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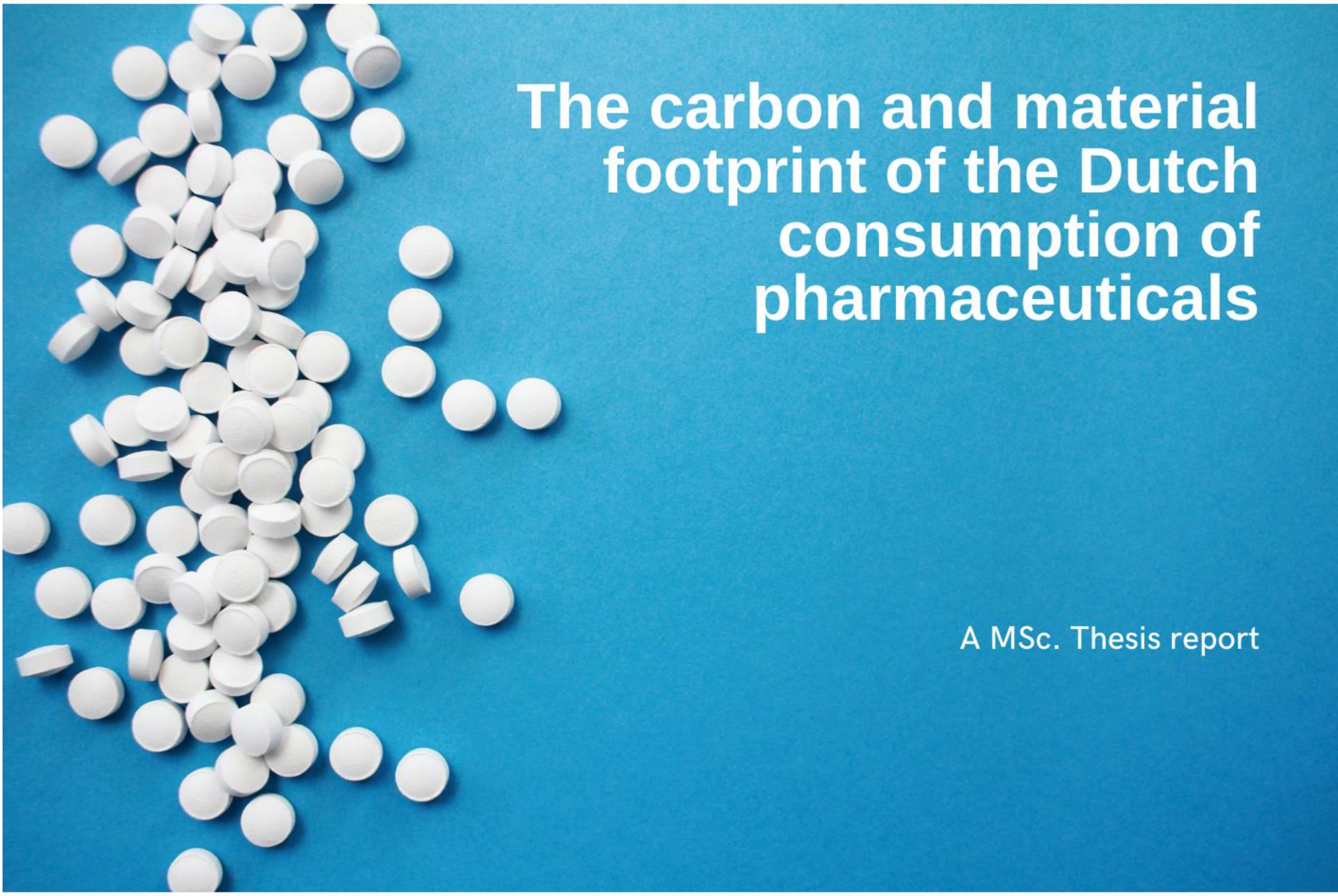

The carbon and material footprint of the Dutch consumption of pharmaceuticals

A MSc. Thesis report

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Rosalie Hagenaars

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Abstract

This thesis explores the relatively large contribution of the product category 'chemicals n.e.c.' (chemicals not elsewhere classified) to the Dutch healthcare sector's carbon and material footprint observed in previous studies. For this, an input-output study using SNAC-EXIOBASE data was performed. SNAC-EXIOBASE uses national statistics for the Dutch part of the multi-regional input-output table. It also distinguishes a separate chemical and pharmaceutical industry in the Dutch part. This can help identify possible aggregation problems in the EXIOBASE category 'chemicals n.e.c.' which is an aggregate of the chemical and pharmaceutical industry sectors. Comparing the carbon and material footprint of pharmaceuticals used in the Dutch health care sector as calculated with (default) EXIOBASE and SNAC-EXIOBASE shows that there is an aggregation problem in the 'chemicals n.e.c.' category. This means that grouping the pharmaceutical industry with the chemical industry greatly influences the carbon and material footprint of pharmaceuticals. The carbon footprint decreases by 11% and the material footprint by 61% when using SNAC-EXIOBASE compared to EXIOBASE data. The multiplier analysis showed that in all cases the Dutch pharmaceutical industry has a lower carbon, mineral and metal intensity (footprint per euro) compared to the Dutch chemical industry or 'chemicals n.e.c.' confirming the aggregation problem. The LCA literature review showed that the range of carbon intensities of individual pharmaceuticals matches the carbon intensity of the 'pharmaceutical industry' in SNAC-EXIOBASE. This study also showed that the material footprint of the Dutch healthcare sector is uncertain and should be used with care. Future research should focus on using MRIOs that better depict the pharmaceutical industry like the ICIO which is based on the ISIC Rev. 4 classification and, therefore, includes a separate pharmaceutical industry. Before performing analyses with the ICIO is possible, higher sectoral resolution and environmental extensions are needed.

Executive summary

This executive summary is made for partners in the GDDZ, RIVM and non-experts in the field of input-output analysis.

Problem statement

Previous studies on the carbon and material footprint of the Dutch healthcare sector showed a large contribution of the consumption of pharmaceuticals to these footprints. This large share of pharmaceuticals was observed in the study by RIVM for the Netherlands as well as in studies of other countries. Carbon and material footprints are calculated with the use of input-output analysis. Input-output analyses are based on economic statistics which are converted to input-output tables (IOTs). These IOTs are available in world (multi-regional input-output tables, MRIOTs) size containing aggregated sectors to describe the economy. In this way, in most MRIOTs the pharmaceutical industry and chemical industry are aggregated into one category: *chemicals not elsewhere classified* (chemicals n.e.c.). Even though all these studies show a large share of the healthcare sector's carbon and material footprint is caused by this category 'chemicals n.e.c.', no studies explain this. Therefore, this studies' research question is**:**

"*How can the relatively large contribution of the product category 'chemicals n.e.c.' to the carbon and material footprints of the Dutch healthcare sector be explained?"*

Approach and methods

Step by step possible reasons that could cause the previously observed high contribution of the consumption of pharmaceuticals to the Dutch healthcare sector's carbon and material footprint were investigated. First, the previous studies were checked for conceptual and calculation errors. Second, the previous study by RIVM was compared to the carbon and material footprint calculated in this study which used SNAC-EXIOBASE data compared to the default EXIOBASE data used by RIVM. SNAC-EXIOBASE uses national statistics for the Dutch part of the MRIOT. It also distinguishes a separate chemical and pharmaceutical industry in the Dutch part. This can help identify possible aggregation problems in the EXIOBASE category 'chemicals n.e.c.' which is an aggregate of the chemical and pharmaceutical industry sectors. Also, a literature review on LCA studies of pharmaceutical products was performed to be able to get a better understanding of the carbon and material footprint of pharmaceuticals and to see if this is in line with the way the pharmaceutical industry is represented in the SNAC-EXIOBASE input-output table. Lastly, if aggregation problems are found, then also possible improvement options based on the results of this study will be mentioned.

Results

No conceptual and calculation errors could be found in previous studies based on a comparison of the use of healthcare expenditure data and a comparison of the total Dutch carbon footprints calculated in these studies. The investigation into the EXIOBASE category 'chemicals n.e.c.' which was used in the RIVM study to described the pharmaceutical industry, showed that this category includes pharmaceuticals but also includes products like inks, paints, make-up, soaps, and bulk chemicals.

The Dutch healthcare sector's carbon footprint calculated in this study consists of 14.26 Mt CO_2 equivalents. The material footprint of the healthcare sector calculated using SNAC-EXIOBASE consists of 15.05 Mt of materials (minerals and metals) and is dominated by mineral use (89%). The mineral footprint consists of a large share of ‘other mineral’ use (69%), which is very remarkable. The mineral group of ‘other minerals’ consists of bitumen, asphalt, precious and semi-stones, graphite, quartz and quartzite, siliceous fossil meals, asbestos, steatite and talc. This large share may be explained by the healthcare products that are made of the minerals that fall under ‘other minerals’. However, because we were not able to quantitively check how much of these ‘other minerals’ are used in the Dutch healthcare sector, this result remains uncertain.

This study shows that there is an aggregation problem in the EXIOBASE category ‘chemicals n.e.c.’. This means that the carbon and material footprint of the Dutch consumption of pharmaceuticals is highly influenced by the grouping of chemicals together with pharmaceuticals. When using SNAC-EXIOBASE data (which distinguishes a separate pharmaceutical sector), the carbon footprint decreases by 11% and the material footprint by 61%, compared to the use of EXIOBASE data and the use of the aggregate product group ‘chemicals n.e.c.’. In all cases, the Dutch ‘pharmaceutical industry’ category has a lower carbon, mineral and metal footprint per euro spent compared to the Dutch ‘chemical industry’ or the aggregate ‘chemicals n.e.c.’ category. This confirms the identified aggregation problem because it shows that the per euro footprints diminishes a lot when splitting the pharmaceutical industry from the chemical industry. Lastly, an analysis of the supply chains of the pharmaceutical industry, the chemical industry and ‘chemicals n.e.c.’ as they are displayed in the input-output tables showed that their supply chains substantially differ.

The literature review on the life cycle analyses (LCA) of individual pharmaceutical products showed that only a small fraction of pharmaceuticals is analysed. It also shows that these studies often do not include the material footprint of pharmaceuticals and only focus on the carbon footprint. This also means that using LCA data to describe input-output analysis is not feasible. The LCA review showed a carbon footprint per euro range of the 44 substances that match the carbon footprint per euro of the pharmaceutical industry as it is described in the SNAC-EXIOBASE input-output tables. This shows that there is no initial reason to think that the pharmaceutical industry is properly displayed in the SNAC-EXIOBASE dataset.

Conclusion

The observed decrease of the carbon footprint by 11% and material footprint by 61% in combination with the carbon footprints per euro, and the structural path analysis of the supply chains showed that there is an aggregation problem in the EXIOBASE ‘chemicals n.e.c.’. This shows that the results observed in previous studies are subject to a substantial aggregation problem, which also makes sense due to the different types of products that are in the ‘chemicals n.e.c’ category. Even though there is a decrease in the carbon and material footprint of the Dutch healthcare sector, it is still reasonable to say that the consumption of pharmaceuticals is a large share of the carbon and material footprint. The ‘pharmaceutical industry’ category has the highest carbon, mineral and metal footprint per euro of all four healthcare-related categories used in this study.

Recommendations

The motivation of this study originates in the Green Deal Sustainable Healthcare in the Netherlands (GDDZ) in which RIVM (Steenmeijer et al., 2022) is creating a knowledge base for the environmental impacts of the Dutch healthcare sector. We advise RIVM to be careful to use the material footprint results for policy advice since the results of their study and this study differ so much, and relatively little research has been done on this subject, which makes it hard to value these findings. Especially the hotspot analysis of the material footprint calculated in this study showed that the large share of ‘other minerals’ is hard to explain. Also, the total minerals extracted per sector in the SNAC-EXIOBASE extension differs compared to the EXIOBASE extension. Without knowing why these values differ, it is unwise to put too much value on these results. Future research should therefore focus on the material footprint of the Dutch healthcare sector.

RIVM is also advised to not base their knowledge base too much on the analysis of one year as creating a knowledge base on the environmental impacts of a healthcare sector benefits from trends over the years. The EXIOBASE dataset is available for many different years and the SNAC-EXIOBASE dataset is available for 2010, 2014 and 2016. It would be interesting to compare default MRIO healthcare studies of other countries to a SNAC approach study, as was done in this study. It would be interesting to see how the results change when using a SNAC approach based on other datasets.

We suggest that future studies on the Dutch healthcare sector should focus on using MRIOs that have a separate pharmaceutical industry as this could solve some of these aggregation issues. The input-output tables developed by the OECD (the ICIO tables) already apply this because they base their IOT on a newer economic classification system (ISIC Rev. 4). Before these can be used for healthcare footprint analyses, environmental extensions should be added and the resolution of sectors in these tables should be increased. Due to the economic analysis focus of the OECD, we do not expect the OECD to add these environmental extensions. As this ICIO table by the OECD is a very recent development we advise RIVM to take these developments into account for future studies as studies based on older economic classification systems (like EXIOBASE) will become outdated. Partnering with PBL could be an option since they have experience in working with the ICIO tables. Lastly, LCA studies can be still very useful to indicate hotspots of emissions or material extraction caused by the healthcare sector. We advise that mitigation measures should be based on low-hanging fruit which can better be found by using LCA.

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1. Introduction

The healthcare sector and rising environmental impacts are intertwined. On the one hand, the healthcare sector must deal with the negative effects of climate change and other environmental impacts. An often-mentioned negative effect of climate change is heat stress, which especially has an impact on the elderly and children (Kovats & Hajats, 2008). On the other hand, the healthcare sector contributes to environmental impacts, like global warming, smog formation, acidification, and more (Eckelman & Sherman, 2016). These environmental impacts are caused by environmental interventions. Some of the environmental interventions caused by healthcare were calculated by Lenzen et al. (2020). For example, according to Lenzen et al. (2020), the global healthcare sector is responsible for the environmental interventions of 54.4 Gt CO_2 equivalent emissions, and 122.2 Mt particulate matter emissions. Of all the indicators used in Lenzen et al. (2020), the healthcare sector causes global environmental impacts that are in the range of 1 to 5 per cent of global impacts, while they are responsible for more than 5% of some countries' national impacts. Belkhir & Elmeligi (2019) even find that the pharmaceutical industry's carbon intensity is around 55% higher than that of the automotive industry. The healthcare sector also uses a lot of materials (De Koning, 2020), which indirectly also causes a lot of environmental impacts during the mining and quarrying stage of these materials.

As part of the Dutch national climate goals, reduction of GHG emissions from the healthcare sector are agreed upon. The Ministry of Health, Welfare, and Sport (VWS: Ministerie van Volksgezondheid, Welzijn en Sport) created a Green Deal Sustainable Public Health (GDDZ: Green Deal Duurzame Zorg) in which agreements between healthcare partners are made on how the healthcare sector can contribute to decreasing GHG emissions, how the circular economy can be stimulated in this sector, how medicine wastes can be diminished, and how a health-promoting living environment can be created (Green Deal, 2019). As part of the commissioned task by the VWS, the Dutch National Institute for Public Health and the Environment (RIVM: Rijksinstituut voor Volksgezondheid en Milieu) work on gaining knowledge on the environmental impacts of the Dutch healthcare sector (Rijksinstituut voor Volkgezondheid en Milieu, n.d.). This collecting of information is one of the focal points of the GDDZ.

