Research Article

Intelligent Ballistic and High-Performance Mechanical Systems: A Systematic Review of Artificial Intelligence, Metaheuristic Optimization, Advanced Materials, Thermofluids, Structural Dynamics, And Reliability

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Abstract

Objective: This systematic review maps the relationships among artificial intelligence (AI), metaheuristic optimization, advanced materials, thermofluids, structural dynamics, and reliability in ballistic and high-performance mechanical systems.

Methods: The review follows PRISMA 2020 guidelines and screens records published from 1 January 2020 to 18 October 2026 across Google Scholar, ScienceDirect, SpringerLink, Wiley Online Library, MDPI, CNKI, and Wanfang Data. A six-domain engineering appraisal framework rates model validation, uncertainty reporting, baseline comparison, reproducibility, scale bridging, and engineering relevance for each included study.

Results: Sixteen studies meet the eligibility criteria. Eight studies use experimental data or tests as their primary validation basis, seven use numerical validation, and one uses statistical inference with experimental data. Materials and structural dynamics appear most frequently, in ten and nine studies respectively. Artificial intelligence appears in seven studies, thermofluids in three, optimization in three, and reliability in three. Two studies couple learning models with optimization, and two studies link learning models with uncertainty quantification. Thermal and structural analysis share one study.

Conclusions: The evidence indicates strong progress within individual domains but weak coupling across domains. Future work requires experimentally validated, uncertainty-aware, surrogate-assisted frameworks for protective and launch systems.

Keywords: intelligent ballistics, machine learning, metaheuristic optimization, armor materials, interior ballistics, structural dynamics, reliability, systematic review.

1 Introduction

Science and high performance mechanical engineering now use techniques from a number of disciplines to help ballistic science [21-22]. Protection systems need to be able to withstand higher threats at a lower mass, and designers must be able to make quick predictions with unpredictable loading. These needs are covered by computational intelligence, materials design, structural analysis, thermofluid modeling and reliability assessment, among others.

Prediction of the terminal ballistic effects applies to a broad range of projectiles and targets, with the help of machine learning [23-25]. Using gradient boosting, NN, SVM-R, and GP regression gives comparable accuracy within the range of data, whereas physics-informed models resort to physical models beyond the data. A hybrid model is used in [2] to predict residual velocity in fiber composites using an energy balance mechanics model and random forests. A method combining the finite element data and learning models is used to rank the properties that influence the penetration depth in ceramic studies [3]. Zhu et al. [4] propose to use support vector machines to classify the penetration state and deep neural networks to predict the residual energy and deformation of the validated finite element models.

Optimization methods are used to solve the problem of multiple simulation [26-28]. An optimization of a RVE is performed using a surrogate built from a support vector regression and the NSGA-II algorithm to minimize the armor residual velocity and areal density, for a titanium, silicon carbide and polyethylene armor [5]. To find out the constitutive parameters of the ultra-high-strength steel by limited experiments, a chaos-based global optimizer is used in this paper [6]. Annunziata et al. [7] use a genetic algorithm topology optimization based on graph to resist bullet and fragment attack.

The models are based on materials research [29-31]. The behavior of alumina, carbon fiber and polyethylene armor under armor-piercing impact is characterized via experiments and FEA [8]. There is an empirical equation that relates ceramic mechanical properties with the ballistic efficacy [9]. The effects of rate, temperature and stress state are needed in order to capture failure in constitutive models of fiber metal laminates [10].

Interior ballistics relates the combustion, flow and the projectile motion [32, 33]. A coupled model which combines classical interior ballistics and computational fluid dynamics is used in underwater launch [11]. The initial pressure wave in a modular charge chamber can be resolved with 3-D gas-solid models [12]. The thermal model delivers the interior ballistic performance results to the finite element model of heat transfer in a 120 mm smoothbore barrel [13].

Structural response data and probabilistic tools anchor validation [34, 35]. Buried charge tests are performed on the Armox 440T plates to yield a deformation benchmark and a regression relation between the size of the charge, plate thickness and deformation [14]. The idea of Maximum likelihood inference is related to a Brownian motion model of estimating probability of perforation based on binary test results [15]. Sun and Liu [16] formulate uncertainty quantification for ballistic impact problems optimally, based on a learning approach, which is developed for magnesium alloys.

Previous reviews have examined specialized aspects of ballistic engineering. Ongaro et al. [19] reviewed mathematical and computational approaches to internal ballistics, whereas Reis et al. [20] examined optimization strategies for multilayered armor systems. These contributions provide important domain-specific insights but do not offer a common evidence map comparing artificial intelligence, metaheuristic optimization, advanced materials, thermofluids, structural dynamics, and reliability. The present review addresses this narrower mapping gap by examining the co-occurrence of these six domains within the selected studies and comparing their research designs, validation approaches, uncertainty reporting, and reproducibility. Its contribution is a descriptive, non-causal framework for identifying methodological patterns and potential directions for further investigation [36, 37]. Figure 1 presents the co-occurrence matrix for the six reviewed domains across the 16 included studies, showing both single-domain frequencies and observed pairwise integration within the evidence base.

