International Journal of Simulation, Optimization & Modelling
ISSN: 3083-967X

Validation and Verification Techniques for Ensuring Accuracy in Modeling and Simulation Systems

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Abstract
Modelling and simulation have become indispensable tools across various scientific and engineering domains, supporting design optimization, risk evaluation, and policy decision-making. However, the increasing reliance on simulation outcomes necessitates rigorous verification and validation (V&V) to ensure model credibility, especially in high-impact fields such as aerospace, biomedicine, climate modelling, and defence. This study aims to review, compare, and synthesize contemporary V&V techniques and evaluate their practical effectiveness through domain-specific applications. Using a structured comparative methodology, we analyze core V&V practices, including code review, formal verification, experimental validation, predictive validation, and uncertainty quantification. A usage intensity scale (1–10) was introduced to quantify technique adoption, revealing that experimental data comparison is the most frequently applied method (9/10), followed by code review and uncertainty quantification (both 8/10). Case studies show that aerospace and defence domains report the highest V&V impact, with confidence gain and decision support rated at 9/10. At the same time, biomedical and climate modelling demonstrate slightly lower scores due to biological variability and system complexity. The novelty of this study lies in presenting an integrated cross-domain V&V framework and in highlighting the growing need for adaptive, hybrid validation methods tailored for emerging AI-driven and data-intensive models. Despite evident benefits, enhanced confidence, reduced costs, and improved decision-making challenges remain, particularly in novel simulation environments with limited validation data. In conclusion, this article reinforces the critical role of V&V in ensuring simulation reliability and calls for innovation in V&V strategies to match the evolving complexity of modern simulation systems.

Article Info	**Keywords**
Received: 02 April 2025	Modeling and Simulation
Revised: 25 April 2025	Verification and Validation
Accepted: 02 May 2025	Uncertainty Quantification
Available online: 21 May 2025	Predictive Validation
	Simulation Credibility

1. Introduction

Modeling and Simulation (M&S) has become indispensable in various engineering and scientific fields, including aerospace engineering, systems biology, manufacturing, and environmental sciences. As systems become complex, the reliance on simulations to support design decisions, risk assessments, and policymaking intensifies. This reliance brings forth a critical need for simulation results to be trustworthy, reproducible, and scientifically credible (Sargent, 2010). The sophistication of the model or the power of the computing platform does not inherently guarantee the accuracy and reliability of simulations. Instead, they are contingent upon rigorous Validation and Verification (V&V) processes. Verification addresses the question: "Are we building the model, right?" focusing on correctly implementing the model's conceptual description into code or a simulation platform. In contrast, Validation answers: "Are we building the right model?" assessing whether the model accurately represents the real-world system or phenomenon it intends to simulate (Roache, 1998).

Despite their conceptual distinctions, validation and verification are interdependent and collectively determine the credibility of simulation outcomes. Neglecting either aspect may lead to erroneous predictions, misinformed decisions, or costly failures in real-world applications, as documented in various high-stakes industries (Schwer, 2007, 2009; Thacker et al., 2004). Recent technological progress has led to increasingly complex systems in engineering and science, where physical experimentation is often costly, time-consuming, or impractical. In this context, modelling and simulation (M&S) have emerged as powerful surrogates for experimentation, enabling researchers and engineers to analyze system behaviour, evaluate design alternatives, and predict performance under varying conditions. Applications range from simulating aerodynamic performance in aerospace systems to evaluating epidemic spread in healthcare modelling. As simulation-based approaches become central to decision-making, ensuring these models produce trustworthy and accurate outputs becomes paramount.

However, building a model is only one aspect of the simulation process. The greater challenge lies in demonstrating that the model behaves as intended and accurately reflects the real-world system it aims to represent. A rigorous discipline has emerged around Verification and Validation (V&V) to formalize this process. These practices are now embedded in industry standards, regulatory protocols, and research methodologies across domains. Numerous studies have underscored that insufficient V&V can lead to significant failures, whether through design flaws in engineered systems, misguidance in policy simulations, or faulty predictions in safety-critical applications (Oberkampf & Roy, 2010; Thacker et al., 2004; WANG, Lin, & YUAN, 2010). This article aims to provide a comprehensive overview of widely accepted V&V techniques, highlighting their roles in ensuring accuracy in simulation models. We review classical and emerging methodologies, discuss practical implementations in selected domains, and explore future directions shaped by advances in artificial intelligence and uncertainty quantification. The scope is intended for researchers, engineers, and practitioners seeking to enhance the fidelity and robustness of their modelling practices through systematic validation and verification.

