

**IMDRF** International Medical  
Device Regulators Forum

## **Proposed Document**

**Title:** **Machine Learning-enabled Medical Devices—A subset of Artificial Intelligence-enabled Medical Devices: Key Terms and Definitions**

**Authoring Group:** IMDRF AIMD Working Group

**Date:** 16 September 2021

This document was produced by the International Medical Device Regulators Forum. There are no restrictions on the reproduction or use of this document; however, incorporation of this document, in part or in whole, into another document, or its translation into languages other than English, does not convey or represent an endorsement of any kind by the International Medical Device Regulators Forum.

Copyright © 2021 by the International Medical Device Regulators Forum.

1	<b>Table of Contents</b>	
2	<b>1.0 Introduction</b> .....	<b>4</b>
3	<b>2.0 Scope</b> .....	<b>5</b>
4	<b>3.0 References</b> .....	<b>5</b>
5	3.1 IMDRF / GHTF .....	5
6	3.2 Standards.....	5
7	3.3 Other Documents .....	5
8	<b>4.0 General Overview of Artificial Intelligence and Machine Learning Concepts</b> .....	<b>7</b>
9	<b>5.0 Key Definitions</b> .....	<b>9</b>
10	5.1 Machine Learning-enabled Medical Device (MLMD).....	9
11	5.2 IMDRF Terms .....	9
12	<b>6.0 Definitions/Reference Definitions/ Technical Standards Definitions</b> .....	<b>10</b>
13	6.1 Bias .....	10
14	6.2 Continuous Learning .....	10
15	6.3 Reference Standard.....	10
16	6.4 Reinforcement Learning .....	10
17	6.5 Reliability .....	10
18	6.6 Semi-Supervised Machine Learning.....	11
19	6.7 Supervised Machine Learning .....	11
20	6.8 Test Dataset .....	11
21	6.9 Training.....	11
22	6.10 Training Dataset.....	11
23	6.11 Unsupervised Machine Learning.....	11
24	<b>7.0 Discussion</b> .....	<b>12</b>
25	7.1 Aspects of MLMD Changes .....	12
26	7.1.1 Changes to MLMD.....	13
27	7.1.2 Changes to MLMD Environment.....	14
28	7.2 Supervised / Unsupervised / Semi-Supervised Learning.....	15
29	7.3 Validation .....	15
30		

31 **Preface**

32  
33 The document herein was produced by the International Medical Device Regulators Forum  
34 (IMDRF), a voluntary group of medical device regulators from around the world. The document  
35 has been subject to consultation throughout its development.

36  
37 There are no restrictions on the reproduction, distribution or use of this document; however,  
38 incorporation of this document, in part or in whole, into any other document, or its translation into  
39 languages other than English, does not convey or represent an endorsement of any kind by the  
40 International Medical Device Regulators Forum.

## 41 **1.0 Introduction**

42 Artificial Intelligence (AI) is a branch of computer science, statistics, and engineering that uses  
43 algorithms or models to perform tasks and exhibit behaviors such as learning, making decisions  
44 and making predictions. The subset of AI known as Machine Learning (ML) allows computer  
45 algorithms to learn through data, without being explicitly programmed, to perform a task.

46  
47 Approaches utilizing ML, sometimes colloquially referred to as AI or AI/ML, have been employed  
48 in several fields, such as the automotive industry, robotics, medicine, finance, and art. ML has  
49 given many sectors an ability to gain new insights from large amounts of data and to support tasks.

50  
51 There has been accelerated adoption and use of ML-enabled approaches in medical devices. We  
52 refer to these medical devices as Machine Learning-enabled Medical Devices, or MLMD. AI  
53 systems are typically implemented as software in medical devices or as Software as a Medical  
54 Device. MLMD have the potential to transform health care by deriving new and important insights  
55 from the vast amount of data generated during all phases of the healthcare process. Examples of  
56 applications include earlier disease detection and diagnosis; identification of new observations or  
57 patterns on human physiology; development of personalized diagnostics and therapeutics;  
58 workflow optimization; and guidance in use of the device with the goal of improving user and  
59 patient experience. One of the greatest benefits of MLMD resides in its ability to learn from real-  
60 world use and experience to improve its performance.