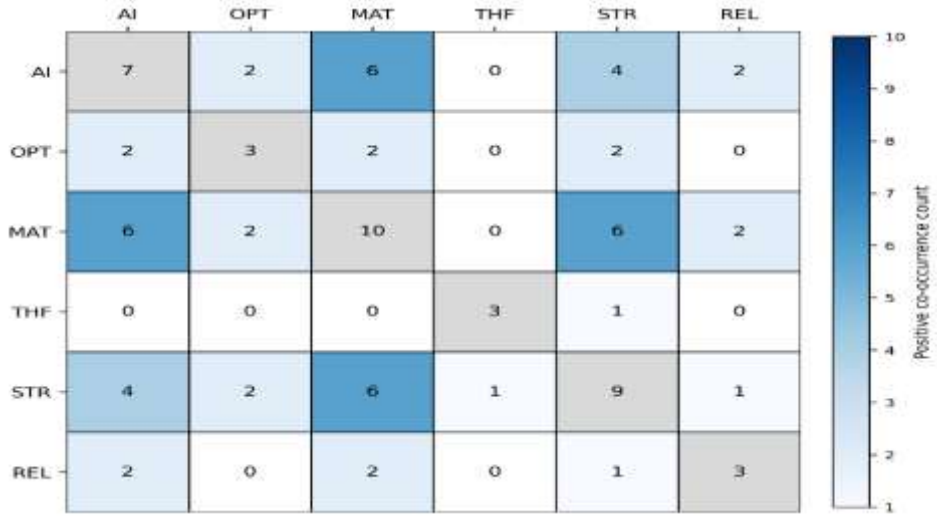


Figure 1. Domain co-occurrence across the 16 included studies. Diagonal values indicate the number of studies assigned to each domain; off-diagonal values indicate the number of studies engaging both domains. Co-occurrence does not imply causation or demonstrated technical integration.

The review is organized around four research questions.

- **RQ1:** Which artificial intelligence, optimization, material, thermofluid, structural, and reliability approaches are investigated, and for which ballistic applications?
- **RQ2:** Which domain pairs are integrated within individual studies, and what evidence supports their reported performance or engineering utility?
- **RQ3:** How do study design, application context, validation source, and uncertainty treatment influence the interpretation of reported outcomes?
- **RQ4:** Which reproducibility, validation, uncertainty, and cross-domain integration gaps warrant priority in future research?

2 Methods

2.1 Review design and reporting

This review, which takes a systematic and evidence-mapping approach, looks at the presence of six engineering domains in single and combined mechanical systems involving ballistics and high performance. The unit of analysis is the included study, which is coded by the substantive domain engagement, application context, the design of the study, the basis for the study's validation, and the reported outcomes. This enables this review to report the frequency of each domain as well as the extent of two domains in the same study. This review is not prospective registered. The reporting of these review methods, eligibility criteria, screening pathway, extraction fields and appraisal rules are therefore transparent to readers and are reported in this manuscript and the supplementary material to allow for examination of the decisions made during the review. Identification, screening, eligibility to include and inclusion in PRISMA 2020 using the framework. The review is descriptive in nature, rather than being a

meta-analysis, due to the variability in the engineering systems, validation settings, outcome measures and performance indicators used in the included studies. For this reason, the synthesis focuses on study-level evidence that can be traced back to the specific study, and doesn't "pooled" unlike numerical outcomes. The review was reported using the PRISMA 2020 statement and its explanation and elaboration guidance [17,18]. The review was not prospectively registered.

2.2 Information sources and search strategy

Records of the search are for publications from 1 January 2020 to 18 October 2026. Google Scholar, ScienceDirect, SpringerLink, Wiley Online Library, MDPI, CNKI and Wanfang Data are the sources used. The search strings, the logic used in different databases, the number of records returned and dates of the searches are recorded in Table S2 and the summary of the search records in Table S19. Publications are also searched in English and Chinese language. The search logic that was used primarily in the English language includes three concept groups: machine learning or metaheuristic methods or optimization; ballistic systems or armor or impact; and composites, ceramics, thermofluids or reliability. The equivalent Chinese search logic is rewritten as: Change the terms in the search logic, and the full search logic is translated as follows: (machine learning OR metaheuristic methods OR optimization) AND (ballistic OR armor OR impact) AND (composite materials OR ceramics OR thermofluids OR reliability). The English version does not introduce any more concepts of the search than the Chinese version. It allows retrieval to be done across databases, while keeping the documentation of the particular syntax for the database. The search sources include engineering publications with multi-discipline coverage, and indexing of Chinese-language publications. The counts and execution dates reported at the database level should be used in conjunction since the coverage and functions of the platforms are different. Search cut-off date is 18th October 2026 and records which are not published after this date are not included.

2.3 Eligibility criteria

Table 1. Eligibility criteria for the systematic review.

Criterion	Inclusion	Exclusion
Topic/context	Ballistic system, impact or penetration, armor, launch system, or closely related high-performance mechanical system	No ballistic or impact context
Domain engagement	At least one of the six domains as primary variable, method, or outcome	No substantive domain engagement
Evidence	Extractable quantitative results or validated framework	No extractable quantitative results
Publication	Peer-reviewed journal article	Review, conference abstract, preprint, thesis
Language	English or Chinese	Other languages
Date	1 Jan 2020–18 Oct 2026	Outside range

Eligibility criteria limit the scope of the evidence map and help to ensure that those studies included are relevant to an engineering problem and address at least one of the review domains. The topic criterion contains ballistic systems, impact or penetration, armor, launch systems and other related high performance mechanical systems. There should be a substantive engagement with artificial intelligence, optimization, advanced materials, thermofluids, structural dynamics or reliability in the domain criterion. For evidence criterion, quantitative results that can be extracted or a validated framework is needed, and for the publication criterion, only peer-reviewed journal articles are allowed. The publications can be in English or Chinese and the period of publication is from 1 January 2020 until 18 October 2026. The exclusion column will explain that any data on the outside of these will not go outside to the final evidence set. These are all criteria that are used together, and not individually as indicators of quality. A paper may be on a topic related to a material or computation topic but if it does not have a ballistic or impact context, it will still not be accepted. Likewise, if the report does not present evidence that can be extracted or a validated framework, then a relevant application is not enough.