2. Fundamentals of Validation and Verification (V&V)

The credibility of a modelling and simulation system hinges on two fundamental processes: Verification and Validation. Though often discussed together, these processes serve distinct purposes and occur at different stages of the simulation lifecycle. Verification confirms that the model has been implemented correctly within the simulation environment. It seeks to answer the question: "Are we building the model, right?" This step involves checking the model's internal consistency, ensuring that the algorithms, numerical methods, and code logic are functioning as intended. Standard techniques include code inspections, software debugging, consistency checks, sensitivity analysis, and convergence testing. The need for order-of-accuracy verification, which uses grid refinement and error estimation to verify numerical solutions' fidelity, is emphasized in previous work (NOOR, Arif, & Rusirawan, 2025; Roache, 1998; Sumarno, Fikri, & Irawan, 2025). Errors at this stage typically stem from programming bugs, discretization errors, incorrect boundary conditions, or misused algorithms (Febrina & Anwar, 2025; Rosli, Xiaoxia, & Shuai, 2025; Sargent, 2010).

On the other hand, Validation refers to the process of determining the degree to which a model accurately represents the real-world system it is intended to simulate. This process answers the question: "Are we building the right model?" Validation often involves comparing simulation outputs to empirical data from experiments, historical datasets, or expert knowledge. Validation requires clear identification of the model's intended use, characterization of uncertainties, and statistical comparisons with observational data (Iqbal, Rosdi, Muhtadin, Erdiwansyah, & Faisal, 2025; WANG et al., 2010; Xiaoxia, Lin, & Salleh, 2025). Models can be "validated" partly for specific conditions but rarely universally validated across all scenarios. Typical sources of validation error include inaccurate input data, poor assumptions about physical behaviour, or mismatched scales between simulation and real systems. The relationship between verification, validation, and model credibility is critical. A model may be correctly verified (i.e., free from programming errors) but still fail to represent the real system, making it invalid. Conversely, a conceptually accurate model that is poorly implemented can produce misleading results due to computational faults. Only through rigorous application of both V&V can a model attain credibility, which is the degree to which stakeholders trust the model to support decision-making (Khayum, Goyal, & Kamal, 2025; Thacker et al., 2004; Yanti, Simajuntak, & Nurhanif, 2025). Familiar sources of errors in modelling and simulation can be grouped into four categories: conceptual model errors, data-related errors, software implementation errors, and user-induced errors. Conceptual errors arise from incorrect assumptions or system abstraction; data-related errors involve noise, bias, or missing information; software errors stem from flawed code or numerical instability; while user-induced errors result from misinterpretation, inappropriate parameter settings, or incorrect usage of simulation tools (Jalaludin, Kamarulzaman, Sudrajad, Rosdi, & Erdiwansyah, 2025; Muhtadin, Rosdi, Faisal, Erdiwansyah, & Mahyudin, 2025; Sargent, 2010). Understanding and mitigating these errors is essential for ensuring model robustness, reproducibility, and defensibility in real-world applications.