61  
62 The purpose of this publication is to establish relevant terms and definitions across the Total  
63 Product Life Cycle (TPLC) to promote consistency, support global harmonization efforts, and  
64 provide a foundation for the development of future guidelines related to MLMD. Terms referenced  
65 herein have either been previously defined in Global Harmonization Task Force (GHTF)  
66 documents or by internationally recognized standards on AI. Some terms and definitions have  
67 been generated by or are discussed by the IMDRF Artificial Intelligence Medical Device (AIMD)  
68 Working Group within this document.

69  
70 The overarching objective of this effort is to promote consistent expectations and understanding  
71 for MLMD, promote patient safety, foster innovation, and encourage access to advances in  
72 healthcare technology.

73

---

## 74 2.0 Scope

75 This document applies to key terms and definitions relating to Machine Learning-enabled Medical  
76 Devices (MLMD).

77  
78 **Note 1** : MLMD are *medical devices*. A product must first meet the definition of a *medical device*  
79 before it can be an MLMD.

80  
81 **Note 2** : Most jurisdictions include "accessories to medical devices" in the definition of "medical  
82 device". Other jurisdictions define "accessories to medical devices" separately. The definitions  
83 and the concepts in this document are intended to apply in both case.

84  
85 **Note 3** : This document does not attempt to define established definitions in the field of computer  
86 science; however, it does strive to highlight and clarify conflicting terms and definitions as  
87 necessary. This document does not provide guidelines for the development, risk management or  
88 evaluation of MLMD.

89  
90 **Note 4** : Terms and definitions that refer technical standards that are under development (e.g., ISO,  
91 IEC, IEEE) may be updated upon final publication of those standards.

92

## 93 3.0 References

### 94 3.1 IMDRF / GHTF

- 95 • IMDRF/SaMD WG/N10 FINAL:2013 Software as a Medical Device (SaMD): Key  
96 Definitions
- 97 • IMDRF/GRRP WG/N47:2018 Essential Principles of Safety and Performance of Medical  
98 Devices and IVD Medical Devices(3.0 Definitions)

### 99 3.2 Standards

100 The standards below were consulted in the writing of this document and may be useful in meeting  
101 the key definition of MLMD discussed herein. This list is not intended as a required or complete  
102 list of standards that can be used to meet the key definition of MLMD.

- 103 • ISO/IEC DIS 22989 Information technology — Artificial intelligence — Artificial  
104 Intelligence Concepts and Terminology

### 105 3.3 Other Documents

- 106 • AAMI, BSI, Turpin, R., Hofer, E., Lewelling, J., & Baird, P. (2020). *Machine Learning*  
107 *AI in Medical Devices: Adapting Regulatory Frameworks and Standards to Ensure Safety*  
108 *and Performance*. AAMI/BSI Initiative on Artificial Intelligence.  
109 [https://www.bsigroup.com/en-US/medical-devices/resources/Whitepapers-and-](https://www.bsigroup.com/en-US/medical-devices/resources/Whitepapers-and-articles/machine-learning-ai-in-medical-devices/)  
110 [articles/machine-learning-ai-in-medical-devices/](https://www.bsigroup.com/en-US/medical-devices/resources/Whitepapers-and-articles/machine-learning-ai-in-medical-devices/)

- 111
- 112
- 113
- 114
- 115
- 116
- 117
- Kohavi, R., & Provost, F. (Eds.). (n.d.). Glossary of Terms: Special Issue on Applications of Machine Learning and the Knowledge Discovery Process.  
<https://ai.stanford.edu/~ronnyk/glossary.html>
  - Kan A. (2017). Machine learning applications in cell image analysis. *Immunology and Cell Biology*, 95(6), 525–530.  
<https://doi.org/10.1038/icb.2017.16>

