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On the Interplay of Legal Requirements, Quality Aspects and Ethical Risks when using Machine Learning in German Official Statistics

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Abstract

Artificial intelligence (AI) with its subfield machine learning (ML) has found its way into administration in general and also into official statistics in Germany in particular. This paper highlights the ethical issues that may arise when using AI/ML in official statistics and examines whether a separate ethical framework is needed to deal with these issues appropriately, as is proposed by institutions of other countries and intergovernmental institutions related to official statistics. The results of the study are presented to show that the implementation of the requirements of the existing and mostly non-AI/ML-specific frames of reference such as law and quality is already sufficient to adequately address the ethical issues based on risk scenarios.

Key Words: Artificial intelligence; Machine learning; Law; Quality; Ethics.

1. Introduction

About a decade ago, national statistical offices began to look into a field of algorithms known as machine learning. Some see these as coming from computer science, others from statistics. But no matter who developed the algorithms, statistical offices can use them and are increasingly doing so. This is being driven by an active community that efficiently implements and further develops machine learning methods in R and Python. While the experimental character was in the foreground at the beginning, organisational, personnel, methodological, legal and ethical questions have emerged over time. Not all of these questions have been answered yet. The same applies to the expectations placed on machine learning in the offices. While a certain scepticism towards the new was often felt at the beginning, expectations were also temporarily overblown. In some cases, it was expected that machine learning (often together with new data sources, keyword Big Data) would solve Holt's 'Olympic challenge of official statistics', namely to enable the production of wider, deeper, quicker, better and cheaper statistics as "official statisticians have benefited from advances in technology to improve performance [...]; for statisticians huge benefits have been derived from technical advances in data collection, processing, and presentation [...] [and] better methodologies and advances in statistical methods and analysis." (Holt, 2007, p. 1) Of course, this did not come true. However, the use of machine learning in the production of official statistics has certainly led to successes, often in phase 5 ('process') of the Generic Statistical Business Process Model (UNECE, 2019), i.e. for tasks such as data integration, classification and coding, editing and imputation. These successes usually consist of the fact that the necessary processing steps are carried out more efficiently. This is in turn made possible by replacing manual routine work with computers trained in machine learning. The case workers thus relieved of simple, repetitive work now have the opportunity to devote themselves to particularly important or difficult cases within the processing steps and to take over the quality control of the algorithm's results. While the work relief is welcomed, concerns have been and are being raised. These concerns often centre on whether the algorithms can be trusted, who is ultimately responsible for a statistical product despite

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automation, and how distortions can be avoided. This has given rise to the field of ethical considerations of machine learning in official statistics.

A note to narrow down the scope: This article only considers the use of machine learning in statistical production (i.e. not in general administration) and within this only in the work on the data. In particular ethical considerations of application examples for so-called generative AI for text summaries, document creation, translations, etc. are not discussed here.

The short contribution to the Proceedings of Statistics Canada Symposium 2024 is structured as follows: First, the ethical risks that German official statistics has identified when using machine learning are presented (Section 2). Subsequently, Section 3 describes how these ethical risks can already be addressed while complying with the requirements of German law and European quality standards. A summary can be found in Section 4.

2. Ethical Risks

2.1 Deriving ethical risks

The first step is to identify the ethical risks. The approach chosen for this was to review existing national and international work on the ethical risks of machine learning in general, but especially with a focus on official statistics, and to identify their key points. Statistics Canada's *Framework for Responsible Machine Learning Processes* (Statistics Canada, 2021), UK Statistics Authority's *Ethical considerations in the use of Machine Learning for research and statistics* (UK Statistics Authority, 2021), and UNECE's *International Framework on Responsible AI for Official Statistics* (UNECE, 2023) were identified as outstanding sources here. The goals of avoiding bias, transparency, explainability, accountability, confidentiality, value, prevention of harm, fairness, privacy, security, reproducibility, quality, valid inference, rigorous modelling, ethical purpose, environmental sustainability, non-discrimination and inclusiveness, robustness, and several more can be found here again and again in a similar form. From these goals, the most important ethical risks can be derived and clustered by taking the opposite of the goals. Subsequently, those clusters that form a particular focal point were used for further consideration.

2.2 Identified ethical risks

In this way, six risks have been identified:

1. Production of incorrect statistics
2. Creation of the transparent citizen
3. Transfer of responsibility to an algorithm and lack of transparency
4. Leakage of sensitive data
5. Amplification of unwanted biases
6. Lack of ecological sustainability

These are described in more detail in the following.

Production of incorrect statistics It may happen that due to the use of AI/ML, statistics (e.g. indicators or tables) are produced incorrectly. This may indirectly cause that misallocations or wrong decisions are made by those who interpret official statistics or use them for their decision-making (e.g. in politics). From a societal perspective, this is harmful and should therefore be viewed negatively.