The first investigations in this programme used environmentally-extended multi-region input-output analysis to investigate the different environmental impacts and material use related to the healthcare sector. Input-output analysis (IOA) is a method often used for calculating the environmental footprints of a national economy or a sector in an economy. The knowledge base study of the RIVM focuses on, the carbon footprint, the material footprint, the land-use footprint, the freshwater footprint, and the waste footprint of the Dutch healthcare sector. It showed that the purchase of pharmaceuticals among the Dutch healthcare sector has the largest contribution to carbon emissions, raw material extraction, freshwater use, land use, and waste production (Steenmeijer et al., 2022). Next to this, explorative research was conducted by De Koning (2020) on the material footprint of the Dutch governmental expenditure. An unexpected finding was that the expenditures of the Dutch government in the product category 'chemicals and chemical products' has a high contribution to the material footprint (19.1%), while the final demand expenditures share is relatively small (2.76%), compared to other final demand categories like 'public administration and defence' (31.43%), that has a similar contribution to the total material footprint (23.4%) (De Koning, 2020). There is still no clear explanation on why the footprints of the chemical category are so large in both studies. Interestingly, in Steenmeijer et al. (2022) (RIVM study) the same chemicals category (chemicals not elsewhere classified) is used for calculating the environmental impact of pharmaceuticals used in the healthcare sector. No disaggregation of this sector was done, which means that it is not clear which part of the environmental impact is caused by pharmaceuticals and which part is caused by other chemicals.

Also, outside the Netherlands, very large shares of the healthcare sector's emissions can be assigned to the consumption of pharmaceuticals. Wu (2019), for example, finds that the consumption of pharmaceuticals is responsible for 55% of the carbon emissions of the Chinese healthcare sector. Also, the study of the UK healthcare sector by Tennison et al. (2021) shows that 32% of the supply chain emissions are caused by the consumption of pharmaceuticals and chemicals.

A further investigation into the environmental impact of the category 'chemicals not elsewhere classified' ('chemicals n.e.c.') could therefore give insight into if the high emission share of pharmaceuticals and chemicals is caused by the healthcare sector or if it is caused by other factors. The societal relevance of this thesis lies in the fact that public health is essential for any society, however, it should be balanced with environmental issues. The findings of this will help in this balancing, as it can be used by RIVM in its knowledge base program on the environmental impacts of the public healthcare sector. By identifying the cause of the healthcare sector's high material and carbon footprints and the contributions of individual pharmaceutical products to this footprint, VWS and the other 200 plus partners in the GDDZ can formulate better policies to reduce these footprints. Next to this, future studies could also benefit from the insights into possible aggregation problems in 'chemicals n.e.c.'.

This thesis addresses the research field of Industrial Ecology as it tries to solve the above-mentioned sustainability problem. Industrial Ecology is an interdisciplinary research field that focuses on society's metabolism to identify, design, and evaluate solutions for sustainability problems from a socio-technical system perspective. The approach of this study is multidisciplinary and uses tools often used in Industrial Ecology which have a background in natural science, social science, and engineering, as input-output analysis and life cycle assessment (LCA) were used to investigate the carbon and material footprint of the Dutch consumption of pharmaceuticals. The healthcare sector is approached from a system thinking perspective, as the GHG emissions and material use caused by the healthcare sector were linked to the healthcare sector by using IOA.

In the next chapter, the problem definition of this thesis will be addressed. After this, in chapter 3, important concepts and the research approach of this study are explained. Chapter 4 shows all methods used to obtain the results. Chapter 5 shows the results obtained, following the research flow diagram. In chapter 6 these results and discussed and put into context. The conclusions are based on the discussion and are presented in chapter 7.

2. Problem definition

Carbon footprint analysis traditionally focussed on the carbon footprint of energy supply, different modes of transportation, different products, food production, and services in general (Minx et al., 2009). In contrast, carbon footprint analyses of specific service sectors have received less attention. As mentioned in the introduction, recently, there have been studies that already used input-output analysis for calculating the environmental impact of the healthcare sector, however, there are relatively few. Pichler et al. (2016), who created methodologically consistent cross-country comparisons of carbon footprints of the healthcare sector, even stated that at that time only four countries (US, England, Australia, and Canada) had done a carbon footprint analysis for the healthcare sector. After this, the Chinese, Austrian, Japanese, and English healthcare sectors' carbon footprints were calculated by Wu (2019), Weisz et al. (2020), Nansai et al. (2020), and Tennison et al. (2021), respectively.

Strangely, the above-mentioned studies and studies focussing on the Dutch healthcare sector, only focused on the carbon footprint (ARUP & Health Care Without Harm, 2019; Gupta Strategists, 2019; Pichler et al., 2016), while other environmental impact indicators are also very relevant. The more recent study of Lenzen et al. (2020), does calculate other environmental footprints, however, the calculation of a raw material footprint is not included. Next to this, this study is a global assessment and thus lacks in detail. Material footprint analyses of the healthcare sector seem to be scarce. A search in the Scopus search engine with the keywords "material", "footprint", "health" and "public" showed there are no studies that specifically focus on calculating the material footprint of the healthcare sector. The only study found in this search that seems to be of relevance is of Ottelin, Heinonen & Junnila (2018). They do calculate the material footprint caused by the welfare state of Finland; however, they do not specifically focus on the healthcare sector, and nothing is stated on the material footprint of pharmaceuticals. While there is a general shortage of studies focussing on the material footprint of the healthcare sector, this study specifically focuses on the Netherlands. Therefore, the first knowledge gap found is the lack of studies calculating the Dutch healthcare sector's material footprint. Steenmeijer et al. (2022) does calculate the Dutch healthcare sector's material footprint, however, this study is not published yet. This lack of material footprint studies on the Dutch healthcare sector also made it difficult for Steenmeijer et al. (2022) to compare their results to previous studies.

The second knowledge gap focuses more on the results of previous studies. From initial investigations by De Koning (2020) and Steenmeijer et al. (2022), the carbon and material footprint of the Dutch sector 'chemicals n.e.c.' is larger than expected. The same is observed for other countries in other studies (Nansai et al., 2020; Tennison et al., 2021; Weisz et al., 2020; Wu et al., 2019). There is no clear explanation for the large share of pharmaceuticals and chemicals of the healthcare sectors' emissions for all these studies. It could be the case that this result represents reality quite well, however, it could also be a misrepresentation of reality. Therefore, this study analyses the following possible reasons why pharmaceuticals and chemicals are responsible for such a large share of the total healthcare emissions:

- Data limitations due to the use of the selected input-output database
- Conceptual errors
- Incorrect calculations

Conceptual errors here refer to errors in the construction of the input-output analyses which could have been prevented if the right concepts and thinking steps were used.

The uncertainty of the results of previous studies also lies in the fact that it is not yet clear if input-output analysis is a suitable tool for analysing the carbon and material footprint of the healthcare sector of a nation. This is because critical assessments of the results are lacking. Therefore, the third knowledge gap is the uncertainty of whether input-output analysis is a suitable tool that produces useful results for the carbon and material footprint of the healthcare sector of a nation.

The three knowledge gaps this study addresses can be summarized as follows:

1. What is the material footprint of the Dutch healthcare sector?
2. Can the relatively high contribution of ‘chemicals n.e.c.’ to the Dutch healthcare sector´s carbon and material footprint as results and indications of previous studies, be explained by data limitations, conceptual errors, or incorrect calculations?
3. To what extent is environmentally-extended input-output analysis a suitable tool to analyse the carbon and material footprint of the Dutch healthcare sector?

Starting from the three knowledge gaps derived in this literature review, this study focused on unravelling why the large contribution of ‘chemicals n.e.c.’ to the Dutch healthcare sector’s carbon and material footprint and what is contributing to this. This study might also be able to give more insight into whether IOA is a useful way to calculate the carbon and material footprints of the healthcare sector and how it could be improved. From this line of reasoning the following main research question is formulated:

How can the relatively large contribution of the product category ‘chemicals n.e.c.’ to the carbon and material footprints of the Dutch healthcare sector be explained?

In this research question, the relatively large contribution of the product category ‘chemicals n.e.c.’ to the carbon and material footprints refer to the finding of the studies of De Koning (2020) and Steenmeijer et al. (2022).

In the next chapter, the core concepts and research approaches that are related to the research question are described. The identification of core concepts helps lay the context of this thesis and is useful to find the general approach for the further analysis of the research question.

3. Concepts and research approach

3.1 Core concepts

The core concepts are subdivided into IOA and healthcare expenditure concepts. IOA concepts are important because IOA is the main tool used in studies that investigate the healthcare sectors' carbon and material footprint. IOA is also relevant for all the identified knowledge gaps. A good understanding of its basics and the state-of-the-art is therefore essential. Next to this, healthcare expenditure is an important concept because it is used to construct input-output calculations for the healthcare sector. Different studies use different definitions of healthcare expenditure, which influences the result of these studies. Insight into the different definitions is, therefore, essential to analyse other studies. It is also useful for choosing a suitable healthcare definition to be used in this study.

3.1.1 IOA

In its basics, an input-output model is a system of linear equations that describe the distribution of an industry's product through an economy which was developed by Wassily Leontief in the 1930s (Miller & Blair, 2009). It shows how demand for products by one industry sector is related to the production of products in other industry sectors and is, therefore, often used for macroeconomic analyses. Economists use IOA to analyse economic events and shocks that are created by different sectors, and the effects these have on the whole economy. Input-output analysis is also an interesting environmental accounting tool. By adding environmental extensions to IOA the environmental impacts along the supply chain of a sector can be calculated (Kitzes, 2013). In contrast to other typical Industrial Ecology tools, IOA is both a macroeconomic tool and a tool for analysing economy-wide potential environmental impacts. For example, the commonly used method of Life Cycle Analysis (LCA) only focuses on specific products or services in a sector (De Haes, 2002; Guinée et al., 2002) and is not easily connected to an economic modelling framework. LCA and IOA have in common that they can consider different environmental indicators (ibid.). Material Flow Analysis (MFA) does have to possibility to look at a global system, however, it only investigates the flows of materials through the economy, while other environmental indicators are not analysed (Bringezu, & Moriguchi, 2002). The fact that input-output tables depict the whole economy and can be used to calculate different environmental indicators, makes it useful for this study. It can provide a general idea of the carbon and material footprint of the Dutch consumption of pharmaceuticals, without having to perform an LCA for all the individual products in this sector or collect all the bottom-up data of the industries, which would be impossible.

3.1.2 Price levels

An input-output table (IOT) is constructed from observed economic data for a specific geographic region, like national accounts (Miller & Blair, 2009). National input-output tables are usually constructed by national statistical agencies according to guidelines described in the "System of National Accounts" (SNA; United Nations [UN], 2009). The SNA describes how all the monetary transactions between economic activities are recorded in input-output tables. Those national statistics usually record the transactions at three different price levels, i.e., basic prices, producers' prices, or purchasers' prices. IOTs are often at basic prices. Figure 1 shows the relationship between, basic prices and purchasers' prices.

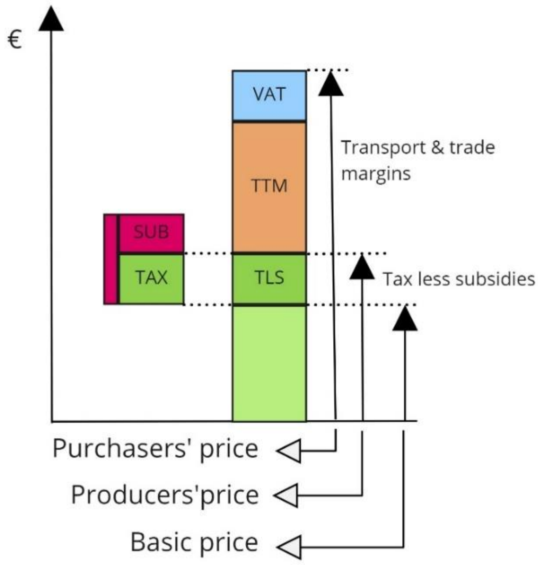

Figure 1: Schematic overview of basic prices, producers' prices and purchasers prices. Based on lectures by Dr Ranran Wang (where VAT refers to Value added tax and SUB refer to subsidies).

The basic price is described by the SNA as *(UN, 2009, p. 101)*:

> *"The basic price is the amount receivable by the producer from the purchaser for a unit of a good or service produced as output minus any tax payable, and plus any subsidy receivable, by the producer because of its production or sale. It excludes any transport charges invoiced separately by the producer."*

Producers' price is described as (UN, 2009, p. 101):

> *"The producer's price is the amount receivable by the producer from the purchaser for a unit of a good or service produced as output minus any VAT, or similar deductible tax, invoiced to the purchaser. It excludes any transport charges invoiced separately by the producer.*

The purchasers' price is described as (UN, 2009, p. 102):

> *"The purchasers' price is the amount paid by the purchaser, excluding any VAT or similar tax-deductible by the purchaser, in order to take delivery of a unit of good or service at the time and place required by the purchaser. The purchasers' price of a good includes any transport charges paid separately by the purchaser to take delivery at the required time and place."*

When national statistical data is used in performing calculations with the input-output table, a conversion between the statistical data from purchasers' or producers' prices is needed, to be able to calculate with comparable numbers. In this study, the conversion will be used to be able to include the healthcare expenditure data provided by Statistics Netherlands (CBS) (which is in purchasers' prices) in the IOT table (which is in basic prices).

3.1.3 Footprint calculation

This study specifically dives deep into the carbon and material footprint of the Dutch healthcare sector. Calculating a footprint is also often called a 'consumption based' approach, as it calculates the resource depletion or emissions of an economy based on the consumption of goods and services and their whole supply chain, instead of only considering the impacts that occur during the production or consumption activity itself, which is a 'production based' approach (Tukker et al., 2016). The material footprint is defined by Wiedmann et al. (2015, p. 6271) as: "the global allocation of used raw material extraction to the final demand of an economy". Used raw materials refer to materials that are extracted and further used in the economy and have an economic value (Bringezu et al., 2003). In contrast, unused materials are extracted to be able to access the used materials, which is often called overburden (Bringezu et al., 2003). The unused materials do not enter the economic system and have no economic value. Wiedmann's definition is not very clear on which materials fall under the material footprint. Raw material extraction can refer to a lot of different materials. It can refer to abiotic materials only, like minerals and metals. While it could also include biotic materials like biomass and fossil fuels (Giljum, Bruckner & Martinez, 2015; Wiedmann et al., 2015). Most importantly, the materials selected for calculations should match the goal of the study.

Wiedmann & Minx (2008, p. 4) define the carbon footprint as "a measure of the exclusive total amount of carbon dioxide emissions that are directly and indirectly caused by an activity or is accumulated over the life stages of a product.". Wiedmann & Minx (2008) explicitly only included carbon dioxide, because at that time other greenhouse gasses were more difficult to quantify because of data availability. Nowadays, most studies also include other greenhouse gasses, like methane (CH_4), nitrous oxide (N_2O), and Fluorinated greenhouse gasses (F-gasses) which are common environmental extensions in input-output databases that in total define the carbon footprint. If these substances are already converted to the common unit of kg CO_2 equivalents (CO_2 eq.) depends on the database. For example, in EXIOBASE, the emissions of the greenhouse gasses are given in kg of CO_2, CH_4, N_2O and SF_6. These emissions need to be converted manually to CO_2 equivalents using global warming potentials (GWP). GWP is the heat that is absorbed in the atmosphere by greenhouse gasses. For CO_2 this value is 1, but this differs for other greenhouse gasses and different time spans (IPCC, 2007). Substances like the HFC's, the CFC's and the PFC's are already expressed in kg CO_2 equivalents in EXIOBASE and many other GHG emission inventories.

Given that environmentally-extended input-output tables are available, we explain how these can be used to set up an environmentally-extended Leontief demand-driven model to calculate the above-mentioned carbon and material footprints. Leontief refers to both the developer of IOA, Leontief Wassily, as well as the Leontief matrix which is essential to IOA and is explained further on. As mentioned, this model is based on economic statistics, which are depicted in the square inter-industry transaction matrix (Z matrix in €/€). Figure 2 shows an example input-output table. The Z-matrix shows the inputs of each industry in the columns and the outputs of each industry in the rows.