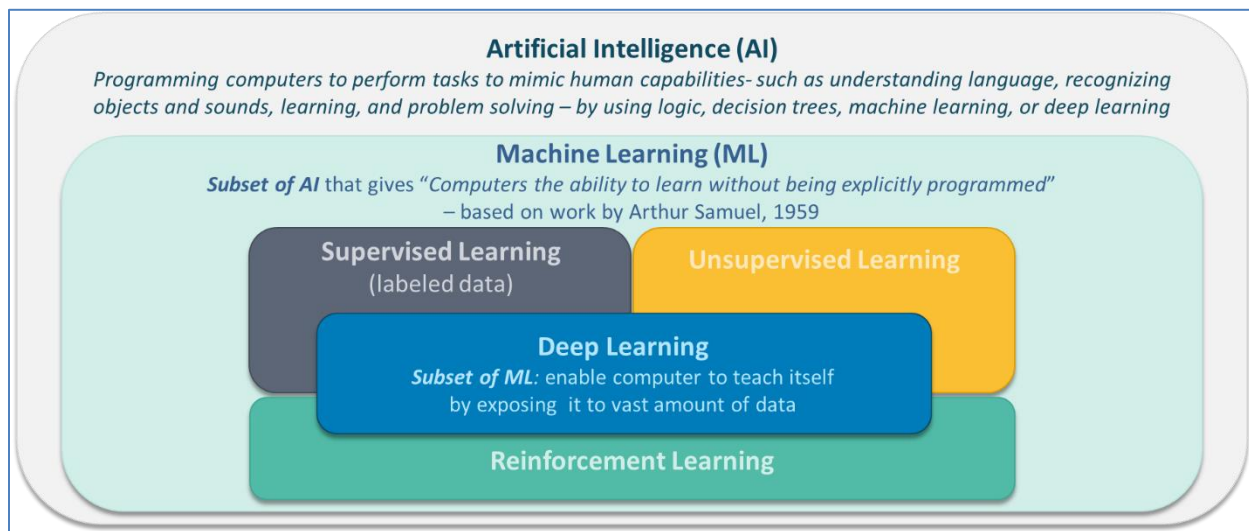
## 118 4.0 General Overview of Artificial Intelligence and Machine Learning 119 Concepts

120 AI systems are able to perform tasks such as visual perception, speech recognition, decision-  
121 making, and translation between languages – by using expert systems (based on rules like decision  
122 trees), machine learning or deep learning.

123  
124 Some AI systems demonstrate a degree of autonomy (capacity to perform tasks in a complex  
125 environment without constant guidance/input from a user) and a capacity for adaptability (ability  
126 to learn from experience and thereby change performance.)

127  
128 ML is a computing system that contains a model or algorithm generated through a computer  
129 learning patterns from data, including classification, inference, or matching previous patterns,  
130 predicting future outputs, etc. ML has been considered as a subset of AI that gives computers the  
131 ability to learn without being explicitly programmed<sup>1</sup>.

132



133  
134

Figure 1 Overview of AI and ML Concepts

135  
136 ISO/IEC’s draft international standard for AI, 22989, defines and discusses ML in terms of being  
137 an ML model parameter optimisation process for the purpose of the ML model’s behaviour  
138 reflecting the data or experience.

139  
140 There are several different types of ML methods, as well as different algorithms. For example,  
141 some applications may use Supervised Learning, others may use Unsupervised or Semi-  
142 Supervised Learning (Section 6.0). Different types of algorithms include neural networks (e.g.,  
143 feed forward neural network, recurrent neural network, convolutional neural network, etc.)

<sup>1</sup> A.L. Samuel, “Some Studies in Machine Learning Using the Game of Checkers.” IBM Journal 1(3), 210–229 (1959)

144 Bayesian networks, decision trees, support vector machine, among others. The learning process  
145 itself may be an iterative process of trial and error, also known as Reinforcement Learning.

146  
147 **Note :** Within this document, the term ML algorithm is used to represent a software procedure  
148 developed using ML, and consisting of mathematics and logic, that can process data. The term ML  
149 model is used here to represent the relationship or function that is the result of Training an ML  
150 algorithm with data.