2.4 Selection process

Records are initially reviewed by title and abstract and then their full text is reviewed and compared to the eligibility criteria listed in Table 1. The process is consistent across all screening with the topic, domain engagement, evidence, publication type, language and date requirements. A record is moved to full-text assessment if its title and abstract suggest a potential application to a ballistic or impact, armor, launch or closely related high-performance mechanical application and a meaningful relationship with one or more of the six review domains. Full-text assessment is used

to check if the publication is a peer-reviewed journal article and whether it has quantitative results that can be extracted or a validated framework. Records which are not meeting the criteria are excluded at the appropriate point. The flow diagram in Figure 2 indicates the number of records identified and the number of records that were duplications, screened, reports were sought, reports were not retrieved, full texts were assessed, and the number of studies included. The counts also are reported in Table S15. The selection arithmetic is verified from stage to stage, to ensure that the number going into each stage is the same as the number going out of the previous stage after exclusions. This results in the absence of two reports and the final evidence set includes 16 studies. The screening pathway is described; the review does not report a statistic about inter-rater agreement which is not present in the provided review records.

2.5 Data extraction and quality appraisal

Data extraction captures author, year, country, domains, design, validation basis, materials or system, key findings, and reported limitations. Table S4 of the supplementary file gives the extraction table. Quality appraisal uses a six-domain engineering framework: (A) model validation, (B) uncertainty reporting, (C) baseline comparison, (D) reproducibility, (E) scale bridging, and (F) engineering relevance. Each domain is rated adequate, unclear, or inadequate. Scale bridging is assessed in relation to the levels of analysis reported in each study. Studies with two or more inadequate domains receive high concern. Studies with one inadequate domain or three or more unclear domains receive moderate concern. All other studies receive low concern. No study is excluded on quality grounds. Table S5 gives the full appraisal, and Table 2 presents the summary distribution.

The appraisal is not designed to give a numerical ranking of the reporting and engineering evidence in each paper, but to describe the evidence in each paper. The six criteria cover complementary aspects of the process of interpreting the study. Model validation is whether the prediction or analysis is compared to a suitable reference and uncertainty reporting is whether there is a description of variability or uncertainty. Baseline comparison: checks if the approach is compared with a comparator. Reproducibility takes into account if information is provided to be able to repeat the analysis. Scale bridging deals with the connection between the level of analysis reported in the study and other relevant levels and engineering relevance is a question of whether the study is relevant to some real engineering question. If there is a report but not enough to make an adequate or inadequate judgement, then ratings of unclear are kept. Studies that have 2 or more inadequate domains are judged to be high concern, 1 inadequate domain or 3 or more unclear domains are judged to be moderate concern, all others studies are judged to be low concern.

Table 2. Number of studies by appraisal rating and domain.

Appraisal domain	Adequate	Unclear	Inadequate	Not applicable
A Model validation	11	5	0	0
B Uncertainty reporting	3	11	2	0
C Baseline comparison	16	0	0	0
D Reproducibility	0	16	0	0
E Scale bridging	0	16	0	0
F Engineering relevance	16	0	0	0

2.6 Synthesis strategy

The synthesis is both descriptive and structured comparison of the narrative. Firstly, for each included study, there is a summary of its application context, research design, primary validation basis and domain tags. The intent of these fields is to describe the evidence base but to not consider different engineering applications to be interchangeable. Secondly, the different frequencies of domains are used across the 16 studies and pairwise co-occurrence is computed where two domains are both marked in the same study. The co-occurrence matrix thus shows co-occurrence of study level engagement, but does not show causality or that one method is better than another. Third, reported outcomes are reported in their original form such as prediction accuracy, residual velocity, penetration response, deformation, pressure, temperature and perforation probability. There are no pooled measures; they are all different in terms of definition, units, test conditions and designs for validating them. Fourth, the synthesis examines the experimental, numerical, empirical, data-driven, hybrid and statistical approaches to highlight the influence of the validation basis on interpretation. Finally, the six appraisal dimensions are summarized as adequate, unclear or inadequate based on the decision rules stated. The description of reported outcomes is provided in Table S18. This way, analyses remain close to the available evidence and differences in the scope of studies and reporting are made apparent.

3 Results

3.1 Study selection

The search identifies 61 records across seven databases. After removing 9 duplicates, 52 records are screened at title and abstract level. Of these, 13 are excluded at that stage, and 39 reports are sought for retrieval. Two reports are not retrieved, leaving 37 reports assessed for full-text eligibility. Twenty-one reports are excluded after full-text assessment, and 16 studies enter the final synthesis. The arithmetic is consistent across the flow: 61 minus 9 equals 52; 52 minus 13 equals 39; 39 minus 2 equals 37; and 37 minus 21 equals 16. The following steps are shown in the PRISMA 2020 flow diagram (Figure 2) and the selection record (Table S15). Records and reports are kept separate to ensure that multiple records can be found for the same publication, and because the full text assessment is made for reports retrieved as a result of a database search, not the original search records. The two reports that are not retrieved are not included in the 21 full-text exclusions since an unavailable full text doesn't allow for determining eligibility for the report. The last group of 16 studies is the denominator for the frequencies of the domain, co-occurrence counts, study characteristics summaries, and study appraisal results presented below.