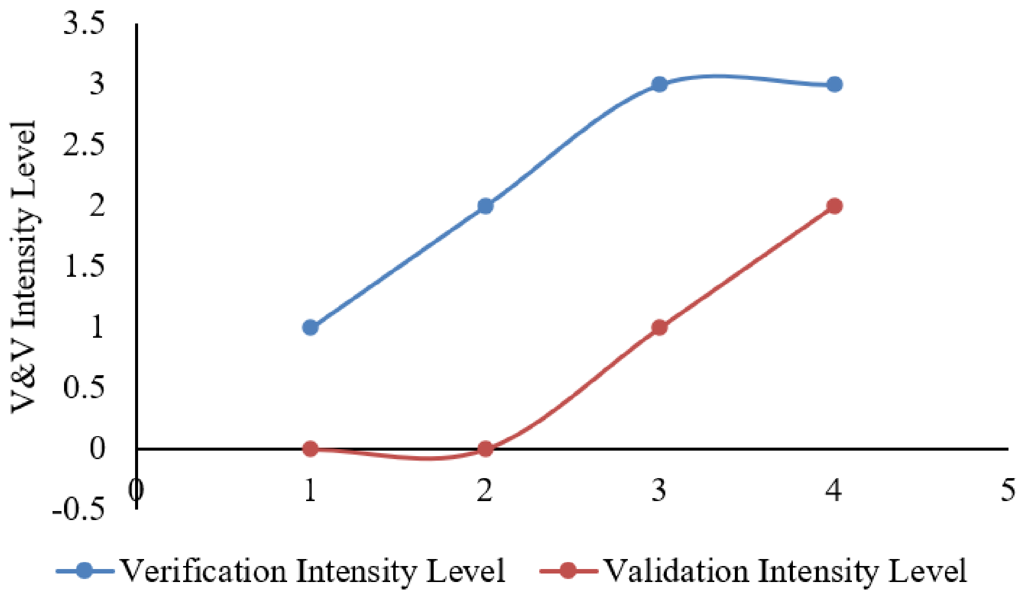

Fig. 1. Progression of Verification and Validation Activities in Modeling

Fig. 1 illustrates the progression of Verification and Validation intensity levels throughout different stages of model development. The chart shows that Verification plays a dominant role in the early and middle phases, from model specification to solution verification. This highlights the importance of ensuring the model is constructed correctly from a computational and algorithmic standpoint. Its intensity peaks during the solution verification stage, where numerical accuracy, code correctness, and stability analysis are most critical. In contrast, Validation begins with low intensity and gradually increases toward the later stages of model development. This is because validation depends heavily on the availability of empirical or observational data, which typically becomes relevant only after the model has been fully implemented and verified. A significant rise in validation efforts is observed during the final stage, where the model is assessed against real-world data to determine its representational accuracy. This progression divergence reflects the two processes' different focuses: Verification ensures internal consistency and correct implementation. At the same time, Validation evaluates the external accuracy of the model in representing real-world phenomena. Both are complementary and essential for establishing model credibility. Understanding how these activities evolve during the modelling lifecycle helps developers plan an efficient and structured approach to V&V execution.

Table 1. Familiar Sources of Error in Modeling and Simulation

Error Category	Description	Impact
Conceptual Model Errors	Incorrect assumptions or misrepresentation of system behaviour.	Misaligned model objectives; invalid outputs.
Data-Related Errors	Noisy, biased, incomplete, or outdated data inputs.	Reduced accuracy and reliability of simulation.
Software Implementation Errors	Programming bugs, numerical instability, or algorithm misuse.	Faulty outputs despite correct model logic.
User-Induced Errors	Improper use of tools, misinterpretation of results, or parameter misconfiguration.	Misleading interpretations and operational errors.

Table 1 categorizes the familiar sources of errors encountered during developing and applying modelling and simulation (M&S) systems. Understanding these error categories is essential for implementing adequate verification and validation (V&V) strategies to ensure the credibility of simulation outcomes. The first category, Conceptual Model Errors, arises from flawed assumptions or an inaccurate abstraction of the real system. These errors often occur during the early stages of model design, where an incorrect understanding of system behaviour leads to invalid outputs and misaligned model objectives. Even if the implementation is technically sound, a model built on the wrong foundation cannot yield meaningful results.

Data-related errors involve issues with the quality and relevance of input data. These may include outdated datasets, biased sampling, or incomplete observations. Since validation relies heavily on accurate data comparisons, such errors significantly reduce the reliability and accuracy of simulation results. Effective data pre-processing and uncertainty quantification are essential to mitigate this class of errors. Software Implementation Errors occur during the coding and computational phase. These may stem from programming bugs, numerical instabilities, or improper algorithm usage. Despite a correct conceptual model, such technical flaws can produce faulty results, undermining the credibility of the simulation. Verification techniques such as code reviews, debugging, and convergence analysis are used to address these issues.

Finally, User-Induced Errors refer to mistakes made during the application or interpretation of the model. These include misuse of simulation tools, incorrect parameter settings, and misinterpreting results. While sometimes overlooked, these errors can lead to critical misjudgments, especially in high-stakes decision-making. Training, user guidance, and robust interface design are vital in reducing human-induced failures. **Table 1** highlights that modelling and simulation errors originate from technical and human factors. Recognizing and addressing each category systematically through V&V practices is key to achieving robust, reliable, and trustworthy simulation systems.

