IJDC | *Brief Report*

FAIR Principles Implementation in ML/AI - Findings from Skills4EOSC Delphi Study

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Abstract

Implementing the FAIR (Findable, Accessible, Interoperable, and Reusable) principles for scientific data management in machine learning (ML) and artificial intelligence (AI) offers numerous benefits, including higher model reliability, more collaborative research, and greater reproducibility. Despite these advantages, there is a lack of clear, practical guidelines for improving the FAIRness of ML/AI outputs, especially the models. To address this gap, Skills4EOSC Task 6.3.3a of Work Package 6: Professional Networks for Lifelong Learning conducted a Delphi Study to gather expert consensus on implementing FAIR principles in ML/AI model development. A Delphi study, involving two rounds of surveys followed by an online meeting, was conducted. In the first round, ML/AI experts from Europe and beyond rated suggested FAIR practices and proposed additional ones. The second round involved feedback and re-evaluation of these practices. The final meeting included detailed discussions on the Top 10 practices for FAIR principles implementation in ML/AI. The resulting Top 10 practices aim to provide guidelines for researchers and data management professionals to implement FAIR principles in ML/AI.

Submitted 29 May 2025 ~ *Accepted* 9 June 2025

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This report is of a Lightning Talk given at International Digital Curation Conference IDCC25, 17-19 February 2025

The *International Journal of Digital Curation* is an international journal committed to scholarly excellence and dedicated to the advancement of digital curation across a wide range of sectors. The IJDC is published by the University of Edinburgh on behalf of the Digital Curation Centre. ISSN: 1746-8256. URL: http://www.ijdc.net/

Introduction

The application of Machine Learning (ML) and Artificial Intelligence (AI) methods in science is steadily growing, driven by the availability of increasingly large and complex datasets. In many cases, the applicability and reliability of these methods are limited by the scarcity of AI-readiness and the quality of research data. In addition, the lack of guidelines for documenting and sharing ML/AI models raises concerns about research integrity, reproducibility, and long-term sustainability.

While the FAIR principles for scientific data management (Wilkinson et al., 2016) (Findable, Accessible, Interoperable, and Reusable) offer a framework to address the AI-readiness of data, their application to ML/AI models remains limited. Although foundational work has been performed to apply FAIR to research software (Barker et al., 2022), specific guidance to make ML/AI models FAIR is emerging, despite the shared challenges around accessibility, documentation, and reuse. Adapting the FAIR principles to AI is essential for fostering responsible reuse and collaboration (Huerta et al., 2023). Therefore, Skills4EOSC Task 6.3.3a conducted a Delphi Study to build expert consensus on a Top 10 list of FAIR practices for ML/AI. Focusing on ML models, the study leveraged synergies with ongoing FAIR-aligned initiatives and expert networks. This report presents the methodology and outcomes of this study to support more open, FAIR-compliant AI research.

Methodology and Results

The project task members conducted a Delphi study as a two-round survey to achieve consensus on a Top 10 list of practices for FAIR principles implementation in ML/AI, followed by an online meeting to gather additional feedback on these (see Figure 1).

The Delphi technique, commonly used in various disciplines, is a systematic and iterative method designed to gather expert consensus on topics with limited objective information to support informed decision-making. Some members of the task team had had previous experience using this method (Cobey et al., 2023), and it presented a way to achieve credible and systematic consensus from our target community.

The Delphi method typically follows six stages, including identifying a research problem, conducting a literature review, developing and distributing questionnaires, and iterating with feedback until consensus is reached (Humphrey-Murto et al., 2017).

Figure 1. Delphi rounds and online meeting.

Preparation Phase of the Delphi Study

The preparation phase involved desk research, a literature review, preliminary identification of FAIR practices relevant to ML/AI, and identification and engagement of ML/AI experts. Key resources were systematically collected and made publicly accessible through a dedicated Zotero library.[1] Potential experts were identified from research groups, laboratories, and AI-related networks. In March 2023, the Research Data Alliance (RDA) FAIR for Machine Learning (FAIR4ML) Interest Group (IG)[2] was identified as a potential collaborator due to their ongoing work towards drafting a white paper on FAIR practices in Machine Learning. The FAIR4ML co-chairs agreed to collaborate with Skills4EOSC.