Creation of the transparent citizen The use of AI/ML links information about a statistical unit (e.g. a natural person) in such a way that the statistical unit becomes 'transparent' and thus enables profiling. Examples show that just a few data points are sufficient to uniquely identify individuals. The large volume of data that can be linked by AI/ML in a statistical office offers a principal opportunity to scale up this possibility. This aspect also contradicts the ideas of society and must therefore be considered harmful.

Transfer of responsibility to an algorithm and lack of transparency The AI/ML processes used are held responsible for decisions that have to be made in the course of statistical production. Examples could be the assignment

of statistical units to certain categories (e.g. occupational groups, economic activities). No person then bears responsibility for an assignment. The decision made automatically by AI/ML cannot be challenged, also because essential steps may not be traceable or documented. In a state (under the rule) of law (“Rechtsstaat”), it is expected that administrative actions can be reviewed. If this is not the case, it is to be regarded as negative.

Leakage of sensitive data It is obviously harmful and incompatible with the public's perception of official statistics if data that requires protection (due to statistical law, data protection, confidentiality obligations of employees or any other standard) leaves the protected area of official statistics. If data, which have been provided in the confidence that they will be used exclusively for statistical purposes, are made available to unauthorised persons, then this will result in a major loss of trust and serious reputational damage for official statistics (in addition to any legal consequences that may arise).

Amplification of unwanted biases It is conceivable in principle that the use of AI/ML could amplify undesirable biases (e.g. in the training data of the algorithms). Occupational groups, for example, that are not sufficiently represented in the training data are classified as negligible by the algorithm and are simply no longer taken into account in subsequent classifications carried out by the algorithm. This can be particularly critical in the case of cross-classifications (e.g. sex, occupational group and region). As a result, the task of describing mass phenomena is no longer carried out correctly by official statistics, which in turn could lead to the risk of producing inaccurate statistics with the corresponding consequences (e.g. in politics or industry, but also in private decisions). This is to be evaluated negatively from both a social and a personal point of view.

Lack of ecological sustainability The use of AI/ML, in particular of so-called deep learning and the large language models belonging to this class, is often computationally intensive and causes an extremely high consumption of energy and water, especially during initial training and any retraining that may be required, but also, albeit often to a lesser extent, during application. This is particularly negative if the use of this class of methods, which may not be ecologically sustainable, is not necessary at all (for example, because more sustainable methods deliver almost equally good results).

3. Countering the risks

3.1 Frames of reference

Various frames of reference are conceivable for countering the ethical risks mentioned above, i.e. answering the question of how to deal with the ethical risks. What do statistical offices have to bear in mind when they produce official statistics using AI/ML?

Official statistics are subject to two frames of reference. Firstly, and with primacy over all other frames of reference, the law with its norms and binding court rulings that are relevant for official statistics. Secondly, (legally permissible) self-commitments made by the official statistics authorities themselves. These can be found in the quality frameworks of official statistics in Germany and Europe (in particular the Quality Assurance Framework, European Statistical System, 2019). Comparable quality frameworks can also be found in many other countries, such as Statistics Canada's Quality Assurance Framework (Statistics Canada, 2017). A corresponding framework can also be found at the United Nations level (United Nations, 2019).

Law The fundamental standards in the legal frame of reference for Germany are the Basic Law of the Federal Republic of Germany, the Federal Statistics Act, the specialized statistics laws (some of these laws even contain very detailed specifications as to which variables may be collected by official statistics) and the ruling of the Federal Constitutional Court on the census in 1983. There is the principle that (with very few exceptions) no official statistic may be gathered without a law. This ensures that it is parliament that weighs up ethical aspects as part of the legislative process. The German Bundestag represents the people and is the decisive legislative body. It is here that society debates what it wishes to permit and what it does not. If higher-ranking law (in particular from the Basic Law) is disregarded or deliberately ignored, the way is open to refer the matter to the Federal Constitutional Court. Other norms contain regulations with regard to information security, data protection or energy efficiency.