3. Techniques and Methodologies for V&V

Various well-established verification and validation techniques have been developed across different disciplines to ensure the trustworthiness of simulation models. These methods are designed to detect errors and inconsistencies in model development and build confidence in using simulation results for decision-making, design, and prediction. Verification techniques are primarily concerned with ensuring the model has been correctly implemented. One foundational method is code review and formal verification, in which simulation code is systematically examined to identify programming flaws, inconsistencies, or logical missteps. Formal methods, such as model checking or symbolic execution, apply mathematical principles to verify that the software adheres strictly to its specifications (Muzakki & Putro, 2025; Nizar et al., 2025; Roache, 1998). Additionally, debugging and error tracing are used extensively during implementation to track abnormal behaviour, trace variables, and identify faulty code segments that may not align with the conceptual model.

Another widely applied technique is sensitivity analysis, which involves systematically varying input parameters to determine their impact on output results. Sensitivity analysis helps uncover instabilities in the model. It can identify parameters that disproportionately influence outcomes, thereby directing attention to parts of the model that require more precise calibration or refinement (Almardhiyah, Mahidin, Fauzi, Abnisa, & Khairil, 2025; Paruggia, 2006; Saltelli, Tarantola, Campolongo, & Ratto, 2004). In parallel, numerical accuracy checks, including mesh refinement, discretization error analysis, and convergence testing, verify that the numerical methods produce results that approximate accurate solutions with acceptable error margins (Mufti, Irhamni, & Darnas, 2025; Pranoto, Rusiyanto, & Fitriyana, 2025; Roache, 1998). Conversely, validation focuses on whether the model accurately represents the real-world system or phenomena it seeks to simulate. A key technique in this process is comparing model results with experimental or observational data. This direct comparison, often supported by statistical metrics such as RMSE, MAE, or R^2, is the most objective means of assessing model validity (Rosdi, Maghfirah, Erdiwansyah, Syafrizal, & Muhibbuddin, 2025; Sargent, 2010; Selvakumar, Maawa, & Rusiyanto, 2025). When experimental data is limited or unavailable, historical data comparisons may be an alternative, particularly in fields such as climate science or epidemiology, where long-term records provide a benchmark for validation.

In early development phases, face validation is frequently employed. This involves the expert review of model logic and behaviour to determine whether results align with expectations based on domain knowledge. While subjective, face validation benefits complex systems or cases with limited data (Balci, 1994; Fitriyana, Rusiyanto, & Maawa, 2025; Muhibbuddin, Hamidi, & Fitriyana, 2025). Predictive validation is more rigorous, where the model is tested against scenarios or datasets not used during development or calibration. If the model demonstrates high accuracy under these conditions, its predictive credibility is strengthened (Bahagia, Nizar, Yasin, Rosdi, & Faisal, 2025; Khalisha, Caisarina, & Fakhrana, 2025; WANG et al., 2010). Researchers often incorporate statistical and uncertainty quantification methods to enhance the validation process's robustness further. Tools such as Monte Carlo simulations, probabilistic sensitivity analysis, and Bayesian inference allow analysts to evaluate the accuracy, uncertainty, and variability in model predictions. These techniques enable a deeper understanding of model behaviour under uncertainty and help quantify output confidence intervals (Kennedy & O'Hagan, 2001; Plumlee, 2017; Yana, Mufti, Hasiany, Viena, & Mahyudin, 2025).

Finally, various standards and frameworks support the structured implementation of these V&V techniques. For example, the IEEE 1516 standard guides verification protocols in distributed simulation environments using the High-Level Architecture (HLA). In engineering contexts, particularly in computational mechanics, the ASME V&V 10-2006 standard offers detailed procedures for verifying and validating solid mechanics models. These frameworks standardize terminology and procedures and promote best practices and documentation to enhance transparency, repeatability, and regulatory compliance. In sum, the rigorous application of these verification and validation methodologies is essential for ensuring the credibility of modelling and simulation systems. As models increasingly inform critical decisions in engineering, science, policy, and industry, the importance of robust V&V practices continues to grow.

