

# <sup>1</sup> DisruptionPy: An open-source physics-based scientific framework for disruption analysis of fusion plasmas

<sup>3</sup> **Gregorio L. Trevisan**   <sup>1¶</sup>, **Yumou Wei**  <sup>1</sup>, **Amos M. Decker**  <sup>1</sup>, **Joshua Lorincz**  <sup>1</sup>, **Samuel L. Jackson**  <sup>2</sup>, **Cristina Rea**  <sup>1</sup>, **Robert S. Granetz**  <sup>1</sup>,  
<sup>5</sup> **and MIT PSFC Disruptions Group**<sup>1</sup>

<sup>6</sup> **1** MIT Plasma Science and Fusion Center, Cambridge MA, USA **2** U.K. Atomic Energy Authority,  
<sup>7</sup> Culham Centre for Fusion Energy, Culham Science Centre, Abingdon, U.K. ¶ Corresponding author

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**Editor:** [Jack Atkinson](#)  

## Reviewers:

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## <sup>8</sup> Summary

<sup>9</sup> Magnetically-confined fusion experiments routinely operate under a wide variety of engineering  
<sup>10</sup> parameters in order to gain invaluable insight into fusion plasmas with the purpose of  
<sup>11</sup> understanding and then harnessing their intrinsic power for energy production. Such exploration  
<sup>12</sup> of a wide parameter space sometimes results in unexpected and rapid loss of confinement  
<sup>13</sup> of the plasma discharge, events which are generically known as ‘disruptions’. Disruptions  
<sup>14</sup> represent a significant danger to both modern experimental machines and, above all, future  
<sup>15</sup> reactor-relevant devices. Therefore preventing disruptions, detecting them, and avoiding them  
<sup>16</sup> are features of paramount importance for any plasma control system. Given the sheer number  
<sup>17</sup> of available diagnostic systems, and possible plasma modeling tools, artificial intelligence and  
<sup>18</sup> machine learning (AI/ML) models are ideal candidates for heavy-duty numerical computation.  
<sup>19</sup> Fast and agile numerical frameworks for database preparation and preprocessing are necessary  
<sup>20</sup> for letting researchers focus on novel algorithms and benchmark different architectures and  
<sup>21</sup> models.

## <sup>22</sup> Statement of need

<sup>23</sup> DisruptionPy ([Cristina Rea et al., 2024; Trevisan et al., 2024, 2026; Wei et al., 2024](#)) is  
<sup>24</sup> an open-source physics-based scientific framework for disruption analysis of fusion plasmas,  
<sup>25</sup> designed with the explicit purpose of streamlining database preparation of experimental fusion  
<sup>26</sup> data to allow efficient AI/ML workflows.

<sup>27</sup> As the Fusion Community prepares for the upcoming burning plasma devices, the multiple  
<sup>28</sup> existing data repositories already face numerous interoperability challenges. Previous community  
<sup>29</sup> reporting ([Humphreys et al., 2020](#)) identified the need to improve several aspects of existing  
<sup>30</sup> platforms, ranging from hardware and technology to software, including development of  
<sup>31</sup> optimized ML-ready workflows for fusion scientific discovery. Therein, the authors highlighted  
<sup>32</sup> the current different data access systems, the various data storage formats, and a lack  
<sup>33</sup> of adequately-labeled data as main challenges that need to be addressed by the research  
<sup>34</sup> community.

<sup>35</sup> DisruptionPy originated as an institutional effort from the Plasma Science and Fusion Center  
<sup>36</sup> within the Massachusetts Institute of Technology (MIT PSFC) to create a shared and validated  
<sup>37</sup> set of feature-extraction routines, and evolved into an open-source scientific framework in order  
<sup>38</sup> to aid disruption scientists everywhere. DisruptionPy natively supports efficiently extracting  
<sup>39</sup> data from MDSplus ([J. Stillerman et al., 2025; J. A. Stillerman et al., 1997](#)), the leading  
<sup>40</sup> open-source storage back-end for most fusion experiments, and enables scientists to carry  
<sup>41</sup> out complicated Python-based computations at scale across entire experimental databases.

42 DisruptionPy also supports extracting data from the open FAIR MAST (Jackson et al., 2024,  
43 2025) dataset, enabling researchers to easily access and analyze historical MAST data without  
44 connection to an institution. DisruptionPy relies on established numerical libraries, e.g. NumPy,  
45 SciPy, Pandas, Xarray, to allow effortless manipulation of either raw or pre-processed data  
46 into complicated feature-extraction workflows for database generation.

47 Additional example of similar frameworks for experimental data retrieval and database  
48 preparation are TokSearch (Sammuli et al., 2018) and DEFUSE (Pau et al., 2023). The  
49 TokSearch library (Sammuli et al., 2018) was developed to efficiently query, process, and  
50 analyze experimental data from DIII-D for ML applications. It leverages a distributed  
51 file format to increase throughput and a dedicated API to transfer data from MDSplus  
52 and export it in Parquet format. TokSearch appears to be established only for DIII-D  
53 workflows. DEFUSE (Pau et al., 2023), the Disruption and Event analysis framework for FUSion  
54 Experiments developed, implements an interface layer to access the data from different fusion  
55 experiments through MDSplus and HDF5. Source data, diagnostics, machine descriptions,  
56 and data-processing schemes are defined in interoperable data libraries in JSON format within  
57 a data abstraction layer. DEFUSE has been applied to several devices, however the framework  
58 has not been open-sourced yet.

59 The heterogeneous set of scripts from which DisruptionPy was developed led to several  
60 high-profile scientific publications (Hu et al., 2021; Keith et al., 2024; Maris et al., 2024;  
61 Montes et al., 2019; C. Rea et al., 2018, 2018; C. Rea et al., 2019, 2020; Spangher et al.,  
62 2025; Tinguely et al., 2019; J. Zhu et al., 2021; J. X. Zhu et al., 2020, 2023). DisruptionPy  
63 itself is now the basis for the scientific work of the entire Disruptions Group at MIT PSFC and  
64 will undoubtedly lead to further high-impact results in the near future.

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