

# Leveraging Statistical Thinking for Digital Innovation: Reframing Uncertainty in Engineering Decision-Making

C.P. Leão<sup>1,\*</sup>, A.M. Gonçalves<sup>2</sup>, M.T. Malheiro<sup>2</sup>

<sup>1</sup>ALGORITMI Research Centre, School of Engineering, University of Minho, Guimarães, Portugal

<sup>2</sup>Centre of Mathematics (CMAT), School of Sciences, University of Minho, Guimarães, Portugal

## Abstract

**INTRODUCTION:** Contemporary engineering operates in a data-rich yet uncertainty-laden landscape, particularly under the technological shifts introduced by Industry 4.0. While foundational, deterministic models frequently fail to address the ambiguity, variability, and incompleteness inherent in real-world data, this paper examines the growing need to embed statistical reasoning within digital engineering decision-making processes to ensure robustness and interpretability.

**OBJECTIVES:** The study aims to investigate how statistical thinking contributes to innovation, transparency, and adaptive decision-making in digitalized engineering systems. It identifies conceptual gaps and underexplored themes in current literature and emphasizes the strategic relevance of probabilistic reasoning in addressing uncertainty across complex industrial settings.

**METHODS:** A hybrid scoping review methodology was applied, combining a semantic AI-driven search via Elicit with a structured bibliographic query in Scopus. The resulting corpus of 928 curated publications was analysed through bibliometric techniques and social network analysis using VOSviewer. This comprehensive process enabled the identification of co-occurrence patterns, thematic clusters, and evolving disciplinary linkages, ensuring the credibility and reliability of the findings.

**RESULTS:** Five primary research clusters emerged: decision optimization, risk management and human factors, machine learning integration, digital information systems, and sustainability. These clusters represent key areas where probabilistic modelling and uncertainty quantification can significantly enhance engineering practices. Although AI and big data analytics are increasingly prevalent, the underrepresentation of probabilistic modelling and uncertainty quantification in these clusters reveals a disconnect between data-centric innovation and risk-aware engineering practice.

**CONCLUSION:** A conceptual shift toward probabilistic reasoning is advocated as a necessary response to the complexity of modern digital engineering environments. Repositioning statistical thinking as a central enabler of digital transformation supports the development of resilient, interpretable, and future-ready engineering systems. Integrating these methodologies into engineering curricula, AI pipelines, and industrial decision-support infrastructures is essential for advancing strategic, uncertainty-aware innovation.

**Keywords:** Statistical Thinking, Uncertainty Management, Digitalization, Industry 4.0, Engineering Innovation, Data-Driven Decision-Making, Probabilistic Models, Resilience in Industrial Systems, AI in Engineering.

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## 1. Introduction

Every day, individuals and organizations make decisions under uncertainty—whether choosing the best route to work, predicting market trends, or designing complex engineering systems. While uncertainty is an unavoidable

\*Corresponding author. Email: [cpl@dps.uminho.pt](mailto:cpl@dps.uminho.pt)

aspect of decision-making, the tools used to navigate it vary widely, from intuition and heuristics to rigorous statistical methods [1]. In engineering, where decisions often have significant financial, safety, and operational implications, the underutilization of statistical thinking limits the ability to systematically manage risks and optimize outcomes [2].

Uncertainty, defined as limited knowledge about future outcomes due to inherent randomness, incomplete data, or systemic complexity, is not a marginal concern in engineering; it is a central and unavoidable reality [3]. Despite this, engineering curricula and industrial practices often emphasize deterministic tools and heuristics, leaving professionals underprepared to make decisions informed by statistical rigor [1,2]. These gaps become increasingly problematic as organizations adopt Industry 4.0 technologies, which integrate sensor-driven systems, artificial intelligence (AI), and cyber-physical infrastructures that generate massive and dynamic datasets with high levels of embedded uncertainty.

