

# Workshop on Mathematical Challenges in Brittle Material Failure

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## ABSTRACT

The Army Research Office funded an invitation-only workshop entitled “Identifying Mathematical Challenges Associated with Failure of Brittle Materials” at the Johns Hopkins University, Maryland on May 20-21, 2019. The workshop brought together mathematicians, statisticians, and mechanics of materials researchers with diverse academic and research backgrounds to discuss the state-of-the-art in brittle material failure prediction and to identify new directions for future research. Three specific goals of the workshop were: (1) to identify the state-of-the-art for modeling failure of brittle materials (e.g., ceramics, glasses); (2) to discuss the major mathematical and statistical challenges experienced by academics and scientists studying brittle failure; and (3) to propose novel and unexplored research collaborations between mechanics researchers and mathematicians to address the identified challenges. This document provides a summary of workshop presentations, discussions, and recommendations for future work (and research funding) that emerged from the workshop. The recommendations for future work are organized into four major thrusts: (i) defining robust quantities of interest; (ii) understanding and modeling variability and stochasticity; (iii) model parameter importance and calibration; and (iv) transitioning from discrete to continuum behaviors. For each thrust, specific future work discussed in the workshop is described.

## INTRODUCTION

Failure of brittle materials by fracture, fragmentation, and comminution is an issue with fundamental academic, industrial, geological, and societal importance. For example, brittle failure is central to geological processes including fault rupture (Scholz 2019), to the design and modeling of protective materials including armor ceramics (Karandikar et al. 2009; Chen et al. 2007), and to the performance of structural and quasi-brittle materials including concrete (Bazant 2019). Practices for predicting the failure of brittle materials by numerical modeling vary dramatically across academia and industry. Such differences include the choice of spatial discretization scheme, numerical solver, and the level of resolved physical detail. There are also challenges with capturing the complex physics and material heterogeneity that are fundamental to brittle failure problems with current mathematical models.

To address these challenges, the Army Research Office (ARO) sponsored a workshop at Johns Hopkins University (JHU) on May 20-21, 2019, titled "Workshop on Identifying Mathematical Challenges Associated with Failure of Brittle Materials". The specific goals of the workshop were to: (1) identify the state-of-the-art for modeling failure of brittle materials (e.g., ceramics, glasses); (2) discuss the major mathematical or statistical challenges experienced by researchers studying brittle failure; and (3) propose *novel and unexplored* collaborations between mechanics researchers and mathematicians to address the identified challenges. This document describes workshop presentations, identifies the major mathematical challenges discussed by participants, and makes recommendations for future work (and research funding) that may address these challenges. Note that the Army has previously organized workshops focused on dynamic failure of brittle materials, including a 2016 Dynamic Failure Forum at Aberdeen Proving Ground, Maryland (Aydelotte et al. 2016). The distinction between prior workshops and the workshop hosted at JHU was the emphasis of the JHU workshop was on identifying paradigm-shifting mathematical approaches from the pure and applied mathematics and statistics community.

The remainder of this document is organized as follows. First, a list of workshop participants and the results of a pre-workshop survey are provided. The pre-workshop survey was intended to

50 help workshop chairpersons design the workshop schedule. Next, a chronological summary of the  
51 workshop is provided, describing the workshop sessions and major open questions discussed by  
52 participants throughout the workshop. Next, results of a final exit-survey are discussed. Finally,  
53 a summary and future-funding recommendations are provided. The recommendations are based  
54 on workshop presentations, more than three hours of structured discussions, a one-hour focused  
55 discussion at the end of the workshop, and an exit-survey completed by participants. The rec-  
56 ommendations for future work (and research funding) are organized into four major thrusts: (i)  
57 defining robust quantities of interest; (ii) understanding and modeling variability and stochasticity;  
58 (iii) model parameter importance and calibration; and (iv) transitioning from discrete to continuum  
59 behaviors. For each thrust, specific future work discussed at the workshop is described.

## 60 **WORKSHOP PARTICIPANTS AND PRE-WORKSHOP SURVEY**

61 The workshop was chaired by Prof. Ryan Hurley (Johns Hopkins University), Prof. James  
62 Hogan (University of Alberta), and Prof. Surya Kalidindi (Georgia Institute of Technology). The  
63 workshop was attended by 24 total participants - 16 university faculty members, 6 scientists from  
64 national laboratories, and 2 program officers from the ARO. Although the workshop chairpersons  
65 selected participants to provide presentations related to brittle failure mechanics (ME) or mathemat-  
66 ical techniques (MA), many participants were experts in both domains. The workshop participants  
67 and their primary expertise were:

- 68 • Michael Bakas (ME), Army Research Office
- 69 • Richard Becker (ME), Army Research Laboratory
- 70 • Florin Bobaru (ME), University of Nebraska-Lincoln
- 71 • Tan Bui-Thanh (MA), University of Texas at Austin
- 72 • Maria Cameron (MA), University of Maryland, College Park
- 73 • Wai-Tong (Louis) Fan (MA), Indiana University, Bloomington
- 74 • George Gazonas (ME), Army Research Laboratory
- 75 • Roger Ghanem (MA), University of Southern California
- 76 • Lori Graham-Brady (ME), Johns Hopkins University

- 77 • Michael Homel (ME), Lawrence Livermore National Laboratory
- 78 • James Hogan (ME), University of Alberta
- 79 • Ryan Hurley (ME), Johns Hopkins University
- 80 • Surya Kalidindi (ME), Georgia Institute of Technology
- 81 • Jia-Liang Le (ME), University of Minnesota
- 82 • Yongming Liu (ME), Arizona State University
- 83 • Bruce Pitman (MA), University at Buffalo
- 84 • Michael Shields (MA), Johns Hopkins University
- 85 • David Stepp (ME), Army Research Office
- 86 • Samy Tindel (MA), Purdue University
- 87 • Andrew Tonge (ME), Army Research Laboratory
- 88 • Dongbin Xiu (MA), Ohio State University
- 89 • Min Zhou (ME), Georgia Institute of Technology

90 Prior to the workshop, participants were requested to complete a brief survey by email that  
91 included several prompts. These prompts were designed to motivate workshop participants to  
92 understand the goals of the workshop, to think about what they wished to get out of the workshop,  
93 and to help the chairpersons design the workshop schedule. To inform the reader of the mindset  
94 of participants prior to the work, two prompts and summarized responses from non-chairperson  
95 participants are provided below:

- 96 1. Prompt: Identify up to three challenges you face in theory, modeling, or experiments related  
97 to brittle failure that are mathematical in nature (for mechanics researchers) **or** three math-  
98 ematical tools that you believe are underutilized in modeling physical systems in general or  
99 brittle fracture in particular (for mathematics researchers).
  - 100 • Summarized responses from mechanics researchers: Quantifying uncertainty and mod-  
101 eling across spatiotemporal scales; deterministic and probabilistic modeling; scalar or  
102 statistical quantities of interest; tools for quantifying complex spatiotemporal patterns  
103 in 3D.

- Summarized responses from mathematics researchers: Spanning spatiotemporal scales with limit theories and stochastic partial differential equations; combining uncertainties across parameters and scales; machine learning; surrogate modeling.

2. Prompt: Identify up to three topics that you would like to discuss or learn at the workshop.

- Mechanics researchers: Uncertainty quantification (UQ) across spatiotemporal scales; machine learning; reduced order modeling; transition between states (e.g., fracture to granular flow); relating microscopic heterogeneities to macroscopic properties; developing new quantities of interest.
- Mathematics researchers: Basics of fracture modeling across scales; Gaussian process learning; bridging scales and collapsing dimensionality; machine learning.

As noted later in this document, survey responses that became primary themes of workshops discussions included: (1) establishing scalar or statistical quantities of interest for characterizing failure; (2) uncertainty quantification in bridging spatiotemporal scales; and (3) new tools for quantifying complex spatiotemporal patterns (e.g., using machine learning, signature functions, etc.).

## **SUMMARY OF PRESENTATIONS AND DISCUSSIONS BY SESSION**

The workshop was organized into six sessions, each of which involved presentations by two to four workshop participants. Sessions were paired, with one focused on material failure followed by one focused on mathematics and statistics. Each pair of sessions was followed by a 45-60 minute discussion by all workshop participants to summarize challenges and potential future research directions. The final workshop schedule is shown in table 1 and a chronological summary of discussions is provided next.

### **Day 1, Morning: Computational Methods for Modeling Fracture & Theoretical and Applied Math and Statistics**

The morning of Day 1 first featured an introduction to the workshop goals and basic fracture mechanics concepts by the workshop chairs. The introduction was followed by presentations by three mechanics and two mathematics researchers in sessions titled “Computational Methods for

131 Modeling Fracture” and “Theoretical and Applied Mathematics and Statistics”, respectively, as  
132 shown in table 1. A talk by a third mathematics researchers (Wai-Tong (Louis) Fan) was provided  
133 on the second day due to travel complications but is considered in the summary provided here, as  
134 intended in the original schedule.

135 The mechanics talks during the “Computational Methods for Modeling Fracture” session pro-  
136 vided an overview of various methods for modeling blast and impact, constitutive relationships and  
137 mesoscale modeling involving the Material Point Method (MPM), and comparisons of simulations  
138 and experimental results for model calibration. Considerable attention was given to modeling  
139 fracture, fragmentation, and granular behavior across multiple length scales (nm to km) and time  
140 scales (ns to ms). Some major mathematical questions related to brittle fracture that emerged from  
141 the discussions and transcended any particular modeling approach included:

- 142 1. How to properly define or initialize material or mechanical property variability and associated  
143 uncertainty in simulations (e.g., fracture energy, strength)?
- 144 2. How to quantitatively characterize and compare complex failure patterns in simulations and  
145 experiments to determine if they are equivalent?
- 146 3. How to mathematically describe local transitions between material states (intact, damaged,  
147 granular) and interactions between neighboring material states in a partially damaged, gran-  
148 ular, or fragmented material?

