of the planar linkage, the lock hook angle was expressed as a function of geometric parameters and joint clearances. Wear degradation was introduced through the Archard law, which related contact force, material properties and sliding distance to the time-dependent growth of clearance in hinge joints. By propagating these clearance changes through the effective link model, the evolution of the lock hook angle error and the corresponding performance margin over operation cycles can be quantified. Four categories of uncertainty were incorporated in this process, including manufacturing deviation, material property variation, environmental stress and threshold uncertainty. Sensitivity analysis further provided a direct basis for design decisions, such as prioritizing tighter tolerances and improved wear resistance in critical hinges, selecting materials with higher hardness stability, and controlling hydraulic load variation to preserve sufficient performance margin throughout service life. This study demonstrates how the reliability science can be applied to reliability modeling, analysis and design guidance, and subsequent studies follow the same paradigm. The same logic applies to rotating machinery such as planetary and harmonic gear reducers [45–47]. These studies used hysteresis error as the core

performance indicator and considered gear wear as the main degradation mechanism, with manufacturing tolerance, load fluctuation and environmental variation treated as uncertain parameters. The results showed that frictional dissipation and operating history jointly determine the evolution of performance and reliability, offering practical insights for reliability design. When multiple physical processes interact, thermo-mechanical systems provide an expanded view. Research on automotive tubular radiators [48] modeled creep-fatigue coupling under cyclic thermal and pressure loads, defining cumulative damage as the measure of performance degradation. Material parameter variability and limited data were represented using uncertainty theory, forming a framework that combines physics-based modeling with epistemic uncertainty quantification. Similar approaches have been applied in fatigue reliability studies [49], where the performance margin was expressed as the distance between current and critical crack lengths. At a higher structural level, precision assemblies highlight reliability behavior dominated by initial accuracy rather than degradation. In the spaceborne synthetic aperture radar antenna deployment mechanism [50], assembly deviations in hinge alignment and rod positioning reduced surface flatness and pointing precision. Reliability was quantified through performance margins defined by allowable tolerance deviation. Related work on satellite-based phased array antennas [51] further linked initial assembly accuracy with long-term degradation, showing that beam pointing error and antenna gain decline progressively as phase shifters and amplifiers age under temperature stress.

Electrical systems offer another domain where reliability science links physical mechanisms with system-level reliability. A representative study on passive RC filters [52] established the performance margin based on cutoff frequency and signal attenuation, and modeled degradation through resistor oxidation and capacitor electrolyte evaporation. Temperature, humidity and voltage were treated as external variables. The results revealed how measurable shifts in circuit response correspond to the degradation of component properties. Device-level analysis under radiation offers a complementary perspective. For CMOS image sensors [53], reliability depends on how total ionizing dose and single-event effects alter key electrical parameters. The study modeled degradation as the cumulative change of these parameters with radiation exposure. The findings of sensitivity analysis provided suggestions for the design and use processes of the CMOS image sensor for reliability improvement. In complex electronic assemblies [54], reliability science principles have been applied to systems subjected to multiple interacting stressors. The proposed structure-overload-performance method analyzed how mechanical, thermal and electrical factors jointly affect solder joints, optocouplers and MOSFETs. This unified approach provides solutions for system-level reliability assessments when different degradation processes act simultaneously.

As mechanical and electrical subsystems become increasingly integrated, reliability science offers a unified framework for analyzing their coupled behavior. Electromechanical systems connect structural motion with electrical conduction, and their reliability depends on how mechanical contact, geometry and load conditions interact during operation. A representative study on a torsion-spring electrical connector [55] captured how structural geometry, contact pressure and load variation affect the performance margin. Degradation was modeled as the decline of electrical contact quality caused by wear and surface oxidation. This framework supports both reliability assessment and design optimization, ensuring reliable performance throughout the connector's life cycle. Another study proposed an attractor-based method to describe the performance evolution of electromechanical systems [56]. The analysis linked system behavior to generalized coordinates, energy functions and damping properties, showing how external loads and dissipation influence the performance margin. A degradation

equation characterized the gradual change of microscopic parameters that lead to macroscopic performance decline. This physically grounded approach provides a general framework for reliability analysis in coupled electromechanical systems.