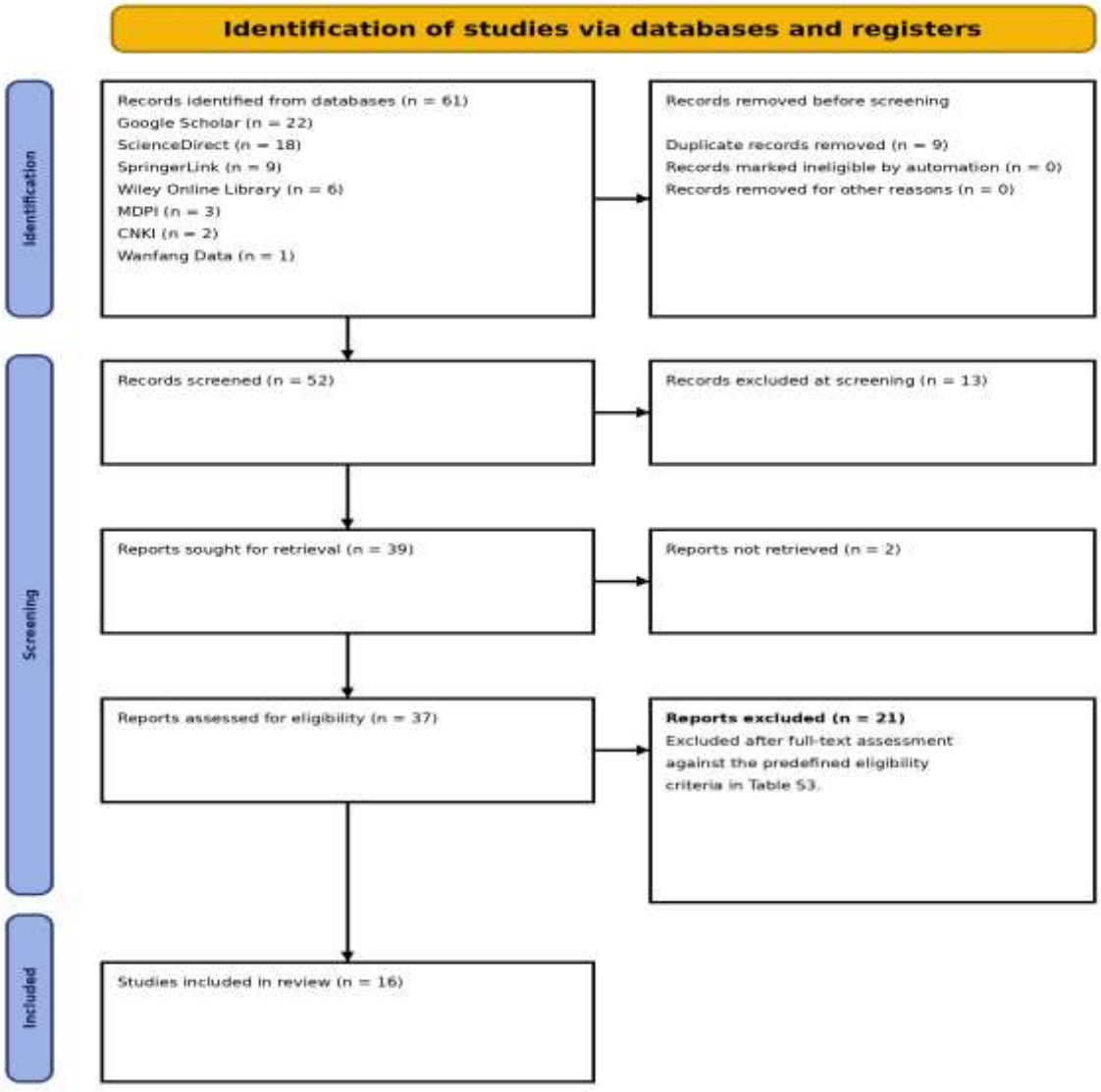


Figure 2. PRISMA 2020 flow diagram of study identification, screening, and inclusion.

3.2 Study characteristics

There are 13 studies of protective structures (S1-S8, S12-S16) and three studies of launch systems (S9-S11). The following components of data-driven or surrogate designs are used in seven studies (S1–S5, S14, S15), four of which are experimental or hybrid designs (S6, S8, S9, S12), three of which are numerical designs (S10, S11, S16), one empirical relation (S7), and one is a statistical inference study (S13).

The study characteristics indicate that the evidence is also focussed on the use of protective structures, and not spread evenly throughout all ballistic applications. The three studies relating to the launch system are of a smaller group and are concerned with the flow in interior-ballistics, behavior of the chamber and heat transfer in the barrel. The methodological diversity is also suggested in the design categories. Seven studies used a data-driven approach and four studies used an experimental (or hybrid) approach. The three numerical studies are followed by one empirical study, and one statistical study. Each study is identified with these labels which indicate the major design communicated in each study, and do not exclude that other supporting designs may be included. The study level assignments are then checked against the author and year, domain tags, design and validation basis, using Table 3. It also indicates that the design label does not necessarily represent a validated design – a data-driven design could be based on an experimental database or on the numerical model outputs. This difference should be taken into account when looking at model performance. The distribution is used as a context for the appraisal and later to compare the reported outcomes with similar contexts across different engineering settings.

Table 3. Characteristics of the included studies.