149 The mathematics talks during the “Theoretical and Applied Mathematics and Statistics” session  
150 provided an introduction to rough paths and stochastic differential equations (SDEs), a description  
151 of quasi-potential solvers for dynamical systems and complex networks, a discussion of rough  
152 path signature functions, and a presentation on methods for solving problems involving expanding  
153 wavefronts. The mathematics talks motivated discussions around several mathematics-focused  
154 questions related to brittle failure, including:

- 155 1. Can the governing equations of mechanics be recast as stochastic partial differential equations  
156 (SPDEs) to leverage SPDE-solving techniques for incorporating variability?
- 157 2. Can rough path signature functions be used to characterize and compare complex failure

158 patterns in 2D images?

- 159 3. Can high dimensional problems be collapsed into smaller parameter spaces for simulations,  
160 as is done for rough complex fields?

161 Additional questions and discussions related to mathematical challenges in brittle failure modeling  
162 that arose during this session are listed in Table 2.

### 163 **Day 1, Afternoon: Computational Methods for Modeling Fracture & Stochastic Simulations**

164 The afternoon of Day 1 involved presentations provided or led by three mechanics researchers  
165 and two mathematics researchers in sessions titled “Computational Methods for Modeling Fracture”  
166 and “Stochastic Simulations”. The mechanics talks in the “Computational Methods for Modeling  
167 Fracture” sessions focused on cohesive zone modeling, fundamentals of peridynamic simulations  
168 for brittle failure simulations, and mesoscale simulations using realistic microstructures. The major  
169 questions emerging from the discussion included:

- 170 1. What are the major quantities of interest that can be used to characterize a material response  
171 across multiple geometries or loading conditions?
- 172 2. Do correlations exist between local material strength and local microstructural features in  
173 problems involving brittle failure?
- 174 3. How can one appropriately decompose a material response into contributions from all gov-  
175 erning material and processing variables?

176 The mathematics talks in the “Stochastic Simulations” session described data-driven model-  
177 ing and probabilistic frameworks for multiscale simulations involving brittle fracture. The major  
178 mathematics-related brittle failure questions emerging from the presentations and ensuing discus-  
179 sions included:

- 180 1. Can material and mechanical variability and uncertainty below sensor capacity during mate-  
181 rial characterization be considered white noise?
- 182 2. Can methods such as A-optimality, D-optimality, and quasi-optimality be employed to deter-  
183 mine which experiments to perform for variable calibration when resources and the number  
184 of available experiments is severely limited?

185 Additional questions and discussions related to mathematical challenges in brittle failure modeling  
186 that arose during this session are listed in Table 2.

## 187 **Day 2, Morning: Probabilistic and Computational Studies of Defects and Fractures & Un-** 188 **certainty Quantification**

189 The morning of Day 2 featured talks by four mechanics researchers and four mathematics re-  
190 searchers in sessions titled “Probabilistic and Computational Studies of Defects and Fractures” and  
191 “Uncertainty Quantification”. The mechanics presentations described the role of defects across  
192 length scales, including their distributions and effects on fracture nucleation and coalescence,  
193 introduced crack band models for quasi-brittle materials, detailed dual high dimensionality require-  
194 ments of physics modeling and uncertainty quantification in brittle failure modeling, and provided  
195 a demonstration of peridynamics approaches for modeling fracture.

196 Key questions related to brittle failure modeling that emerged from ensuing discussions included:

- 197 1. Can both 2D and 3D images be analyzed together using probabilistic relationships to learn  
198 how to characterize 3D failure from 2D images?
- 199 2. How can one rigorously transition from diffused to localized cracks in the absence of any  
200 closed-form solutions?

201 The mathematics presentations in the “Uncertainty Quantification” session provided an in-  
202 troduction to UQ methods, a description of data and uncertainty-driven reduction models for  
203 PDE-based models, and a discussion of UQ and material model uncertainty.

204 Key questions that emerged from the discussions included:

- 205 1. Can a simple forecasting model that avoids complex physics but includes simple scaling  
206 statistics perform well in predicting material failure?

207 Additional questions and discussions related to mathematical challenges in brittle failure modeling  
208 that arose during this session are listed in Table 2.