Z Matrix	Industry A	Industry B	Industry C	Final demand (y)	Total output (x)
Industry A	0	20	35	45	100
Industry B	15	0	50	100	165
Industry C	0	70	0	60	130
Value added (v')	85	75	45		
Total input (x')	100	165	130		

Figure 2: Basic input-output table

In this square both in the rows (*i*) and columns (*j*), the same industries are depicted. The z_{ij} elements in the matrix represent interindustry transactions per sector *i* to all sectors *j*, including the sector itself. The total output of industry *A* can be calculated by adding the outputs of all industries plus the final demand for sector *A*. The total input of sector *A* can be calculated by adding the inputs from all industries plus the value-added of sector *A*.

By dividing each z_{ij} element by the total output (*x*) of sector *j*, we obtain the technical coefficients matrix *A*, as shown in equation 1. An element in the A matrix shows the direct requirements of 1 euro of the total output of *j* from sector *i*. Figure 2 also shows the A table constructed from the example *Z* table.

$$A = Z\hat{x}^{-1} \qquad \textit{Eq. 1}$$

A Matrix	Industry A	Industry B	Industry C
Industry A	0	0.12	0.27
Industry B	0.15	0	0.38
Industry C	0	0.42	0

Figure 3: The A matrix constructed from the basic input-output table shown in figure 2.

The Leontief inverse is the key to performing an IOA. The Leontief matrix represents the scaling factor (multiplier) of how the total output of and industry responds to changes in the final demand for this product. The Leontief inverse helps us see the impact of this in all industries in the economy, as it shows how the output of all these industries changes due to this effect. Important to note is that this covers both direct and indirect effects. The Leontief inverse is constructed using this *A* matrix by taking the inverse of the Identity matrix minus *A*, as shown in equation 2.

$$L = (I - A)^{-1} \quad \text{Eq. 2}$$

L Matrix	Industry A	Industry B	Industry C
Industry A	1.04	0.29	0.39
Industry B	0.19	1.25	0.53
Industry C	0.08	0.53	1.23

Figure 4: Leontief matrix based on the A matrix shown in figure 3

An element in the Leontief matrix (L_{ij}) shows the total requirements of sector *i* per euro of final demand of sector *j*, which includes the direct and indirect requirements.

The total output vector (*x*) can also be calculated by multiplying the Leontief matrix with the final demand.

$$x = Ly \quad \text{Eq. 3}$$

As mentioned, the Leontief matrix can give an idea of the output changes induced by a change in demand. Figure 5 shows this change in total output due to a change in final demand. In the example, the total output is calculated by using equation 3. The new final demand vector is based on an increase in final demand for industry A by 40%.

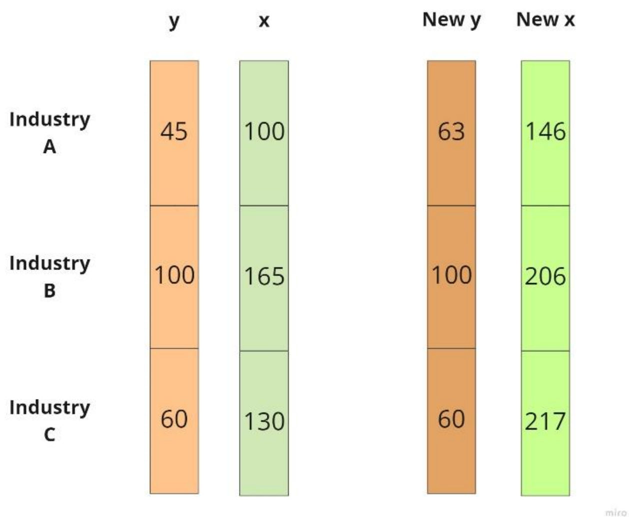

Figure 5: The change in total output induced by the change in final demand of industry A by 40% (numbers are rounded).

For using environmentally-extended input-output analysis (EE-IOA) the Leontief inverse is again important, as it shows us the direct and indirect requirements of the sectors *i* per euro of final demand of sector *j*. This is essential for calculating the environmental footprint of a sector, as this enables covering all the emissions that are caused along the supply chain by producing the products of this sector. Therefore, the environmental footprint is calculated by multiplying the Leontief matrix with the final demand and the direct environmental coefficients vector plus the direct emissions caused by households, as shown in equation 4.

$$E = f'Ly + Ehh \qquad \text{Eq. 4}$$

In general, this environmental footprint now shows the environmental intervention caused directly and indirectly by a certain final demand of different industries. Where *E* represents the total environmental footprint, *f* is the direct environmental coefficients vector (environmental intervention per €), *L* is the Leontief matrix, *y* is the final demand vector, and *Ehh* is the emissions directly occurring in households.

Important to note is that footprints are expressed in the total amount of environmental intervention. Environmental interventions are defined as flows entering the economy from the natural environment or going from the economy (waste) into the natural environment (e.g., carbon dioxide, natural resources, and land use) (Guinée et al. 2002). Environmental interventions can be converted to environmental impacts indicators like global warming, material depletion, and land-use change, in a lifecycle impact assessment (LCIA).

3.1.4 Multi-Regional Input-Output analysis

According to Tukker et al. (2016) environmentally-extended multi-regional input-output analysis (EE-MRIO) is one of the most promising ways to calculate consumption-based indicators like carbon and material footprints because it can easily deal with the complex relation of value creation and production of emissions in the various countries of the supply chain. Figure 6 shows the basics of an EE-MRIO. It shows that imported products for consumption can be traced back to where they are produced, the final use for domestic and imported products, and factor inputs for each region. The production of each country is linked to the extraction of resources in that country. In this way, consumption of products by Dutch consumers can for example be traced back to mineral extraction abroad.

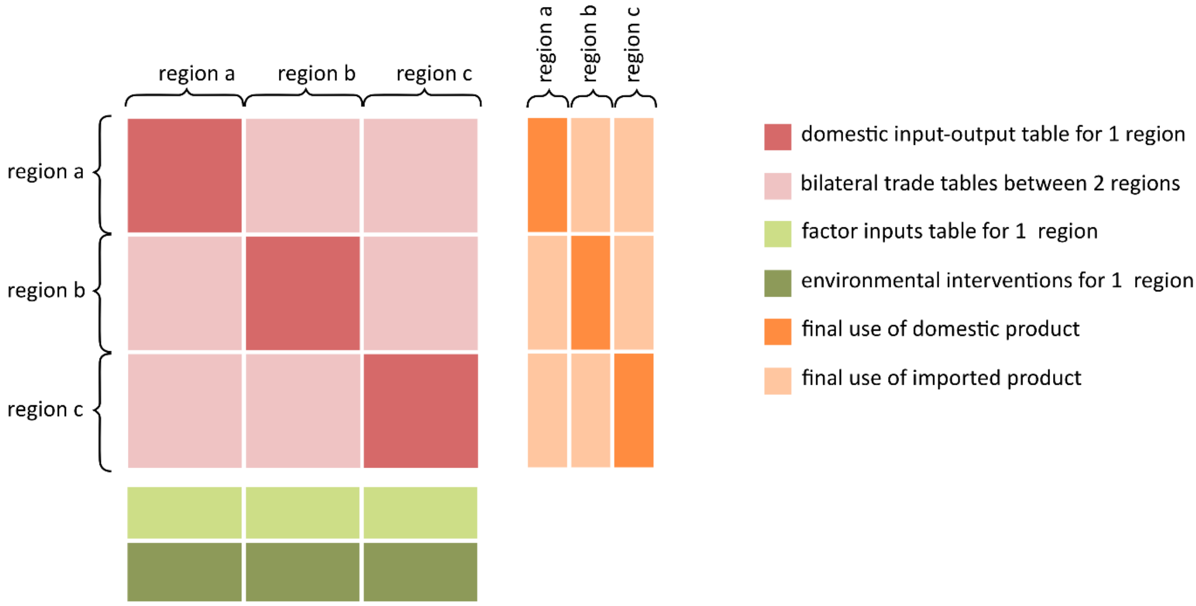

Figure 6: A hypothetical EE-MRIO of 3 regions (Tukker et al., 2016)

Nowadays MRIO datasets can have a very detailed resolution and geographically cover the whole world. The resolution refers to the number of industries and products that are covered in the dataset for all the countries. The EXIOBASE 3 dataset has a resolution of 163 industries by 200 products and covers 44 countries (28 EU, 16 major economies, and 5 rest of the world regions) (Stadler et al., 2018). Tukker et al. (2016) mention that this high resolution is crucial for calculating environmental footprints because environmental pressures in the economically less relevant sectors can be essential for different environmental footprints.

Important to note is that this MRIO approach to calculating the carbon and material footprint has several advantages and limitations. The main limitation of using MRIO to calculate environmental footprints is that products with different physical characteristics are grouped into one product group with the same unit of economic value (the homogenous product group assumption). A downside of this is that it implies an economic allocation of the environmental impacts, which is based on the monetary transaction. However, if footprints are calculated with the use of physical allocations, the monetary MRIO data cannot be translated to physical transactions, as the monetary value per weight can differ between the different supply chains of the different products in one product category (Weisz & Duchin, 2006). To clarify this problem an example is shown in table 1. The table shows the per euro carbon footprint used in ‘chemicals n.e.c.’ which is the EXIOBASE category in which both ascorbic acid (vitamin C) and sulfuric acid fall. As mentioned, in input-output analysis, both substances get the same environmental coefficient per euro as shown with the value of 2.51 kg CO_2 eq./€ spent on 'chemicals n.e.c.'. Table 1 also shows the carbon footprint per kg of the substance, based on the LCA database ecoinvent. This carbon footprint per kg of the substance can be converted to a carbon footprint per euro, using the weight per euro of the substances (Sigma-Aldrich, 2022; Zorginstituut, 2021). The price of ascorbic acid is based on the pharmacotherapeutic compass (Farmacotherapeutisch Kompas) and the price of sulfuric acid is based on Sigma-Aldrich. They follow the same assumptions as later described in chapter 4.3 The numbers are based on calculations performed by De Koning (2021), which can be found in appendix B.

Table 1: Example showing the main limitation of calculating environmental footprints using MRIO.

	Ascorbic acid (vitamin C)	**Sulfuric acid (98%)**
Weight [kg] per **euro**	0.01	0.09
EXIOBASE carbon footprint **per euro** (WE)	2.51	2.51
Ecoinvent carbon footprint **per kg** (RER)	3.09	0.10
Ecoinvent carbon footprint translated to **per euro** (RER)	0.03	0.01

Table 1 clearly shows that the per euro carbon footprint calculated using ecoinvent and EXIOBASE differ a lot. The ecoinvent data is based on a cradle-to-grave assessment of the environmental interventions occurring during the life cycle of these products. Therefore, a more detailed environmental impact per euro of the substance is represented by the ecoinvent carbon footprint per euro. This indicates that the aggregated footprint per euro 'chemicals n.e.c.', therefore, is not suitable for some individual products, e.g., sulfuric acid. This example shows that the aggregation within MRIO may lead to multiple orders of magnitude overestimation or underestimation of the carbon footprint of specific products that are estimated with the aggregate carbon footprint of the whole group. The calculation of the example can be found in appendix A.

Another limitation of MRIOs is that they usually are too geographically aggregated to calculate agricultural or water footprints (Weinzettel et al., 2014). However, for the material and carbon footprint, this is seen as less of a problem. The main advantages of using an MRIO approach is that it covers the whole world and that the environmental interventions are related to the demand of products, meaning that these cannot be lost in the calculations as they are based on material balancing principles (Tukker et al., 2016).

3.1.5 SNAC Datasets

A lot of studies that calculate the environmental footprints of the healthcare sector use EE-MRIO tables. As this study focuses specifically on the Netherlands, the best available data for the Netherlands should be used that is linked to an MRIO. Datasets like this already exist and are called Single National Accounts-Multi Regional Input-Output models (SNAC-MRIO). Statistics Netherlands created a SNAC-MRIO for the Netherlands and based it on the EXIOBASE database, therefore is called the SNAC-EXIOBASE dataset (Walker et al., 2017). In regular stock multi-regional databases, the data of the countries is adjusted to be able to match and balance all countries, which means that data for the Netherlands would not match the original national statistical data anymore (Edens et al, 2015). Edens et al. (2011) show that when using the MRIO GTAP7 the Netherlands is a net importer of emissions, while when using international trade statistics and the Dutch national accounts the Netherlands is a net exporter of emissions. This difference showcases that using MRIO data for a national analysis can be problematic. In SNAC databases, the national statistics are adhered to as closely as possible, while the rest of the MRIO is adapted to this one country's national statistics. This makes the datasets preferable when performing a national analysis.

3.1.6 Healthcare expenditure

Another core concept is healthcare expenditure because it is a term that can be defined in several ways. Statistics Netherlands defines total healthcare expenditure by three different definitions (Centraal Bureau voor de Statistiek [CBS], 2021d). The difference in these definitions on the one hand lies in if it only includes healthcare or if it also includes wellbeing, youth care and childcare (CBS, 2021a). On the other hand, the difference lies in if the total Dutch expenditure entails expenditure by Dutch residents only or if it entails all healthcare expenses that happen in Dutch territory. Lastly, there is also a healthcare sector definition that only entails the expenses on compulsory health insurance. Data on healthcare expenditure is available at Statistics Netherlands for all three definitions of healthcare. Table 2 shows that there are several combinations of the definitions are possible. This table also shortly describes what these combinations of definitions entail.

Table 2: Division of healthcare definitions and healthcare expenditure definitions

Healthcare expenditure definition/healthcare sector definition	Broad definition	International definition	Compulsory insurances
Healthcare	Medical care and long-term care expenses that happen in Dutch territory.	Consumption of healthcare by Dutch residents including abroad consumption abroad of medical and long-term care.	Expenses on medical and long-term healthcare under compulsory insurances.
Healthcare and wellbeing	Medical care, long-term care, wellbeing, youth care, and childcare expenses that happen in Dutch territory.	-	Expenses on medical care, long-term healthcare, wellbeing, youth care, and childcare under compulsory insurance.

Important to note is that there is an international definition of defining healthcare (expenditure) developed by the System of Health Accounts (SHA). In this definition healthcare expenditure of a country entails all expenditure by its residents, which can also be abroad. The total expenditure on health includes all activities with the main aim of improving, maintaining, and preventing the deterioration of the health of persons, and limiting the consequences of ill health through the application of qualified knowledge of health. Healthcare includes the following groups of activities, (which includes the use of medicines and aids and support services such as ambulance transport):

1. Health promotion and prevention.
2. Diagnosis, treatment, cure, and rehabilitation of disease.
3. Care for the chronically ill.
4. Care for persons with health limitations or disabilities.
5. Palliative care.
6. Providing public health programs.
7. Governance and management of health care and its financing.

This definition only includes a small part of social care in comparison with the broad definition, which is why it is also a blank element in table 2.

On the other hand, there is a definition of healthcare in the broad sense. This definition includes expenditure on medical care, long-term care, wellbeing and social services, youth care and childcare. Care includes both provisions of services and goods. Expenditure on mutual deliveries between care providers does not count, it only concerns the ultimate (final) expenditure. This definition considers expenditure on healthcare goods and services by all institutions, practices, and organizations that provide those goods and services; providers for whom it is not their most important work also count. The expenses include the care provided to non-residents by Dutch healthcare providers. Lastly, the healthcare expenditure in the broad sense is also available without the social care expenditure, which is why this element in table 2 is filled in.

The healthcare expenditure definition of compulsory insurance is of less relevance to this study, as the total expenses of the Dutch healthcare sector will be used to calculate the carbon footprint. Therefore, it is not explained in more detail.

Lastly, another important concept in this study is extramural healthcare expenses. The previous definitions were all for defining total healthcare expenses, which in any of these definitions always includes extramural expenses. Extramural expenses are expenses by clients that are not staying in health institutions, like for example hospitals. It includes all expenses at the general practitioners and the pharmacy. This distinction between the consumption from the healthcare institution and extramural expenses is important for how the final demand of healthcare will be modelled in this study. This is explained in chapter 4.

3.2 Research approach

3.2.1 Sub-questions

The research approach follows the 3 identified knowledge gaps. From these knowledge gaps, sub-questions were defined to be able to fill these gaps and answer the main research question.