While advancements in AI and big data analytics offer powerful means for automation and optimization, they frequently obscure the probabilistic nature of inference, leading to opaque models and potential overconfidence in algorithmic outputs. Here, statistical thinking provides a complementary lens, enhancing interpretability, transparency, and robustness in digitalized engineering systems. Recent studies suggest, techniques such as Bayesian modelling, uncertainty quantification, and experimental design underrepresented in both research and practice, particularly in their integration with emerging digital tools [4].

This paper addresses this gap by investigating the role of statistical thinking as a driver of digital innovation in engineering. It explores how probabilistic frameworks can enhance decision-making under uncertainty, particularly in environments characterized by complex data ecosystems. The study is guided by the following research question (RQ):

“How can statistical thinking be leveraged to support innovation and decision-making under uncertainty in digitalized engineering contexts?”

To explore this question, a scoping review was conducted using Elicit, a generative AI-based literature discovery tool, guided by the research question RQ previously defined. Elicit facilitated the identification of relevant studies by analysing patterns in existing research and surfacing key contributions related to statistical thinking and uncertainty in engineering [5].

Building on these insights, a targeted search was then performed in Scopus, a leading scientific database, using a carefully curated set of keywords to ensure a systematic and comprehensive exploration of the relevant literature. These complementary sources enabled a broad and systematic retrieval of relevant publications from the past 15 years. Bibliometric and cluster analysis, supported by the VOSviewer platform [6,7], allowed the identification of research trends and knowledge gaps across domains

such as optimization, risk assessment, machine learning, and sustainability.

This extended paper expands upon a previously presented conference version [8] by offering a deeper conceptual analysis, refined bibliometric insights, and a novel framing of statistical thinking as an enabler of digital transformation. The remainder of the paper is structured as follows: Section 2 presents the theoretical framework, situating statistical thinking within the broader context of digital engineering ecosystems. Section 3 outlines the methodology detailing the scoping review and bibliometric analysis. Section 4 presents the findings and discussion, highlighting the main research clusters and thematic relationships identified through bibliometric mapping. Section 5 offers a conceptual contribution by examining the role of statistical thinking as a catalyst for digital innovation and by discussing its educational and professional implications. Finally, Section 6 synthesizes the key insights and proposes strategic directions for future research and application.

## 2. Theoretical Framing: Engineering Uncertainty in the Digital Era

In contemporary engineering practice, uncertainty is not an exception but a structural feature that is embedded in all stages of the decision-making process. As Industrial systems evolve through digital transformation, new forms of complexity emerge, ranging from sensor noise and data heterogeneity to real-time constraints and human-machine interaction. These developments challenge the traditional reliance on deterministic models, which often fall short in capturing the variability, ambiguity, and dynamic adaptation required for robust decision-making. In response, the field must embrace statistical thinking as a central pillar of digital innovation.

### 2.1. Rethinking Uncertainty in Digitalized Engineering

Uncertainty in engineering manifests in several forms: aleatory (stemming from inherent randomness), epistemic (arising from limited knowledge), and systemic (linked to model inadequacy or complexity) [3]. While deterministic models may be effective in controlled or well-defined environments, their limitations become apparent in real-time decision systems, such as predictive maintenance platforms, digital twins, or cyber-physical networks. These systems increasingly depend on streaming data, adaptive algorithms, and probabilistic reasoning to maintain performance under uncertain and changing conditions [9].

Emerging paradigms, such as Industry 4.0 and smart manufacturing, further intensify these challenges by embedding intelligence into distributed systems. The integration of IoT, AI, and automation into engineering workflows calls for frameworks that not only process data but also manage uncertainty in a principled manner. As

demonstrated in the public sector, even high-stakes automated decision-making systems can lack robustness if uncertainty is not properly quantified or communicated [10]. Their systematic review emphasizes the necessity of context-sensitivity, feedback mechanisms, and model transparency, dimensions that statistical frameworks are uniquely suited to address.

## 2.2. Statistical Thinking: From Back-End Tool to Strategic Competence

Traditionally, statistical tools in engineering have been applied post hoc for quality control, design validation, or compliance. However, the rise of data-driven engineering ecosystems shifts the role of statistical thinking from an auxiliary to a foundational one. In the context of digital systems, statistical competence enables a shift from static optimization toward adaptive, uncertainty-aware decision-making.