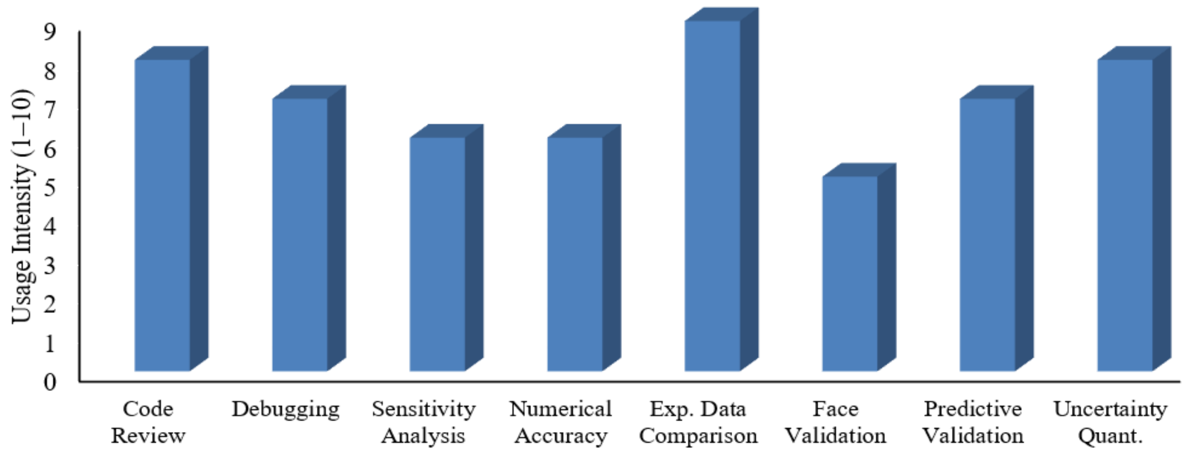

Fig. 2. Common Techniques Used in Verification and Validation (V&V)

Fig. 2 illustrates the relative intensity of various verification and validation (V&V) techniques within the modelling and simulation (M&S) community. The vertical axis represents usage intensity on a scale of 1 to 10, with higher values indicating broader or more frequent application across domains. The chart reveals that experimental data comparison is the most frequently employed technique, with a usage intensity of 9. This reflects the high value placed on empirical validation, where model outputs are benchmarked directly against observed or measured data. Such comparisons are considered one of the most objective and robust forms of validation. Code review and uncertainty quantification also exhibit high usage (8 out of 10), emphasizing the importance of early-stage verification and post-simulation analysis to ensure reliability under uncertain inputs. Debugging and predictive validation score moderately high (7), underscoring their dual role in providing technical soundness and forward-looking credibility, respectively.

Sensitivity analysis and numerical accuracy checks have a usage intensity of 6, indicating their role in refining model performance and assessing solution stability. While essential, they are typically used in more specialized applications or after baseline verification. Face validation, scoring 5, is the least frequently used among the listed techniques. Although subjective, it remains valuable in the early stages of model development or when data is limited, as it allows domain experts to assess the realism of model behaviour. Overall, the figure highlights that no single V&V technique suffices in isolation. Instead, a combination of methods is typically employed depending on the model's complexity, application domain, data availability, and decision-making context. The diversity in usage intensity reflects the flexibility and layered structure of the V&V process in modern simulation practice.

Table 2. V&V Techniques Summary

Technique	Purpose	Application Phase
Code Review	Detect implementation errors and code flaws	Verification
Formal Methods	Prove the logical correctness of the model	Verification
Debugging	Identify and resolve runtime anomalies	Verification
Sensitivity Analysis	Assess the influence of input variation on outputs	Verification
Numerical Accuracy Checks	Verify convergence and numerical accuracy	Verification
Experimental Data Comparison	Validate outputs against empirical measurements	Validation
Historical Data Comparison	Use past datasets for indirect validation	Validation
Face Validation	Subjective review by domain experts	Validation
Predictive Validation	Test predictions under unseen scenarios	Validation
Uncertainty Quantification	Quantify output uncertainty due to input variability	Validation

Table 2 concisely overviews key techniques employed in the Verification and Validation (V&V) process within modelling and simulation workflows. Each method is categorized based on its primary purpose and role within either the verification or validation phase, offering valuable guidance for simulation practitioners to select appropriate methods. In the verification phase, techniques ensure the model has been correctly implemented according to its conceptual design. Code review is a foundational method that involves the inspection of source code to detect implementation errors or logical inconsistencies. Formal methods, though more mathematically rigorous, are especially valuable in critical applications, as they help prove the correctness of algorithms based on formal logic. Debugging is a practical approach to identifying and resolving runtime anomalies during model execution. Sensitivity analysis and numerical accuracy checks are analytical tools to ensure that the model behaves consistently when parameters are varied and that numerical results converge as expected key indicators of model stability and fidelity.