The three knowledge gaps this study addresses can be summarized as follows:

1. What is the material footprint of the Dutch healthcare sector?
2. Can the relatively large contribution of ‘chemicals n.e.c.’ to the Dutch healthcare sector´s carbon and material footprint as results and indications of previous studies, be explained by data limitations, conceptual errors or incorrect calculations?
3. To what extent environmentally-extended input-output analysis a suitable tool to analyse the carbon and material footprint of the Dutch healthcare sector?

The first sub-question tries to solve the second literature gap. It is defined as: “To what extent can the results of previous studies be explained by conceptual and calculation errors?” This sub-question is based on the suggestions for future research which were proposed by RIVM and De Koning (2020). The observed large contribution of ‘chemicals n.e.c.’ to the Dutch healthcare sector’s carbon and material footprint could have different origins. Firstly, it is not certain that the analyses of Steenmeijer et al. (2022) and De Koning (2020) do not contain any conceptual or calculation errors. To rule this out, the first sub-question investigates several possible sources of conceptual and calculation errors that may explain the previous studies’ results.

The second sub-question is defined as: “What is the material and carbon footprint of the Dutch healthcare sector calculated in this study?” Except for the study by Steenmeijer et al. (2022), no material footprint studies on the Dutch healthcare sector exist (to the best of our knowledge). Therefore, this study helps fill the knowledge gap on the Dutch healthcare sector’s material footprint (first knowledge gap). As explained in chapter 3.1.5, the SNAC-EXIOBASE dataset ensures better data quality. It distinguishes a separate chemical and pharmaceutical industry in the Dutch part, while it also has both a ‘care and wellbeing’ sector and a ‘healthcare’ sector, which EXIOBASE does not. The Dutch healthcare sector’s carbon and material footprint calculated in this study, therefore, is mainly aimed at a better description of the Dutch healthcare sector in the IOT.

The third sub-question dives deeper into data limitations as a possible explanation of the results and therefore tries to solve the second knowledge gap as well. The sub-question is defined as: “To what extent can the results of previous studies be explained by data limitations?” For this, the Dutch healthcare sector’s carbon and material footprint calculated in this study (using SNAC-EXIOBASE data) will be compared to previous studies. Since the SNAC-EXIOBASE distinguishes a separate chemical and pharmaceutical industry in the Dutch part, using this dataset can help identify possible aggregation problems in the EXIOBASE category ‘chemicals n.e.c.’ which is the aggregate of the chemical and pharmaceutical industry sectors. Next to this, multiplier analyses and structural path analysis were performed to get more insight into why the contribution of ‘chemicals n.e.c.’ in previous studies is so large, and if this result is mainly caused by data limitations in the EXIOBASE dataset.

The fourth sub-question helps understand the carbon and material footprint of the Dutch consumption of pharmaceuticals as calculated with the use of IOA by investigating the carbon and material footprints of individual pharmaceutical products. It is defined as: “What are the carbon and material footprints of individual pharmaceutical products?” The fourth sub-question helps understand if the observed carbon footprint of previous studies matches the carbon and material footprints of individual pharmaceutical products. De Koning (2020) recommended finding out in more detail which products are in 'chemicals n.e.c.' and how these different products influence the results. This also helps identify if 'chemicals n.e.c.' is too aggregated and gives a first impression of the representativeness of the category 'pharmaceutical industry' in SNAC-EXIOBASE. For this sub-question, bottom-up data from LCA studies were used for the relevant product groups identified in sub-question 1. The LCA data which is normally expressed in carbon footprint per kg of the product was converted to a per euro carbon footprint, as is common in input-output analysis.

The last sub-question was optional. If previous sub-questions show that 'chemicals n.e.c.' is too aggregated to be used for calculating the carbon and material footprint of the Dutch consumption of pharmaceuticals, improvements on this had to be found. The last sub-question is, therefore, defined as: "What are the possibilities for solving the aggregation problems in 'chemicals n.e.c.' to better calculate the carbon footprint of the pharmaceutical industry?" This sub-question helps answer the third knowledge gap. The aim of this sub-question is not to do an in-depth analysis of all possibilities; however, it will list several options that can logically be derived from the results observed in this study.

3.2.2 Research flow and approach

In figure 7, the research steps including the sub-questions, methods, and data needs, are schematically depicted. Figure 7 also shows when the knowledge gaps can be answered. The research approach is based on systematically ruling out possible reasons that could explain the high carbon and material footprint of the Dutch healthcare sector after which the main research question can be answered.

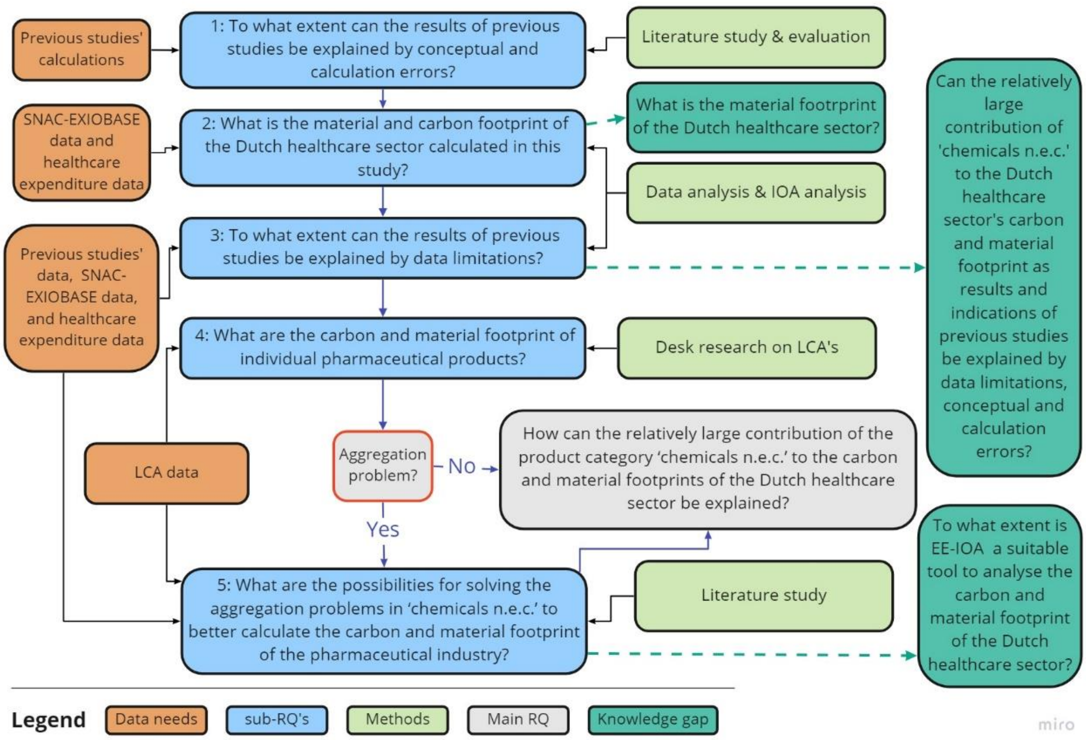

Figure 7: Research flow diagram

This study, therefore, takes a quantitative modelling approach. Mainly because input-output tables are an analytical framework (or model) (Miller & Blair, 2009) with which the main analyses of this study were conducted. In this study, the national accounts of all countries are quantitative data. By translating this data into a SNAC-EXIOBASE, it can be used as an analytical framework.

3.2.2 Limitations of research approach

Choosing a research approach also has limitations. The main limitations of the research approach of this study can be summarized as follows:

1. The analysis was only conducted for one reference year, which makes it difficult to generalize the results found in this study.
2. Only two impact categories were taken into account, meaning that trade-offs between different impact categories are difficult to identify.

The SNAC-EXIOBASE dataset exists for the years 2010, 2014, and 2016 (Walker et al., 2017). As the SNAC-Datasets are not publicly available, a SNAC dataset was requested by Statistics Netherlands. Due to the scope, and time frame for this study, one reference year was chosen. The reference year of this study is 2014 because this version was provided by Statistics Netherlands. Only reviewing one year is a limitation, since this makes it difficult to generalize the results found in this study.

Another limitation is the limited impact categories calculated in this study, which makes it difficult to identify trade-offs between environmental impact categories. Only the carbon and material footprint were included. The reasons for this study were the relatively high carbon, material, blue water consumption, land-use and waste-generation footprints of the consumption of Dutch pharmaceuticals as identified by De Koning (2020) and Steenmeijer et al. (2022). Of these impact categories, only the carbon and material footprint (mineral and metal extraction) are available in the SNAC-EXIOBASE dataset. Due to the time scope of this thesis, we did not search for data for the other environmental extensions. Next to the convenience of selecting these two impact categories, it is also an interesting combination because the calculation of the material footprint and carbon footprint differ a lot. Materials are only delved in a few sectors at the beginning of the supply chain, while for the carbon footprint every step in the supply chain is interesting. Therefore, the aggregation of the category 'chemicals n.e.c.' could influence the results of the material footprint more.

Before answering the sub-questions and knowledge gaps mentioned in this chapter, the methods used for this will be discussed in the next chapter.

4. Methods

This section describes per sub-question the collection, the methods for creating the SNAC-EXIOBASE calculations, and the methods for the analyses performed.

4.1 Analysing the correctness of previous studies

To rule out if the relatively high carbon and material footprint of the Dutch healthcare sector identified in De Koning (2020) and Steenmeijer et al. (2022) is not caused by conceptual or calculation errors these studies are reviewed. First, the expenditure on healthcare in both studies was reviewed. As the Leontief demand-driven model was used to calculate the footprints in these studies, the expenditure on healthcare can be seen as a driver of these footprints and is, therefore, carefully examined. The healthcare expenditure data used by Steenmeijer et al. (2022) (table 3) was checked by using the original data from Statistics Netherlands (Centraal Bureau voor Statistiek [CBS], 2021a) and calculating the basic price with the use of the Eurostat 2016 supply table (Eurostat, 2022).

After this, the 'chemicals n.e.c.' sector which is used to depict pharmaceuticals in Steenmeijer et al. (2022) was broken down into sub-categories using economical statistical classification schemes. This gives a first impression of the suitability of the category 'chemicals n.e.c.' for calculating the Dutch carbon and material footprint. For this disaggregation of 'chemicals n.e.c.', concordance tables provided by EXIOBASE were used (Stadler et al., 2018). The disaggregation was done for the NACE classification and the CPA 2002 classification. The NACE classification was chosen because the categories in EXIOBASE are based on NACE (NACE Rev. 1.1). The CPA classification was chosen because it is more detailed. The product group names corresponding to the NACE codes are also collected from Eurostat (Eurostat, 2008). The CPA product group names were already listed in the concordance table (Appendix C).

Lastly, the total carbon footprints of the two studies were compared to other studies, to see if these are similar or if they deviate. This helps point out if De Koning (2020) and Steenmeijer et al. (2022) are outliers, which could indicate conceptual and calculation errors.

4.2 The material and carbon footprints of the Dutch healthcare sector and how they can be explained

The methods of the second and third sub-question are combined as they overlap a lot. For the second sub-question, identifying the material footprint of the Netherlands, a new input-output study was performed using SNAC-EXIOBASE 2014 data. This new study is also useful to identify how the Dutch healthcare carbon and material footprint calculated with SNAC-EXIOBASE data compares to the footprints with the standard EXIOBASE data (sub-question 3). The footprints are calculated according to the theory described in section 3.1.3.

4.2.1 Calculating the Dutch healthcare sector's carbon and material footprint

The SNAC-EXIOBASE data are available through Statistics Netherlands. Originally SNAC-EXIOBASE was used to calculate Dutch carbon footprints with data that is as close as possible to official Dutch statistics. The SNAC-EXIOBASE dataset contains 49 countries. It represents 2014 data and is in industry-by-industry (ixi) format. The Dutch Z-matrix contains 76 sectors and there are 21 final demand categories. All other countries contain 163 sectors and 7 final demand categories, following the original EXIOBASE format. The 21 final demand categories follow the structure of the Dutch national accounts. Appendix D shows the metadata of the dataset, which also explains the different final demand categories of the Netherlands. Important to note is that in the SNAC-EXIOBASE dataset the Netherlands only has about only half as many sectors as in the normal EXIOBASE set up, which means that this part is more aggregated, and inherently details are lost. However, using SNAC-EXIOBASE is very interesting for this study since it includes separate Dutch 'pharmaceutical industry' and 'chemical industry' categories, whereas in the original EXIOBASE dataset the chemical and pharmaceutical industries are aggregated in one category 'chemicals n.e.c.'. The environmental extensions of the SNAC-EXIOBASE dataset include carbon, biomass, minerals, metals, and fossils resources.

In this study, only the carbon, minerals, and metals extensions were used. The SNAC environmental extensions were constructed from the EXIOBASE extensions. Appendix D shows the metadata of the SNAC-EXIOBASE dataset.

The carbon extension was used for the carbon footprint analyses. As shown in appendix E, the SNAC-EXIOBASE dataset takes 22 EXIOBASE environmental emissions into account for constructing the carbon extensions. Important to note is that the SNAC-EXIOBASE dataset already converts the substances to CO_2 equivalents as follows:

- 1 kg CO_2 = 1 kg CO_2 eq.
- 1 kg CH_4 = 25 kg CO_2 eq.
- 1 kg N_2O = 298 kg CO_2 eq.
- 1 kg F-gasses = 1 kg CO_2 eq.

In the SNAC-EXIOBASE dataset, it is therefore not possible to easily change the global warming potentials per substance, while in EXIOBASE this is possible because the practitioner of the input-output analysis must assign these to CO_2, CH_4, and N_2O themselves. This possibility to change the global warming potentials is very useful because global warming potentials differ for the time span you take, e.g., 100 years. Global warming potentials are also subject to change due to ongoing research (Trottier, 2015). Therefore, this lack of flexibility in the SNAC-EXIOBASE dataset is a downside. EXIOBASE includes more substances than SNAC-EXIOBASE does and offers the possibility for the practitioner of the input-output analysis to decide which substance should be included in the footprint calculation. For a broad carbon footprint analysis, often the problem-oriented approach baseline CML 1999 of and a GWP of a 100-year time span is used, as described in the DESIRE characterisation matrices (Van Bree & Slob, 2016) (see appendix F). Comparing the substances used for the carbon extension with the DESIRE characterisation, it becomes clear that NMVOC is excluded in the SNAC-EXIOBASE carbon extension, while it is available in EXIOBASE.

For the material footprint, only the mineral and metal extensions were used. Biomass was excluded from the material footprint analysis as this study does not focus on a food or crop system, making it less relevant. The fossil resources extension was also excluded from the material footprint analysis because of three reasons. First, it overlaps with the carbon footprint, as the carbon extension already shows the effect of using fossil fuels, and the fossil resources extension is, therefore, less interesting. Second, if fossils would be included in the material footprint, this would dominate the material footprint, as in our economies a lot of fossils are used, making it more interesting to exclude them. Third, Steenmeijer et al. (2022) also do not include fossil resources in their material footprint, excluding these extensions, makes these studies more comparable. This third argument also holds for excluding biomass from the material footprint. SNAC-EXIOBASE extensions are built up from the EXIOBASE extensions. Appendix E shows which EXIOBASE extensions fall under the aggregated SNAC-EXIOBASE extensions. The metal and mineral extensions only include the 'domestic extraction used' minerals and metals, as explained in the core concepts.

Before any analyses were performed, the total carbon footprint of the Netherlands was calculated to compare it to the carbon footprint calculated by Walker et al. (2017) as a validation of the results obtained in this study. For this, the direct emissions by households based on Statistics Netherlands data were used, which can be found in Appendix G (CBS, 2020). For calculating the carbon and material footprint of the Dutch healthcare sector, a demand stimulus had to be constructed. Before being able to construct this demand stimulus, a suitable healthcare expenditure definition for this study had to be chosen. This study used the broad healthcare expenditure definition which also includes care and wellbeing. This definition is suitable as the SNAC-EXIOBASE dataset also includes a care and wellbeing sector, and because in this sector also pharmaceuticals are used, which is the interest of this study. This definition includes all expenses on health care made in Dutch territory. An advantage of selecting this definition is that it was also used in Steenmeijer et al. (2022), which makes the studies easier to compare.