151  
152 The following sections provide key definitions that are relevant to ML when used in medical  
153 devices (Section 5.0), definitions from technical standards (Section 6.0), followed by a discussion  
154 of common ML terms (Section 7.0).

155



---

## 156 5.0 Key Definitions

### 157 5.1 Machine Learning-enabled Medical Device (MLMD)

158

159 A medical device that uses machine learning, in part or in whole, to achieve its intended  
160 medical purpose.

161

### 162 5.2 IMDRF Terms

163 Medical Device: Any instrument, apparatus, implement, machine, appliance, implant, reagent for  
164 in vitro use, software, material or other similar or related article, intended by the manufacturer to  
165 be used, alone or in combination, for human beings, for one or more of the specific medical  
166 purpose(s) of:

- 167 • diagnosis, prevention, monitoring, treatment or alleviation of disease,
- 168 • diagnosis, monitoring, treatment, alleviation of, or compensation for, an injury,
- 169 • investigation, replacement, modification, or support of the anatomy, or of a physiological  
170 process,
- 171 • supporting or sustaining life,
- 172 • control of conception,
- 173 • cleaning, disinfection or sterilization of medical devices,
- 174 • providing information by means of in vitro examination of specimens derived from the  
175 human body;

176 and does not achieve its primary intended action by pharmacological, immunological, or  
177 metabolic means, in or on the human body, but which may be assisted in its intended function  
178 by such means.

179

180 **Note 1** : Products which may be considered to be medical devices in some jurisdictions but  
181 not in others include:

- 182 • disinfection substances,
- 183 • aids for persons with disabilities,
- 184 • devices incorporating animal and/or human tissues,
- 185 • devices for in-vitro fertilization or assisted reproduction technologies.

186

187 **Note 2** : For clarification purposes, in certain regulatory jurisdictions, devices for  
188 cosmetic/aesthetic purposes are also considered medical devices.

189

190 **Note 3** : For clarification purposes, in certain regulatory jurisdictions, the commerce of  
191 devices incorporating human tissues is not allowed.

192

193 Editorial issue has been corrected from IMDRF/GRRP WG/N47:2018.

194

---

## 195 6.0 Definitions/Reference Definitions/ Technical Standards Definitions

### 196 6.1 Bias

197 *Systematic difference in treatment of certain objects, people, or groups in comparison to*  
198 *others. (ISO/IEC DIS 22989)*

199 **Note :** Bias is used in both data science and in legal discussions. When used in data science,  
200 bias is the tendency of a statistic to overestimate or underestimate a parameter. From a legal  
201 point of view, however, bias is any prejudiced or partial personal or social perception of a  
202 person or group. For the purposes of this document, bias is a data science term, and not a  
203 legal one. Bias can be introduced into study design, conduct or analysis. Sources of bias  
204 include selection bias (of study sample), operational bias, and analyses that do not account  
205 for missing data.

### 206 6.2 Continuous Learning

207 Training that leads to change of an MLMD with each exposure to data that takes place on  
208 an ongoing basis during the operation phase of the MLMD life cycle. (Modified from  
209 ISO/IEC DIS 22989)

210 **Note :** Batch Learning is a training that leads to the change of an MLMD that involves  
211 discrete updates based on defined sets of data that take place at distinct points prior to or  
212 during the operation phase of the MLMD life cycle.  
213

### 214 6.3 Reference Standard

215 An objectively determined benchmark that is used as the expected result for comparison,  
216 assessment, training, etc. (e.g., ground truth, gold standard).