## 209 **WORKSHOP EXIT SURVEY**

210 An exit survey was completed by participants prior to the end of the workshop. Three survey  
211 prompts and summarized responses from non-chairperson participants are provided below:



- 212 1. Prompt: Identify areas where you see potential for new collaborations between mechanics  
213 and mathematics researchers.
- 214 • Summarized participant responses: Identifying quantities of interest; solving inverse  
215 problems; UQ; machine learning; reduced-order modeling and UQ; efficient SPDE  
216 solving; classification of failure patterns using rough paths signature functions; quanti-  
217 fying spatiotemporal fracture metrics from experiments to validate simulations.
- 218 2. Prompt: Identify new ideas or directions you developed during the workshop.
- 219 • Summarized participant responses: Inverse problem framework for parameter calibra-  
220 tion in brittle failure simulations; quantifying uncertainty and developing reduced order  
221 modeling for brittle failure; signature function analysis of crack patterns; round robins  
222 of dynamic fracture.
- 223 3. Prompt: Identify any specific mathematical or other tools you would like to learn more about  
224 following the workshop, either through subsequent workshops, collaborations, or conference  
225 symposia.
- 226 • Summarized participant responses: Gaussian Markov random fields; SPDEs and sig-  
227 nature functions; fractional PDEs.

## 228 **SUMMARY AND RECOMMENDATIONS**

229 Figure 1 illustrates four major themes that emerged from the workshop presentations, discus-  
230 sions, and surveys. These four major themes capture the general thrust of recommended future  
231 work (and research funding). The following summary and recommendations focus on these themes  
232 and the future work that supports their exploration. Table ? contains additional questions that  
233 were raised by workshop participants during discussions or surveys but were not deemed to be the  
234 highest priority recommendations when considering goal number (3) of the workshop (see Abstract  
235 and Introduction). The remainder of this section summarizes the four themes conveyed in Fig. 1  
236 and provides more detail regarding future research directions.

## 237 **Theme 1: Defining Robust Quantities of Interest (QoIs)**

238 Workshop participants agreed that clear quantities of interest (QoIs) must be defined for a  
239 given application related to brittle material failure. A QoI can be a scalar, a set of scalars, or a  
240 field whose value correlates with a desired material performance. The sentiment that QoIs must  
241 be defined for a given application emerged in the morning of Day 1 of the workshop and was  
242 echoed continuously throughout the workshop both by mechanics and mathematics researchers.  
243 However, it became clear throughout the workshop that there are no widely-agreed-upon QoIs for  
244 many applications involving brittle material failure, either because material response is material-  
245 dependent, or because of challenges in establishing simple scalars that correlate well with desired  
246 performance. For instance, in confined compression applications, the value of a frictional strength  
247 parameter may be the appropriate QoI (Chocron et al. 2010). In applications such as sphere impact,  
248 the presence and angle of cone cracks, the number of radial cracks, or the area of comminuted  
249 material have all been studied (Leavy et al. 2010) as QoIs. However, many of these features  
250 (e.g., the presence of comminuted material) are strongly material dependent (LaSalvia et al. 2005;  
251 LaSalvia et al. 2009) or have not been clearly correlated to material performance. The workshop  
252 participants identified three *novel* ways in which mathematical techniques not previously applied  
253 to brittle failure may aid in the development of QoIs. These included:

- 254 1. Relating 2D or 3D fields (e.g., images containing fractures or damaged area) to scalar QoIs  
255 via rough path signature functions (Boedihardjo et al. 2016).
  - 256 • Signature functions are the main ingredients of rough paths theory. Signatures charac-  
257 terize 1D paths and 2D images and have unique mathematical and invariance properties  
258 (Boedihardjo et al. 2016). Signatures may provide a simple way of constructing a scalar  
259 representation of complex patterns such as the 2D fracture or damage patterns typically  
260 studied in the context of brittle material failure (e.g., cone cracks, radial cracks, com-  
261 minuted area). New mechanics research may explore the generation of these datasets  
262 in a controlled manner, while parallel mathematics research may explore extensions of  
263 signatures to 2D and their use in translating fracture and damage images to scalar QoIs.

264 2. Comparing performance across loading conditions using rough path signature functions.

- 265 • Beyond relating 2D and 3D fields to scalar QoIs using signature functions, an impor-  
266 tant goal of brittle failure research is developing QoIs applicable to multiple loading  
267 geometries and conditions. Future mechanics research may explore how brittle material  
268 performance can be deemed “equivalent” in different loading and failure scenarios. Par-  
269 allel mathematics research may employ signature functions that return mathematically  
270 equivalent signatures.

271 3. Developing robust QoIs from multiple experimental fields (e.g., temperature, stress).

- 272 • A distinct but related avenue for future research is the development of QoIs incorporat-  
273 ing multiple fields. For instance, temperature, stress, and damage fields may all limit  
274 material performance and are each now measurable *in-situ* (e.g., (Keyhani et al. 2019a;  
275 Keyhani et al. 2019b)). Establishing new multi-field QoIs is a possible future mechan-  
276 ics research direction, while developing signature functions that can produce similar  
277 scalar metrics from consideration of multiple fields could be a supporting mathematics  
278 research direction.