Quality The various quality frameworks (including the Quality Assurance Framework, the European Statistics Code of Practice, and the Qualitätshandbuch as the German adaptation of the former frameworks) include requirements for the institution (the statistical office), its processes and its products. Principles here include, for example, professional independence, sound methodology, accuracy and reliability, timeliness and punctuality, or accessibility and clarity (European Statistical System, 2019). A derivation of quality dimensions for AI/ML in official statistics from the general quality frameworks, as well as a proposal for operationalizing them in the form of quality guidelines, can be found in Saidani et al. (2023), a paper that is in turn based on Yung et al. (2022) and thus on joint preliminary work in a UNECE project. The quality dimensions from Saidani et al. (2023), namely accuracy, robustness, explainability, reproducibility, timeliness and punctuality, and cost-effectiveness, have since been classified as binding for official statistics in Germany. Also the quality guidelines have been defined – in a slightly modified form – as a binding basis for AI/ML projects in German official statistics. Examples of these quality guidelines are for accuracy *“Machine learning methods follow standard scientific methodology in relation to statistics and ML. The methodology used was documented (including reasons for selecting a particular method) and communicated with the target audience.”* and for robustness *“The desired object of robustness analyses was defined: specific predictions, model coefficients, accuracy metrics or aggregate values of the target variable.”*

The law necessarily represents the primary frame of reference to be applied. This primacy of the law relates, on the one hand, to the second frame of reference (quality) and would also apply to a hypothetical ethical framework. The fact that an ethical framework established by an authority, such as a statistical office, cannot be of a higher order than laws created by parliament, is derived from the Basic Law. Furthermore, such an ethical framework would have to be in line with the values of the Basic Law, in particular the fundamental rights, including the EU Charter of Fundamental Rights, and the state objectives.

3.2 Detailed view on the risks

Production of incorrect statistics The principles that methodology and procedures used should correspond to the current state of scientific research and that the results of a statistic should be accurate (Principles 7, 8 and 12 of the Quality Assurance Framework) imply the obligation to bring about and also verify this accuracy. Of course, it is in the nature of statistics and all statistical methods (including AI/ML) that estimates and predictions often do not meet exactly the “true” value when applied to an individual case. This is the price to be paid for the fact that not all the information needed can be collected directly without measurement errors and without delimitation and interpretation difficulties. When it comes to the specific application of AI/ML (and this also applies to the use of other methods) the assignment of, e.g., a particular person to a job classification may not be correct. However, as long as it is ensured that the statistics themselves meet the accuracy requirements, this is not critical. The ethical risk of inaccurate statistics is thus addressed by the quality frame of reference.

Creation of the transparent citizen The ethical risk of creating a transparent citizen cannot arise in German official statistics, as it is already excluded by the legal frame of reference and here in particular by the census ruling of 1983. This ruling explicitly states that it is not permissible to combine statistics and personal data in such a way that profiling is made possible. Furthermore, the Federal Statistics Act requires the statistical offices to delete auxiliary characteristics (e.g. name, address) as early as possible and prohibits attempts at re-identification. The data from which statistics may be merged at all is also explicitly regulated by law. In all of this, it is irrelevant whether AI/ML is used or not. This ethical risk is thus addressed by the legal frame of reference.

Transfer of responsibility to an algorithm and lack of transparency From a legal point of view, it is never an algorithm (or an AI) that acts, but always the statistical office, which merely makes use of the algorithm. This is where the responsibilities are defined. In addition, data protection law grants people the right not to be made the subject of automated decision-making. In principle, this can of course also apply to official statistics processes. Furthermore, the use of algorithms must not lead to a situation in which essential steps of the activity are neither comprehensible nor documented (violation of transparency and accountability obligations), because this could mean that official activity can no longer be controlled by the courts (violation of the Basic Law's guarantee of legal recourse) and that control instances (in particular supervisory authorities, parliaments) can no longer control administrative action (violation of the principle of the lawfulness of administrative action in the Basic Law). Furthermore, the Quality Assurance Framework states that the management (i.e. persons) of the official statistics producers bear sole responsibility for the determination of statistical methods, standards and procedures (Indicator 1.3). Additionally, the Quality Assurance

Framework Indicators 6.4 (public accessibility of the methods and procedures used) and 15.6 (informing users about the methodology of statistical processes) as well as the quality dimension ‘explainability’ in Saidani and others (2023, p. 279 ff.) provide guidelines for transparency from a quality perspective. The ethical risk of transfer of responsibility to an algorithm and lack of transparency is thus addressed by both, the legal and the quality frame of reference.

Leakage of sensitive data The Federal Statistics Act and the European Statistics Regulation already require that the statistical offices take all necessary legal, administrative, technical and organisational measures to ensure the physical and logical protection of confidential data. There are also special legal requirements for the processing of personal data. The relevant legal norms thus prohibit harmful actions, and actions not prohibited by the legal norms are acceptable from the perspective of the legislator. Furthermore, to ensure statistical confidentiality is required by the ESS Quality Assurance Framework’s Principle 5.