### 217 6.4 Reinforcement Learning

218 *Machine learning utilizing a reward function to optimize either a policy function or a value*  
219 *function by sequential interaction with an environment. (ISO/IEC DIS 22989)*

220 *Note 1 to entry: Policy functions and value functions express a strategy that is learned by*  
221 *the environment.*

222 *Note 2 to entry: The environment can be any stateful model.*

### 223 6.5 Reliability

224 *Property of consistent intended behavior and results. (ISO/IEC DIS 22989)*

---

## 225 6.6 Semi-Supervised Machine Learning

226 *Machine learning that makes use of both labelled and unlabelled data during training.*  
227 (ISO/IEC DIS 22989)

228 **Note 1** : Descriptive information can be broader than just labelling. Annotation is the  
229 process of attaching descriptive information to data, such as metadata, labels, or anchors.  
230 The data itself is unchanged in the annotation process.<sup>2</sup>

231 **Note 2** : Additional information about this term can be found in Section 7.4

## 232 6.7 Supervised Machine Learning

233 *Machine learning that makes use of labelled data during training.* (ISO/IEC DIS 22989)

234 **Note 1** : Descriptive information can be broader than just labelling. Annotation is the  
235 process of attaching descriptive information to data, such as metadata, labels, or anchors.  
236 The data itself is unchanged in the annotation process.<sup>2</sup>

237 **Note 2** : Additional information about this term can be found in Section 7.4

## 238 6.8 Test Dataset

239 A subset of the data that is never shown to the ML model during training, used to verify  
240 what the model has learned. (Modified from ISO/IEC DIS 22989)

## 241 6.9 Training

242 Process intended to establish or to improve the parameters of a machine learning model,  
243 based on a machine learning algorithm, by using training data. (Modified from ISO/IEC  
244 DIS 22989)

## 245 6.10 Training Dataset

246 *Subset of input data samples used to train a machine learning model.* (ISO/IEC DIS 22989)

## 247 6.11 Unsupervised Machine Learning

248 *Machine learning that makes use of unlabelled data during training.* (ISO/IEC DIS 22989)

249 **Note 1** : Descriptive information can be broader than just labelling. Annotation is the  
250 process of attaching descriptive information to data, such as metadata, labels, or anchors.  
251 The data itself is unchanged in the annotation process.<sup>2</sup>

252 **Note 2** : Additional information about this term can be found in Section 7.4

---

<sup>2</sup> ISO/IEC DIS 22989 Information technology — Artificial intelligence — Artificial Intelligence Concepts and Terminology

## 253 **7.0 Discussion**

254 The following sub-sections contain discussions of concepts that warranted more detail than a  
255 concise definition. In particular, the aspects of MLMD changes, supervised and unsupervised  
256 learning, and validation are discussed.  
257

### 258 **7.1 Aspects of MLMD Changes**

259 MLMD offer unique benefits, flexibility, and challenges related to their capacity for change.  
260 The transparent communication of the various aspects of these changes is important to the safety,  
261 performance, and effectiveness of MLMD.

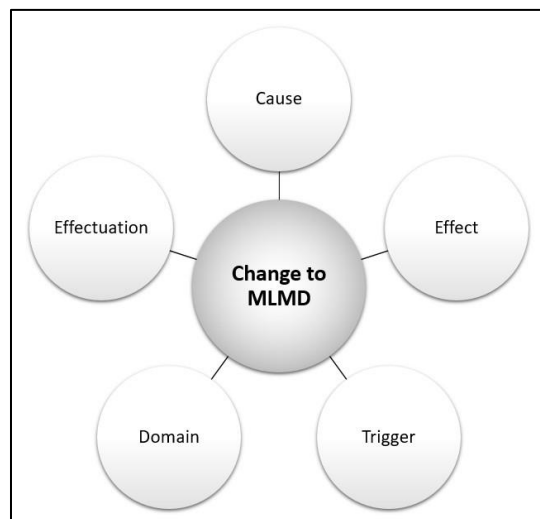
262  
263 The examples outlined in this discussion are not exhaustive and the relevant information may  
264 expand over time. It is important to note that changes , such as software patches, operating system  
265 updates, cybersecurity improvements, etc., can impact both MLMD and non-MLMD medical  
266 devices and, although important, these changes are not within the scope of this discussion.