Based on the literature review, a preliminary list of 26 potential practices was drafted by the project task members. These practices were further refined based on the feedback from the FAIR4ML IG members, resulting in a more precise definition and a final list of 20 practices to be presented in the Delphi questionnaire (see Figure 2).

Figure 2. Overview of Delphi preparation phase

Execution Phase of the Delphi Study

Delphi study round 1

Participants were invited via personalised invitations to complete an online survey hosted on EUSurvey.[3] The data collected was managed in accordance with the General Data Protection Regulation (GDPR).

The survey included three structured sections:

1. **Participant information.** Demographic data, institutional affiliation, career stage, and professional roles;
2. **List of 20 practices for FAIR in AI to vote for (voting section).** The list of 20 practices related to the application of FAIR principles to ML/AI models was presented here. Participants rated each practice on a 5-point Likert scale (1= Not Recommended to 5 = Strongly Recommended) based on whether they believed it should be included in the Top 10 list. In addition, participants could suggest additional related practices;
3. **Any other recommended additional practices.** Participants were invited to suggest any additional practices not included in the initial list of 20.

Data for the survey were collected between July and September 2024. In total, 183 individual invitations were sent, and representatives of 43 AI networks were contacted. Of the 84 experts who confirmed participation, 67 eventually completed the survey. The participant pool was diverse, including experts from 15 different countries, with the majority being from Europe.
Analyses of the survey results and comments by participants were conducted using custom R scripts (R version 4.2.1, Rstudio version 2022.07.0) (Osmenaj et al., 2025a). Consensus

[1] Skills4EOSC Zotero Library: https://www.zotero.org/groups/5142191/skills4eosc/library
[2] RDA: https://www.rd-alliance.org/groups/fair-machine-learning-fair4ml-ig/activity/
[3] EUSurvey: https://ec.europa.eu/eusurvey/

for each recommended practice was defined as at least 60% of responses converging on a single point of the Likert scale. Practices achieving a strong recommendation (score of 5) were automatically included in the Top 10 list. As a result, six practices met the threshold for Strongly Recommended, and another six were identified as borderline. Eight recommendations were less favourably evaluated and eliminated at this stage.

Delphi study round 2

All 67 respondents from Round 1 were invited to participate in Round 2, and 54 ultimately participated. Participants re-voted on the six borderline practices as well as six new recommendations extracted by the project task members from Round 1 suggested practices. These new items were re-formulated for better interpretation and evaluated using the same Likert scale as in Round 1.
Following the same consensus criteria and analyses used in Round 1, four practices reached consensus, adding to the six from Round 1 and resulting in the "Top 10 practices for FAIR in ML/AI" (see Figure 3).

a: (Practice 2 - Consensus reached in Round 2)

Definition: Globally unique persistent identifiers should be assigned to ML/AI models and included in their metadata.
Description: For instance, a DOI (or another globally persistent and unique identifier) should be assigned to the ML/AI model to make it findable for both humans and machines via indexing in searchable resources. This would increase the model's findability. In model updates, new identifiers could be generated to distinguish the updated versions from the original.

b: (Practice 3 - Consensus reached in Round 1)

Definition: ML/AI models should be described with rich metadata.
Description: Rich metadata (descriptive keywords and contextual information, etc.) enhances findability and reuse.

c: (Practice 5 - Consensus reached in Round 2)

Definition: ML/AI models and their metadata should be retrievable through persistent identifiers using a standardised communications protocol that is open, free, and universally implementable.
Description: This practice would enable ML/AI models' accessibility through standard, widely adopted tools. Where necessary, the protocol should allow for an authentication and authorisation procedure.

d: (Practice 9 - Consensus reached in Round 1)