4.2.2 Analysing the Dutch healthcare sector's carbon and material footprint

Several analyses were performed to explain the Dutch healthcare sector's carbon and material footprint calculated in this study. To identify consumption drivers of emissions, contribution analyses were performed. A contribution analysis helps quantify emissions embodied in different product categories of the demand stimulus. A contribution analysis is sometimes also called a consumption perspective. The equation used for a contribution analysis is shown in equation 5.

$$\Delta e' = f' L \widehat{\Delta y} \qquad \textit{Eq. 5}$$

To identify where in the supply chain emissions, occur, hotspot analyses were performed. A hotspot analysis is sometimes also called a production perspective. This study performs a hotspot analysis per sector and per country, to get even more detail into where emissions occur. Next to this the SNAC-EXIOBASE mineral and metal extensions are disaggregated to the material groups used in EXIOBASE, to be able to perform a hotspot analysis per material group.

The equation used for the hotspot analysis is shown by equation 6.

$$\Delta e = \hat{f} L \Delta y \qquad \textit{Eq. 6}$$

For the hotspot analysis per material group, the EXIOBASE extension was copied for all countries except for the Netherlands. As the Dutch part of the SNAC-EXIOBASE database contains 76 sectors instead of 163 in EXIOBASE, a concordance table was made to assign the EXIOBASE extensions to SNAC-EXIOBASE sectors (Appendix H). This concordance table is based on the SBI (standard bedrijfs indeling) classification and the EXIOBASE products (CPA 1996 codes) (Kruiskamp, 2021). The concordance table was only used for the mineral extension, as according to the SNAC-EXIOBASE metal extension, no metal extraction is occurring in the Netherlands. In some cases, several EXIOBASE sectors should be linked to multiple SNAC-EXIOBASE sectors, which means that a distribution key is needed. Because finding a suitable distribution key is very difficult, first, a check was made for the sectors where mineral extraction occurs in the Dutch part of the SNAC-EXIOBASE dataset. All these sectors have one or multiply relevant EXIOBASE sectors whose minerals extension can be linked to it, which all are not linked to another sector that has mineral use occurring in it. This one-to-many relationship makes the concordance table created in this study not suitable to use for the carbon extension because distribution keys would have to be added.

Several multiplier analyses were performed to get more insight into the differences between emissions and extraction caused by different sectors. Equation 6 shows how the multiplier analyses were conducted. Where *p* represents the per euro footprint (intensity), and the diagonalized f represents one extension that is diagonalized.

$$p = \hat{f}(I - A)^{-1} \qquad \textit{Eq. 7}$$

The carbon, mineral, and metal intensity of the SNAC-EXIOBASE 'chemicals n.e.c.' categories were compared per country and with the Dutch 'chemical industry' and 'pharmaceutical industry' categories available in the SNAC-EXIOBASE dataset. The carbon, mineral, and metal intensity of the Dutch 'chemicals n.e.c.' sector in the 2014 EXIOBASE dataset was also compared to the Dutch 'chemical industry' and 'pharmaceutical industry' categories in the SNAC-EXIOBASE dataset. This comparison will identify if there is an aggregation problem in 'chemicals n.e.c.'

Lastly, also a structural path analysis (SPA) was performed to get more insight into where in the supply chain of the Dutch chemical and pharmaceutical industries a large part of the environmental intervention occurs (Peters & Hertwich, 2006). This was also done for the Dutch EXIOBASE category 'chemicals n.e.c.'. The method of the structural path analysis is derived from the earlier mentioned equation 3.

$$x = Ly = (I - A)^{-1} \qquad \textit{Eq. 8}$$

The Leontief inverse can also be written as a Taylor expansion (Lenzen, 2007; Waugh 1950) which is shown in equation 9:

$$L = (I - A)^{-1} = I + A + A^2 + A^3 + \cdots \qquad \textit{Eq. 9}$$

Each element in this expansion represents a production layer in the input-output system. In theory, this expansion goes to infinity, however, in an input-output system, there is a limited amount of production layers. Similarly, the environmental intervention (excluding household direct emissions), can be calculated by using this Taylor expansion (Peters & Hertwich, 2006):

$$fLy = f(I - A)^{-1}y = fIy + fAy + fA^2y + fA^3y + \ldots \qquad \textit{Eq. 10}$$

The contribution of each layer '*t'*, to the environmental intervention, can then be written as $fA^t y$. The SPA conducted in this study *fIy* (the zeroth production layer), represents the direct emissions emitted by the chemical and pharmaceutical manufacturers. To produce a pharmaceutical product, however, inputs from other industries are necessary, therefore the emissions emitted during the production of these products should also be counted, which is done by the second tier *fAy*. This expansion goes until the end of the production chain $fA^n y$, where *'n'* represents the deepest production layer.

Often, the largest contribution to the environmental intervention does not occur in the zeroth tier but is caused somewhere up in the supply chain (Treloar, 1997). Interestingly, SPA can show which production linkages (small set of steps in a supply chain) contributes a lot to the total environmental intervention of producing a certain product.

The SPA algorithm is based on the following equations. The simplest thing is to think of the supply chain as a tree, where the number of nodes grows exponentially with each tier (resulting in each tier having n^{t+1} nodes). The zeroth tier shows the direct contribution of each production layer:

$$F_i y_i \qquad \textit{Eq. 11}$$

Then the first-tier nodes (n^2 nodes) are evaluated by equation 12, which shows a path from *i* to *j*:

$$F_j A_{ji} y_i \qquad \textit{Eq. 12}$$

Continuing to the second-tier, the nodes are evaluated by equation 13, which shows a path from *i* to *j* to *k.*

$$F_k A_{kj} y_j \qquad \textit{Eq. 13}$$

For all other tiers, the same is pattern is performed. By calculating all nodes, the production paths that contribute the most to the total environmental intervention can be identified.

The open-access python package 'pyspa', developed by André Stephan and Paul-Antoine Bontinck was used in this study (Stephan & Bontinck, 2019). The 'pyspa' package is based on the code of Treloar (1998). In this SPA package, the stages (tiers) and thresholds can be set to preferred numbers. The package instructions recommend setting the stages to at least 8 for an IOA. Therefore, this study sets the stages at 8. Thresholds are set so that all paths combined represent at least 75% of the total environmental intervention. A SPA was conducted for the Dutch 'chemical industry' and 'pharmaceutical industry' categories as available in the SNAC-EXIOBASE dataset, as well as for the category 'chemicals n.e.c.' in EXIOBASE. The carbon extension used in the EXIOBASE extension contains the same substances and weighting factors as the SNAC-EXIOBASE carbon extension, to make the SPA comparable between the categories.

4.3 Carbon and material footprints of individual pharmaceutical products

First, a small literature review was conducted to find out if there are already scientific papers and reports that researched the carbon and material footprint of individual pharmaceutical products and their contribution to the total healthcare footprint. This showed that for identifying the carbon and material footprint of individual pharmaceutical products data from LCA studies was needed. RIVM already worked on collecting data on the carbon footprint of different pharmaceutical products, by doing a literature review on LCA (Pieters et al., 2022). The papers found in this search have partially been used in this study. This literature review was based on a selection of papers which were found using keywords relating to LCA and pharmaceuticals (TITLE-ABS-KEY (LCA OR LCIA OR "Life Cycle Assessment" OR "Life Cycle Analysis" OR "Life Cycle Inventory Assessment" OR "Life Cycle inventory") AND TITLE-ABS-KEY (API OR "active pharmaceutical ingredient*" OR "drug packaging" OR "metered dose inhaler") (Pieters et al., 2022). In this search, 87 papers were found of which 17 were selected by RIVM based on the following selection criteria of the paper should be modelling an LCA and should be about a pharmaceutical product or related to it (e.g., packaging of pharmaceuticals) (Pieters et al., 2022). Several studies have been added to the list identified by Pieters et al. (2022) by snowballing the papers. Eventually, 11 studies were suitable for this study, meaning that their functional unit could be translated to '1 kg of API or 1 kg of chemical'.

Most LCA studies described the carbon footprint per kg active pharmaceutical ingredient (API). By converting the carbon footprint per kg, to a monetary carbon footprint, the range in LCA results could be compared to the carbon intensity of the input-output sector 'chemical industry' and 'pharmaceutical industry' categories in SNAC-EXIOBASE. This gives a first impression of how individual products carbon intensity compared to the aggregated carbon intensity of input-output analysis and can therefore give an idea of the range of the carbon intensity of individual products. The online Dutch pharmacotherapeutic compass (Farmacotherapeutisch Kompas) was used, which is a reference site for medical professionals, which provides information on the dose, API, side effects, and prices of pharmaceutical products (Zorginstituut Nederland, 2021). When possible, the prices of a substance were gathered from the Farmacotherapeutisch Kompas (pharmacotherapeutic compass). The Farmacotherapeutisch Kompas is preferred over other sources because it represents the Dutch situation and is reliable because it is developed by Dutch pharmacists and medical physicians and is a product of the Dutch Healthcare Institution (Zorginstituut Nederland, 2021). The Farmacotherapeutisch Kompas is also convenient because it is open-source, meaning that the data used for calculations in this study can be verified.

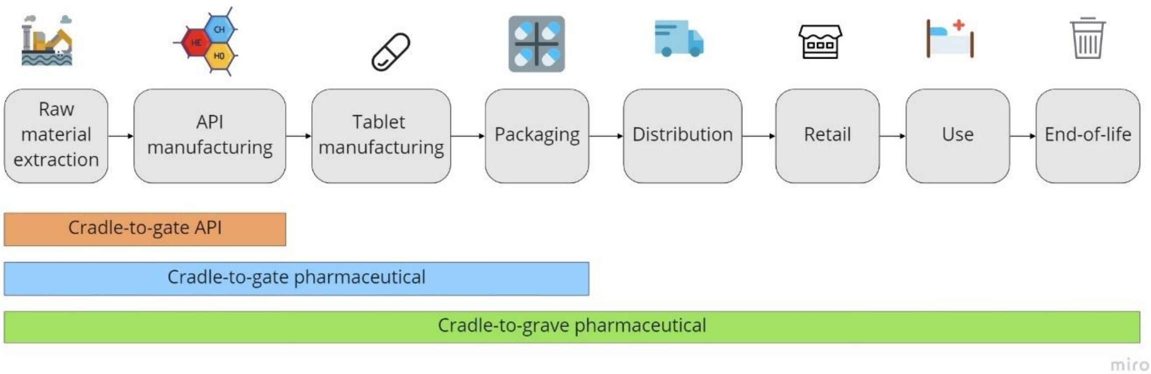

Figure 8: Different scopes that can be used in LCA studies of pharmaceuticals

The reviewed LCA studies that will be used to calculate a carbon intensity (kg CO_2 eq./ €), either performed a cradle-to-gate or cradle-to-grave analysis. A cradle-to-grave LCA study takes the environmental interventions occurring at every step of the supply chain into account starting from resource extraction until waste disposal (end-of-life), as can be seen in figure 8. A cradle-to-gate LCA study only takes into account environmental interventions occurring from the resource extraction to the factory gate. A lot of LCA studies related to pharmaceutical products are cradle-to-gate. More specifically, these are cradle-to-gate studies for API production. For example, for paracetamol, this means that the production of the tablet and the packaging of the tablets are excluded from these studies, as can be seen in figure 8.

The difference in scope of the LCA study results in different types of prices that are suitable to use per scope. For the cradle-to-gate studies, prices are needed at the gate of the manufacturer of the AP., Unfortunately, these industry prices are not available on the Farmacotherapeutisch Kompas, which only describes the costs of the pharmaceutical formulation in consumer prices. To find the industry prices, first alternative websites were consulted. These were mostly online marketplaces that provide little information on what the average prices for 1 kg of API is based on (PharmaCompass, n.d.). This makes using these prices unreliable. An example of such a marketplace is PharmaCompass (PharmaCompass, n.d.). Because of the lack of reliable industry prices, the lowest available price on the Farmacotherapeutisch Kompas of the pharmaceutical in question was used to represent the industry price. This assumption is based on the following reasoning. For most medicinal options, the Dutch Farmacotherapeutisch Kompas lists several formulations that Dutch healthcare practitioners could prescribe to a patient, for instance, the original (patented) compound and several alternatives. The final product that a patient receives is in many cases dependable on the type of healthcare insurance the patients have. Among these alternatives, one finds the generic pharmaceuticals (generiek), which are brandless alternatives (with no patent). Generic pharmaceuticals often have lower prices, due to market forces. Of course, the lowest prices (which are often generic prices) found on the Farmacotherapeutisch Kompas, also include costs that should not be included in the industry API prices, e.g., labour costs, transportation costs, and packaging costs. For the industry, margins on generic products are often very low, and the final product price will therefore be largely constituted by API purchase (industry) price. This assumption results in the prices of the pharmaceuticals for which a cradle-to-gate study is performed to be on the high side. The use of these high prices results in lower carbon intensities than when real industry prices would be used because the carbon footprint is divided by a larger number than in the case of lower prices.

For the cradle-to-grave LCA studies' products, consumer prices are needed. The prices available on the Farmacotherapeutisch Kompas are, therefore, suitable. Because for many pharmaceuticals multiple formulations are listed on the Farmacotherapeutisch Kompas, an average of the prices of these formulations is used.

Lastly, the study by Raymond et al. (2010) does contain any LCA results on pharmaceuticals, however, it focussed on solvents and the comparison of solvents to commodity chemicals. This study was included, because, in the production process of API, 80-90% of the mass can be assigned to solvent use (Raymond et al., 2010). This means that solvents are common products used in the pharmaceutical industry, and therefore also interesting for this study. The prices of the solvents and commodity chemicals are not available on the Farmacotherapeutisch Kompas, which is why the prices available on Sigma-Aldrich were used. Sigma-Aldrich is a large supplier to the Life Sciences industry. They guarantee a high quality and purity of their products, which is why their prices are quite high. This high quality is needed for the labs to which they sell, which is on a smaller scale compared to the large pharmaceutical companies who mainly buy in bulk. Prices of larger quantities are usually lower. However, the industry prices of solvents and raw materials used by these large pharmaceutical companies are often confidential. Therefore, the prices of the solvents and commodity chemicals derived from Sigma-Aldrich are based on the largest quantities available, mimicking these bulk purchases.

The assumptions made for collecting price data were discussed with Dr Kweekel, a Dutch hospital pharmacist (D. Kweekel, personal communication, January 7, 2021). The assumption made for the conversion of the LCA studies to a carbon intensity per substance are summarized as follows:

1. The pharmaceutical product prices were converted to basic prices using the conversion rate of 0.73 to basic prices based on the SUT category 28: Basic Pharmaceuticals and Preparations (as explained in chapter 5.2.1.).
2. Prices of bulk chemicals (often solvents) are based on the largest quantity available on Sigma-Aldrich website.
3. For the pharmaceuticals where a cradle-to-gate LCA was performed, the lowest prices of pharmaceuticals available on www.farmacotherapeutischkompas.nl were used.
4. For the pharmaceuticals where and cradle-to-grave LCA study was performed an average of all alternative formulations available on www.farmacotherapeutischkompas.nl was used.
5. For Hexane and Toluene, the prices of PharmaCompass were used as they were not available on all the above-mentioned sites.

4.4 Improving the calculation of the carbon and material footprint of the Dutch healthcare sector

In the last sub-question, two possible improvements on the methods used to calculate the carbon and material footprint of the healthcare sector are suggested based on the findings of this study. For this no literature is performed to find all possible improvement options, however, the most logical improvement options from this study are represented to get a first idea of how to proceed in future studies.