267  
268 There are a number of unique changes related to MLMD, including changes to the ML model or  
269 to the environment of use relative to the ML training data. The following discussion highlights  
270 these important aspects in two sections, MLMD Changes and MLMD Environmental Changes.  
271

### 272 7.1.1 Changes to MLMD

273 A change to the device could include a modification to the machine learning model, algorithm,  
274 weights, or parameters. MLMD is in a locked state when changes are not permitted. Aspects that  
275 describe these changes include the cause, effect, trigger, domain, timing, and effectuation. These  
276 attributes describe what changes, as well as why, where, when, and how the MLMD change occurs.  
277

278 **Note :** The word "locked" has been used by the community in a number of different ways. Some  
279 have defined a "locked device" as one that has been developed using ML methods but for which  
280 the developer does not have an intention of modifying at the present time. Others have used the  
281 term "locked device" as any device that does not perform "continuous learning." When using the  
282 word "locked" it is important to provide clarifying language around its use to communicate how it  
283 is being used.



284  
285 **Figure 2 Aspects of MLMD Changes**

286 The cause refers to the source of the change to the MLMD, for example, re-training with new or  
287 appended data or new training methods, algorithm/model, tuning, etc.

288  
289 The effect refers to the resulting change to the MLMD, which can include amended intended  
290 use/indications for use; modified performance, changes in inputs, outputs, etc.

291  
292 The trigger refers to the event that prompts or instigates the change to the MLMD, which can  
293 include performance thresholds, training data batch-size thresholds, exposure to new  
294 data/experiences, scheduled time intervals, MLMD environmental changes, user feedback, etc.

295  
296 The domain refers to the scope or applicable extent of the change to the MLMD, which can be  
297 categorized as either homogeneous or heterogeneous. A homogeneous change is a uniform change  
298 that occurs universally (sometimes referred to as a global adaptation, note that global does not

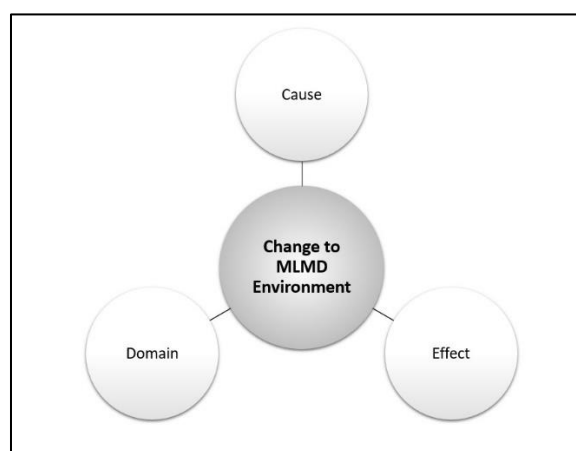
299 denote around-the-world). Heterogeneous changes are non-uniform changes that can be specific  
300 to one clinic, region, demographic, etc. (sometimes referred to as local adaptations).<sup>3</sup>

301  
302 The effectuation refers to where the mechanism for change implementation resides, which can  
303 either be external (i.e., updated by the developer or user) or internal (i.e., updated by a change-  
304 control-algorithm within the device).

### 305 7.1.2 Changes to MLMD Environment

306 An MLMD environmental change is a modification to the setting of the MLMD relative to the  
307 ML development data. Aspects that describe an MLMD environmental change include the cause,  
308 effect, and domain.

309



310

311 **Figure 3 Aspects of MLMD Environmental Changes**

312 The cause of an MLMD environmental change refers to the source of the change relative to the  
313 development environment. Examples of such causes include changes to the format or quality of  
314 the MLMD inputs (e.g., changes to third party image processing, incidents of adversarial machine  
315 learning); changes in the patient population (e.g., demographic shift); changes in clinical practice  
316 (e.g., earlier interventions that mask features used by the model for classification), etc.

317

318 The effect of an MLMD environmental change can involve deteriorated or improved performance,  
319 effectiveness, or safety.

