Combining deep neural networks, a rule-based expert system and targeted manual coding for ICD-10 coding causes of death of French death certificates

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Abstract

Cause-of-death (CoD) statistics are key indicators in epidemiology and public health. These statistics come from death certificates (DC) completed by physicians and coded usually by official statistics authorities according to the standards of the WHO International Statistical Classification of Diseases and Related Health Problems (ICD-10) to construct time and cross-country comparable statistics.

Causes of death in DC are usually coded, either by automated rule-based expert systems, or by coding experts. Based on dictionaries of medical expressions, text standardization steps, and on thousands of decision rules in decision tables maintained internationally according to WHO official updates and recommendations, rule-based expert systems ensure homogeneity of ICD coding. However, the entire process requires significant human resources if expert systems are unable to fully automatically code a sufficient number of certificates.

In France, 37% of DCs in 2018 and 2019 could not be fully automatically coded, and a complementary traditional manual coding campaign could not be carried out due to a lack of human resources.

State-of-the-art deep neural network (DNN) algorithms are expected to perform well for this type of classification task and can be trained on previously labeled data. Several research works showed that if trained on sufficiently large sets, they can achieve very high coding accuracy on most of certificates. Despite these encouraging results, few countries have gone as far as a full production rollout for official CoD statistics. Indeed, having several coding modes cohabitating in production requires developing a strategy to articulate them with specific constraints such as the human resource available.

In this article, we present the new approach developed and implemented for producing CoD statistics of 2018 and 2019 in France in the context of catch-up mentioned above. To code the DCs for these two years, we use the predictions of seq-to-seq DNNs trained (i.e. estimated) on past data (AI, 34%) and manual coding (3%), the latter targeting DCs of particular public health interest and those for which the AI predictions have a low confidence index. A loop of interaction between the three coding modes is introduced. This is the first time that France has used deep learning to produce [part of] official CoD data. We evaluate the performance of the retained approach and its consistency with a traditional coding campaign on a test sample that is representative of the entire population of deaths and is not used in the training of the algorithms.

Key-words: causes of death, mortality, ICD-10, coding, deep learning

1. Introduction

Cause-of-death (CoD) statistics are key indicators in epidemiology and public health. These statistics are derived from death certificates (DCs) completed by physicians and are usually coded by official statistics authorities according to the standards of the WHO International Statistical Classification of Diseases and Related Health Problems (ICD-10) to construct time- and cross-country-comparable statistics. [1] The WHO provides a standard for describing the chain of morbid events leading directly to death and sets out precise rules for ICD coding entities and for determining the underlying cause of death (UCOD), i.e., the cause that initiates the chain of morbid events leading directly to death. To meet user needs, these data must be produced following best practices in official statistics and disseminated in the timeframes required by European regulation. [2,3]

Causes of death in DCs are usually coded, either by automated, rule-based expert systems or by coding experts. Rule-based expert systems, such as the Iris software, which are based on medical expression dictionaries, text standardization steps, and thousands of international decision rules according to official ICD WHO updates, ensure that the standards of ICD coding entities are met. [4] However, in France, the Iris software is used to code only 63% of DCs. The remaining 38% of DCs, approximately 220,000 DCs per year, are to be manually coded by the coding team for one year. For several years, a increasing backlog had accumulated especially due to lack of resources. A traditional campaign combining automated coding by the expert system and assisted coding by the coding teams was not sufficient to respect the European dissemination regulatory deadlines. Indeed, European member states have to deliver annual COD data to Eurostat within the 2 years following the year of death. The coding team is indeed capable of coding approximately 100,000 certificates a year.

The challenge was therefore to develop a complementary coding method adapted to the production of an official statistic to catch up and to enter into regular production. This method had to be consistent with best European statistical practice, i.e., it should be based on sound methodology, privacy-preserving, with no bias, and replicable, to guarantee the reliability and objectivity of the produced statistics. [2]

State-of-the-art deep neural network (DNN) algorithms are expected to perform well for this type of classification task and can be trained on previously labeled data. Several studies have shown that if trained on sufficiently large sets, supervised natural language processing (NLP) DNNs can achieve very high coding accuracy on most certificates. [5,6,7,8,9]

Despite these encouraging results, few countries have gone as far as a full production rollout for official CoD statistics. With the exception of the US with Medcoder and Portugal with AUTOCODE, most countries are still using expert system coding, allowing either batch or

manual/interactive coding via the assisted coding interface. [10,11] Indeed, having several coding modes cohabitating in production requires developing a strategy to articulate them with specific constraints such as the available human resources.

In this article, we present the new approach developed and implemented for producing CoD statistics for 2018 and 2019 in France in the context of catch-up mentioned above. To code the DCs that were not automatically coded by the Iris software, we use the predictions (i.e., fitted values) of seq-to-seq DNNs trained (i.e., estimated) on past data. Overall, 34% of the DCs were coded using these predictions (AI). The 3% of DCs that are coded by the coding team are selected to with in mind an optimal allocation of human work. They correspond to DCs of a particular public health interest and those for which the AI predictions have a low confidence index. A loop of interaction between the three coding modes is introduced. This is the first time that France has used deep learning to produce (part of) official CoD data, and for this reason, particular attention has been given to evaluating the performance of the retained approach and its consistency with a traditional coding campaign. This evaluation is carried out on a test sample that is representative of the entire population of deaths and is not used to train the algorithms.

This work builds on and continues previous work on the use of deep learning and, more generally, machine learning for the CoD coding task. [5,12,13,14,15][1]. The present article corresponds in great part to the accepted manuscript version of a journal article in press the International Journal of Medical Informatics [29].