At its core, statistical thinking includes the capacity to:

- Model probabilistic relationships in complex systems, such as through subset simulation techniques used to accurately estimate rare-event probabilities in high-dimensional engineering contexts [11];
- Quantify variability and risk through resampling and simulation approaches [12];
- Design efficient experiments under constrained resources [13]; and
- Update model parameters dynamically with Bayesian inference, enabling real-time uncertainty quantification in digital twin applications [9].

These capabilities enable engineers to move beyond deterministic assumptions, fostering confidence estimation, robust inference, and system resilience in the face of ambiguity. Such skills are not only valuable but essential in systems where data uncertainty directly affects operational reliability and innovation outcomes. For example, in digital twins, improper handling of uncertainty may lead to misaligned systems or untrustworthy predictions, issues that statistical modelling can mitigate effectively [14].

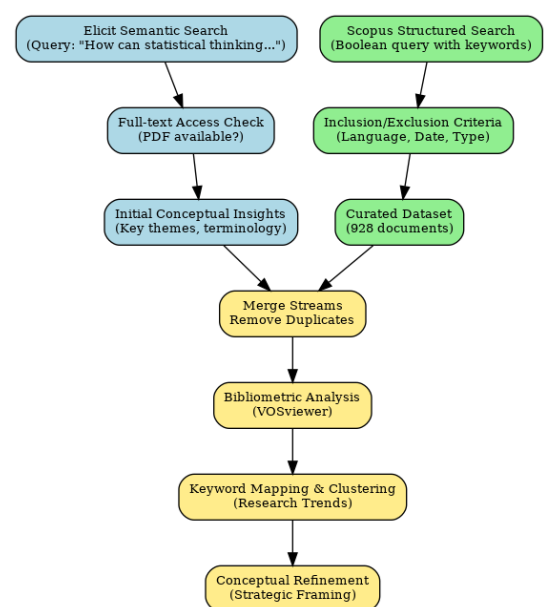
## 3. Methodology

To investigate the role of statistical thinking in supporting innovation and decision-making under uncertainty within digitalized engineering contexts, a hybrid scoping review (SR) approach was adopted [15]. This approach was considered appropriate given the study's exploratory nature, which aimed to map foundational concepts, identify disciplinary intersections, uncover conceptual and methodological issues, and identify gaps in integrating statistical thinking within digitalized engineering contexts. Furthermore, the review seeks to identify barriers to

adoption and emergent opportunities for innovation-driven applications of statistical frameworks.

The process followed five structured stages: (1) definition of the research question, (2) identification of relevant studies through hybrid discovery strategies, (3) application of inclusion and exclusion criteria for study selection, (4) extraction and categorization of bibliometric and thematic data, and (5) synthesis of key findings to reveal dominant trends, conceptual clusters, gaps, and future research directions.

Figure 1 illustrates the workflow for visually summarizing this hybrid approach. The color-coded flow illustrates three core stages of the review process: the blue segment represents semantic exploration using Elicit, the green segment outlines the structured search and curation process via Scopus, and the yellow segment covers data synthesis, thematic clustering, and bibliometric visualization using VOSviewer [6,7].



**Figure 1.** Hybrid Review Workflow: color-coded stages show the integration of Elicit (blue), Scopus (green), and synthesis and analysis (yellow).

The research team conducted all review stages collaboratively to ensure transparency, methodological rigor, and analytical consistency. One author coordinated the review process, while all team members contributed to data retrieval, eligibility assessment, and synthesis. Their combined expertise enabled a comprehensive analysis of the topic, ultimately guiding the study toward its conclusions.

### 3.1. Elicit Semantic Search

The first phase of the review employed Elicit, an AI-driven literature discovery tool, to perform a semantic search

based on the guiding query: “How can statistical thinking unlock untapped potential in engineering decision-making under uncertainty?” The search was conducted in January 2025 and was intentionally unrestricted by year, publication type, or source database to maximize conceptual breadth.