With the progression of electromechanical systems toward higher autonomy and precision, control systems become essential for maintaining stable operation under varying conditions. Reliability science provides a unified framework linking physical performance, control dynamics and uncertainty representation. A representative study on the coarse-tracking system of a satellite optical communication terminal [41] illustrated this integration. The model took tracking accuracy as the key performance indicator and included the physical properties of sensors, actuators and mechanical parts together with external variables such as radiation, temperature fluctuation, contact stress and vibration. Degradation was modeled through radiation damage in sensors, motor demagnetization and bearing wear, which collectively reduced performance margin. The results showed how control performance evolved under coupled degradation and environmental variation. A related study evaluated the reliability of a proportion integration differentiation feedback control system [57]. It linked the loss of tracking accuracy to time-dependent degradation of sensors and actuators while accounting for multiple uncertainty sources. Further studies extended this framework by focusing on epistemic uncertainty in control dynamics [58].

Building on the stability achieved by control systems, information and software systems extend reliability considerations into the cyber domain. In information systems, reliability extends to encompass the stability of information flow, resource allocation and decision processes. A representative study examined the reliability of cloud data centers modeled as service systems composed of computational resources, network links and scheduling mechanisms [42]. Using a generalized Petri net framework, the analysis defined service reliability through task scheduling efficiency, resource utilization and delay propagation. The results showed how reliability science can be applied to systems that couple physical mechanisms with informational processes. In software systems, reliability depends on how faults are detected, corrected and prevented during development and testing. A representative study proposed a software reliability growth model grounded in reliability science principles [59, 60]. The model incorporated testing coverage as a key factor affecting the performance margin, recognizing that limited coverage allows latent faults to remain and restricts reliability improvement. Performance degradation was represented by the change in failure intensity over time, capturing both the loss and recovery of functional capability during testing. By quantifying epistemic uncertainty through limited statistical data, the framework enabled rational reliability evaluation under incomplete information.

As engineering systems become increasingly coupled across physical domains, reliability science offers a unified framework for integrating multidisciplinary mechanisms (e.g. mechanical, electrical and chemical) within a single analytical structure. Lithium-ion batteries provide a representative example where electrochemical degradation governs long-term reliability. One study modeled capacity fade by combining internal variables such as active lithium content, SEI film density and anode surface area with external variables including temperature, discharge current and depth of discharge [61]. The gradual loss of capacity defined the performance margin and enabled reliability evaluation for life prediction and health management. Research on large-scale battery packs in renewable energy systems further linked cell-level electrochemical behavior with system-level dynamics [62]. Key parameters such as state of charge, open-circuit voltage and internal resistance were coupled with environmental factors like temperature and discharge rate, while the degradation of energy output over time represented system-level performance loss. In extreme environments,

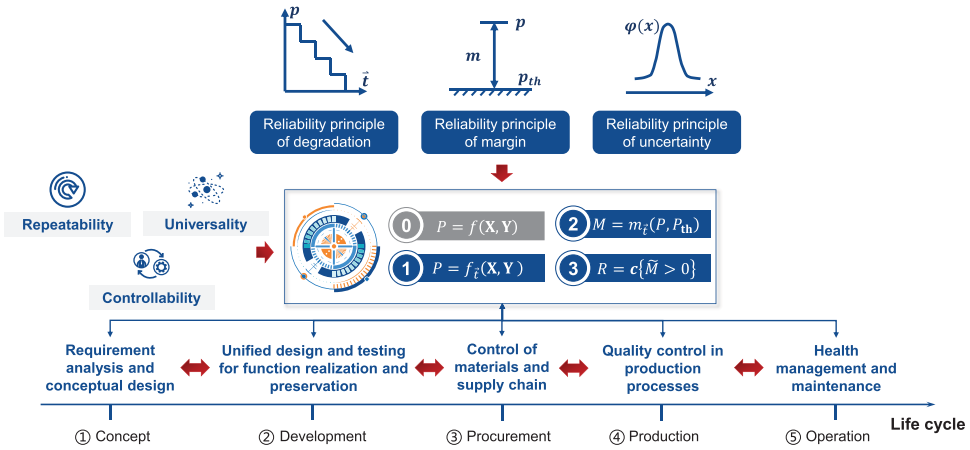


Figure 6. Guidance of reliability science on the entire product lifecycle.