2. Methods

2.1. Loop of interactions among the three coding modes

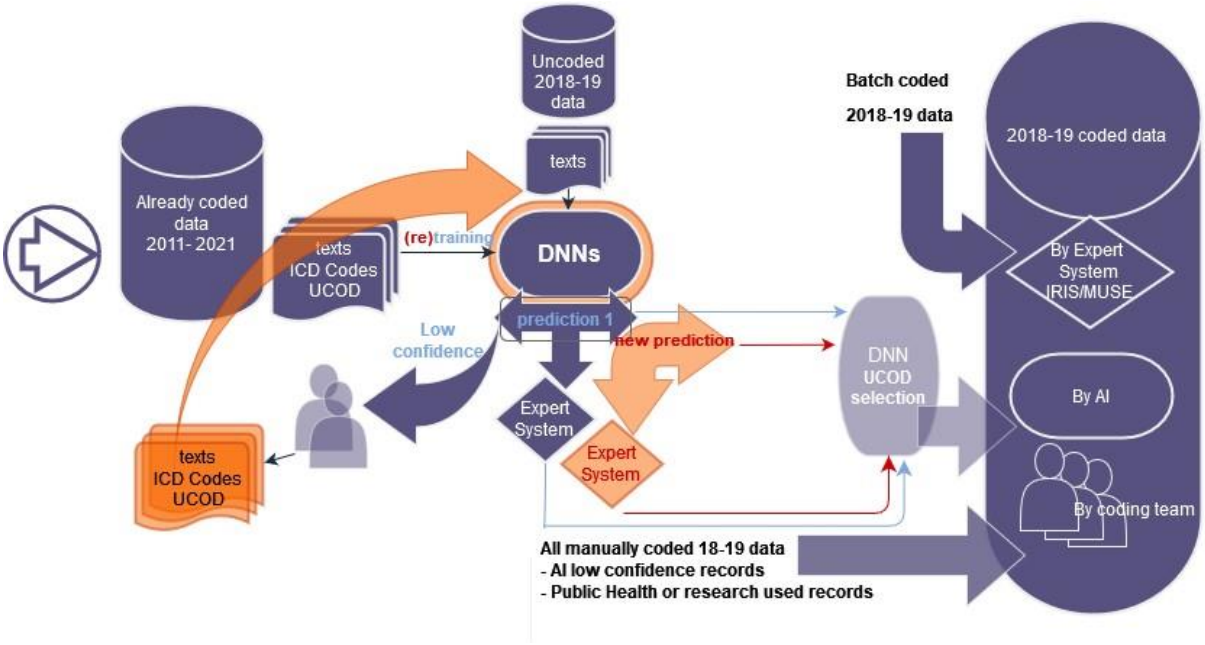
Batch coding with the expert system Iris remains the starting point of the coding strategy, but it is capable of fully coding (i.e., ICD coding of multiple causes and determination of the underlying cause) only 63% of DCs. For 37% of DCs, which need further intervention, we developed a strategy that accounts for two main constraints:

- situations with a poor likelihood of DNN predictions need to be identified and sent for manual coding
- the (restricted) volume of manual coding need to be controlled

[1] Provisional data disseminated in December 2022 relied only on expert-system batch automated coding and AI automated coding. The manual coding phases were conducted between February and June 2023.

The coding campaign is hence based on a loop among AI, the expert system and manual coding (Figure 1). First, DNNs are trained on already coded data (including batch-coded records for the years 2018 and 2019) to predict ICD-10 codes for multiple causes and the underlying cause (UCOD). DNNs are then used to get a first prediction of UCOD and multiple cause ICD codes for 2018 and 2019 uncoded DCs (prediction 1). An indicator of confidence in that prediction is also calculated for each DC. The DCs for which the prediction has low confidence are sent for manual coding. In the second step, the training sets are updated with part of the new manual codings, and DNNs are retrained on these data (interaction loop/orange in Figure 1). New predictions for the uncoded 2018 and 2019 records are obtained. The expert system Iris is applied to the predicted multiple cause ICD codes to obtain an alternative UCOD proposal. Then, a specific algorithm chooses between all the UCOD proposals of the various versions of the algorithms combined or not combined with Iris (UCOD selection). The ICD-coded data for 2018 and 2019 correspond to the AI-coded certificates, those batch-coded by the expert system and those for which manual coding was performed.

Figure 1. 3-mode coding campaign



2.2. Seq-to-seq Transformer-type DNNs predict multiple causes and propose an underlying cause

The adopted approach is based on supervised learning. Seq-to-seq transformer DNNs are trained to translate the text written on the DC into a sequence of ICD codes for multiple causes and to predict a UCOD. [5,16,17,18]. Transformers are encoder/decoder-type algorithms that account for the links between the words in the sentence due to their “attention” mechanisms.

These methods rely on highly parallel computations, which allow rapid training and can be fully implemented on conventional infrastructures. They are implemented with TensorFlow and Keras, which are deep learning open libraries that are maintained over time. [19,20] The main Transformer algorithm, k5, contains 96,000,000 parameters (weights) to estimate. The algorithm improves upon the Transformer k4 used to produce 2018 and 2019 provisional data with more input features. More details, including the codes, architecture and training strategy, are available in [18,29].

The input sequences are concatenations of the texts written on each line of the certificate, separated by the line label, including additional variables present on the DC that may impact the coding. These data include gender, age group, year of death, electronic/paperback DC, 1997 or 2017 DC form,[2] and manner of death, a new variable introduced in the 2017 form to better identify external causes. These are considered tokens and are implemented in the vocabulary (input dictionary) as follows:

Paper-back/elec_certificate CertificateVersion sex agegroup yearofdeath sepLine1 text_ written_on_line_1 sepLine2 text_written_on_line2 … … sepLine7 MannerOfDeath sepUC

Example: Paperback CertificateVersion2017 Women 55yo year2017 sepLine1 cardiorespiratory arrest sepLine2 pleural effusion sepLine3 lung metastases sepLine4 breast cancer sepLine7 natural death sepUC

The output sequence has the same structure as the input sequence, with the exception that the ICD codes replace texts/words. The output sequence ends with the UCOD ICD code:

Paper-back/elec_certificate certificateVersion sex agegroup yearofdeath sepLine1 ICDcod11 ICDcod12 sepLine2 ICDcod2 … … sepLine7 sepUC ICDcodeUC

Example (following): Paperback CertificateVersion2017 Women 55yo year2017 sepLine1 r092 sepLine2 j90 sepLine3 c780 sepLine4 c509 sepLine7 sepUC c509

After being standardized for accounting for special characters, the input and output sequences are split into words (tokens) following the word-piece method with the Keras Tokenizer. The resulting input dictionary contains 17,443 tokens (words), and the output dictionary contains 6,155 tokens (ICD codes).