ID	Study	Domains	Design	Validation basis
S1	Ryan et al., 2024 [1]	AI, STR	Data-driven	Experimental database
S2	Beylergil et al., 2026 [2]	AI, MAT, STR, REL	Data-driven	Experimental (literature data)
S3	An et al., 2024 [3]	AI, MAT	Data-driven	Numerical (JH-2 finite element)
S4	Zhang et al., 2025 [5]	OPT, AI, MAT, STR	Surrogate + optimization	Numerical comparison
S5	Wei et al., 2026 [6]	OPT, AI, MAT	Data-driven + optimization	Experimental (limited tests)
S6	Mutu and Özer, 2024 [8]	MAT, STR	Experimental + numerical	Experimental (ballistics tests)
S7	Ganor, 2024 [9]	MAT	Empirical relation	Experimental data
S8	Zeng et al., 2024 [10]	MAT, STR	Experimental + numerical	Experimental (impact tests)
S9	Sun et al., 2024 [11]	THF	Experimental + numerical	Experimental (underwater launch tests)
S10	Yang et al., 2025 [12]	THF	Numerical	Numerical
S11	Susantez, 2022 [13]	THF, STR	Numerical	Numerical
S12	Elgy et al., 2021 [14]	STR, MAT	Experimental	Experimental (buried charge tests)
S13	Tahenti et al., 2024 [15]	REL	Statistical inference	Experimental data
S14	Zhu et al., 2025 [4]	AI, MAT, STR	Data-driven	Experimental (validated FE model)
S15	Sun and Liu, 2023 [16]	AI, REL, MAT	Data-driven	Numerical + experimental
S16	Annunziata et al., 2024 [7]	OPT, STR	Optimization	Numerical

AI, artificial intelligence. OPT, metaheuristic optimization. MAT, advanced materials. THF, thermofluids. STR, structural dynamics. REL, reliability and uncertainty.

3.3 Methodological quality

For descriptive classification, each included study was assigned one primary validation category: experimental-data or test-based evidence, numerically led validation, or statistical inference supported by experimental data. These categories are mutually exclusive for counting purposes, although individual studies may combine experimental and numerical methods. The categories should not be interpreted as equivalent levels of independent validation.

The primary basis of experiment data or experiment tests is used in 8 studies, numerical in 7 studies and statistical inference based on experiment data in 1 study. The evidence base is not based on one validation pathway as demonstrated in this distribution. Experimental validation directly relates to actual observed behavior via ballistic

testing, impact testing, underwater launch testing, and deformation measurements. Numerical validation enables analysis of quantities that are hard to measure in a system – such as pressure fields, thermal response and the finite element prediction. In the statistical-inference study, the results obtained from the experiments are used to make an estimation of the probability of perforation. These can be used to categorize the main basis of each study and do not mean that there is only one type of evidence in a study. The 10 most common materials and structural dynamics studies are the same, with materials being the most common study and structural dynamics being the second. Seven studies mention the AI, and three each mention thermofluids, optimization and reliability. Using the decision rules stated above with the study-level ratings in Table S5, three studies that were rated as low concern, and thirteen that were rated as moderate concern, were identified, while there was no study rated as high concern. Baseline comparison and engineering relevance were rated adequate in all 16 studies. Reproducibility and scale bridging were rated unclear in all 16 studies. For uncertainty reporting, three studies were rated adequate, eleven unclear, and two inadequate. Three studies report adequate levels of uncertainty, 11 studies report unclear levels of uncertainty, and two studies report inadequate levels of uncertainty.

Using the above mentioned decision rules with the study-level ratings in Table S5, we have determined that there are three studies of low concern and thirteen studies of moderate concern. There is no study that is given a high concern classification. The domain-level ratings are summarized below in Table 2.

3.4 Domain evidence (RQ1)

Artificial intelligence: Seven studies apply machine learning. Ryan et al. [1] use the gradient boosting, neural networks, support vector regression, and Gaussian process regression on two data sets with approximately 1000 samples. All four models come into close agreement within the training range and are different from one another outside the training range. The accuracy is significantly enhanced with the physics-informed constraints as compared to classical models and basic regression and the learned models are orders of magnitude faster than finite element solvers. Beylergil et al. [2] combine an energy balance model to random forests. The median R^2 value over the six datasets of literature is in the range of 0.93 to 0.96 and the typical RMSE value is 10 to 30 m/s. Random forest check achieves R^2 value of 0.992 on fit data, and 0.835 ± 0.145 on 5 fold cross validation. An et al. [3] demonstrate that the residual penetration depth is mainly influenced by density, dynamic compressive strength, quasi-static compressive strength and Hugoniot elastic limit. Zhu et al. [4] fuse SVM with DNN to classify penetration state and to predict residual energy and deformation. Sun and Liu [16] employ the optimal uncertainty bounds for ballistic impact of magnesium alloy using a neural-network approximation.

Metaheuristic optimization: Three studies use optimization. Zhang et al. [5] use a support vector regression surrogate to predict residual velocity and areal density of a titanium, silicon carbide, and polyethylene armor, and NSGA-II then searches the structural parameters. The optimized armor shows better anti-penetration performance than a traditional spliced armor in numerical comparison. Wei et al. [6] use a two-stage framework with chaos-based global optimization to identify Johnson-Cook parameters and a pressure cutoff from limited experiments, and a learning stage maps mechanical test results to ballistic response. Annunziata et al. [7] apply graph-based genetic algorithm topology optimization for protection against bullets and fragments. This small number is important when compared with the frequency of material and structural studies, because optimization is represented by three studies rather than forming a routine component of every design workflow. The examples also use different optimization purposes. Zhang et al. [5] search structural parameters against residual velocity and areal density, Wei et al. [6] identify constitutive parameters and a pressure cutoff, and Annunziata et al. [7] optimize protective topology against bullets and fragments. The evidence therefore covers surrogate-assisted multi-objective design, parameter identification, and topology optimization. These approaches should not be treated as directly comparable because they address different design variables and objectives. The reported numerical comparison in Zhang et al. [5] supports the use of the optimized configuration within that study, while the other studies provide complementary routes for reducing uncertainty in material or structural design. Across the group, optimization is connected to AI in two studies, materials in two, and structural dynamics in two, as shown in Table 4.