## 279 **THEME 2: ROLES OF VARIABILITY AND STOCHASTICITY**

280 Workshop participants agreed that incorporating material and mechanical property variability  
281 into modeling is a paramount challenge for predicting the brittle failure of materials. This challenge  
282 is often addressed by including an initial defect or strength distribution (e.g., via Weibull modulus)  
283 in a simulation (e.g., (Tonge and Ramesh 2016)). The mathematics participants at the workshop  
284 had particular expertise in stochastic partial differential equations (SPDEs), which helped identify  
285 two *novel* ways in which mathematical techniques not previously applied to brittle failure prediction  
286 may aid in understanding the roles of material variability and stochasticity. These included:

- 287 1. Using stochastic formulations of governing equations to capture material variability and  
288 stochasticity.
  - 289 • Several mathematical methods exist for solving SPDEs with various types of variabil-  
290 ity and stochasticity. A new direction combining novel mechanics and mathematics

291 research may examine reformulations of governing equations (e.g., balance of lin-  
292 ear momentum, wave equations) that contain physically-meaningful stochastic terms.  
293 Mathematics approaches to solution may yield new insight into how specific types  
294 of material variability or stochasticity give rise to specific varieties of macroscopic  
295 responses.

296 2. Exploring white noise and other stochastic processes to capture sub-measurement-resolution  
297 uncertainty.

- 298 • Similar to stochastic formulations of governing equations, treating sub-measurement-  
299 resolution uncertainty via stochastic terms in governing equations was raised by work-  
300 shop participants as a future research direction. Research in this direction may in-  
301 volve identifying resolution limits to typical measurement techniques (e.g., of defects  
302 in tomography images) and constructing appropriate white noise terms in governing  
303 equations to capture their potential effects on material performance.

304 **THEME 3: MODEL PARAMETER IMPORTANCE, CALIBRATION**

305 Several workshop participants gave presentations related to quantifying the relative importance  
306 of model and processing parameters. This task is very important to material performance and  
307 material processing simulations, both of which typically involve complex models containing many  
308 parameters (e.g., (Tonge and Ramesh 2016)). Workshop discussions covered a variety of methods  
309 for identifying the importance or quantitative value of parameters, such as polynomial chaos  
310 expansions (Crestaux et al. 2009), surrogate modeling (Queipo et al. 2005), quasi-optimality (Shin  
311 and Xiu 2016a; Shin and Xiu 2016b), and failure forecast modeling (Voight 1987; Voight 1988a;  
312 Voight 1988b). These discussions led to the identification of at least three *novel* ways in which  
313 mathematical techniques not previously applied to brittle failure prediction may aid in studies of  
314 model parameter importance and calibration. These included:

315 1. Exploring A-, D-, and quasi-optimality methods for experiment design.

- 316 • These methods fall within the discipline of design of experiments (Pukelsheim 2006) and  
317 allow material model parameters to be estimated without statistical bias and with as few

318 measurements as possible. Employing these methods for designing future experiments  
319 for specific applications of brittle materials may aid researchers in extracting as much  
320 information as possible from scarce data when testing resources are limited, as is typical  
321 in experiments performed to study brittle failure.

322 2. Comparing surrogate modeling, deep learning, and other methods for identification of dom-  
323 inant material and process parameters.

324 • A number of distinct approaches for identifying the relative contribution of material and  
325 process parameters on simulation results were discussed, including surrogate modeling,  
326 deep learning, and polynomial chaos expansions. A thorough comparison of these  
327 methods and their relative performance would yield insight into which of them may be  
328 optimal for identifying parameters with the strongest influence on material behavior or  
329 processing.

330 3. Exploring the performance of failure forecasting prediction models that do not contain  
331 detailed physics.

332 • Methods have been proposed for predicting the occurrence of geologic events such as  
333 volcanic ruptures that do not contain detailed physical laws and instead employ simple  
334 empirical scaling relationships (e.g., (Voight 1987; Voight 1988a; Voight 1988b)). Ex-  
335 ploring whether similar methods can accurately predict the failure of brittle materials  
336 may provide a powerful and simple alternative to development and use of complex con-  
337 stitutive laws. Many workshop participants were interested in exploring this approach  
338 to brittle failure modeling.