The first training is performed on 5.3 million certificates from 2011 to 2021 that are already coded, either manually or automatically by batch, and 20% of the observations are used for validation. Training takes 4 days on one GPU of 48 GO RAM. Predicting 100,000 certificates

[2] The DC forms have changed as of 2018 and the use of the new form was gradual.

requires one day. At the end of the campaign, DNNs are retrained in a fine-tuning step on an updated training set that includes part of the 2018-2019 targeted manually coded DCs and DCs from 2021 manually coded in between (42,000 DCs).

2.3. Using AI to predict which certificates are sent for manual coding

Manual coding is prioritized and targeted to two types of 2018-2019 DCs:

- certificates with a public health or research interest, such as AIDS, maternal deaths, and neonates, which account for approximately 3,000 per year, and certificates entering a research panel database (approximately 10,000 per year).
- certificates with the lowest confidence in AI predictions (6,000 per year).

The confidence index is derived from linear probability model estimates of the predicted UCOD equal to the observed UCOD conditional on individual characteristics of the certificate. This model is trained on the training sample. These individual characteristics include the predicted UCOD grouped in European shortlist categories, [21] sex, age group, number of words in the certificate, number of multiple causes, whether the predicted sequence of causes is automatically codable by Iris, whether Iris yields the same UCOD as DNN, the probability associated with the predicted UCOD and the difference between this probability and the probability of the second most likely UCOD (discriminatory power of the DNN). We focus on certificates in the 12 European shortlist categories for which we estimate, based on deaths in 2016 and 2017, that the precision, i.e., the number of correctly predicted UCODs over the number of predicted UCODs in the category, does not reach 90% (P1) resp. 92.5% (P2). We then simulate the additional manual coding rate required to achieve these precisions if the certificates with the lowest confidence indicators were sent for manual coding by order. These rates are then applied to the 2018/2019 counts. In practice, the coding team coded all certificates classified as P1, 64% of those classified as P2 for 2018, and 82% of those classified as P2 for 2019 in 2 months.

2.4. Choosing the UCOD prediction

DNNs directly predict a UCOD, but it is also possible to apply Iris to the predicted multiple-cause ICD sequence to obtain a UCOD. The two DNNs k4 and k5 can predict different UCODs and different sequences of multiple causes, which can lead to, after Iris is applied, up to 4 UCOD proposals. A bidirectional long short-term memory (BiLSTM) model is trained to respond to a 5-class classification task, indicating which of the algorithms, k4, k5, k4+Iris, k5+Iris or none, should be selected to provide the final UCOD for a given DC and, by extension, the final multiple causes. [22,23] In the case in which none of the models leads to a good prediction (6% in the train), we use by default the k5+Iris proposition. The input sequence of

the BiLSTM model concatenates the different predicted UCODs at the ICD-10 finest level, at the European shortlist level, the different predicted multiple causes, the count of equal propositions between k4, k5, k4+Iris, and k5+Iris, and the same individual variables as previously used (certificate version, year…). More details, including codes, preprocessing, and architecture, are available in [18,29].

2.5. Performance analysis strategy – building a reference test population

To assess the accuracy between the final data in 2018 and 2019 and what would have been obtained after a traditional coding campaign, we constructed a test reference population representative of the distribution of COD in the death population in a given year. We use 332,183 observations that were manually coded in a traditional campaign, not included in the different trainings of the models, and complete it with 465,468 batch-coded certificates. We simulate which of these certificates would have been manually coded in the targeted manual coding. We use this test reference population as our test sample and estimate the accuracy (% DCs for which the 3-method campaign UCOD equals the traditional campaign UCOD), assuming that by construction, the UCOD remains the same as that in a traditional campaign when automatically coded by batch and manually coded. We also estimate the precision and recall for detailed categories. Precision is the proportion of correct predictions relative to all predictions in the category; recall is the proportion of observations correctly predicted by the model in the category relative to all observations actually in the category; and F-measure is the harmonic mean of the two.

3. Results

3.1. 3.1. Overall accuracy

The accuracy of the ICD-10 UCOD predicted by k5 reaches 78.5% for records that would have been manually coded in a traditional coding campaign. Using Iris rules on the predicted sequence of ICD-coded causes adds 1 percentage point (pp) of accuracy, the BiLSTM adds 2 pps, and the targeted manual coding adds another 2 pps (Table 1). In total, 84% of UCODs are correctly coded in the ICD-10 (89.3% for the European shortlist). If we account for the fact that 62% of the batch-coded records are coded the same as in a traditional campaign, 93.4% of the UCODs are correctly ICD-10 coded (95.6%).