multidisciplinary reliability frameworks have been applied to aerospace systems. The thermal protection system of reentry vehicles combines heat conduction, radiation and material ablation with aerodynamic heating [63]. Degradation of thermal resistance under prolonged heat flux was modeled explicitly, forming a coherent analysis of high-temperature reliability. Studies on three-grid ion thrusters showed how aperture wear causes performance degradation in electrical propulsion systems [40, 64]. Reliability modeling coupled geometric and operational parameters such as grid thickness, aperture size, discharge voltage and current, providing a quantitative basis for lifetime prediction and experimental design. At the system scale, reliability science principles have been extended to renewable energy generation. A representative study of wind farms developed a performance margin model based on rotor-equivalent wind speed and analyzed how wind distribution, direction and wake effects influence output power and system reliability [65].

Across these examples, reliability science provides a unifying framework for engineering systems. This unified logic allows reliability to be evaluated across diverse domains, from components and subsystems to cyber-physical infrastructures, showing that the same scientific principles govern reliability throughout the engineering systems.

Beyond its application to different classes of engineering systems, reliability science also provides a unified logic for guiding engineering activities across the entire product lifecycle, as illustrated in figure 6. This guidance arises from the reliability disciplinary equations derived from the principles of margin, degradation and uncertainty. These equations establish the causal relationship between reliability and the decisions made at each stage of the life cycle. In the conceptual phase, the performance thresholds of requirements are transformed into the required reliability level, which are then distributed to the performance margins of subsystems. In the development phase, the internal variables, such as component materials and dimensions, as well as system relationships, including functional principles and fault-tolerant logic, are designed to meet the allocated margin requirements. In the procurement phase, selections are made for the internal variables that form the system. In the production phase, internal variables and system relationships are realized into physical form. In the operation phase, external variables, the performance threshold of requirements and the irreversible time are specified, assessing the repeatability of system function across time and space. As a result, reliability science links the main tasks of each stage with the resulting system reliability, forming a model-based reliability systems engineering framework. In this way, reliability science offers not only an

explanatory theory but also a practical foundation for accurate closed-loop control of system reliability.

4.2. Beyond engineering systems

4.2.1. Generality of systems in reliability science. According to the scientific definition of reliability proposed in this paper, reliability is defined as the repeatability of system function across time and space. From the perspective of system science, a system represents a fundamental form of existence of real-world entities, rather than being restricted to traditional engineering artifacts. Consequently, the notion of 'system' in reliability science is not specific to engineering systems, but refers to any organized entity in which a meaningful system function can be identified. Under this interpretation, reliability is a general system-level property. Therefore, reliability science naturally extends beyond conventional engineering systems to domains such as biological systems, social systems and other complex socio-technical systems. These extensions do not introduce new principles, but apply the same reliability principles of margin, degradation, and uncertainty to different types of functional systems.

It should be emphasized that extending reliability science beyond engineering systems does not imply that all such systems admit the same form of controlled experiment. According to the multilevel expansion of controlled experiments in reliability science established in section 3.2 (see figure 2), reliability experiments form a hierarchical system ranging from controlled observation dominated by condition selection, to system-level controlled experiments with manipulable internal variables, and further to physical-level controlled experiments governed by fundamental physical laws. Within this framework, different types of systems are naturally associated with different experimental levels. For engineering systems, reliability investigations can often reach system-level or even physical-level controlled experiments. For biological or social systems, reliability studies may primarily reside at the level of controlled observation, where subjects control and repeat observation conditions rather than fully manipulate the internal mechanisms that determine system behavior. Notably, in the strict sense of controlled observation, the object should be independent of the subject. However, in social systems and other systems involving human subjects, the subject itself often participates in the system. When the object contains subsets involving subjective mental states, behavioral intentions or imagined social interactions, the corresponding activity is more appropriately characterized as pseudo-controlled observation. Nevertheless, as long as margin, performance and performance requirement can be defined, and observations under the same conditions are repeatable and inter-subject consistent, such investigations still constitute valid reliability experiments within the scope of reliability science.