Elicit’s algorithm generated semantically relevant studies and offered structured metadata for each entry, including abstracts, study focus, research methodologies, application domain, and key findings. Relevance was iteratively refined through query adjustment and manual validation. To ensure consistency during content analysis, only documents with accessible full-text PDFs were included. Papers not available in PDF format or requiring restricted institutional access were excluded from the analysis.

Given Elicit’s adaptive and non-replicable algorithmic filtering, this phase prioritized exploratory coverage over strict reproducibility. To address this limitation and enhance the depth of bibliometrics, a complementary structured search was conducted using Scopus.

### 3.2. Scopus Structured Search

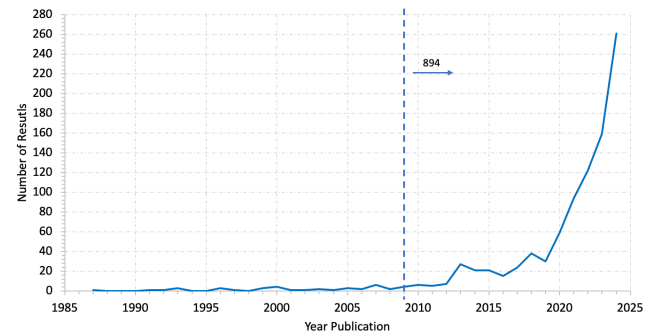
A structured Boolean search was conducted in the Scopus database using the following keyword combination to refine query precision and enhance result retrieval:

("statistical thinking" OR "statistical literacy" OR "data-driven decision-making")  
AND  
("engineering decision-making" OR "uncertainty in engineering" OR "risk assessment")

This initial search yielded over 1,000 documents. To ensure data relevance and manageability, the following inclusion and exclusion criteria were applied:

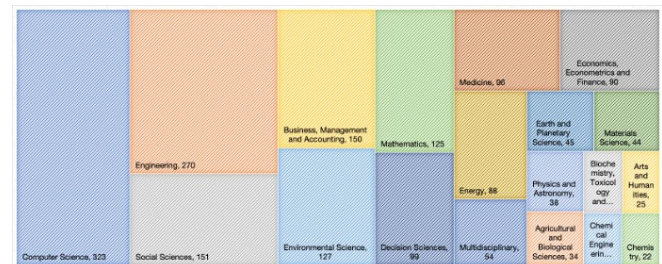
Document Type – peer-reviewed sources (Articles, Conference Papers, Review Papers, and Book Chapters);  
Language – Only English-language publications were included to ensure accessibility and consistency in interpretation;  
Publication Year – To focus on recent and relevant contributions, the search was restricted to studies published in 2024 or earlier;  
Publication Stage – Only works classified as final publications were selected, excluding preprints and in-progress works, to ensure the inclusion of fully vetted research.

After applying these filters, a curated dataset of 928 documents spanning from 1987 to 2024 was assembled. Temporal analysis revealed a sharp increase in relevant research beginning in 2009; hence, the final analytical focus was narrowed to the most recent 15-year window (2009-2024) to more accurately reflect contemporary trends (Figure 2).



**Figure 2.** Number of Documents per year (inflection line in 2009).

The dataset’s disciplinary classification showed that Computer Science (18%) and Engineering (15%) were the most represented subject areas. These were followed by Social Sciences (8%), Business, Management, and Accounting (8%), Environmental Science (7%), and Mathematics (7%), reinforcing the topic’s interdisciplinary relevance (Figure 3).



**Figure 3.** Distribution of Documents by subject area (2009-2024).

Regarding document type, articles accounted for 63% of the corpus, followed by conference papers (15%), with the remainder distributed among review papers and book chapters. This distribution highlights the predominance of peer-reviewed research contributions in the dataset.