Table 1 - % of UCOD correctly predicted (accuracy) on reference test population

Accuracy	K5	K5IrisMuse	K4	K4IrisMuse	UCOD choice	UCOD choice + targeted manual coding	N. Obs
Detailed ICD-10 level							
w. h. b. manually coded	0.785	0.796	0.768	0.769	0.819	0.841	332,183
all DCs	0.910	0.915	0.903	0.904	0.925	0.934	797,651
European short-list level							
w. h. b. manually coded	0.856	0.861	0.83	0.829	0.878	0.894	332,183
all DCs	0.940	0.942	0.929	0.929	0.949	0.956	797,651

Reading: In 78.5% of cases that would have been (w. h. b.) manually coded in a traditional campaign, the underlying cause directly predicted by k5 exactly matches the manually coded one at the finest ICD level. In 85.6% of cases, the underlying cause predicted by k5 falls into the same Eurostat shortlist category as the manually coded underlying CoD. In 91.5% of cases, the 4-position UC obtained by batch coding where possible or by k5 prediction combined with IRIS/MUSE (iris5) is the same as that which would have been obtained by a conventional coding campaign combining batch and assisted manual coding only. This results in an accuracy of 94.2% for the European shortlist level

3.2. Precision, recall, F-measure, and counts per ICD UC code group

The 3-mode coding campaign achieves high levels of consistency (in terms of precision and recall) with a traditional coding campaign for ICD chapters (Table 2) and most European shortlist categories (Table 3). The average F-measure per shortlist category is 0.94. F-measures remain below 0.9 for only 10 of the 71 shortlist categories: viral hepatitis, blood and hematopoietic diseases, pharmacology, skin diseases, rheumatoid arthritis, other musculoskeletal diseases, genitourinary diseases, accidental intoxications, undetermined intentions and other external causes. The trends and counts in these categories should be interpreted with caution. In particular, both statistically significant discrepancies and significant volume discrepancies (Poisson tests) are found for 03, blood diseases; 11.2, other diseases of the musculoskeletal system; 17.1.4, accidental poisoning; and 17.5, other external causes. At the ICD chapter level, this leads to significant discrepancies for Chapters III and XIII and, to a lesser extent, Chapters I, XII, XIV, and XVII and for some types of external causes.

Table 2 – Precision, recall, F-measure, counts per ICD chapter on reference test population

UCOD - ICD Chapter	**Real UCOD**	**Precision**	**Recall**	**F-measure**	**Pred. UCOD**	**Pred/Real UCOD - 1**	**Sign of diff**
I - Certain infectious and parasitic diseases	14304	0.927	0.918	0.923	14161	-0.010	
II - Neoplasms	222311	0.988	0.989	0.989	222413	0.000	
III- Diseases of the blood …	3491	0.902	0.837	0.868	3239	-0.072	****
IV- Endocrine, nutritional and metabolic …	29712	0.945	0.935	0.940	29372	-0.011	***
V- Mental and behavioural disorders	33756	0.946	0.963	0.954	34378	0.018	****
VI- Diseases of the nervous system	50154	0.966	0.968	0.967	50276	0.002	
IX- Diseases of the circulatory system	184220	0.97	0.972	0.971	184611	0.002	
X- Diseases of the respiratory system	53173	0.958	0.959	0.958	53239	0.001	
XI- Diseases of the digestive system	32214	0.946	0.949	0.947	32320	0.003	

XII- Diseases of the skin and subcut. tissue	2067	0.899	0.898	0.898	2065	-0.001	
XIII- Diseases of musculoskeletal system …	5263	0.895	0.858	0.876	5049	-0.041	****
XIV- Diseases of the genitourinary system	14675	0.927	0.914	0.920	14466	-0.014	**
XV- Pregnancy childbirth and puerperium	54	1.000	1.000	1.000	54	0.000	
XVI- Certain cond. origin. in perinatal period	2048	0.992	1.000	0.996	2064	0.008	
XVII- Congenital malformations, …	2105	0.946	0.896	0.920	1993	-0.053	***
XVIII- Symptoms, not classified elsewhere	60757	0.977	0.987	0.982	61379	0.010	***
XIX and XX - Injury, poisoning … external causes	51667	0.962	0.943	0.952	50606	-0.021	****
XXI - COVID codes	35680	0.981	0.989	0.985	35966	0.008	*
Total	**797651**				**797651**		

Note: significance levels of counting differentials come from equality tests assuming real occurrences were Poisson distributed., * pval<.2, ** pval<.1, *** pval<.05, **** pval<.01

3.3. CoD statistics of deaths in 2018 and 2019

The counts and standardized mortality rates per ICD chapter of the UCOD for 2018 and 2019 are compared with those for 2016, 2017 and 2020, indicating chapters for which the performance analysis suggests that there is a risk of under/over estimation (Tables 4 and 5).

4. Discussion, limitations and future work

The combination of a fully automated expert system and human and DNN codings allowed France to produce CoD statistics for 2018 and 2019, with the same ICD-10 UCOD as in a traditional campaign in 92.5% of cases (94.9% for the European shortlist groups), with only 3% of DCs being manually coded. Targeting DCs sent by order for human coding allows us to approach an optimal allocation of work when human resources are limited.

Risks of under- and overestimation appear for certain ICD-10 categories and are quantified in the performance analysis. These limitations encourage us to carefully examine the quality of the training dataset for these particular cases. Indeed, the latter may correspond not only to

changes in the ICD rules but also to coding errors or bugs, either manual or automatic, and can be corrected. This raises the issue of maintaining the quality of a training dataset, which is fundamental for AI. These limitations also encourage us to increase the volume of DCs sent for human coding expertise for 2021 onward, generalizing the targeting approach to tend toward an optimal allocation of DCs among the 3 coding modes. In the future, targeting should also account for the coding quality of multiple causes.