4.2.2. Living systems. Living systems differ from engineering systems in that they arise naturally rather than through human design, possessing the intrinsic ability to self-organize and adapt. Their fundamental function is survival, achieved by maintaining internal balance under external and internal disturbances. In human beings, this balance defines health, while its decline manifests as disease and its complete loss results in death. Systems medicine, as developed by Jin *et al* [66], applies systems theory to interpret the human body as a dynamic and self-regulating system. It explains health as a stable state maintained by the coordination of multiple subsystems and views disease as the excessive deviation of this stability. The theory emphasizes that treatment should respect and support the body's inherent capacity for recovery rather than rely solely on external intervention. From this viewpoint, the maintenance of health depends on sustaining sufficient margin to resist perturbation and preserve

systemic stability. This understanding converges naturally with the reliability science principles, where performance margin represents the quantitative boundary between normal function, degradation and failure. Thus, systems medicine provides conceptual and empirical evidence that the fundamental logic of reliability, including function, margin, degradation and uncertainty, is equally applicable to living systems.

Following this conceptual connection, recent studies have applied reliability science to specific physiological and pharmacological processes, translating the theoretical principles of systems medicine into quantitative models that describe how biological functions evolve under uncertainty. Liu and Kang established an uncertain differential equation model to describe the pharmacokinetics of digoxin within a two-compartment structure consisting of plasma and tissue distributions [67]. The model incorporated intrinsic physiological processes such as drug transfer and elimination, along with biological noise representing external influences. The decline of drug concentration over time was interpreted as performance degradation, while epistemic uncertainty arising from individual variability and metabolic complexity was quantified through uncertainty theory. Building on this framework, subsequent studies analyzed broader pharmacological processes, including drug absorption and elimination under varying bioavailability and dosage conditions [68], and extended the approach to extravascular administration and nonlinear kinetics based on the Michaelis–Menten model [69]. Across these studies, reliability was defined as the belief degree that concentration remains within the therapeutic range, showing how reliability science unifies pharmacokinetic dynamics with uncertainty quantification in living systems.

Beyond studies on biochemical drug metabolism, another line of research has examined the reliability of physiological regulation at the system level. The human baroreflex provides a representative example, functioning as a closed-loop control process that stabilizes blood pressure through coordinated neural and vascular responses. As illustrated in figure 7, this regulation can be understood as a feedback loop in which blood pressure changes are first sensed by baroreceptors, transmitted through afferent neural pathways, integrated by central neural control, and translated into cardiac and vascular responses that restore equilibrium. Through this loop, physiological mechanisms give rise to measurable indices and, collectively, to the baroreflex regulation function. From the perspective of reliability science, the baroreflex therefore acts as a feedback system whose performance depends on the integrity and coordination of multiple physiological processes. Following this perspective, Shangguan *et al* [70] developed a control-based reliability model of the baroreflex, in which regulation error and control effort describe changes in system performance and reserve capacity. The analysis showed that reliability can be represented as the probability that baroreflex regulation remains effective within physiological limits, linking functional stability with control dynamics. Complementary to control-based modeling, Li *et al* [71] investigated baroreflex regulation under resting conditions using entropy-based methods, building on the physiological structure shown in figure 6. By characterizing systolic blood pressure (SBP), heart rate (HR), HR variability (HRV), and baroreflex sensitivity (BRS) as emergent indices of the underlying feedback loop, they introduced a physiological entropy index to quantify regulatory capacity and systemic uncertainty. Increased entropy in blood pressure indicates weakened stability, whereas reduced entropy in neural or cardiac signals reflects declining regulatory responsiveness. Together, these studies demonstrate that reliability science provides a coherent framework for understanding how living systems sustain stable performance under uncertainty.