In contrast, the validation phase assesses whether the model accurately represents the real-world system it is intended to simulate. Experimental data comparison remains the most direct and robust validation technique, involving the alignment of simulation outputs with measured empirical data. When such data is unavailable, historical data comparison offers an alternative by leveraging past observations for validation. Face validation provides a qualitative assessment wherein domain experts evaluate whether the model behaves as expected based on their knowledge. Predictive validation furthers the assessment by testing the model's ability to generalize and predict unseen conditions, strengthening its external validity. Lastly, uncertainty quantification addresses the inherent variability in input data and models by analyzing its effect on outputs, an essential technique for evaluating model robustness and confidence levels. Overall, Table 2 underscores that effective V&V requires a multi-faceted approach. No single technique suffices across all scenarios. Instead, an integrated framework that combines several methods tailored to the simulation's objective, complexity, and data availability ensures the development of reliable, credible, and decision-worthy models.

4. Case Studies and Applications

Practising verification and validation (V&V) techniques across diverse domains have significantly improved simulation accuracy, credibility, and decision support. This section presents selected case studies from key industries such as aerospace, biomedical modelling, climate simulation, and defence, illustrating the benefits and challenges of rigorous V&V practices. In the aerospace industry, V&V is critical to ensuring the safety and performance of flight systems. For instance, NASA's development of computational fluid dynamics (CFD) models for spacecraft re-entry relied heavily on solution verification through grid convergence testing and model validation using wind tunnel data (Gani, Saisa, et al., 2025; Irhamni, Kurnianingtyas, Muhtadin, Bahagia, & Yusop, 2025; Oberkampf & Roy, 2010). Similarly, Boeing integrates predictive validation and uncertainty quantification in the structural simulation of aircraft components to meet FAA certification requirements. These practices reduce the need for physical prototyping, saving time and cost while enhancing safety assurance (Gani, Zaki, Bahagia, Maghfirah, & Faisal, 2025; Maghfirah, Yusop, & Zulkifli, 2025; Roache, 1998). V&V is increasingly applied to patient-specific models such as cardiovascular simulations, orthopedic implants, and drug delivery systems in biomedical engineering. For example, V&V is essential in silico trials to ensure regulatory acceptance (Morrison, Stitzel, & Levine, 2023; Selvakumar, Gani, Xiaoxia, & Salleh, 2025; Viceconti, Henney, & Morley-Fletcher, 2016). Using clinical data for validation and finite element verification for mesh sensitivity enables accurate predictions of physiological responses. Despite advances, challenges persist due to biological variability and limited access to high-resolution experimental data.

Climate and environmental modelling represent another complex domain where V&V plays a vital role. Global climate models (GCMs) are validated using historical data and satellite observations to predict future climate scenarios. However, climate systems' nonlinear and chaotic nature makes verification and validation inherently difficult (Hourdin et al., 2017; Schmidt et al., 2017; Zaki, Adisalamun, & Saisa, 2025). Ensemble simulations and statistical comparisons are thus used to assess model reliability. Here, V&V provides confidence for policymakers in climate risk assessment and mitigation planning. In defence, simulation models are used for training, mission planning, and threat assessment. To ensure operational relevance, the U.S. Department of Defense (DoD) mandates adherence to the DoD Modeling and Simulation Verification, Validation, and Accreditation (VV&A) framework. A key benefit is enhanced decision-making speed during combat simulations, attributed to pre-validated model libraries and structured V&V protocols (Davis & Anderson, 2004; Efremov & Kumarasamy, 2025; Li, Ikram, & Xiaoxia, 2025). However, incorporating real-time sensor feedback and adapting to evolving battlefield conditions pose continuous validation challenges.

Across various domains, the application of rigorous verification and validation (V&V) techniques has demonstrated multiple benefits. One of the most significant is the improved confidence in simulation results, which is especially critical in safety-critical systems where decisions must be based on trustworthy outcomes. Additionally, using reliable predictive models enhances the quality of decision-making by providing stakeholders with greater clarity and foresight. Another significant advantage is the reduction in overall development costs and time, as rigorous V&V practices reduce the need for extensive physical experimentation or prototyping by confirming model fidelity early in the design cycle. Despite these advantages, implementing V&V remains challenging, particularly in emerging or data-scarce fields. A primary obstacle is the limited availability of high-quality validation data, often in areas such as synthetic biology or autonomous systems. Moreover, defining appropriate validation metrics becomes increasingly complex when dealing with multi-scale, highly nonlinear, or stochastic models. The computational cost of performing thorough uncertainty quantification, especially involving extensive ensemble simulations, also presents a significant barrier. Another emerging difficulty lies in verifying models driven by artificial intelligence or machine learning, which frequently lack clear interpretability and do not conform to formal specifications (Allah, Toor, Shams, & Siddiqui, 2025; He, Dai, & He, 2025; Neudecker et al., 2020). In response to these challenges, recent research has proposed hybrid V&V approaches integrating data-driven modelling techniques with physics-based constraints. Furthermore, adaptive V&V frameworks are gaining traction, which allows validation protocols to evolve alongside the growing complexity and maturity of the models they support. These developments offer a promising path for maintaining simulation credibility in increasingly dynamic and data-intensive environments.