Our integration of AI in CoD statistics production was guided by European best practices in official statistics. With the objectives of sound methodology, transparency, cost-effectiveness, and privacy preservation, we chose to develop end-to-end deep neural networks with simple architectures, for which training and inference can be performed in-house, from scratch, on conventional infrastructures. We have deliberately left out more complex, pretrained models. These choices ensure full control of training data, models, and full replicability of the coding of a given year, but they may also lead to a loss in accuracy that needs to be measured in future work. In future work, we should also consider increasing robustness by simplifying our models using methods such as knowledge distillation, quantization or pruning. Posttraining pruning could provide a way to accelerate inference without retraining models. [24,25] We should also consider gains in robustness by considering unlabeled data, with techniques such as unsupervised data augmentation and uncertainty-aware self-training, especially when we need to adapt the strategy for transitioning to ICD-11. [26, 27] We will indeed have far fewer data already labeled in the new classification (ICD-11) and combining ICD-10 coded data and unlabeled data, with only some ICD-11 coded data may certainly be needed. Another direction of future work, consistent with best practices in official statistics, concerns explainability. The latter is required to develop the trust of users in the statistics produced with AI. Many XAI methods may provide valuable insights. [28]

The question of transitioning to the ICD-11 is for the moment completely open, as the models presented here are completely adherent to the classification on which they were trained (and behind the classification used for the already coded data), in this case, the ICD-10. At the very best, they can provide a way to code future ICD-10 data and reduce the resources needed for bridge coding campaigns. Moving toward the ICD-11 means adapting the models—the abovementioned avenues are worth exploring—or investing in different models, such as large language models and text-to-text models—while maintaining the general coding campaign strategy presented here.

5. Conclusion

The final data for 2018 and 2019 were produced using the presented approach. The combination of the three coding methods, and in particular the targeting by AI of samples sent to human coders, appears to be effective. This finding illustrates how AI, automated and human coding methods are mutually enriching. However, limitations (risks of under- or overestimation) appear for certain categories of ICD codes, with the advantage of being quantifiable. France continues to work on including AI coding as part of its usual CoD data production process. The transition to the ICD 11 remains an open question.

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Tables

Table 3 – Precision, recall, F-measure, counts per European shortlist category on reference test population

UCOD European shortlist	Real UCOD	Precision	Recall	F-measure	Pred. UCOD	Pred/Real UCOD - 1	Sign of diff
01.1- Tuberculosis	476	0.946	0.891	0.918	448	-0.059	
01.2- AIDS (HIV diseases)	332	0.979	1	0.99	339	0.021	
01.3- Viral hepatitis	560	0.86	0.879	0.869	572	0.021	
01.4- Other infectious and parasitic diseases	12936	0.928	0.918	0.923	12802	-0.01	
02.1.01-Malignant neoplasms of lip, oral cavity, pharynx	4996	0.969	0.945	0.957	4869	-0.025	**
02.1.02-Malignant neoplasms of oesophagus	4797	0.979	0.978	0.979	4791	-0.001	
02.1.03-Malignant neoplasms of stomach	5790	0.98	0.974	0.977	5756	-0.006	
02.1.04-Malignant neoplasms of colon, rectum, anus	23061	0.981	0.981	0.981	23056	0	
02.1.05-Malignant neoplasms of liver and intrahepatic bile ducts	11426	0.976	0.971	0.973	11361	-0.006	
02.1.06-Malignant neoplasms of pancreas	15433	0.991	0.99	0.99	15415	-0.001	
02.1.07-Malignant neoplasms of larynx	1271	0.951	0.94	0.946	1256	-0.012	
02.1.08-Malignant neoplasms of trachea, bronchus, lung	40493	0.982	0.982	0.982	40491	0	
02.1.09- Malignant neoplasms of skin	2241	0.958	0.965	0.962	2257	0.007	
02.1.10-Malignant neoplasms of breast	16601	0.981	0.981	0.981	16600	0	
02.1.11-Malignant neoplasms of cervix uteri	1048	0.973	0.969	0.971	1043	-0.005	

02.1.12-Malignant neoplasms of other and unspecified parts of uterus	3630	0.976	0.961	0.969	3574	-0.015	
02.1.13-Malignant neoplasms of ovary	4424	0.982	0.98	0.981	4412	-0.003	
02.1.14-Malignant neoplasms of prostate	11882	0.979	0.976	0.978	11853	-0.002	
02.1.15-Malignant neoplasms of kidney	4626	0.977	0.96	0.968	4546	-0.017	
02.1.16-Malignant neoplasms of bladder	6874	0.975	0.977	0.976	6882	0.001	
02.1.17-Malignant neoplasms of brain and central nervous system	5232	0.974	0.97	0.972	5212	-0.004	
02.1.18-Malignant neoplasms of thyroid	490	0.956	0.924	0.94	474	-0.033	
02.1.19-Hodgkin disease and lymphomas	6393	0.971	0.974	0.972	6416	0.004	
02.1.20- Leukaemia	7856	0.974	0.978	0.976	7890	0.004	
02.1.21-Other malignant neoplasms of lymphoid and haematopoietic tissue	4290	0.973	0.967	0.97	4265	-0.006	
02.1.22-Other malignant neoplasms	29282	0.929	0.945	0.937	29770	0.017	****
02.2-Non-malignant neoplasms (benign and uncertain)	10175	0.925	0.93	0.927	10224	0.005	
03 Diseases of the blood and blood-forming organs and certain disorders involving the immune mechanism	3491	0.902	0.837	0.868	3239	-0.072	****
04.1- Diabetes mellitus	16008	0.956	0.944	0.95	15809	-0.012	*
04.2- Other endocrine, nutritional and metabolic diseases	13704	0.925	0.915	0.92	13563	-0.01	
05.1- Dementia	25311	0.951	0.973	0.962	25914	0.024	****
05.2- Alcohol abuse (including alcohol psychosis)	3230	0.909	0.929	0.919	3302	0.022	
05.3 - drug dependence, toxicomania	308	0.901	0.831	0.865	284	-0.078	*
05.4 - Other mental and behavioural disorders	4907	0.917	0.912	0.914	4878	-0.006	
06.1- Parkinson's disease	8866	0.973	0.978	0.975	8905	0.004	