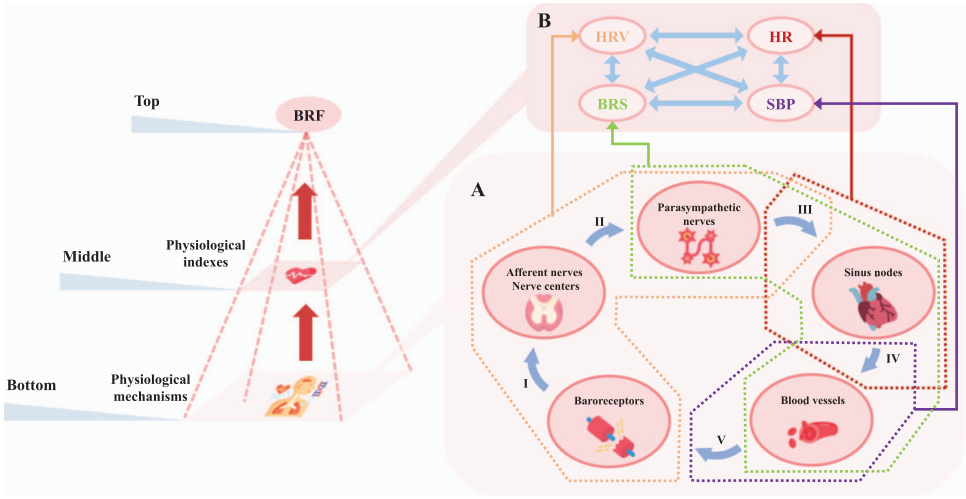


Figure 7. Emergence from physiological mechanisms to physiological indices and baroreflex regulation function (BRF) [71]. (A) In the context of physiological mechanisms, nodes represent organs or tissues, while arrows denote physiological processes, where (I) baroreceptors detect changes in blood pressure through the stretching of blood vessel walls and convert these mechanical changes into neural impulses, which are transmitted along afferent pathways to central neural centers for integration; (II) neural centers process the incoming signals and generate regulatory commands, mainly by activating parasympathetic responses under resting conditions; (III) parasympathetic nerves convey these commands to the cardiac sinus node, leading to adjustments in HR; (IV) changes in heart rate alter cardiac output and blood pressure, thereby modifying the degree of blood vessel stretching; (V) the altered vessel stretching is sensed again by baroreceptors, completing the feedback loop. Dashed regions indicate the emergent physiological indices corresponding to different organs, tissues, and regulatory processes. (B) Physiological indices, i.e. BRS, SBP, HR, and HRV, emerge from physiological mechanisms. Arrows indicate the possible interactions among indices.

4.2.3. Social systems. In contrast to engineering and living systems, social systems emerge from the collective interactions of individuals, organizations and institutional rules. They operate through communication, cooperation and coordination, enabling resources, information and decisions to circulate within structured networks. The fundamental function of a social system is to sustain organized activity and ensure the continuity of essential functions under changing internal and external conditions. From the perspective of reliability science, the stability of such systems depends on their ability to maintain structural connectivity, functional coordination and adaptive capacity despite disturbances. Performance degradation appears as reduced efficiency, loss of coordination or breakdown of connectivity, while uncertainty originates from incomplete information, behavioral variability and unpredictable external influences. Reliability analysis in this context focuses not on physical failure, but on the persistence of systemic performance under uncertainty, providing a framework to evaluate how social infrastructures such as communication, transportation and demographic systems remain stable and functional in dynamic environments.