Advanced materials: Ten studies address materials. Mutu and Özer [8] show that alumina ceramic of 12 mm thickness backed by 10 mm of carbon fiber and polyethylene composite shows partial penetration in all tested arms under 7.62 × 51 mm armor-piercing bullets, and finite element results match the tests. Zeng et al. [10] find that for fiber metal laminates, Johnson-Cook and elastoplastic models fail to reproduce the observed failure, and a model with Lode angle, temperature, and strain rate dependence matches the failure pattern. Ganor [9] relates ceramic mechanical properties to ballistic efficacy and offers an alternative to finite element models for novel ceramics. The material studies therefore span ceramic armor, fiber composites, fiber metal laminates, and other protective configurations. Their findings illustrate why material performance cannot be summarized by a single property. The ceramic study relates mechanical properties to ballistic efficacy, while the composite armor study evaluates a layered ceramic and backing configuration under a specified projectile threat. The laminate study emphasizes constitutive response under impact and indicates that temperature, strain rate, and Lode-angle dependence affect the ability of a model to reproduce observed failure. Other included studies use material properties as inputs to

data-driven prediction or optimization. This breadth explains why materials appear in ten studies and why the domain frequently co-occurs with structural dynamics and artificial intelligence. However, the review does not infer that one material system is superior across all applications. Projectile type, geometry, backing configuration, loading conditions, and validation basis differ across the studies. The evidence supports application-specific material characterization and careful reporting of the conditions under which ballistic performance is measured.

Thermofluids: Three studies address thermofluids. Sun et al. [11] use a coupled interior ballistics and fluid dynamics model with underwater launch tests to show that shorter barrels give muzzle velocities up to 492 m/s with complete propellant combustion, and longer barrels raise drag and slow the projectile. Yang et al. [12] use a three-dimensional gas-solid model to show that raising the initial breaking angle of the cartridge end cap from 0° to 120° cuts the propellant particle difference between breech and forcing cone from 12.2% to 0.6%. The same change reduces the initial negative pressure difference from 1.62 MPa to 0.76 MPa and delays projectile start-up from 2.82 ms to 2.94 ms. Susantez [13] feeds projectile position, velocity, gas temperature, and mass fraction from an interior ballistics code into finite element heat transfer for a 120 mm smoothbore barrel. These studies represent different parts of the launch process and use distinct levels of computational description. The underwater-launch study compares barrel lengths and relates projectile velocity to drag and propellant combustion. The modular-charge chamber study examines the three-dimensional gas-solid flow field and quantifies changes in particle distribution, pressure difference, and projectile start-up time as the initial breaking angle changes. The barrel heat-transfer study links interior-ballistics outputs with a finite element thermal model. Together, the studies show that thermofluid analysis can provide pressure, velocity, temperature, and flow information relevant to launch-system performance. However, only one study is tagged with both thermofluids and structural dynamics, and no thermofluid study in this sample is tagged with AI, optimization, materials, or reliability. The small number of studies means that broad conclusions about the entire field are not warranted. The evidence instead identifies a focused opportunity to connect flow and combustion models with thermal, structural, and reliability analyses in future launch-system research.

Structural dynamics: Nine studies engage structural response. Explicit finite element models support the armor and laminate studies [8, 10]. Elgy et al. [14] compare a standard and a low-cost deformation measurement method for buried charge tests on Armox 440T plates. The low-cost method shows variability up to 5% of the mean, and its peak deformation values run systematically 20% higher in a consistent manner. This consistent offset allows a multivariate regression among deformation, charge size, and plate thickness. The structural domain includes studies that examine deformation, impact response, and the behavior of protective materials under dynamic loading. The finite element studies of composite armor and fiber metal laminates connect structural response with material constitutive behavior [8, 10]. Elgy et al. [14] provide a measurement-focused contribution through buried-charge tests on Armox 440T plates. Their comparison indicates that the low-cost measurement method has variability up to 5% of the mean and produces peak deformation values that are systematically about 20% higher than the standard method. Because the offset is consistent, the measurements can still support a multivariate regression involving deformation, charge size, and plate thickness. Structural dynamics appears in nine studies and co-occurs most often with materials. It also appears with AI in four studies and with optimization in two. These patterns show that structural response provides a shared engineering context for material characterization, prediction, and design search. The results remain specific to the studied configurations and do not establish a universal deformation or impact-response model.

Reliability: Three studies address reliability or uncertainty. Tahenti et al. [15] use a Brownian-based model that couples response variability with physics to describe perforation probability. The earlier estimation approach needs a large experimental database, and the study introduces maximum likelihood inference for parameter estimation with results that agree with experiments. Beylergil et al. [2] report uncertainty bounds alongside predictions. Sun and Liu [16] develop learning-based optimal uncertainty quantification for ballistic impact problems. The three studies illustrate different ways to represent uncertainty in ballistic performance. Tahenti et al. [15] use a Brownian-based model to describe perforation probability while accounting for response variability and physical behavior. The study introduces maximum likelihood inference for parameter estimation and reports agreement with experiments. Beylergil et al. [2] provide uncertainty bounds alongside predictions of ballistic response in fiber composites. Sun and Liu [16] develop a learning-based optimal uncertainty quantification method for ballistic impact problems in magnesium alloys. These contributions address probabilistic response, prediction intervals, and uncertainty bounds, but they do not form a common quantitative framework that can be pooled across studies. Reliability appears in three studies and co-occurs with AI and materials in two studies each and with structural dynamics in one. The reviewed set contains no reliability–optimization pairing, although the presence of probabilistic models and surrogate-assisted optimization elsewhere in the evidence suggests a potential direction for future work. Such integration requires explicit validation of the uncertainty model and its relevance to the design decision.