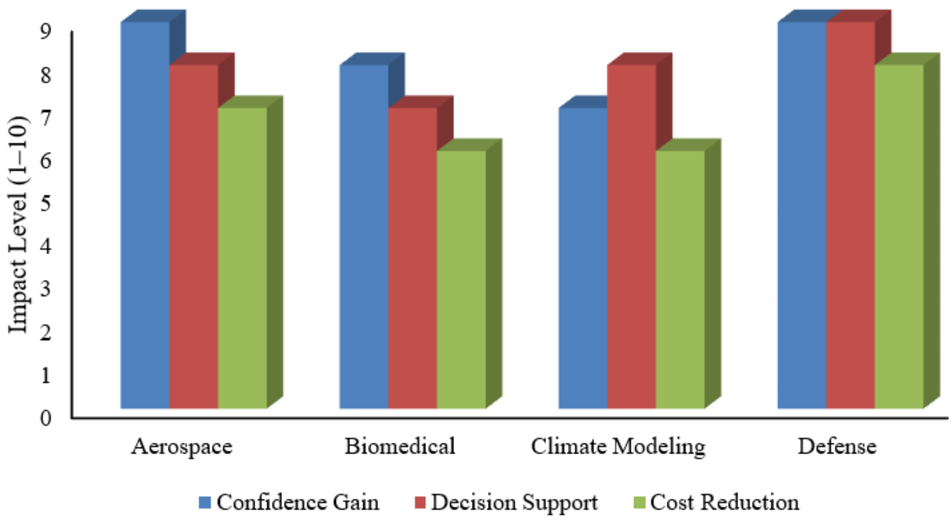

Fig. 3. Impact of V&V Across Different Application Domains

Fig. 3 illustrates the perceived impact of Verification and Validation (V&V) practices across four major domains: aerospace, biomedical, climate modelling, and defence. The effect is assessed based on three key criteria: confidence gain, decision support, and cost reduction, each measured on a scale from 1 to 10. In the aerospace domain, V&V demonstrates the highest level of effectiveness across all three criteria. Confidence gain reaches a peak of 9, underscoring the critical role of V&V in ensuring system reliability and safety, especially for flight-critical applications. Similarly, high scores in decision support (8) and cost reduction (7) reflect the value of V&V in streamlining the design process and minimizing reliance on costly physical testing. The biomedical sector also benefits significantly from V&V practices, particularly in enhancing model confidence (score: 8) and supporting clinical decision-making (score: 7). However, the slightly lower score in cost reduction (6) highlights the ongoing challenge of accessing sufficient and consistent patient-specific data for validation purposes.

V&V contributes substantially to informed decision-making for climate modelling, with an impact level of 8 for decision support. This is critical for policy formulation and climate risk assessments. The relatively lower scores for confidence gain (7) and cost reduction (6) reflect inherent challenges in validating highly nonlinear and chaotic environmental systems and the computational resources required for ensemble simulations. In the defence domain, all three impact indicators score highly on confidence gain, decision support at 9, and cost reduction at 8, highlighting the maturity of structured V&V frameworks such as the DoD VV&A process. These practices support rapid and reliable mission simulations, increasing operational readiness and reducing the risks and costs associated with real-world exercises. Overall, the figure emphasizes that while the degree of impact may vary by domain, the implementation of rigorous V&V consistently leads to improved model credibility, enhanced decision-making capability, and operational efficiency. It also illustrates that the effectiveness of V&V is closely tied to the availability of domain-specific data, computational resources, and regulatory frameworks.