Transportation systems provide a representative example, where performance depends on the collective interaction of infrastructure, human behavior and environmental factors. Yi *et al* [72] developed an uncertain percolation semi-Markov model that integrated road conditions, traffic demand, driver behavior and signal malfunctions within a unified analytical framework. In this model, performance degradation was described through capacity reduction and signal failure, both influencing system performance margin. By jointly addressing random and epistemic uncertainties, this approach captured the evolutionary behavior of traffic reliability. Subsequent research has examined travel-time

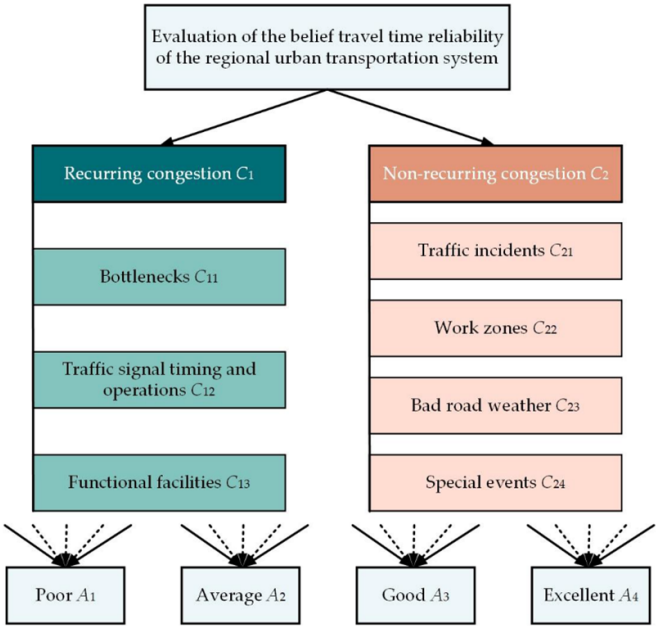


Figure 8. The hierarchical structure of the belief travel time reliability [73].

reliability as a practical measure of system performance [73]. The results revealed that traffic performance margin was influenced by both regular factors, such as bottlenecks and signal control, and irregular events, including accidents, construction and extreme weather, as illustrated in figure 8. Although no performance degradation was involved, fluctuations in travel time effectively reflected the variations of system performance. Beyond transportation, reliability principles have also been extended to population systems [74]. In migration-driven population dynamics, population density was modeled as a state variable affected by external migration sources. The instability or decline of population density corresponded to performance degradation, while uncertainty in migration processes was represented through uncertainty theory. This framework demonstrated how reliability science can be applied to social contexts, where performance was defined by systemic stability rather than physical durability.

5. Disciplinary big picture of reliability science

Through the preceding analyses across engineering, living and social systems, the universality of reliability science has been empirically demonstrated. Reliability embodies both the empirical authenticity of controlled experiments and the symbolic coherence of an axiomatic system. On this foundation, it becomes possible to articulate the disciplinary big picture of reliability science. Wu [75] has emphasized that every mature discipline should answer a common set of foundational questions : what it studies, the problems it addresses, the ways of thinking it adopts, the analytical methods it employs, and how it relates both to other fields and to the world at large. For reliability science, which is here positioned as an emerging yet independent discipline, such a big picture defines not only its scope but also its intellectual identity. It situates reliability within the broader history of science, clarifies its boundaries, and points toward its future trajectory. Table 1 outlines the disciplinary big picture of reliability science.

The research objects are inherently systemic, recognizing that any system exists within and interacts with a larger system that includes its environment.

Table 1. The disciplinary big picture of reliability science.

Discipline aspect	Description in reliability science
Typical research objects	Everything is a system: the system together with its environment forms a larger system
Typical research problems	Systems must be reliable: how systems achieve reliability and how they fail
Typical ways of thinking	Systems thinking: integrating internal and external causes, static and dynamic perspectives, capabilities and requirements, certainty and uncertainty
Typical analytical methods	Combination of reductionist and emergent approaches: decomposing system failures into element failures, integrating element reliabilities into system reliability
Relationship with other disciplines	Emergent integration of theories from other disciplines
Relationship with the world	Establishing a worldview that accepts mortality, a life philosophy that faces uncertainty, and a value system that aspires to lifelong reliability