320

321 The domain of an MLMD environmental change refers to the scope or applicable extent of the  
322 change, which can be categorized as either homogeneous or heterogeneous. Heterogeneous  
323 changes are non-uniform changes that can be specific to one clinic, region, demographic, etc.  
324 (sometimes referred to as local changes). Homogeneous changes are changes that occur uniformly  
325 (universally, globally) over some groups or settings/context. Note that global does not denote  
326 around-the-world.

---

<sup>3</sup> “Introduction to Online Machine Learning: Simplified”,  
<https://www.analyticsvidhya.com/blog/2015/01/introduction-online-machine-learning-simplified-2/>

---

## 327 7.2 Supervised / Unsupervised / Semi-Supervised Learning

328 Supervised and Unsupervised Machine Learning are two methods that are commonly used to train  
329 machine learning algorithms, but they are not the only methods available. The terms “supervised”  
330 and “unsupervised” in a machine learning context refer to the training methods, and specifically  
331 whether labelled or unlabelled data are used. Supervised Machine Learning utilizes labelled data  
332 during Training to learn the relationship between independent attributes and a designated  
333 dependent attribute (the label). In other words, supervised learning is a task to learn a mapping  
334 from input to output values, where the correct output values are known (labelled training data).  
335 Most induction algorithms are developed through supervised learning. Unsupervised Machine  
336 Learning utilizes unlabelled data during Training to group data without a pre-specified dependent  
337 attribute. In other words, unsupervised learning is the ability to find patterns from input values,  
338 where the output values are unknown. Examples of unsupervised learning include some types of  
339 algorithms that perform clustering or dimensionality reduction.

340  
341 Machine learning systems can use a mix of supervised and unsupervised learning (sometimes  
342 referred to as semi-supervised learning), as well as other learning methods such as Reinforcement  
343 Learning.

344  
345 The terms “Supervised Machine Learning ” and “Unsupervised Machine Learning ” are often  
346 misunderstood. When used in a machine learning context, “supervised” or “unsupervised” does  
347 not refer to the presence or absence of a human supervisor overseeing the software. “Supervised”  
348 or “unsupervised” does not refer to the role that the software plays in a clinical environment, i.e.,  
349 it does not describe the level of “autonomy” in practice. “Supervised” or “unsupervised” also does  
350 not refer to whether the software updates itself in a self-effectuating update process, i.e., whether  
351 it performs its own updates or adaptations.

352

## 353 7.3 Validation

354 The term validation has been used to represent different concepts within the fields of medical  
355 device development and machine learning algorithm development.

356  
357 Validation within the context of medical device development has been defined as follows:

358  
359 *Validation means confirmation by examination and provision of objective evidence that the*  
360 *particular requirements for a specific intended use can be consistently fulfilled.*<sup>4</sup>

361  
362 The term validation has also been used within the field of machine learning to refer to either data  
363 curation (sometimes referred to as data validation<sup>5</sup>) or model tuning (sometimes referred to as  
364 validation<sup>5</sup>).

---

<sup>4</sup>Design Control Guidance for Medical Device Manufacturers (GHF.SG3.N99-9)

<sup>5</sup>Ripley, B. (1996). Glossary. In Pattern Recognition and Neural Networks (pp. 347-354). Cambridge: Cambridge University Press. doi:10.1017/CBO9780511812651.013

365  
366 Data curation and model tuning can occur throughout the product lifecycle. Data curation refers  
367 to the selection, management and assessment of the quality attributes of data sets. Model tuning is  
368 a particular phase of model development during which ML model hyper-parameters are tuned; this  
369 optional tuning phase can be combined with the Training phase to optimize the ML model selection.

370  
371 MLMD manufacturers, regulators, and users should be aware of the conflicting interpretations of  
372 the term validation and ensure that communication regarding the development phases and the  
373 associated datasets is clear to avoid confusion between data validation, model tuning, and medical  
374 device validation. It is recommended that the use of the term “validation” be accompanied by the  
375 context when referring to model tuning, data curation, and the associated datasets. Alternatively,  
376 the use of the term validation that refers to the training and tuning process may be avoided in the  
377 context of medical device development.

378