5. Results

5.1. Conceptual comparison of previous studies

In this chapter, the first sub-question is answered. The study by De Koning (2020) and Steenmeijer et al. (2022) were compared to each other to be able to identify errors and conceptual mistakes. This comparison is also useful for deciding how to construct new input-output-output calculations using SNAC-EXIOBASE data. The studies are compared on the amount and source of healthcare expenditure they use, and how they depict the pharmaceutical industry. The Dutch carbon footprint of Steenmeijer et al. (2022) is also compared to other studies to identify if it stands out, which could indicate a conceptual or calculation error.

5.1.1 Dutch expenditure on healthcare

To be able to answer sub-question 1 first the healthcare expenditures used in the study of De Koning (2020) and Steenmeijer et al. (2022) are compared and evaluated.

As mentioned in the core concepts section, the healthcare sector can be defined in different ways. Steenmeijer et al. (2022) defined healthcare according to the broad definition of healthcare and wellbeing. The healthcare expenditure data of Steenmeijer et al. (2022) was classified according to the System of Health Accounts (SHA) classification (World Health Organization, 2011). De Koning (2020) calculated the governmental expenditure and investments based on the EXIOBASE expenditure of 2010 which follows but is not exactly classified according to NACE Rev. 1.1. De Koning (2020) calculated the governmental expenditure and investments based on the EXIOBASE expenditure of 2010. Relevant EXIOBASE categories are chemicals and chemical products (‘chemicals n.e.c.’), health and social work (HSW), and medical precision and optical instruments. Following EXIOBASE, the total Dutch demand for these categories is 81.56 billion euros, as can be seen in table 3. Table 3 shows that the governmental demand for these categories’ totals 66.39 billion euros. In the study of De Koning (2020), this governmental demand is used to calculate the material footprints of these categories. Interestingly, when comparing the market share of the Dutch government to all expenditure in the healthcare-relevant sectors, the government market share is quite large, especially in the HSW category, where it is about 30% (table 4). These findings are in line with ARUP & Health Care Without Harm (2019), who also find that healthcare has a share of 30% of the Dutch governmental expenditure.

Table 3: Total final demand for healthcare-relevant sectors derived from EXIOBASE for the year 2010 (De Koning, 2020).

Code	CPA level 3 category	Final demand [billion euros]
80	Health and social work	68.80
74	Manufacture of chemicals and chemical products	8.66
33	Manufacture of medical, precision and optical instruments, watches and clocks	4.1
Total		81.56

Table 4: Sum of the final demand and investments of the Dutch government in 2010. Including the share of the product groups' final demand of the total governmental demand (De Koning, 2020).

Code	CPA level 3 category	Final demand [billion euros]	Share of total Dutch governmental expenditure [%]
80	Health and social work	58.7	30.01
74	Manufacture of chemicals and chemical products	5.4	2.76
33	Manufacture of medical, precision, and optical instruments, watches and clocks	2.29	1.17
Total		66.39	33.94

Table 5: The market share of the Dutch government per category for the year 2010 (De Koning, 2020).

Code	CPA level 3 category	Market share of the Dutch government [%]
80	Health and social work	84
74	Manufacture of chemicals and chemical products	23
33	Manufacture of medical, precision, and optical instruments, watches and clocks	19

The amount of Dutch expenditure in the broad definition of healthcare and wellbeing provided by Statistics Netherlands and used by Steenmeijer et al. (2022) is 94.84 billion euros for the year 2016 (CBS, 2021d). However, this expenditure is still in purchaser price, while the EXIOBASE expenditure is in basic prices. This means that the expenditure data provided by Statistics Netherlands still had to be converted to basic prices. This is done per category for all the relevant sectors, as can be seen in table 7. For the conversion to basic prices, the same conversion rate is used as holds for the Eurostat supply table of 2016's similar category, as these tables are both available in basic and purchasers' prices. For example, for the expenditure of pharmaceuticals, the Dutch national statistics category 'HC51: medicines and aids' are used, and the corresponding supply table category is 'Basic Pharmaceuticals and Preparations (28)' (Eurostat, 2022). The calculation of the conversion rates is shown in table 6.

Table 6: Conversion rates from basic to purchasers' prices used in Steenmeijer et al. (2022) based on Eurostat (2022)

Sector	SUT category	Basic prices [million euros]	Purchasers' price [million euros]	Ratio
Medicines and consumables	28. Basic Pharmaceuticals and Preparations	16446	24452	0.67
Therapeutic tools	33. Computer, electronic and optical products	92968	113372	0.82
Healthcare	83.Human health services	44463	44635	0.996
	84. residential care and social work services	36223	36223	1

There seems to be almost no conversion rate between the purchasers' and basic price of the health services, therefore it is kept the same. The expenditure on health services is based on the total expenditure of healthcare – the purchasers' prices of HC51 and HC52: 91.842 – 5.639 – 3.107 = 86.10 billion euros. The total expenditure on healthcare in basic prices is therefore 92.53 billion euros.

Table 7: Conversion from purchasers' prices to basic prices of the expenditure on the Dutch healthcare sector for the year 2016 as used in the Steenmeijer et al. (2022)

Category	Purchasers' prices [billion euros]	Basic prices [billion euros]
HC51: Medicines and aid	5.64	3.80
HC52: Therapeutical tools	3.11	2.55
Health services	86.10	86.10
Total	94.84	92.45

From this comparison, it can be derived that the healthcare expenditure in both studies is quite similar, however, De Koning (2020) is interested in governmental demand only. If we include private consumer demand, the healthcare expenditure rises by about 6 billion euros. Generally, using national statistical data is preferred over internationally compiled data like the data provided by EXIOBASE. Next to this, the Statistics Netherlands data on healthcare expenditure can provide the total picture, while EXIOBASE can only provide us with the governmental expenditure, which is close to the total healthcare expenditure, or to the total demand for the healthcare-relevant sectors, which means that non-healthcare demand is also included. Lastly, De Koning uses 2010 data as EXIOBASE only has real data until the year 2010, after this now-casts are used to predict the near future (Stadler et al., 2018). This means that after 2010 the use of Statistics Netherlands data is even more preferred. Steenemeijer et al. (2022) uses expenditure data from 2016 and insert it into the EXIOBASE version of 2016. In conclusion, it can be said that the studies' relatively large carbon and material footprint for the category 'chemicals n.e.c.' cannot be explained by errors in the way the final demand vector is constructed to represent the consumption of Dutch healthcare.

5.1.2. Comparing different categories used for pharmaceuticals in input-output analysis and economic statistics

The main interest of this study is to unravel the carbon and material footprint of the Dutch consumption of pharmaceutical products. It is interesting to dive deeper into the different relevant categories for pharmaceuticals in input-output analysis on the one hand, and the national statistics on the other hand. Specifically, we investigate if the studies of De Koning (2020) and Steenmeijer et al. (2022) assigned expenditures in the healthcare sector on pharmaceuticals to the correct product categories.

EXIOBASE

As mentioned, the pharmaceutical industry is not specifically defined in EXIOBASE. EXIOBASE follows NACE Rev. 1.1 for economic activities and CPA 1996 for products. In EXIOBASE, pharmaceuticals fall under an aggregated category 'chemicals n.e.c.' (63). This section investigates which products fall under 'chemicals n.e.c.'. To be able to investigate what falls under the category 'chemicals n.e.c.' (63) in EXIOBASE we have to make use of the relationships between the classifications that are used for economic activities, products and (traded) goods. The linkages between classification systems are shown in figure 9. Figure 9 shows that classification systems are either on the level of economic activities, products, or goods. EXIOBASE is classified based on NACE Rev. 1.1. Figure 9 proves, that even though EXIOBASE is based on NACE Rev. 1.1, other classifications like PRODCOM or CPA are also suitable to find out which products fall under 'chemicals n.e.c.' In theory, these classification systems are linked to each other, however, in practice, this linkage is often quite difficult to use. The sector 'chemicals n.e.c.' is subdivided into smaller parts using several of the different economic classification systems available (as can be seen in appendixes C, I, J).

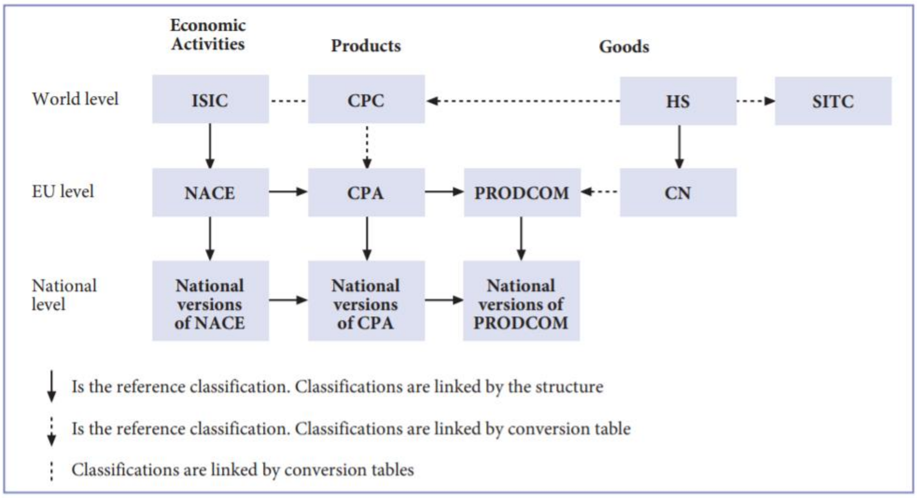

Figure 9: The internationally different economic classification systems and their relationships (Eurostat, 2008).

NACE-Rev. 2

NACE codes are assigned by the European Union to classes of economic activity for creating economic statistics and overviews (Eurostat, 2008). The NACE Rev. 2 classification is based on the ISIC Rev. 4 classification, which is the international standard classification of products. Appendix C shows that the NACE class/group of 21: 'Manufacture of chemicals and chemical products' is relevant for this study, while also the NACE group of 20: 'Manufacture of basic pharmaceutical products and pharmaceutical preparations' is relevant. Some of the bulk chemicals that fall under group 20 are also bought in by hospitals and pharmaceuticals manufacturers are indirectly also used for producing pharmaceuticals. The NACE classification is not very detailed, however, it does identify that 'chemicals n.e.c.' is a category that also includes products like paint, printing ink, soap, industrial gasses, etc.

PRODCOM level 2

The PRODCOM classification has 3 levels of detail and is linked to the CPA classification. The level 2 classification lists 178 products that are in the EXIOBASE category 'chemicals n.e.c.'. These can be found in appendixes I and J. Appendix I shows the complete overview of both level 2 and 3 PRODCOM products that fall under 'chemicals n.e.c.'. It also shows which products are relevant for the manufacturing of pharmaceuticals at classification level 3. The relevant products are marked yellow. The non-relevant products are mentioned with "no", and the products that might also be used for other products and of which is not sure if they are used in the production of pharmaceuticals, the field is left empty. (D. Kweekel, personal communication, October 12, 2021).

National statistics

In the Dutch national statistics provided by Statistics Netherlands, the Dutch expenditure on pharmaceuticals is described in the category 'HC5: Medicines and aids. This category is split into HC51: Medicines, Consumables' (Geneesmiddelen, Verbruiksartikelen), and 'HC52: therapeutic tools. HC51 includes prescription medicines, over-the-counter medicines, and other medical consumables. Other medical consumables are for example bandages. HC52 includes vision aids (such as glasses), hearing aids, orthopaedic aids (such as special footwear), medical-technical appliances (such as wheelchairs), and other durable medical goods (e.g., blood pressure monitors).

In conclusion, can be said that the consumption of pharmaceuticals is defined quite differently in national statistics than in input-output databases like EXIOBASE. While input-output tables are structured per products groups or industries, these are too aggregate to properly display the pharmaceutical industry. Pharmaceuticals only fall in one category; however, this category also contains other chemicals that are not used in the production of pharmaceuticals. This could distort the footprints calculated using these input-output sectors, as the other chemicals' environmental impacts are also weighed in these calculations. From this initial separation, it becomes clear that 'chemicals n.e.c.' contains a lot of product groups that are not relevant for pharmaceutical production. Next to this, it also contains a lot of product groups that could be used in pharmaceutical products in some instances, but they also are sometimes used in the chemical industry (e.g., enzymes and glycerol). This makes subdividing 'chemicals n.e.c.' into a separate pharmaceutical industry category in EXIOBASE difficult as product groups could belong in both the chemical and pharmaceutical industries. Lastly, this section also shows the heterogenous character of ´chemicals n.e.c.´.

5.1.3 Comparison of the Dutch carbon footprint

The studies of De Koning (2020) and Steenmeijer et al. (2022) can also be checked by comparing the carbon footprint of the Netherlands with carbon footprints calculated independently by others. As already mentioned in the introduction, several carbon footprint calculations of the Dutch healthcare sector already exist. These studies are included in the comparison of the total Dutch carbon footprint of table 8. RIVM made it possible to also calculate the numbers for the year 2014, to be able to better compare their study with this study, which uses the 2014 SNAC-EXIOBASE database.

Table 8: Total Dutch carbon footprint as calculated by the Statistics Netherlands official and relevant studies that did calculate the Dutch healthcare carbon footprint as well.

Study	**Reference year**	**Dutch carbon footprint in Mt CO_2 eq.**
Meijer-Cheung, Schoenaker Schenau (2016) (SNAC by Statistics Netherlands)	2014	175
Statistics Netherlands official	2014	188
Gupta Strategists (2019)	2017	163
ARUP & Healthcare Without Harm (2019)	2014	225[1]
Steenmeijer et al. (2022) (RIVM)	2014	227[2]
Steenmeijer et al. (2022) (RIVM)	2016	241
Pichler et al. (2019)	2014	221[3] /195[1]
Lenzen et al. (2020)	2015	231[3]/ 333[1]

From table 8 can be derived that the total Dutch carbon footprint calculated in these studies range from 163-333 Mt CO_2 equivalents. The study of Lenzen et al. (2020) stands out because table 8 shows 2 numbers for the Dutch carbon footprint. The 333 Mt CO_2 eq. is derived from the supplementary information (SI) of the paper, in which the Dutch carbon footprint is derived from the healthcare carbon footprint and the share of the healthcare carbon footprint of the national footprint. The 333 Mt CO_2 eq. of Lenzen et al. (2020) is also the outlier of the studies compared in table 8. When comparing this to the Eora explorer, the Dutch carbon footprint is reported as 231 Mt CO_2 eq. As Lenzen et al. 2020 is performed with the full Eora dataset, the number found in the SI of the study is alarming. Pichler (2019) also uses Eora, however, the difference between the reported carbon footprint in the Eora explorer is lower. Pichler (2019) also only includes CO_2 in its analysis, which could explain the lower national footprint based on the study compared to the Eora explorer. Gupta

[1] Based on the CF of healthcare and the share of the national footprint
[2] Not reported in the referenced study, calculated for the purpose of this study
[3] Sourced or inferred from Eora explorer on its website

Strategists (2019) records the lowest total Dutch carbon footprint of the compared studies. The study of Steenmeijer et al. (2022) is in the middle to the higher range of all studies, indicating no initial errors.

In conclusion, the conceptual comparison of previous studies showed that both the construction of the final demand vector, as well the calculation of the total Dutch carbon footprint seems to be conducted correctly, or at least is not the reason why the carbon and material footprint of the Dutch consumption of pharmaceuticals is relatively high. Section 5.1.2 also showed that the carbon and material footprint of the category 'chemicals n.e.c.' could be a misrepresentation of the carbon and material footprint of the consumption of pharmaceuticals. This idea of misrepresentation of 'chemicals n.e.c.' comes from the fact that it both contains products that are not used and products that only in some cases are used in the pharmaceutical industry. To get a better picture of the carbon and material footprint of the Dutch consumption of pharmaceuticals, less aggregated data could give more insight into the actual carbon and material footprint of the Dutch consumption of pharmaceutical products. Due to trade secrets, and the diversity of the pharmaceutical industry, it is difficult to exactly know which products and in which quantity they are used in the production of pharmaceutical products. Therefore, a dataset already containing a pharmaceutical sector is preferred.