06.2 - Alzheimer's disease	25747	0.979	0.983	0.981	25851	0.004	
06.3- Other diseases of the nervous system and the sense organs	15541	0.932	0.931	0.931	15520	-0.001	
07.1.1-Acute myocardial infarction	18023	0.96	0.969	0.964	18197	0.01	*
07.1.2-Other ischaemic heart diseases	24438	0.946	0.946	0.946	24445	0	
07.2-Other heart diseases	67415	0.954	0.956	0.955	67567	0.002	
07.3-Cerebrovascular diseases	41319	0.952	0.957	0.954	41553	0.006	
07.4- Other diseases of the circulatory system	33025	0.939	0.934	0.937	32849	-0.005	
08.1 - Influenza	1668	0.963	0.973	0.968	1685	0.01	
08.2 - Pneumonia	16322	0.954	0.958	0.956	16400	0.005	
08.3.1 - Asthma	1077	0.945	0.938	0.941	1069	-0.007	
08.3.2-Other chronic lower respiratory diseases	13006	0.948	0.958	0.953	13145	0.011	
08.4- Other diseases of the respiratory system	21100	0.939	0.932	0.936	20940	-0.008	
09.1 - Ulcer of stomach, duodenum, jejunum	1081	0.926	0.933	0.93	1090	0.008	
09.2 - Cirrhosis, fibrosis, and chronic hepatitis	8986	0.957	0.962	0.96	9033	0.005	
09.3- Other diseases of the digestive system	22147	0.933	0.935	0.934	22197	0.002	
10 Diseases of the skin and subcutaneous tissue	2067	0.899	0.898	0.898	2065	-0.001	
11.1- Rheumatoid arthritis and osteoarthristis	726	0.909	0.866	0.887	692	-0.047	
11.2- Other diseases of the musculoskeletal system/connective tissue	4537	0.888	0.853	0.87	4357	-0.04	****
12.1-Diseases of kidney and ureter	10646	0.93	0.917	0.924	10497	-0.014	*
12.2- Other diseases of the genitourinary system	4029	0.906	0.893	0.899	3969	-0.015	

13 Complications of pregnancy, childbirth and puerperium	54	1	1	1	54	0	
14 Certain conditions originating in the perinatal period	2048	0.992	1	0.996	2064	0.008	
15 Congenital malformations and chromosomic abnormalities	2105	0.946	0.896	0.92	1993	-0.053	***
16.1- Sudden infant death syndrome	179	0.972	0.983	0.978	181	0.011	
16.2- Unknown and unspecified causes	20174	0.957	0.971	0.964	20471	0.015	***
16.3- Other symptoms, signs, ill-defined causes	40404	0.974	0.982	0.978	40727	0.008	*
17.1.1 - Transport accidents	3678	0.968	0.953	0.961	3619	-0.016	
17.1.2 - Accidental falls	11146	0.938	0.953	0.946	11326	0.016	**
17.1.3 - Drowning and accidental submersion	1090	0.941	0.969	0.955	1122	0.029	
17.1.4 - Accidental poisoning	2163	0.92	0.848	0.883	1995	-0.078	****
17.1.5 - Other accidents	18254	0.917	0.909	0.913	18092	-0.009	
17.2 - Suicide and intentional self-harm	11281	0.973	0.97	0.972	11245	-0.003	
17.3- Homicide, assault	499	0.938	0.936	0.937	498	-0.002	
17.4-Event of undetermined intent	1709	0.85	0.767	0.806	1541	-0.098	****
17.5- Other external causes of injury and poisoning	1847	0.871	0.551	0.675	1168	-0.368	****
18- COVID	35680	0.981	0.989	0.985	35966	0.008	*
Total	**797651**			**797651**			

Note: significance levels of counting differentials come from equality tests assuming real occurrences were Poisson distributed., * pval<.2, ** pval<.1, *** pval<.05, **** pval<.01

Table 4 – CoD statistics in 2018 and 2019 and recent trends per ICD chapter

	Number of deaths					Standardized mortality rates					
UCOD - ICD Chapter	**2016**	**2017**	**2018**	**2019**	**2020**	**2016**	**2017**	**2018**	**2019**	**2020**	**risk**
I - Certain infectious and parasitic diseases	10504	11605	11304	11853	11056	15.2	16.3	15.6	16.1	14.8	
II - Neoplasms	171202	171217	170291	171073	170805	267.1	261.9	256.0	252.2	248	
III- Diseases of the blood …	2291	2570	2876	2784	2802	3.3	3.6	4.0	3.8	3.7	underest.(F,P)
IV- Endocrine, nutritional and metabolic …	21255	22116	21936	22405	23597	30.4	30.5	29.7	29.7	30.9	
V- Mental and behavioural disorders	26014	25918	28014	27842	25386	35.0	33.8	35.7	34.6	31.0	overest.(P)
VI- Diseases of the nervous system	38881	39570	39644	38808	37615	53.1	52.8	52.1	50.2	48.1	
IX- Diseases of the circulatory system	143530	143622	143653	138628	134761	204.4	198.4	194.1	183.2	176.1	
X- Diseases of the respiratory system	41333	44757	45108	45510	38708	61.2	64.0	63.4	62.0	53.0	
XI- Diseases of the digestive system	24177	24170	24398	24885	24977	35.9	35.1	34.7	34.9	34.4	
XII- Diseases of the skin and subcut. tissue	1489	1623	1519	1656	1639	2.0	2.1	1.9	2.1	2.0	underest.(F)
XIII- Diseases of musculoskeletal system …	4154	4002	3779	3987	4023	5.9	5.5	5.1	5.3	5.2	underest.(F,P)
XIV- Diseases of the genitourinary system	10122	10857	10645	11456	12090	15.0	15.5	14.8	15.7	16.2	
XV- Pregnancy childbirth and puerperium	40	41	39	32	41	0.1	0.1	0.1	0.1	0.1	
XVI- Certain cond. origin. in perinatal period	1501	1685	1622	1558	1443	1.9	2.2	2.1	2.1	2	
XVII- Congenital malformations, …	1675	1624	1489	1600	1502	2.4	2.3	2.1	2.3	2.2	
XVIII- Symptoms,…, not classified elsewhere	55443	59519	62011	67316	67770	78.4	81.4	82.9	88.1	86.9	
XIX and XX - Injury, poisoning … external causes	38460	39402	39492	40020	40032	58.0	57.9	57.2	57.0	56.4	underest (F,P)
XXI - COVID codes	0	0	0	0	69249	0	0	0	0	93.4	
Total	**592072**	**604298**	**607820**	**611413**	**667497**	**869.2**	**863.3**	**851.6**	**839.2**	**904.3**	