Table 3. V&V Case Studies Summary

Domain	V&V Benefits	Key Challenges
Aerospace	High safety assurance, reduced prototyping cost	High complexity of fluid-structure interaction models
Biomedical	Regulatory compliance, patient-specific accuracy	Limited clinical data, biological variability
Climate Modeling	Credible forecasts, policy support	Nonlinearity, limited observability
Defence	Fast, reliable mission simulations	Adapting models to real-time battlefield updates

Table 3 summarises the benefits and challenges of implementing Verification and Validation (V&V) techniques across four key domains: aerospace, biomedical, climate modelling, and defence. Each domain showcases distinct motivations for applying V&V, as well as unique obstacles that influence the effectiveness and feasibility of these processes. In the aerospace sector, applying V&V yields critical benefits such as high safety assurance and a significant reduction in prototyping costs. This is primarily due to the ability of simulation models to predict performance under extreme conditions without the need for extensive physical testing. However, the domain is also characterized by the high complexity of fluid-structure interaction models, which require rigorous numerical verification and sophisticated experimental validation procedures, often involving wind tunnel data and high-fidelity simulation.
The biomedical domain leverages V&V to meet regulatory compliance standards and enhance patient-specific models' accuracy. This is particularly relevant in virtual clinical trials, implant simulations, and drug delivery systems. Nonetheless, a significant challenge lies in the limited availability of clinical data and biological variability among individuals, which complicates the verification of model mechanics and the validation against empirical outcomes. For climate modelling, V&V supports credible forecasting and evidence-based policy formulation. Validation typically relies on historical records and observational datasets, which serve as benchmarks for global and regional climate predictions. However, the nonlinearity of climate systems and limited observability of certain atmospheric and oceanic variables make model validation a significant scientific challenge. Ensemble methods and uncertainty quantification are frequently employed to enhance model reliability.
V&V enables fast and reliable mission simulations in the defence domain, which is essential for operational planning and real-time decision-making. Benefits are observed in improved readiness and lower cost compared to live exercises. Still, adapting simulation models to real-time battlefield updates introduces complexity, as models must remain accurate and valid while dynamically integrating sensor data and evolving scenarios. Overall, Table 3 illustrates that while the benefits of V&V are substantial and domain-specific, the challenges are often technical, computational, or data-related. Addressing these challenges requires customized V&V strategies, integration of hybrid modelling approaches, and ongoing investment in data infrastructure and modelling tools tailored to each domain.

5. Conclusion

This article has comprehensively examined the techniques, applications, and benefits of Verification and Validation (V&V) in modelling and simulation (M&S) systems across multiple domains. As simulation increasingly becomes the backbone of design, prediction, and decision-making, especially in high-stakes fields such as aerospace, biomedicine, climate science, and defence, the demand for rigorous and adaptive V&V frameworks continues to grow. From the analysis, experimental data comparison emerged as the most widely applied validation method, scoring a usage intensity of 9/10, followed closely by code review and uncertainty quantification (8/10) across disciplines. These figures reflect the strong preference for empirical validation and robust error estimation to ensure simulation reliability. The domain-specific impact analysis also revealed notable findings. Aerospace and defence sectors reported the highest V&V benefits, with confidence gain and decision-making impact reaching 9/10. At the same time, biomedical and climate modelling domains scored slightly lower due to inherent challenges such as data scarcity and model complexity. In addition, the defence sector highlighted

V&V's role in achieving real-time simulation reliability, an increasingly crucial capability in modern adaptive and autonomous systems. Across all case studies, three significant benefits of rigorous V&V were consistently evident: (1) enhanced confidence in model credibility, (2) improved decision-making capabilities, and (3) significant reductions in development costs and testing cycles.

However, several challenges persist, particularly in emerging fields like synthetic biology or AI-integrated systems, where traditional V&V frameworks struggle due to limited interpretability, lack of formal specification, and high uncertainty. Addressing these issues calls for hybrid V&V approaches that integrate data-driven modelling with physics-informed constraints and the development of adaptive validation workflows that evolve with model maturity and complexity. In conclusion, while V&V methodologies have matured significantly and demonstrated substantial value, the next frontier lies in expanding their applicability to novel, complex, and learning-based models. As such, future research must prioritize scalable, explainable, and automated V&V solutions to ensure that simulation remains a reliable foundation for decision-making in an increasingly digital and dynamic world.

Acknowledgement

The authors would like to sincerely thank all contributors involved in preparing this work. This research was conducted without external financial support and fully funded by the authors. No grants, sponsorships, or institutional funding were received from governmental, commercial, or non-profit organizations. The independent nature of this work reflects the shared commitment of the authors to advancing the understanding and application of verification and validation techniques in modelling and simulation systems.

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