3.5 Cross-domain integration (RQ2)

Advanced materials and artificial intelligence are paired together in six studies, and structural dynamics as well as AI in four. In six studies, advanced materials are coupled with the dynamics of the structures. The combination of AI and optimization is featured in two studies, and the combination of optimization and materials and structural dynamics is featured in two studies each. In two studies, reliability is coupled with AI and materials in two studies each, with materials; structural dynamics is coupled with reliability in one study. In one study, thermofluids is coupled with the structural dynamics. The complete matrix is provided in Table 4 and the evidence in the studies in Table S9.

The co-occurrence matrix gives a succinct overview of the interplay between the six domains in the individual studies. The values along the diagonal indicate the number of studies labeled with each domain and the off-diagonal values indicate the number of studies with both domains. The matrix is symmetrical since study tagged by AI and materials is equally contributing to both the AI–MAT and MAT–AI cells. The largest off-diagonal numbers are six in the cases of AI–MAT and MAT–STR. Four studies have AI–STR, and two each have AI–OPT, OPT–MAT, OPT–STR, AI–REL and MAT–REL. One study is for each of the following combinations: THF–STR and STR–REL. There are no counts for the other pairings. These values represent co-occurrence, rather than the degree of technical interaction, or the influence of one domain over the other. Traceability of the counts of aggregates is provided by the study level identifiers in Table S9. Combined, Table 4 and Table S9 provide an overview of the overall evidence structure, as well as the specific studies that provide evidence for each observed connection.

Table 4. Co-occurrence of domains across the 16 included studies.

Domain	AI	OPT	MAT	THF	STR	REL
AI	7	2	6	0	4	2
OPT	2	3	2	0	2	0
MAT	6	2	10	0	6	2
THF	0	0	0	3	1	0
STR	4	2	6	1	9	1
REL	2	0	2	0	1	3

Diagonal cells give the number of studies per domain, and other cells give the number of studies that engage both domains. AI, artificial intelligence. OPT, metaheuristic optimization. MAT, advanced materials. THF, thermofluids. STR, structural dynamics. REL, reliability and uncertainty.

The study-level matrix identifies AI–OPT co-occurrence in two studies (S4 and S5), AI–MAT in six (S2, S3, S4, S5, S14, S15), AI–STR in four (S1, S2, S4, S14), and MAT–STR in six (S2, S4, S6, S8, S12, S14). Reliability co-occurs with AI and materials in two studies each and with structural dynamics in one study. Table S9 lists the study IDs for each pair.

Thermofluids couples with structural dynamics in one study through the thermal-loading analysis reported by Susantez [13]. No thermofluid study in this included set is tagged with AI, optimization, materials, or reliability. These zero counts describe the 16 included studies and define specific opportunities for future integration.

3.6 Sources of heterogeneity (RQ3)

The evidence provided is different with each application, research design and validation basis. Thirteen papers focus on structures which provide protection and three papers focus on launch systems. This imbalance is reflected in the domain map, which is mostly based on research in the field of the protection system, and in the lesser body of evidence base research that supports the applications related to the launch. The 16 included studies comprise seven data-driven or surrogate studies, four experimental or hybrid studies, three primarily numerical studies, one empirical study, and one statistical-inference study. These categories reflect each study's primary research design, although individual studies may combine multiple methodological approaches. Further separation of evidence occurs when the evidence is based on validation. Experimental studies provide test results including partial penetration, variability in deformation and muzzle velocity. Numerical studies present measures like pressure, temperature or residual velocity – sometimes in the form of a computer model. The statistical-inference study calculates the probability of perforation, based on experimental data. The reported performance parameters are the R^2, the RMSE, the ballistic limit error, the perforation probability, the pressure and the temperature. They have different definitions, units, test conditions and data structures which render meaningful pooling difficult. Therefore, the heterogeneity can help guide the synthesis of the narrative structure, and highlights the need for caution in using ranking approaches based on any one cross-study performance measure.

Further separation of evidence occurs when the evidence is based on validation. Experimental studies provide test results including partial penetration, variability in deformation and muzzle velocity. Numerical studies provide

numerical data on field quantities like pressure, temperature and residual velocity. There is no pooling as reported measures are R^2, RMSE, ballistic limit error, perforation probability, pressure, and temperature.

3.7 Methodological gaps (RQ4)

There are a number of common priorities for reporting and validation highlighted in the appraisal. Two of the 16 studies report inadequate uncertainty reporting, eleven studies report unclear uncertainty reporting and three studies report adequate uncertainty reporting. In the pattern, uncertainty is not always attended to in the same manner nor is it consistently represented in a manner that facilitates its comparison across applications. The ratings for the reproducibility of all 16 studies are unclear, and for scale bridging, 16 are unclear. The ratings reflect the lack of a consistently documented path to reproducing the analyses and the lack of connections between the results at different scales in the information available in the reviewed reports. They are not intended to imply that the studies were not reproducible, or that there are not scale effects, but rather that the published information does not allow a confident appraisal, based on the criteria used here. Seven studies based on numerical validation, eight based primarily on experimental data or tests and one based on statistical inference with experimental data. There is also a lot of variation in how cross domain integration is done. While there are plenty of combinations of materials and dynamics, some of the thermofluidic combinations and reliability-optimization relationships are not present in the sample provided. These gaps can be filled in the future by reporting data, model settings, model validations, uncertainties, and scale assumptions in greater detail [38, 39].