Note: standardized mortality rates use the European Standard Population as reference population. Over/underest (F) denotes risk of over/under-estimation of counts or rates and F-measure below 90%; over/underest. (P) denotes risk of under/overestimation of countings indicated by Poisson tests of differential significant at 1%.

Source: CépiDc, Causes of death, final data for 2018 and 2019. Scope: All deaths of French residents deceased in France.

Table 5 – CoD statistics in 2018 and 2019 and recent trends per European shortlist category

	Number of deaths					**Standardized mortality rates**					
UCOD - European shortlist category	2016	2017	2018	2019	2020	2016	2017	2018	2019	2020	Risk
01.1- Tuberculosis	403	402	351	347	295	0.6	0.6	0.5	0.5	0.4	
01.2- AIDS (HIV diseases)	334	237	241	237	202	0.5	0.4	0.4	0.4	0.3	
01.3- Viral hepatitis	587	773*	423	390	351	0.9	1.2	0.6	0.6	0.5	overest. (F)
01.4- Other infectious and parasitic diseases	9180	10193	10289	10879	10208	13.2	14.2	14.1	14.7	13.6	
02.1.01- Malignant neoplasms of lip, oral cavity, pharynx	3936	3809	3713	3527	3636	6.3	6.0	5.8	5.4	5.5	underest. (P)
02.1.02- Malignant neoplasms of oesophagus	3902	3865	3772	3784	3630	6.3	6.2	5.9	5.9	5.5	
02.1.03- Malignant neoplasms of stomach	4602	4612	4614	4474	4258	7.3	7.2	7.0	6.7	6.3	
02.1.04- Malignant neoplasms of colon, rectum, anus	18029	17996	17327	17360	17197	27.4	26.8	25.4	25	24.4	
02.1.05- Malignant neoplasms of liver and	8776	8551	8536	8579	8727	14.2	13.6	13.4	13.2	13.1	

intrahepatic bile ducts											
02.1.06- Malignant neoplasms of pancreas	11300	11467	11774	12199	12476	17.3	17.2	17.4	17.6	17.8	
02.1.07- Malignant neoplasms of larynx	1069	1000	946	868	827	1.8	1.7	1.5	1.4	1.3	
02.1.08- Malignant neoplasms of trachea, bronchus, lung	31877	31402	31054	30957	30935	51.7	50.1	48.7	47.6	46.9	
02.1.09- Malignant neoplasms of skin	1748	1767	1762	1825	1756	2.7	2.7	2.7	2.7	2.6	
02.1.10- Malignant neoplasms of breast	12936	13013	12958	12834	13008	16.9	16.8	16.5	16.0	16.0	
02.1.11- Malignant neoplasms of cervix uteri	801	817	858	779	769	1.1	1.1	1.2	1.1	1.1	
02.1.12- Malignant neoplasms of other and unspecified parts of uterus	2838	2903	2910	2886	2845	3.7	3.7	3.6	3.6	3.5	
02.1.13- Malignant neoplasms of ovary	3495	3545	3373	3495	3341	4.7	4.7	4.4	4.5	4.2	
02.1.14- Malignant	9022	9212	9271	9302	9178	17.2	17.1	16.8	16.4	15.9	

neoplasms of prostate											
02.1.15-Malignant neoplasms of kidney	3597	3612	3443	3325	3483	5.7	5.7	5.3	4.9	5.1	
02.1.16-Malignant neoplasms of bladder	5349	5146	5331	5218	5345	9.0	8.5	8.5	8.2	8.3	
02.1.17-Malignant neoplasms of brain and central nervous system	3964	4087	3812	4064	4035	6.2	6.3	5.8	6.1	6	
02.1.18-Malignant neoplasms of thyroid	378	420	433	388	362	0.6	0.6	0.6	0.5	0.5	
02.1.19-Hodgkin disease and lymphomas	4869	4936	4670	4766	4875	7.5	7.4	7.0	7.0	7.0	
02.1.20-Leukaemia	6016	6134	6008	6012	6165	9.3	9.3	8.9	8.8	8.9	
02.1.21-Other malignant neoplasms of lymphoid and haematopoietic tissue	3433	3230	3296	3352	3283	5.3	4.9	4.8	4.8	4.7	
02.1.22-Other malignant neoplasms	21738	22106	22739	23338	23018	33.5	33.5	33.8	34.1	33	overest. (P)
02.2-Non-malignant neoplasms (benign and uncertain)	7527	7587	7691	7741	7656	11.2	11.0	10.9	10.7	10.4	