Definition: The ML/AI model's metadata should report evaluation results (e.g., accuracy, precision, recall, and train versus test error, etc).
Description: Specify your model's evaluation results in a structured way in the ML/AI model metadata.

e: (Practice 11 - Consensus reached in Round 1)

Definition: ML/AI model metadata should document any prerequisites on the input data format and structure, including any required preprocessing, and output data format.
Description: If the referred training data is altered through preprocessing steps or there is a post-processing of the output of the model, this must be noted and described in the metadata for the model to promote transparency and reuse options.

f: (Practice 12 - Consensus reached in Round 1)

Definition: ML/AI model metadata should use a documented, accessible, and ideally broadly used format.
Description: As with metadata for other outputs, the metadata for ML/AI models should be in a standardised format that is accessible for either humans or machines.

g: (Practice 14 - Consensus reached in Round 2)

Definition: ML/AI model metadata should include qualified references to any related/required research objects, including code libraries, environments, and code dependencies etc.
Description: Qualified references should be made available in the metadata using references to globally unique persistent identifiers, as well as in the documentation using best practices to link code libraries. In addition, semantics should be used to define the relationships among different elements in the model workflow. This would ensure maximum reusability, reproducibility, and collaboration in the development and deployment of AI models.

h: (Practice 16 - Consensus reached in Round 1)

Definition: ML/AI models should have clear and accessible licences attached to them.
Description: Clearly stated licensing terms are important for the reusability of the ML/AI model. For instance, Open Responsible AI Licences (Open RAIL) are licences designed to permit free and open access, reuse, and downstream distribution of derivatives of AI artefacts.

i: (Practice 17 - Consensus reached in Round 2)

Definition: Any ethical considerations/analyses during model development should be reported.
Description: There should be proactive consideration of possible bias, discrimination, and known limitations in AI systems, which can perpetuate unfair outcomes and hinder inclusivity. Privacy, security, and surveillance concerns need to be addressed to protect individuals' rights.

j: (Practice 19 - Consensus reached in Round 1)

Definition: Clear instructions on how to deploy the ML/AI model should be provided.
Description: Deployment instructions ensure that users could effectively utilise the model in various environments, enhancing reproducibility.

Figure 3. List of top 10 best practices for FAIR in ML/AI (Delphi study results).

Online Meeting

A final online meeting was held on 31 January 2025. Participants and task members were given the opportunity to meet and discuss the implementation of FAIR principles in ML/AI, focusing on the Top 10 practices and the other practices presented during the study for voting but not included in the Top 10 list. All 67 Delphi study participants were invited to participate, with 17 responding positively and five attending on the designated day. Participants discussed practical solutions and challenges related to metadata, interoperability, and reproducibility in AI. Key topics included the need for minimal, standardised metadata, the role of platforms like HuggingFace and MLFlow, and the importance of tools such as containerisation for reproducibility. Emphasis was placed on balancing technical feasibility with social adoption and on enabling machine-readable metadata for automated model accessibility.

Conclusion and Next Steps

The Top 10 practices aim to provide low-threshold guidelines for researchers and data professionals to implement FAIR principles for ML/AI models. The rationale behind working with the community to compile this Top 10 list was that researchers could identify the practices they considered most important and discuss the feasibility of their implementation in practice. The methodology and results of the study were presented at the "International Digital Curation Conference" on 18 February 2025, The Hague, the Netherlands (Osmenaj et al., 2025b) as well as described in the Project Deliverable (Sharma et al., 2025c). Possible next steps to this work would be returning to those researchers and networks originally contacted and re-engaging them to obtain more insights from a practical point of view.

Acknowledgements

This work was funded by the Skills4EOSC project (GA 101058527). We would like to acknowledge the support and input of the FAIR4ML IG, which provided expert opinion and facilitated visibility to this task through their regular IG meetings and at RDA Plenaries. In addition, we would like to thank all participants in our study for sharing their expertise, opinions, and time.

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