4 Discussion

4.1 Principal findings

The review finds that there is a significant amount of research in the areas of advanced materials, structural dynamics and AI, and a smaller amount of work that combines several fields [40, 41]. One of the most common combinations is that of materials and structural dynamics, as each of these is found in six studies. In six other studies, AI is found to co-occur with materials and in four others, with structural dynamics. The patterns indicate that learning methods are beginning to be employed in conjunction with the characterization of materials and with analysis of structural response, but do not imply an integrated workflow that is standardized [42, 43]. Of all of the possible links between thermofluids and structural dynamics, only one has been observed in the 16 studies in this sample. The matrix is a description of the contents of the evidence provided and should not be applied to all of the research literature. In addition, the design of validation is one of the key findings. There are eight studies based on experimental data or tests for primary validation, seven of the studies is based on numerical validation and one is statistical inference on experimental data. This is a field of two studies combining the principles of AI and optimization. Additionally, probabilistic perforation models and learning-based uncertainty quantification are included, but an optimization study which explicitly includes these uncertainty techniques is not identified in the review. The results reveal therefore that methodological components are available and that there are limited connections between these methodological components.

4.2 Relational framework

The six domains are represented as a map of co-occurrence of the observed studies in Figure 1. The links show the number of studies where two domains co-occur; and the number of zero-count pairs, show combinations which are not present in this evidence set. This framework is of a relational type and not causal. The absence of a link does not show that the combination is technically impossible and the presence of a link does not show that there is an improvement in the other. Rather, the map is intended to offer a systematic means of pinpointing the areas and focus of research activity, as well as where the reviewed sample has fewer integrated examples of research. The strongest ones observed are advanced materials with structure dynamics and AI with advanced materials. In the two studies, reliability is related to artificial intelligence and to materials, and in the one study, to structural dynamics. In one study, thermofluids is associated with structural dynamics. Since there are no other thermofluidic connections, there is a clear path for further investigation of the possibility of integration, but any proposed integration must be validated in the physical system of interest. For instance, there is potential to integrate reliability-based design optimization with surrogate-assisted search, as an example [44, 45, 46]. Learning surrogates also may alleviate the repeated computation costs during an interior ballistics analysis [47, 48]. For such examples, research directions are suggested based on the methods that have been mapped, not provided by the studies included.

4.3 Practical implications

The results could be relevant to the design and testing of protection and launching systems. In the case of protective structures, learning models can aid in the quick search of material and geometric design space, but experimental testing is still needed to assess them, if a model is employed to select a candidate design [49, 50]. Surrogate-assisted optimization can help decrease the number of costly simulations that are required as long as the surrogate is trained

and tested in a well-defined domain. These tools can be supplemented by reliability methods which can capture the variability in material properties, loading, and predicted response [51, 52]. For launch systems, only one of the thermofluidic–structural connections is observed, and the value of bringing together the output of the interior ballistics and the thermal and structural analysis is demonstrated. The review supports four research priorities: experimentally validated learning models, surrogate-assisted armor optimization, coupled thermal and structural analysis of launch systems, and reliability-informed design under material and loading uncertainty [53, 54]. The learning, optimization, thermal-loading and probabilistic studies performed in the review are utilized in these priorities [55, 56]. Results should be reported with the source and size of the datasets, the model architecture and settings, training and validation splits, test conditions, uncertainty bounds and limits of model applicability to facilitate comparisons with future results. This reporting would allow the reader to consider whether any of this performance was an interpolation or evidence of reliable engineering outside of the original validation context.

4.4 Limitations

The results of the review should be regarded in the context of the scope and composition of the review [57, 58]. The search covers seven named sources and publications dated from 1 January 2020 to 18 October 2026. In total, there are 16 studies in the final evidence base of which 13 focus on protective structures and 3 focus on launch systems. The domain frequencies and pairwise counts thus reflect this targeted sample, and can vary depending on other databases, search terms, publication types or later research. The review is based on explicit Eligibility Criteria, and presents the numbers of selections, extraction fields and appraisal framework in six domains. In this case, the review wasn't prospectively registered, but this is noted in the Methods section. The synthesis is descriptive, because the studies included use different participants in the studies, test conditions, test designs of validation, and measures of outcomes. The available body of evidence would be insufficient to provide a quantitative estimate[59-61]. The appraisal also identifies an unfocused reporting from a methodologically flawed report. In particular, the information reported in the papers included in the database is often inadequate to make an accurate assessment based on the criteria stated, due to unclear reproducibility and scale bridging. The narrative synthesis provides a description of reported outcomes and validation designs, without providing an estimated reporting bias for the respective design. The boundaries should inform the interpretation of the identified research priorities.

5 Conclusions

This review traces 16 studies in six categories of mechanical systems that function with high speed and/or under ballistic conditions. The term "Advanced materials," "Structural dynamics" and "Artificial intelligence" are used most often. Advanced materials with structural dynamics and AI with advanced materials are the top two areas of pairing integration, whereas the other areas were less pronounced. There are fewer cross domain links in the evidence for thermofluids and reliability. There are eight studies written on a basis of experimental data or experiments, seven studies are validated numerically, and one study uses a statistical inference based on experimental data. Future work needs to concentrate on: transparent reporting of uncertainty, reproducible model description, scaling up, experimentally validated learning and optimization, and integrated reliability and thermofluidic workflows. These priorities are based on the evidence reviewed and its scope and composition.

The areas and topics that need to be further explored in the future include the use of experimentally validated learning models, reliability-based optimization, and coupled thermal and structural analysis of launch systems. The objective is not only intelligent ballistic systems but systems that can be trusted in making predictions.

Declarations

Conflict of interest: The author declares no competing financial or personal relationships that could influence this work.

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Ethical considerations: This study reviews published literature, and no human participants take part. Ethical approval is not required.

Data availability: No new dataset is generated. All data derive from the cited studies. The supplementary file contains the PRISMA 2020 checklist, search strings, extraction table, appraisal table, and lists of excluded reports.

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