#### 339 **THEME 4: BRIDGING SPATIOTEMPORAL SCALES**

340 A common theme of presentations by both mechanics and mathematics researchers was that  
341 of bridging spatiotemporal scales. For instance, mechanics presentations discussing Weibull dis-  
342 tributions of material strength, capturing “effective” continuum properties of discrete defects, and  
343 models such as crack band models all discussed the importance of making connections across  
344 spatial length scales. Similarly, a mathematics presentation on individual-based discrete models

345 for solving stochastic wave equations provided an interesting method of building an understanding  
346 of connections between processes operating at different length scales. From these presentations,  
347 workshop discussions led to the identification of at least one novel way in which mathematical  
348 techniques not previously applied to brittle failure modeling may aid in the an understanding of  
349 spatiotemporal scale-bridging. This approach was:

350 1. Developing particle and individual-based discrete models to understand spatiotemporal scale-  
351 bridging transitions in brittle failure.

- 352 • Particle and individual-based discrete models were discussed as tools for solving con-  
353 tinuum equations governed by PDEs and SPDEs and understanding transitions between  
354 length scales. Specific examples were provided in the context of solving a stochastic  
355 reaction-diffusion equation that arises throughout ecology, physiology, combustion, and  
356 plasma physics, known as the FKPP (Fisher-Kolmogorov-Petrovsky-Pskunov) equation  
357 (e.g., see related work in (Houchmandzadeh and Vallade 2017)). Examples of solving  
358 other SPDEs are also found in the literature (e.g., (Durrett et al. 2016)). Many work-  
359 shop participants were interested in exploring such particle or individual-based discrete  
360 models for solving stochastic versions of the PDEs governing mechanical systems (e.g.,  
361 balance of linear momentum or the wave equation) in order to understand transitions  
362 from discrete (local) to continuum (effective) behavior.

363 In conclusion, themes and recommendations discussed in this article provide exciting and  
364 impactful directions for future inter-disciplinary and collaborative research opportunities. The  
365 advancements made through joint activities between mechanics and mathematicians will greatly  
366 improve the fundamental understanding and simulations of brittle failure. Together, this will lead  
367 to the development of improved brittle materials across many industrial sectors (e.g., security,  
368 construction, natural resources).

## 369 REFERENCES

370 Aydelotte, B. B., Meyer, C. S., and Rubinstein, A. A. (2016). “Summary and findings of the

371 arl dynamic failure forum.” *Report No. ARL-TR-7834*, Army Research Lab Aberdeen Proving  
372 Ground Md Weapons and Materials Research.

373 Bazant, Z. P. (2019). *Fracture and size effect in concrete and other quasibrittle materials*. Routledge.

374 Boedihardjo, H., Geng, X., Lyons, T., and Yang, D. (2016). “The signature of a rough path:  
375 uniqueness.” *Advances in Mathematics*, 293, 720–737.

376 Chen, W. W., Rajendran, A., Song, B., and Nie, X. (2007). “Dynamic fracture of ceramics in armor  
377 applications.” *Journal of the American Ceramic Society*, 90(4), 1005–1018.

378 Chocron, S., Anderson Jr, C. E., Nicholls, A. E., and Dannemann, K. A. (2010). “Characterization  
379 of confined intact and damaged borosilicate glass.” *Journal of the American Ceramic Society*,  
380 93(10), 3390–3398.

381 Crestaux, T., Le Maitre, O., and Martinez, J.-M. (2009). “Polynomial chaos expansion for sensitivity  
382 analysis.” *Reliability Engineering & System Safety*, 94(7), 1161–1172.

383 Durrett, R., Fan, W.-T. L., et al. (2016). “Genealogies in expanding populations.” *The Annals of*  
384 *Applied Probability*, 26(6), 3456–3490.

385 Houchmandzadeh, B. and Vallade, M. (2017). “Fisher waves: An individual-based stochastic  
386 model.” *Physical Review E*, 96(1), 012414.

387 Karandikar, P., Evans, G., Wong, S., Aghajanian, M., and Sennett, M. (2009). “A review of ceramics  
388 for armor applications.” *Advances in Ceramic Armor IV*, 29, 163–175.

389 Keyhani, A., Rong, Y., and Zhou, M. (2019a). “Microscale in-situ high-speed imaging of temper-  
390 ature and deformation fields.” *Bulletin of the American Physical Society*.

391 Keyhani, A., Yang, R., and Zhou, M. (2019b). “Novel capability for microscale in-situ imaging of  
392 temperature and deformation fields under dynamic loading.” *Experimental Mechanics*, 1–16.

393 LaSalvia, J., Normandia, M., Miller, H., and MacKenzie, D. (2005). “Sphere impact induced  
394 damage in ceramics: I. armor-grade sic and tib2.” *Advances in Ceramic Armor: A Collection of*  
395 *Papers Presented at the 29th International Conference on Advanced Ceramics and Composites,*  
396 *January 23-28, 2005, Cocoa Beach, Florida, Ceramic Engineering and Science Proceedings,*  
397 *Vol. 26, Wiley Online Library, 170–181.*

398 LaSalvia, J., Normandia, M., Miller, H., and MacKenzie, D. (2009). “Sphere impact induced  
399 damage in ceramics: II. armor-grade 34c and.” *Advances in Ceramic Armor: A Collection of*  
400 *Papers Presented at the 29th International Conference on Advanced Ceramics and Composites,*  
401 *Jan 23-28, 2005, Cocoa Beach, FL*, Vol. 296, John Wiley & Sons, 183.