## 4. Findings and Discussion

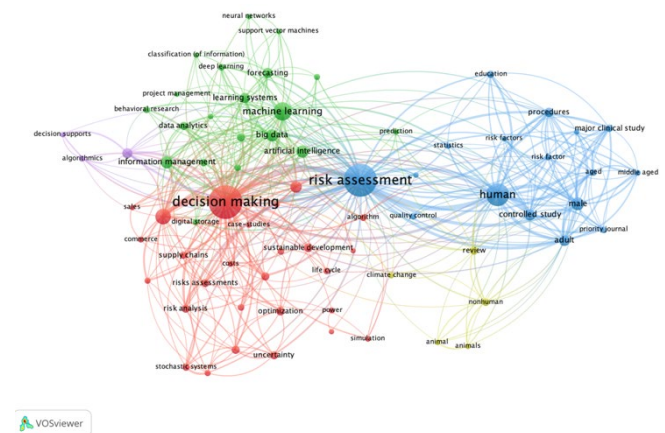
To gain a comprehensive understanding of the role of statistical thinking in engineering decision-making under uncertainty, this section presents an integrated analysis of both semantic and bibliometric search results. The dual-approach, combining exploratory AI-enhanced search using Elicit with a structured Scopus search, enabled a comprehensive investigation of how statistical methods are being adopted, discussed, and applied across digitalized engineering domains.

### 4.1. Semantic Insights from Elicit Search



- Red cluster: decision-making and optimization;
- Blue cluster: risk assessment and human factors;
- Green cluster: machine learning and Artificial Intelligence integration;
- Purple cluster: information systems and algorithms support; and
- Yellow cluster: sustainability and environmental risk.

At the core of the visualization, the red cluster highlights decision-making as a central theme. It encompasses key topics such as uncertainty, risk analysis, optimization, supply chains, and commerce, reflecting the complexity of making informed choices under uncertain conditions. The strong interconnections within this cluster suggest a focus on how decision-makers navigate risks in economic and operational contexts, particularly in relation to cost management and digital storage.



**Figure 4.** Network visualization based on index keywords.

Closely linked to decision-making, the blue cluster ranges around risk assessment and human factors. This cluster includes controlled studies, risk factors, quality control, and procedures, indicating a strong connection to medical, social, and organizational risk management. The presence of demographic terms such as adult, male, aged, and middle-aged suggests that research in this area often intersects with healthcare, education, and human-centred

decision-making, where understanding risk implications is crucial.

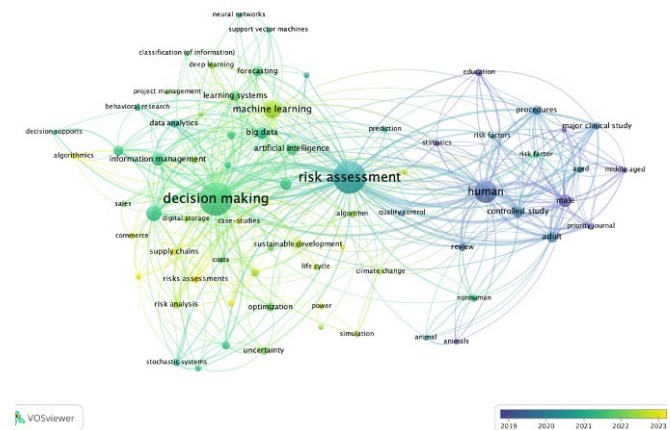
The green cluster introduces a technological perspective, focusing on machine learning, artificial intelligence, big data, and deep learning. This cluster highlights the growing role of data-driven decision-making, where predictive analytics, neural networks, and learning systems are increasingly used to enhance forecasting and information classification. The strong links between machine learning and decision-making suggest that statistical and computational methods progressively shape modern risk assessment and optimization strategies.

Complementing these clusters, the purple cluster focuses on information management, algorithms, and decision-support systems. Acting as a bridge between machine learning (green) and decision-making (red), this cluster underscores the importance of structured data processing and algorithmic approaches in improving decision outcomes. The connections within this cluster suggest a focus on how information is organized, analysed, and utilized to enhance decision-making accuracy.

Finally, the yellow cluster brings an environmental and sustainability perspective, linking risk assessment with climate change, sustainable development, and life cycle analysis. The presence of terms such as simulation and power indicates that environmental decision-making relies heavily on modelling techniques to assess long-term impacts and sustainability strategies. This cluster highlights the integration of statistical methods and simulation tools in addressing global environmental risks and energy management challenges.