5.2 Carbon and material footprint of the Dutch healthcare sector based on SNAC-EXIOBASE

This chapter shows the results of the second sub-question: “What is the material and carbon footprint of the Dutch healthcare sector calculated in this study?” It also answers the second knowledge gap: “What is the material footprint of the Dutch healthcare sector?”

5.2.1 Construction of final demand stimulus

For calculating the carbon and material footprint of the Dutch healthcare sector, the construction of the final demand stimulus was important. This demand stimulus is based on 4 SNAC-EXIOBASE sectors, as shown in table 9. The two SNAC-EXIOBASE sectors ‘Gezondheidszorg’ and ‘Zorg en welzijn’ together are the equivalent of the Health and Social Work sector in EXIOBASE. Table 9 also shows the corresponding healthcare function (from Statistics Netherlands) that was used to link the Dutch healthcare expenditure to the SNAC-EXIOBASE sectors, which are based on the standard company classification system of the Netherlands (SBI) (Kruiskamp, 2021).

Table 9: Linking Statistics Netherlands healthcare expenditure function to the SNAC-EXIOBASE sectors.

SNAC sector (including SBI code)	Healthcare function (Statistics Netherlands)
86. Healthcare (Gezondheidszorg)	Medical and long-term care (Geneeskundige landgdurige zorg) (HC1-HC9 excluding HC5)
87-88. Care and wellbeing (Zorg en welzijn)	Welbeing, youth care and childcare (Welzijn, Jeugdzorg en kinderopvang)
21. Pharmaceutical industry (Farmaceutische industrie)	HC51: Medicines and consumables (Geneesmiddelen, verbruiksartikelen)
32. Other industries (Overige industrie)	HC52: Therapeutic tools (Therapeutische hulpmiddelen)

The demand stimulus is a vector of zeros, except for the positions of the relevant SNAC-EXIOBASE sectors mentioned in table 9, where the healthcare expenditure is filled in. Table 9 shows the healthcare expenditure per SNAC-EXIOBASE category based on this. The expenditure on ‘medical and long-term care’ and ‘wellbeing, youth care and childcare’ is from Statistics Netherlands (CBS, 2021a) and the expenditure on the HC categories are from Statistics Netherlands (Centraal Bureau voor de Statistiek, 2021c) as well. As the Statistics Netherlands data is available in purchasers’ prices, a conversion to basic prices was needed. Table 9 shows this conversion. The conversion was based on conversion rate calculated using similar categories in the 2014 supply table which contains both purchasers’ and basic prices (appendix K). This conversion rate was used for the conversion of the Statistics Netherlands data. The conversion rate calculations are shown in table 10.

Table 10: Conversion rates from basic prices to purchasers' prices used in this study.

Sector	**SUT category**	**Basic price [million euros]**	**Purchaser price [million euros]**	**Ratio**
Medical and long-term care	83. Human health services	42949	43019	1.00
Wellbeing, youth care and childcare	84. Residential care and social work	35752	35306	1.01
Medicines and consumables	28. Basic Pharmaceuticals and Preparations	19607	26876	0.73
Therapeutic tools	33. Computer, electronics and optical instruments	81225	98163	0.83

Appendix L also shows that the total expenditure on care and wellbeing from Statistics Netherlands (CBS, 2021d) is divided into 'medical and long-term care', 'wellbeing, youth care and childcare' and 'policy and management'. In the SNAC-EXIOBASE dataset, this expenditure from either the healthcare sector or the care and wellbeing sector include policy and management expenses, as can be observed in the A matrix column of these sectors in appendix M. Therefore, this expense is proportionally divided over both categories as shown below.

<u>Division of policy and management expenses over 'healthcare' and 'care and wellbeing' sectors</u>
Expenditure on 'policy and management': 3945 million euros
Total expenses without policy and management = 80116 +7866 = 8798280
Share of 'medical and long-term care' of total: 80116/87982 = 0.91
Share of 'wellbeing, youth care and childcare': 7866/87982 = 0.09
Expenditure on 'medical and long-term care' = 80116 + (3945×0.91) = 83706
Expenditure on wellbeing, youth care and childcare' = 7866 + (3945×0.09) = 8221

In Statistics Netherlands the expenses on both 'medical and long-term care' and 'wellbeing, youth care and childcare' are given in total expenditures, which means that the extramural expenses on therapeutic tools, medicines and consumables should be subtracted from this. Appendix L shows that summing the whole HC-categories is equal to the total expenses on 'medical and long-term care', therefore the extramural expenses on therapeutic tools, medicines and consumables should be subtracted from this expenditure category as shown below.

Expenditure on healthcare (in million euros) = 83706 - 8553 (HC5) = 75152

Table 11: Total Dutch expenditure on healthcare using the broad healthcare and wellbeing definition for the year 2014.

Category	Purchasers' prices [million euros]	basic prices [million euros]
Medical and long-term care (Geneeskundige landgdurige zorg)	75152	75002
Wellbeing, youth care and childcare (Welzijn, Jeugdzorg en kinderopvang)	8221	8303
HC51: Medicines and consumables (Geneesmiddelen, verbruiksartikelen)	5355	4230
HC52: Therapeutic tools (Therapeutische hulpmiddelen)	3199	2355
Total	91927	89890

Lastly, it is important to note is that in this study the therapeutic tools and medicines are assumed to be sourced completely domestically. Since only the Dutch part of the MRIOT distinguishes a pharmaceutical industry, this is the only to better depict the pharmaceutical industry in the calculations. In this is assumed that the Dutch SNAC-EXIOBASE category 'pharmaceutical industry' is representative of the pharmaceuticals that are bought in the Netherlands. However, this creates a trade-off between a better depiction of the pharmaceutical industry compared to more realistic sourcing.

5.2.2 Carbon footprint

The total Dutch healthcare sector's carbon footprint calculated in this study is 14.26 Mt CO_2 equivalents. The indirect carbon footprint of the Dutch healthcare sector as constructed in this study consists of 12.6 Mt CO_2 equivalents, as shown in table 12. The direct impacts consist of the direct emissions of the healthcare sector as documented by Statistics Netherlands (CBS, 2020). Important to note is that for this study, anaesthetic gasses (direct emissions) and emissions from using pressurized metered-dose inhalers (indirect emission that occurs in households) are excluded while Steenmeijer et al. (2022) do include these. ARUP & Healthcare Without Harm (2019) do also include direct emissions from anaesthetic gasses. Travel emissions are also not taken into account, while other studies calculating the Dutch carbon footprint do include these (Gupta Strategists 2019; Steenmeijer et al., 2022). This means that there are differences in the scope of these studies. However, it goes beyond the scope of this study to include them, as the focus lies on the indirect emissions of 'chemicals n.e.c.'.

Table 12: The breakdown of the Dutch carbon footprint of the healthcare sector as calculated in this study

Breakdown emissions	Emissions [Mt CO_2 eq.]
Indirect	12.61
Direct from Statistics Netherlands	1.65
Total	14.26

Hotspot analyses

Table 13 shows that mainly energy-related sectors are high contributors to the Dutch healthcare sector's carbon footprint, which is to be expected. After all, according to Statistics Netherlands, 48.6 Mt (about 25%) of GHG emissions occurring in the Netherlands is caused by electricity generation (Centraal Bureau voor de Statistiek, 2021b). The sector of interest for this study, 'chemicals n.e.c.', is responsible for a large share (8.06%) of the Dutch healthcare carbon footprint, which is in line with previous studies.

Table 13: Hotspot analysis of the Dutch carbon footprint of the healthcare sector per sector where emissions occur (top five sectors).

Sector	**Emissions [Mt CO_2 eq.]**	**Share of total [%]**
Direct emissions	1.65	11.54
Production of electricity by coal	1.63	11.43
Energy companies (Dutch SNAC-EXIOBASE sector)	1.36	9.54
'Chemicals n.e.c.'	1.15	8.06
Healthcare (Dutch SNAC-EXIOBASE sector)	0.97	6.80
Extraction of natural gas and services related to natural gas extraction, excluding surveying	0.76	5.33

Of the 14.26 Mt of CO_2 equivalents, the largest share occurs in the Netherlands (47.8.%). Next to this, 10.24% occurs in China, which seems logical in any carbon footprint as it is such a large manufacturing country. Specifically for the healthcare sector, China also is a large player in both the pharmaceutical industry and the medical devices industry (which also includes disposables like masks). China was the second-largest pharmaceutical market in the world in 2017, with over 100 billion US dollars in revenues (World Health Organization, 2017). Chinese pharmaceutical companies first were mainly focused on the production of basic chemicals, intermediate products and APIs, while recently they also have shifted towards finished pharmaceutical products. In 2011 the Chinese medical device industry output accounted for the share of 1.4% of the Chinese GDP (Zhang et al., 2016), after which it has become a large market player. Between 2015 and 2019 the exports grew by about 10% per year (Deloitte, 2021).

Table 14: Hotspot analysis of the Dutch carbon footprint of the healthcare sector per country where emissions occur (top five countries).

Country	**Emissions [Mt CO_2 eq.]**	**Share of total [%]**
The Netherlands	6.82	47.83
China	1.29	9.05
Belgium	0.94	6.59
Russia	0.81	5.68
Germany	0.78	5.33

The emissions occurring in Russia can for a large part be attributed to Russian natural gas extraction, which is imported by the Netherlands (74.44%). As neighbouring countries to the Netherlands, the emissions occurring in Belgium and Germany also make sense. The Belgium emissions are mainly caused by 'chemicals n.e.c.' (73.41%), which is in line with the fact that Belgium is the third-largest exporter of pharmaceuticals in Europa, after Switzerland and Ireland (Janssen, n.d.). Germany has a large share (25% in 2020) in the medical device market of Europe (MedTech Europe, 2021). The emissions occurring in Germany are also energy-related and are mainly caused by the electricity production by coal (44.87%). More detailed information on the hotspot analyses can be found in appendix N.

Contribution analyses

Table 15 shows the emissions caused per sector where expenses are made for calculating the carbon footprint of the healthcare sector. The expenses here refer to expenses gathered from Statistics as explained in table 11. Most emissions occur due to expenses on services provided by the healthcare sector, which is also where the most expense occur. The second-largest share of the emissions of the Dutch healthcare sector in total is caused by the pharmaceutical industry in which actually half the amount of expenses occurs compared to the care and wellbeing sector. When comparing the carbon intensities, the pharmaceutical industry has the highest carbon intensity, followed by the medical appliances in 'other industries'. The fact that the healthcare sector's and care and wellbeing sector's carbon intensity are lower than the pharmaceutical industry and the medical appliances can be explained by the fact that expenses in the healthcare sector and care and wellbeing sector are much more dominated by labour than in the manufacturing industries. More detailed information on the contribution analysis can be found in appendix N.

Table 15: Contribution analysis per sector where expenditure occurs

SNAC-EXIOBASE category	**Emissions [kt CO_2 eq.]**	**Expenses [million euros]**	**Carbon intensity [kg CO_2 eq./€]**
Healthcare	9748	75002	1.30×10^{-1}
Pharmaceutical industry	1283	4230	3.05×10^{-1}
Care and wellbeing	961	8303	1.16×10^{-1}
Other industries (medical appliances)	618	2355	2.63×10^{-1}

5.2.3 Material Footprint

The material footprint only consists of indirect impacts, as material extraction caused by expenses to the Dutch healthcare only occurs at the beginning of the supply chain at the mining and quarrying sectors. The total material footprint of the Dutch healthcare sector as calculated in this study consists of 15.05 Mt of materials. This material footprint is mainly dominated by mineral extraction (88.97%).

Table 16: The material footprint of the Dutch healthcare sector as calculated in this study

	Minerals [Mt]	**Metals [Mt]**	**Total [Mt]**
Material footprint	13.39	1.66	15.05

Hotspot analyses

As material extraction only occurs in the extraction sector, it is not very interesting to perform a hotspot analysis per sector. However, it is interesting to identify where in the world the Dutch healthcare sector influences material extraction. Table 17 shows that most minerals are extracted in China (30.19%) and India (26.73%). The occurrence of China, and Germany as large contributors to the mineral and in the case of China also the metal footprint can be explained by the fact that they are large players in the healthcare industries (MedTech Europe, 2021; Word Health Organisation [WHO], 2021). India is also expected to have a large share in the mineral footprint, due to its large pharmaceutical industry (WHO, 2021). These countries differ for metal extraction as can be seen in table 18. In the Netherlands only sand, gravel, and salt are extracted, and no metals are extracted. The high share (12.61%) of Sweden in the metal footprint of the Dutch healthcare sector can be explained by the fact that it is one of the largest EU ore and metal producing countries (Ministry of Enterprise Energy and Communications Sweden, 2013). Especially most of Europe's iron ore comes from Sweden (Ministry of Enterprise Energy and Communications Sweden, 2013). More detailed information of the hotspot analyses can be found in appendix N.

Table 17: Hotspot analysis of the Dutch mineral footprint of the healthcare sector per country where extraction occurs (top five countries).

Country	**Minerals (kt)**	**Share of total [%]**
China	4043	30.19
India	3579	26.73
Germany	715	5.34
The Netherlands	670	5.00
RoW Middle East	625	4.67

Table 18: Hotspot analysis of the Dutch metal footprint of the healthcare sector per country where extraction occurs (top five countries).

Country	**Metals [kt]**	**Share of total [%]**
RoW America	448	26.94
Sweden	210	12.61
Indonesia	172	10.38
China	153	9.18
United States	121	7.29

The above-mentioned material footprint and the hotspot analyses still lack some essential information. What kind of minerals and metals are extracted the most due to the Dutch healthcare sector? Therefore, the mineral and metal extensions were disaggregated as explained in section 4.2.

Important to note is that the EXIOBASE minerals and metal extensions were used to disaggregate the hotspot analysis instead of the SNAC-EXIOBASE extension, as explained in section 4.2. This means that the total mineral and metal footprint with disaggregated material groups is different from the original material footprint calculated in this study. This difference can be explained by the fact that when summing the EXIOBASE material extensions to 'minerals' and 'metals' a difference in the total minerals and metals in several sectors can be observed (see Appendix O). Therefore, using this method, the material footprint using the SNAC-EXIOBASE extensions compared to the EXIOBASE extensions, do not match. This can be prevented by scaling the extensions to the total extraction occurring in the SNAC-EXIOBASE dataset. However, in this also the EXIOBASE data is altered based on an assumption, which is why it is not automatically a better solution. The general idea is that SNAC-EXIOBASE data ensures better quality than EXIOBASE data, therefore the originally calculated mineral and metal footprint will be used whenever is referred to the total mineral and metal footprint.

Table 19 shows that other minerals dominate the mineral footprint of the healthcare sector (65.46%), which is quite unusual. Usually, the mineral footprint is dominated by gravel and sand extraction, which is also large in this analysis (23.67%). The category 'other minerals' consist of (Eurostat, 2013):

- **Bitumen and (natural) asphalt**
- **Precious and semi-precious stones,** which are mainly used in industrial processes (e.g., pumice stone, emery, corundum).
- **Graphite** which is mainly used in refractories.
- **Quartz and quartzite** which is used in metal manufacturing and the optical industry.
- **Siliceous fossil meals** which are mainly used as an absorption agent or as material for heat insulation.
- **Asbestos**
- **Steatite and talc** which are used in different industries (ceramics, architecture, paper making, plastic, paint and coatings, rubber, electric cable, food, pharmaceuticals, and cosmetics).
- **Feldspar** which is used in the glass and ceramic industry.

With this disaggregation, the contribution of other minerals to the total mineral footprint can be explained for a part. For example, pumice (precious and semi-precious stones) is often used as soap, which again is part of 'chemicals n.e.c.' (see appendix I) whose mineral extension is used for the Dutch 'pharmaceutical industry' category of SNAC-EXIOBASE in this disaggregation (appendix H). Next to this, all other countries only have the 'chemicals n.e.c.' sector and not a separate pharmaceutical sector. Talc is also used in the pharmaceutical industry, cosmetic industry, paint and coating industry, and the paper industry, which again produce products that fall under 'chemicals n.e.c.'. Corundum is used as a grinder for optical glass, which falls under therapeutic tools, which are used in the healthcare sector. Quartz is used in spectroscopy, which also falls under therapeutic tools. Feldspar is used in industrial cleaning, as well as in the paint and glass industry. However, without actually quantifying the healthcare-related products in which 'other minerals' are used we cannot be sure if this result is correct.