402 Leavy, R. B., Brannon, R. M., and Strack, O. E. (2010). “The use of sphere indentation experiments  
403 to characterize ceramic damage models.” *International Journal of Applied Ceramic Technology*,  
404 7(5), 606–615.

405 Pukelsheim, F. (2006). *Optimal design of experiments*. SIAM.

406 Queipo, N. V., Haftka, R. T., Shyy, W., Goel, T., Vaidyanathan, R., and Tucker, P. K. (2005).  
407 “Surrogate-based analysis and optimization.” *Progress in aerospace sciences*, 41(1), 1–28.

408 Scholz, C. H. (2019). *The mechanics of earthquakes and faulting*. Cambridge university press.

409 Shin, Y. and Xiu, D. (2016a). “Nonadaptive quasi-optimal points selection for least squares linear  
410 regression.” *SIAM Journal on Scientific Computing*, 38(1), A385–A411.

411 Shin, Y. and Xiu, D. (2016b). “On a near optimal sampling strategy for least squares polynomial  
412 regression.” *Journal of Computational Physics*, 326, 931–946.

413 Tonge, A. L. and Ramesh, K. (2016). “Multi-scale defect interactions in high-rate brittle material  
414 failure. part i: Model formulation and application to alon.” *Journal of the Mechanics and Physics*  
415 *of Solids*, 86, 117–149.

416 Voight, B. (1987). “Phenomenological law enables accurate time forecasts of slope failure.” *Int.*  
417 *Soc. Rock Mechanics, 7th International Congress of Rock Mechanics, Montreal, Canada*.

418 Voight, B. (1988a). “Materials science law applies to time forecasts of slope failure.” *Landslide*  
419 *News*, 3, 8–11.

420 Voight, B. (1988b). “A method for prediction of volcanic eruptions.” *Nature*, 332(6160), 125.



421

**List of Tables**

422

1 Workshop schedule. . . . . 18

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2 Important workshop discussions or questions distinct from main recommendations. 19

**TABLE 1.** Workshop schedule.

Day	Presentation Title	Speaker
1	Introduction to workshop and fracture mechanics concepts	Ryan Hurley
Session I: Computational Methods for Modeling Fracture		
1	Computational Methods for Fracture Modeling: Introduction and Overview	Richard Becker
1	Simulating comminution problems with the Material Point Method	Michael Homel
1	Attempts to use uncertainty quantification and calibration approaches in brittle systems subjected to impact loading	Andrew Tonge
Session II: Theoretical and Applied Mathematics and Statistics		
1	Some applications of stochastic processes	Samy Tindel
1	Computing the quasipotential for nongradient SDEs	Maria Cameron
1	Introduction to rough paths techniques and applications	Samy Tindel
1	Discussions of challenges and possible future research directions	All participants
Session III: Computational Methods for Modeling Fracture		
1	Introduction to some ARO challenges	Michael Bakas
1	Peridynamic modeling of dynamic fracture in solids	George Gazonas
1	Quantitative relations between macroscopic fracture behavior and mesoscale heterogeneous structures	Min Zhou
Session IV: Stochastic Simulations		
1	Introduction to stochastic simulation approaches	Roger Ghanem
1	Data driven modeling	Dongbin Xiu
1	Probabilistic frameworks for multiscale simulations of brittle fracture	Roger Ghanem
1	Discussions of challenges and possible future research directions	All participants
Session V: Probabilistic and Computational Studies of Defects and Fractures		
2	Probabilistic and Computational Studies of Defects and Fractures: Introduction	Lori-Graham Brady
2	Generalized crack band model for static and dynamic quasi-brittle fracture	Jia-Liang Le
2	Dual high-fidelity requirement of physics modeling and uncertainty quantification for brittle failure prediction	Yongming Liu
2	Stochasticity and homogenization in modeling brittle fracture when the microstructure matters	Florin Bobaru
Session VI: Uncertainty Quantification		
2	Introduction to Uncertainty Quantification	Michael Shields
2	Data and Uncertainty-Driven Reduction Methods for PDE-Constrained Parameter Calibration Problems	Tan Bui-Thahn
2	Uncertainty Quantification and Material Models	Bruce Pitman
2	Stochastic spatial models for expanding wavefronts	Wai-Tong (Louis) Fan
2	Discussions of challenges and possible future research directions	All participants