### 4.3. Temporal Evolution of Research Topics

The overlay visualization (Figure 5) provides insights into the evolution of indexed research topics over time, with colours indicating the average publication year of documents associated with each term. Older research (2019-2020) is represented in darker shades (blue/purple), indicating foundational work on traditional decision-making and deterministic modelling. More recent developments (2022-2023) are represented in brighter shades (green/yellow), highlighting the increasing relevance of machine learning, sustainability, and AI-driven decision-making.



**Figure 5.** Overlay visualization of index keywords over the years.

#### 4.4. Strategic Role of Statistical Thinking in Digital Engineering Ecosystems

Findings from both the semantic and bibliometric analyses confirm that statistical thinking plays a pivotal role in the reliability, adaptability, and transparency of decision-making within digital systems. Key applications include:

- **Digital Twins and Predictive Maintenance:** Probabilistic models enable real-time uncertainty quantification in adaptive systems, informing model calibration and diagnostics;
- **Sensor Networks and Data Fusion:** Statistical reasoning facilitates the integration of heterogeneous sensor data through filtering, regression, and confidence estimation;
- **AI-Supported Human Decision-Making:** Dashboards enriched with uncertainty intervals, posterior distributions, or probabilistic forecasts enable experts to interact with algorithmic systems more effectively; and
- **Quality Control in Smart Manufacturing:** Tools like design of experiments (DoE) and multivariate control charts offer proactive mechanisms for digital quality assurance.

#### 4.5. Mapping to Digital Maturity and Innovation Trends

The convergence of statistical thinking and digital innovation aligns with key dimensions of Industry 4.0 and 5.0 maturity models, particularly in:

- Resilience: Ability to adapt under uncertainty through dynamic modelling;
- Transparency: Statistical approaches improve the explainability of automated systems;

- **Human-Centricity:** Techniques support ethical, informed, and inclusive decision-making; and
- **Integration:** Seamless coupling of probabilistic tools with AI, simulation, and cyber-physical infrastructures.

These findings suggest that future research should move beyond treating statistical analysis as a back-end tool and instead embed statistical thinking as a foundational layer in the digital innovation pipeline.

## 5. Conceptual Integration: Statistical Thinking as a Driver of Digital Transformation

The findings of this study underscore a critical shift: statistical thinking is not merely a support function in engineering workflows but a strategic enabler of innovation in digitalized systems. This section synthesizes the role of statistical reasoning in engineering innovation, drawing connections between bibliometric trends and conceptual needs for forward-looking practices.

Recent literature has highlighted the importance of uncertainty quantification in AI-driven systems, particularly digital twins, where probabilistic calibration improves model validity [24,25]. In such settings, data-driven methods that incorporate Bayesian updating and Monte Carlo simulations enhance real-time decision-making while safeguarding model transparency. Recent integrative reviews confirm that the convergence of Machine Learning, Digital Twins, and Edge AI is redefining industrial automation, enabling self-learning and uncertainty-aware decision-making in real time [26]. These findings reinforce the argument that probabilistic reasoning and statistical thinking are central to achieving transparent and resilient digital innovation in engineering practice.

Figure 6 shows how statistical thinking supports uncertainty management. It does this through systematic treatment of unknowns and variability. Both statistical thinking and uncertainty management directly support digital innovation. The framework shows strong links between probabilistic analysis, uncertainty quantification, and AI-based cyber-physical systems. Embedding these principles in human-centred education and professional practice builds resilience, encourages openness, and supports sustainable innovation in engineering.



**Figure 6.** Conceptual Framework: Statistical Thinking as an Enabler of Digital Innovation.

Moreover, digital ecosystems increasingly require data fusion from diverse sources, including sensor arrays and IoT infrastructures, which connect digital and physical devices. Statistical approaches, including sensor data fusion techniques such as Kalman filtering and multivariate regression, are essential for integrating heterogeneous sensor inputs within industrial cyber-physical systems. As Krishnamurthi and co-authors [27] show, when embedded into human-in-the-loop decision architectures, these methods enhance interpretability by quantifying confidence intervals and error bounds, thereby strengthening trust in real-time algorithmic outputs.