Amplification of unwanted biases Saidani et al. (2023) summarize fairness as a circumstance in which statistical aggregates for certain subgroups are not systematically over- or underestimated (Saidani et al., 2023, p. 292 f.). Official statistics must reflect the prevailing conditions as they are. However, how these conditions are reacted to is a political, economic or personal decision, and not one for official statistics. For a correct, unbiased representation, it is crucial that all relevant subgroups are equally correctly represented by the statistical methods in the production process. This must be ensured by official statistics through their quality requirements. The risk of reinforcing unwanted biases is therefore already addressed by the quality frame of reference.

Lack of ecological sustainability To the knowledge of the authors of Dumpert et al. (2025a, 2025b), the aspect of (ecological) sustainability is not currently addressed comprehensively by the above-mentioned frames of reference (law and quality). Attempts to derive corresponding guidelines for ecological sustainability initially remain indirect, vague or non-binding. The fact that the guidelines here are not as clear as for the other ethical risks means that particular attention must be paid to this risk in the future.

4. Summary and Outlook

The implementation of the requirements of the existing and mostly non-AI/ML-specific frames of reference, such as law and quality, is already sufficient to adequately address the ethical issues based on risk scenarios. A special ethical framework is therefore not required for German official statistics. As long as the legal and quality frames of reference exist and are strictly implemented, there is – apart from the case of ecological sustainability – no particular need for action from an ethical point of view when using AI/ML in statistical production. Nevertheless, conceivable changes in the frames of reference or in the development of AI/ML require that the circumstances be kept in mind at all times and that it be regularly reviewed whether the frames of reference continue to answer all ethical questions for official statistics.

References

- Dumpert, F., Reichel, J., Oertel, E., Leerhoff, H., and Salwiczek, C. (2025a), “Ethische Fragen beim Einsatz von KI/ML in der Produktion amtlicher Statistiken – Teil 1: Identifikation”, *WISTA – Wirtschaft und Statistik*, 77, (1), pp. 15–24. An English version will appear on https://www.destatis.de/EN/Methods/WISTAScientificJournal/_publikationen-articles-en.html.
- Dumpert, F., Reichel, J., Oertel, E., Leerhoff, H., and Salwiczek, C. (2025b), “Ethische Fragen beim Einsatz von KI/ML in der Produktion amtlicher Statistiken – Teil 2: Auseinandersetzung”, *WISTA – Wirtschaft und Statistik*, 77(1) pp. 25–36. An English version will appear on https://www.destatis.de/EN/Methods/WISTAScientificJournal/_publikationen-articles-en.html.
- European Statistical System (2019), “Quality Assurance Framework of the European Statistical System (Version 2.0)”, available at <https://ec.europa.eu/eurostat/web/quality/european-quality-standards/quality-assurance-framework>.

- Holt, D. (2007), “The Official Statistics Olympic Challenge: Wider, Deeper, Quicker, Better, Cheaper”, *The American Statistician*, 61(1), pp. 1–8.
- Saidani, Y., Dumpert, F., Borgs, C., Brand, A., Nickl, A., Rittmann, A., Rohde, J., Salwiczek, C., Storfinger, N., and Straub, S. (2023), “Qualitätsdimensionen maschinellen Lernens in der amtlichen Statistik”, *ASTA Wirtschafts- und Sozialstatistisches Archiv*, 17(3+4), pp. 253–303.
- Statistics Canada (2017), “Quality Assurance Framework”, 3rd edition, Available online at <https://www150.statcan.gc.ca/n1/pub/12-539-x/12-539-x2019001-eng.htm>.
- Statistics Canada (2021), “Framework for Responsible Machine Learning Processes at Statistics Canada“. <https://www150.statcan.gc.ca/n1/en/pub/89-20-0006/892000062021001-eng.pdf?st=dILLbFjWUK>.
- UK Statistics Authority (2021), “Ethical considerations in the use of Machine Learning for research and statistics“. <https://uksa.statisticsauthority.gov.uk/publication/ethical-considerations-in-the-use-of-machine-learning-for-research-and-statistics/pages/1/>.
- UNECE (2019), “Generic Statistical Business Process Model (GSBPM)”. Paper available at https://unece.org/sites/default/files/2023-11/GSBPM%20v5_1.pdf.
- UNECE (2023), “International Framework on Responsible AI for Official Statistics”, forthcoming publication.
- United Nations (2019), “United Nations National Quality Assurance Frameworks Manual for Official Statistics”, <https://unstats.un.org/unsd/methodology/dataquality/references/1902216-UNNQAFManual-WEB.pdf>.
- Yung, W., Tam, S.-M., Buelens, B., Chipman, H., Dumpert, F., Ascari, G., Rocci, F., Burger, J., and Choi, I. (2022), “A quality framework for statistical algorithms”, *Statistical Journal of the IAOS*, 38(1), pp. 291–308.