03 Diseases of the blood and blood-forming organs and certain disorders involving the immune mechanism	2291	2570	2876	2784	2802	3.3	3.6	4.0	3.8	3.7	underest. (F)
04.1- Diabetes mellitus	11848	11927	11419	11424	12264	17.4	17.0	16.0	15.7	16.5	
04.2- Other endocrine, nutritional and metabolic diseases	9407	10189	10517	10981	11333	13	13.5	13.7	14.1	14.4	
05.1- Dementia	19755	19661	21306	21003	18595	25.6	24.4	25.9	24.8	21.4	overest. (P)
05.2- Alcohol abuse (including alcohol psychosis)	2577	2460	2680	2672	2472	4.1	3.9	4.2	4.2	3.8	
05.3 - drug dependence, toxicomania	230	189	219	241	229	0.4	0.3	0.4	0.4	0.4	underest. (F)
05.4 - Other mental and behavioural disorders	3452	3608	3809	3926	4090	4.9	5.1	5.2	5.3	5.4	
06.1- Parkinson's disease	6642	6826	6912	6828	7013	10.2	10.2	10.2	9.9	10	
06.2 - Alzheimer's disease	21111	20962	20457	19251	18243	26.2	25.2	24	22.1	20.7	
06.3- Other diseases of the nervous system and the sense organs	11128	11782	12275	12730	12359	16.7	17.4	17.9	18.2	17.5	

07.1.1-Acute myocardial infarction	14031	13976	13450	13270	12922	21.3	20.8	19.6	19	18.4	
07.1.2-Other ischaemic heart diseases	18985	19053	19028	18461	18170	29.1	28.3	27.7	26.5	25.8	
07.2-Other heart diseases	53184	53652	54918	50894	48060	74.1	72.5	72.3	65.1	60.9	
07.3-Cerebrovascular diseases	32213	31776	31780	31969	31112	44.9	42.9	42.1	41.7	39.9	
07.4- Other diseases of the circulatory system	25117	25165	24477	24034	24497	34.9	33.9	32.4	30.9	31.1	
08.1 - Influenza	961	2501	2297	2795	871	1.4	3.4	3.2	3.7	1.2	
08.2 - Pneumonia	13305	13920	14313	14518	11559	19.2	19.4	19.6	19.1	15.4	
08.3.1 - Asthma	929	914	847	840	719	1.2	1.2	1.1	1.1	0.9	
08.3.2-Other chronic lower respiratory diseases	10416	10747	10910	10787	9373	16.4	16.4	16.2	15.6	13.6	
08.4- Other diseases of the respiratory system	15722	16675	16741	16571	16186	23	23.6	23.4	22.5	21.9	
09.1 - Ulcer of stomach, duodenum, jejunum	867	862	819	815	837	1.3	1.2	1.1	1.1	1.1	
09.2 - Cirrhosis, fibrosis, and chronic hepatitis	6914	6775	6749	6715	6777	11.1	10.7	10.5	10.3	10.3	
09.3- Other diseases of the digestive system	16396	16533	16830	17355	17363	23.6	23.2	23.1	23.4	23	

10 Diseases of the skin and subcutaneous tissue	1489	1623	1519	1656	1639	2.0	2.1	1.9	2.1	2.0	amb. sign
11.1- Rheumatoid arthritis and osteoarthristis	565	578	585	528	583	0.7	0.7	0.7	0.6	0.7	underest. (F)
11.2- Other diseases of the musculoskeletal system/connective tissue	3589	3424	3194	3459	3440	5.1	4.8	4.4	4.6	4.5	underest. (F)
12.1-Diseases of kidney and ureter	7572	8105	7695	8333	8579	11	11.4	10.6	11.3	11.4	
12.2- Other diseases of the genitourinary system	2550	2752	2950	3122	3511	3.9	4.1	4.2	4.4	4.8	underest. (F)
13 Complications of pregnancy, childbirth and puerperium	40	41	39	32	41	0.1	0.1	0.1	0.1	0.1	
14 Certain conditions originating in the perinatal period	1501	1685	1622	1558	1443	1.9	2.2	2.1	2.1	2.0	
15 Congenital malformations and chromosomic abnormalities	1675	1624	1489	1600	1502	2.4	2.3	2.1	2.3	2.2	underest (P)
16.1- Sudden infant death syndrome	176	139	184	132	114	0.2	0.2	0.2	0.2	0.2	

16.2- Unknown and unspecified causes	27198	29680	30442	34736	34657	39.9	42.3	42.7	47.5	46.6	
16.3- Other symptoms, signs, ill-defined causes	28069	29700	31385	32448	32999	38.3	38.9	39.9	40.4	40.1	overest (P)
17.1.1 - Transport accidents	3186	3054	2692	2568	2144	5.0	4.8	4.2	4.0	3.3	
17.1.2 - Accidental falls	7781	8262	8902	9008	9073	11.2	11.5	12	11.9	11.8	overest (P)
17.1.3 - Drowning and accidental submersion	920	884	857	719	668	1.4	1.4	1.3	1.1	1.0	
17.1.4 - Accidental poisoning	1800	1725	1366	1236	1505	2.7	2.6	2.0	1.8	2.2	underest. (F)
17.1.5 - Other accidents	13694	14202	13240	14085	14271	19.9	20	18.2	19.0	19.0	
17.2 - Suicide and intentional self-harm	8591	8367	8868	8822	8986	13.9	13.4	14.1	13.9	14.1	
17.3- Homicide, assault	312	281	437	474	472	0.5	0.4	0.7	0.7	0.7	
17.4-Event of undetermined intent	785	1102	1275	1394	1552	1.3	1.8	2.0	2.2	2.4	underest. (F)
17.5- Other external causes of injury and poisoning	1391	1525	1855	1713	1361	2.1	2.2	2.7	2.4	1.9	underest. (F)
18- COVID	0	0	0	0	69249	0	0	0	0	93.4	
Total	**592071**	**604298**	**607820**	**611413**	**667496**						

Note: standardized mortality rates use the European Standard Population as reference population. Over/underest (F) denotes risk of over/under-estimation of counts or rates and F-measure below 90%; over/underest. (P) denotes risk of under/overestimation of countings indicated by Poisson tests of differential significant at 1%.

Source: CépiDc, Causes of death, final data for 2018 and 2019. Scope: All deaths of French residents deceased in France.