**TABLE 2.** Important workshop discussions or questions distinct from main recommendations.

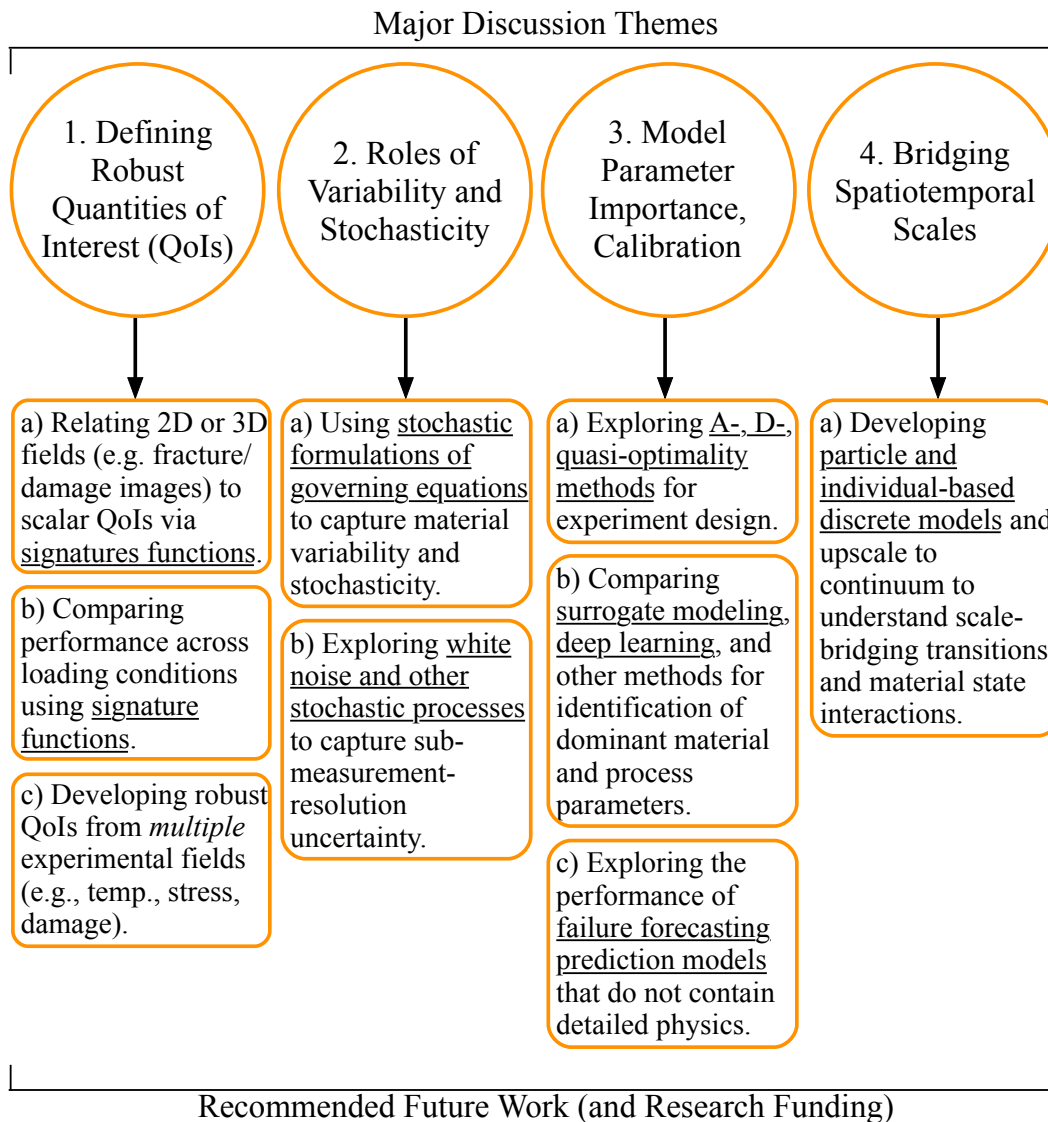
Question or Discussion
Can we develop a canonical model for important input and output parameters to help focus our efforts for materials development?
What new type of standard validation experiments can we perform (Kalthoff, edge-on-impact, expanding rings, thin plate perforation, modified sharp, Brazilian disk experiments, crack speed versus $G_c$ )?
How can neural networks be applied to analyze crack paths?
How do we model crack coalescence and interactions through direct or dynamic perturbation models?
Can we make a common data set available for validation?
How do we combined very accurate simulations with lower-order modelling to yield insightful results in a reasonable time?
How do we compare results across the different modelling approaches?
What are methods for distinguishing between material vs. experimental variability?
How to optimize the experimental sample size when attempting to determine variability parameters?
How many tests need to be performed before a reasonable match with simulations is decided?
What is the next-most-challenging problem after the ones we can currently solve (damage evolution laws through load-unload experiments with fragmentation characterization)?

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## List of Figures

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**Fig. 1.** Major discussion themes and recommended future work and research funding.