Accordingly, the central research problem of reliability science is dual in nature: to explain how systems achieve reliable functioning and to understand how and why they fail. The characteristic way of thinking is systems thinking, which unites diverse perspectives: integrating internal and external causes, reconciling static descriptions with dynamic evolution, aligning capabilities with requirements, and balancing certainty with uncertainty. Methodologically, reliability science synthesizes reductionist and emergent approaches. Traditional reliability engineering is predominantly reductionist, analyzing systems by decomposing them into components and tracing failures down to elemental mechanisms at the material or physical level. This decomposition is often carried out through a series of simplifying assumptions that make detailed analysis feasible. However, when results are projected back to the system level, the interactions and dependencies that were simplified or neglected during decomposition are rarely reconstructed explicitly. As a result, system reliability is either treated as a black-box quantity inferred from aggregated component measures, or evaluated without establishing a clear structural link between component behavior and system performance. In this way, while reliability at the system level appears as an emergent outcome, the pathway through which component mechanisms, interactions and uncertainty collectively give rise to that outcome remains unclear. Belief reliability theory provides a theoretical framework in which this emergent process is explicitly represented. It focuses on how system reliability arises from the structured integration of component behavior, interacting mechanisms and multiple sources of uncertainty, rather than assuming system behavior as a black-box outcome. Reliability science, as framed here, synthesizes reductionist analysis with explicit emergence, enabling both detailed component-level investigation and coherent system-level integration. In its relationship to other disciplines, reliability science is the emergent integration of other sciences, which we have discussed in section 3.4. Its relationship to the world extends beyond technical performance to broader implications. By formalizing how systems sustain function under change and uncertainty, reliability science supports a worldview that acknowledges failure as inevitable, a practical philosophy that confronts uncertainty, and a value orientation that emphasizes dependable operation over the entire lifecycle of systems. In this sense, reliability science is not only a technical discipline but also a scientific framework that connects physical law, system behavior and human purpose. Its disciplinary big picture is therefore a direct reflection of its scientific structure, demonstrating how reliability can be understood, analyzed and designed across domains within a coherent and unified science.

Acknowledgment

This work was supported by the National Natural Science Foundation of China [Grant Number 51775020], and the National Natural Science Foundation of China [Grant Number 62073009].

ORCID iDs

Xiao-Yang Li 0000-0002-4046-2934
Shi-Shun Chen 0000-0003-0590-7114
Waichon Lio 0009-0006-6622-4383
Rui Kang 0000-0002-4488-6574

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Xiao-Yang Li received a PhD degree in aerospace systems engineering from Beihang University, Beijing, China, in 2007. She is currently a Professor, and the director of the Belief Reliability Center with the School of Reliability and Systems Engineering, Beihang University, Beijing, China. Her research interests include belief reliability theory, reliability experiment theory, and systematic medicine centered medical-industrial crossover.



Shi-Shun Chen received a Bachelor's degree in safety engineering from Beihang University, Beijing, China, in 2021. He is currently pursuing a PhD degree at the School of Reliability and Systems Engineering, Beihang University, Beijing, China. He was also a visiting PhD student with the Energy Department, Politecnico di Milano, Milan, Italy, from 2024 to 2025. His research interests include belief reliability theory, reliability experiment and uncertainty analysis.



Waichon Lio received a PhD degree in operations research and control from Tsinghua University, Beijing, China, in 2021. He is currently an Associate Professor with the School of Reliability and Systems Engineering, and the Deputy Director with the International Relations Department, Beihang University, Beijing, China. His research interests include belief reliability theory, uncertain statistics, and reliability mathematics.



Rui Kang received Bachelor's and Master's degrees in electrical engineering from Beihang University, Beijing, China, in 1987 and 1990, respectively. He is currently a Distinguished Professor with the School of Reliability and Systems Engineering, Beihang University. He has published eight books and more than 200 research papers. His research interests include belief reliability theory, reliability-centered systems engineering, resilience modeling and evaluation for complex system.