Significantly, the demand for statistical thinking extends beyond tools into education and training. To cultivate future-ready professionals, curricula must be restructured to include interdisciplinary competencies in statistical reasoning, data ethics, and uncertainty visualization. Initiatives such as hybrid learning platforms and industrial-academic partnerships have shown promise in this direction [28].

Collectively, these insights underscore the importance of statistical reasoning as a fundamental component in engineering education and the design of digital systems. Rather than relying solely on statistics to interpret results, engineers should integrate probabilistic reasoning from the outset, ensuring solutions remain precise and adaptable in the face of uncertainty.

## 6. Conclusions

This study investigated how statistical thinking can serve as a strategic enabler for engineering decision-making under uncertainty in digitalized industrial contexts. Combining an AI-powered semantic search via Elicit with a structured bibliometric analysis of 928 documents from

Scopus, the study employed a rigorous hybrid scoping review methodology to map research trends, uncover conceptual gaps, and synthesize cross-disciplinary insights.

Findings from both the semantics and bibliometric analyses show that while artificial intelligence, machine learning, and big data are increasingly integrated into engineering research, the explicit application of statistical methodologies for uncertainty quantification remains relatively underdeveloped. Despite their potential to increase robustness, transparency, and adaptability, probabilistic tools such as Bayesian inference, resampling methods, and uncertainty modelling techniques are not yet fully integrated into digital engineering workflows.

The overlay visualization of indexed keywords reveals a temporal trend toward digital innovation, with recent clusters highlighting machine learning, sustainability, and intelligent decision-support systems. However, the underrepresentation of statistical keywords signals a disconnection between data-driven technological advances and the epistemological rigor required for managing uncertainty.

This paper argues that statistical thinking should not be viewed merely as an analytical add-on but as a foundational competence for navigating complex and ambiguous systems. The discussion has shown that statistical methods can enhance interpretability in cyber-physical systems, support human-in-the-loop decision-making, and improve predictive reliability in dynamic and incomplete data environments. Sensor fusion architectures, for example, benefit from statistical models such as Kalman filters and multivariate regressions, particularly when embedded in frameworks where engineers must interpret uncertainty ranges in real-time.

To bridge current gaps, future research and practice should prioritize:

- Embed statistical literacy in digital engineering education: curricula must integrate foundational and advanced statistical reasoning to prepare future engineers for uncertainty-aware practice;
- Foster interdisciplinary collaboration: synergies between engineering, data science, and statistics are essential to develop hybrid decision-making frameworks that are both rigorous and application-ready;
- Develop AI-integrated statistical models: embedding statistical frameworks within AI pipelines can enhance algorithm interpretability, reliability, and trustworthiness in real-time industrial contexts;
- Promote real-world implementation: case studies and digital twin applications should demonstrate the practical value of statistical thinking in improving resilience, sustainability, and innovation outcomes.

These findings underscore the need for a paradigm shift. They advocate for the widespread integration of statistical thinking to enhance decision accuracy, improve risk mitigation, and support long-term sustainability strategies.

This study contributes to the ongoing discourse on uncertainty management in engineering by demonstrating that statistical thinking is not merely a supplementary tool but a core enabler of enhanced decision accuracy. Unlike deterministic models, which often oversimplify complex problems, probabilistic frameworks provide a more nuanced risk evaluation and optimization.

The key added value of this research lies in demonstrating that systematic integration of statistical thinking can lead to more cost-effective resource allocation, minimizing inefficiencies caused by conservative risk estimates; improved predictive capabilities, enhancing forecasting accuracy in engineering processes, and greater robustness in decision-making, thereby strengthening the resilience of engineering solutions under uncertainty.

Future research should advance the operationalization of this integration through collaborative design of uncertainty-aware tools, educational reform, and institutional support for data-driven innovation ecosystems.

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