Salt already has a smaller share. Its share is also explainable as it is essential in the healthcare sector. Medical drips consist of 0.9% NaCl to make the fluid isotone, which is essential to safely administer drips. Next to this, it is also commonly used in the production of pharmaceuticals as salt enables a higher concentration in the solution of the pharmaceutical (Serajuddin, 2007; Elder et al., 2013).

Table 19: Hotspot analysis sorted per mineral group

Mineral group	**Minerals (kt)**	**Share [%]**
Other minerals	10095	68.46
Gravel and sand	3491	23.67
Salt	402	2.73
Chemical and fertilizer minerals	376	2.55
Limestone, gypsum, chalk, dolomite	340	2.30
Clays and kaolin	42	0.29
Slate	0.61	0.004
Building stones	0.19	0.001
Total	14747	
Original total	13390	

As explained, the total mineral footprint calculated for the disaggregation of the different minerals differs quite a bit from the originally calculated mineral footprint using the original SNAC-EXIOBASE data (difference of 9.2%).

The metal footprint is dominated by iron and copper ore extraction. Both are commonly extracted metals. Gold extraction is also responsible for a large share of the metals extracted due to the Dutch healthcare sector. This is odd as gold is mostly used in jewellery (83%), and electronics (11%) (European Commission, 2017). However, it is also used in dental and medicine applications (2% and other applications (4%) (European Commission, 2017). Specifically, gold is used as a medicinal application in the way of radiotherapy as part of cancer treatments (Hainfeld et al. 2008). However, this use is quite small. One of Europe's main mining countries of gold is Sweden (European Commission, 2017), which could explain the hotspot results of table 18.

Table 20: Hotspot analysis sorted per material group

Metal group	Metals (kt)	Share [%]
Iron ores	476	29.02
Copper ores	424	25.83
Gold ores	179	10.88
Zinc ores	106	6.46
Tin ores	102	6.20
Silver ores	97	5.96
aluminium ores	89	5.44
Nickel ores	66	4.05
Other non-ferrous metal ores	65	3.93
Lead ores	23	1.38
Uranium and thorium ores	8	0.49
Metal Ores - PGM ores	6	0.36
Total	1640	
Original total	1661	

The total metal footprint calculated within the disaggregation of the metals is very similar to the original total metal footprint calculated using the original SNAC-EXIOBASE data. More detailed results of the disaggregated mineral and metal footprint can be found in appendix P.

Contribution analyses

Tables 21 and 22 show the contribution analyses per sector where expenditure occurs for the mineral and metal footprint of the healthcare sector. The expenses here refer to expenses gathered from Statistics Netherlands as explained in table 11. The sectors where expenditure occurs for the Dutch healthcare sector are sorted based on the minerals and metals extracted due to this expenditure. For both minerals and metals, this order is the same, while for the carbon footprint the order differs, where the expenditure in the 'care and wellbeing' industry causes more emissions than the therapeutic tools, while for materials the order is the other way around. Table 21 and 22 also shows that the mineral and metal intensity of the pharmaceutical industry is the highest of all healthcare sectors, which could also explain why the pharmaceutical industry and 'chemicals n.e.c.' in previous studies was responsible for such a large share of the Dutch healthcare sector's material footprint. More detailed results of the contribution analysis can be found in appendix N.

Table 21: Contribution analysis per sector where expenditure occurs for the mineral footprint of the Dutch healthcare sector

SNAC-EXIOBASE category	Minerals [kt]	Expenses [million euros]	Mineral intensity [kg minerals/€]
Healthcare	10619	75002	1.42×10^{-1}
Pharmaceutical industry	1636	4203	3.89×10^{-1}
Other industry (therapeutic tools)	581	2355	2.47×10^{-1}
Care and wellbeing	554	8303	6.67×10^{-2}

Table 22: Contribution analysis per sector where expenditure occurs for the metal footprint of the Dutch healthcare sector

SNAC-EXIOBASE category	Metals [kt]	Expenses [million euros]	Metal intensity [kg metals/€]
Healthcare	1220	75002	1.72×10^{-2}
Pharmaceutical industry	199	4203	4.72×10^{-2}
Other industry (therapeutic tools)	96	2355	4.09×10^{-2}
Care and wellbeing	75	8303	8.97×10^{-3}

5.3 The healthcare carbon and material footprint using SNAC-EXIOBASE compared to other studies

This chapter identifies if there is a data limitation that could explain the relatively large contribution of 'chemicals n.e.c.' to the Dutch healthcare sectors' carbon and material footprint.

As identified in the previous section, the study of De Koning (2020) was one of the starting points of this study and the main research question. However, it is more useful to compare the results described in 5.2 to studies that specifically focus on the healthcare sector. Therefore, the new results will be compared to the studies mentioned in the study by Steenmeijer et al. (2022). This would help identify if results based on the SNAC-EXIOBASE data, that crucially distinguishes a separate Dutch 'pharmaceuticals industry' category, shows completely different results, and thus if the initial remarkable results of De Koning (2020) and Steenmeijer et al. (2022) can be attributed to data limitations.

Table 23 shows important methodological and data decisions made in the different studies. All these decisions influence the results and should therefore be mentioned. Also, the healthcare definition used in the studies differ.

Table 23: Methodology and data comparison of different studies that calculate the carbon footprint of the Dutch healthcare sector. Table adapted from Steenmeijer et al. (2022).

	Gupta Strategists (2019)	**ARUP (2019)**	**Steenmeijer et al. (2021)**	**Pichler (2019)**	**Lenzen et al. (2020)**	**This study (2022)**
Reference year	2017	2014	2016	2014	2015	2014
MRIO	UK MRIO (2004)[4]	WIOD (2016)	EXIOBASE v3 (2018)	EORA v199.82 (full version)	EORA full version	SNAC-EXIOBASE
Carbon emissions and GWP	N/A	CO_2, CH_4, N_2O, HFCs, PFCs, SF_6, GWP not N/A	CO_2 = 1 CH_4 = 25 N_2O = 298 SF_6 = 26087 F-gasses (HFC, PFC) = 1 (is converted in EXIOBASE)[5]	Only CO_2	CO_2 = 1 CH_4= 25 N_2O = 298 HFC = 3772 CFC = 8925 SF_6 =22800 NF_3 = 17200	CO_2 = 1 CH_4 = 25 N_2O = 298 F-gasses (HFC, PFC, SF_6) = 1 (is converted in SNAC-EXIOBASE)
Healthcare definition	Broad definition healthcare	SHA, internationally comparable definition	Broad definition healthcare and wellbeing	SHA, Internationally comparable definition	Healthcare and social work services, Internationall y comparable definition	Broad definition healthcare and wellbeing
Total footprint	Adding scope 1, 2 and 3	Footprint calculation based on final demand.	Adding scope 1, 2 and 3	No division in scopes. Footprint calculation based on final demand.	Footprint calculation based on final demand.	No division in scopes. Footprint calculation based on final demand.
Scope 1	Estimated total gas consumption based on annual reports of Dutch healthcare institutions, then linked to CO_2 emission factors.	Direct CO_2 eq. emissions of SHA-WIOD sectors from environmental extensions.	Direct CO_2 eq. emissions of the healthcare sector reported by Statistics Netherlands plus direct emissions from anaesthetic gasses.	Direct CO_2 eq. emissions from SHA-EORA sectors from the environmental extension.		Direct CO_2 eq. emissions of the healthcare sector as reported by Statistics Netherlands.
Scope 2	Estimated total energy and heat purchasing from a bottom-up approach based on annual reports of Dutch healthcare institutions, subsequently linked to CO_2 emission factors.	Footprint calculations based on total purchase of energy and heath of all SHA-WIOD sectors.	Indirect emissions based on expenditure on energy and heat (under EXIOBASE i40) from the Health and Social Work sector	Footprint calculation for total purchasing categories of all SHA-EORA sectors		Footprint calculation for total healthcare purchasing categories.
Scope 3	Purchase expenditure adopted from the UK, scaled with the ratio of healthcare expenditure between NL and UK. Loose estimate for travel movements based on data for NL and UK.	Scope 3 = total - scope 1 - scope 2). The indirect footprint is calculated for the contribution of all industries in the chain	Indirect emissions are calculated for the total purchasing by the Health and Social Work sector (minus scope 2) and the expenditure on pharmaceuticals and medical equipment.			

[4] National IO table of the ONS refined and extended to MRIO with data from Eurostat, GTAP, OECD and IDE-JETRO (2004)

[5] Steenmeijer et al. (2022) use the characterisation according to DESIRE, while the F-gasses are already converted to CO_2 equivalents

5.3.1 Comparison healthcare carbon footprint

First, the total carbon and material footprint of the Netherlands was calculated and compared to earlier studies to identify if large differences could be observed, which could indicate data limitations. As seen in table 24, the total Dutch carbon footprint of this study is quite similar to the one calculated by Statistics Netherlands (CB), who made the SNAC-EXIOBASE dataset and also used it for their study (Walker et al., 2017). The difference is only 5 Mt CO_2 equivalents. After consultation with Walker and Wilking, can be concluded this difference is likely caused by the difference in aggregation levels in the public SNAC-EXIOBASE which is used in this study, and the more detailed one that is only available to Statistics Netherlands (A. Walker & H, Wilting, personal communication, October 15, 2021).

Table 24 also shows the direct emissions of the healthcare sector and the total carbon footprint of the healthcare sector as calculated in each study. Important to note is that not all studies use the same definition of healthcare expenditure and that they use different scopes, as explained in table 23. This makes them fairly incomparable, but it shows a range of the Dutch healthcare carbon footprint, which is also interesting. To be able to compare Steenmeijer et al. (2022) to this study, the calculation was also performed for the year 2014. Important to note is that Walker et al. (2017) and Meijer-Cheung, Schoenaker, and Schenau (2016) only performed an analysis for the total Dutch carbon footprint.

Table 24: Total Dutch carbon footprint, direct emissions in the healthcare sector and carbon footprint of the healthcare sector in Mt CO_2 eq. calculated with SNAC-EXIOBASE 2014 and other studies (ARUP & Health Care Without Harm, 2019; Gupta Strategists, 2019; Pichler et al., 2016; Steenmeijer et al., 2022. Walker et al., 2017). (for the definition of healthcare sector used in the different studies see table 23)

Study	**Year**	**Dutch carbon footprint**	**Direct emissions healthcare sector**	**Total healthcare sector**	**Share healthcare of total** [%]
This study	2014	180	1.65	14	8
Walker et al. (2017) (SNAC-EXIOBASE)	2014	175	-	-	-
Statistics Netherlands official (CBS)	2014	188	-	-	-
Gupta Strategists (2019)	2017	163	-	11	7
ARUP & Healthcare Without Harm (2019)	2014	220[6]	2.26	13	6
Steenmeijer et al. (2022) (RIVM)	2014	227[7]	1.95[7]	18[7]	8[7]
Steenmeijer et al. (2022) (RIVM)	2016	241	1.87	19	8
Pichler et al. (2019)	2014	195[6]	-	16	8
Lenzen et al. (2020)	2015	231[6,8]/ 333[9]	1.78[8]	13	4[8] /6[9]

As already became clear in table 8 was that the total Dutch carbon footprint calculated in different studies has quite a range. The difference between the total Dutch carbon footprint as calculated by Steenmeijer et al. (2022) and this study can be assigned to data differences, as both studies perform a similar method of calculating the total carbon footprint. Table 24 shows that there is also a large range for the healthcare sector's carbon footprint. However, the share of the Dutch healthcare carbon footprint of the total Dutch carbon footprint ranges less (6-8%). Another important finding is that this share is the same for the Steenmeijer et al. (2022) using EXIOBASE, as for this study which uses the

[6] Based on the CF of healthcare and the share of the Dutch national footprint
[7] Not reported in the referenced study, calculated for the purpose of this study
[8] Sourced or inferred from Eora explorer on its website
[9] Based on supplementary information of Lenzen et al. (2020)

SNAC-EXIOBASE database, while the studies use different scopes and approaches and have a very different total healthcare carbon footprint due to this. This study has the lowest direct emissions of all studies, which can be explained by the fact that only the direct emissions reported by Statistics Netherlands are used, and emissions caused by anaesthetic gasses are not included.

5.3.2. Comparison healthcare material footprint

Table 25 compares the material footprint of this study with the material footprint of Steenmeijer et al. (2022) for the year 2014. The material footprint calculated by Steenmeijer et al. (2022) is more than double the material footprint calculated in this study. This difference cannot be explained by the different scope of the study, as for the material footprint the only part that is not included in this study is the travel by patients and visitors, which is 106 kt. The difference could partially be explained by the difference in approach of the two studies. This study assumes that all Dutch consumption of pharmaceuticals is sourced domestically, while Steenmeijer et al. (2022) assumed the sourcing to be proportional to the sourcing distribution of the 'chemicals n.e.c.' in the total final demand (for national consumption). Next to this, we used a dedicated pharmaceutical industry to calculate the healthcare sectors' carbon and material footprint, while Steenmeijer et al. (2022) used 'chemicals n.e.c.' to represent the pharmaceutical industry. This difference is much smaller for the indirect carbon footprint, which is why it is also shown in table 25. For this comparison, it is better to use the indirect carbon footprint, as these are more comparable than the total carbon footprint. Next to this, this comparisons' goal is to show the effect different datasets used has on the environmental footprints, which only affects the indirect footprint

Table 25: Comparison of the Dutch healthcare sector's indirect carbon and material footprint of this study with Steenmeijer et al. (2022)

	Carbon [Mt CO_2 eq.]	**Materials [kt]**
This study	12.61	15051
Steenmeijer et al. (2022) (RIVM)	14.01	38068

In conclusion, the comparison shows that the material footprint is 61% smaller and the carbon footprint is 11% smaller when using the SNAC-EXIOBASE data instead of using the default EXIOBASE data. The fact that both footprints diminish when using SNAC-EXIOBASE data implicates that there actually might be a data limitation in using EXIOBASE data. The conclusion follows the initial idea that aggregation problems will have a larger effect on the material footprint as it occurs only at the beginning of the supply chain, while carbon emissions occur in every step along the supply chain. This possible aggregation problem will be further investigated by calculating the carbon, mineral and metal intensities of 'chemicals n.e.c.', the initial sector of concern.

5.3.3 Carbon, mineral and metal intensities of 'chemicals n.e.c.' in different countries

The carbon, mineral and metal intensities of all countries' 'chemicals n.e.c.' available in the SNAC-EXIOBASE dataset as well as for the Dutch 'pharmaceutical industry' and the 'Dutch chemical industry' available in the same dataset are calculated in this section to find out if there is an aggregation problem in 'chemicals n.e.c.'. These intensities are also compared to the Dutch 'chemicals n.e.c.' sector available in EXIOBASE. More detailed results of the multiplier analysis are available in appendix Q & R.

Carbon

High carbon intensity of 'chemicals n.e.c.' can either be caused by the fact that the techniques used by the country for producing one euro of 'chemicals n.e.c.', or by the type of products that are produced in the country as some products are inherently more polluting. Figure 10 shows how many times a certain carbon intensity of 'chemicals n.e.c.' or the Dutch 'pharmaceutical industry' and the Dutch 'chemical industry' in the SNAC-EXIOBASE dataset are observed. The number of observations thus refers to the number of categories that have this carbon intensity. The carbon intensity of the Dutch 'pharmaceutical industry' (3.05×10^{-1} kg CO_2 eq./€) is three times smaller than the carbon intensity of the Dutch 'chemical industry' (1.05 kg CO_2 eq./€). The average carbon intensity of all 'chemicals n.e.c.' sectors including the Dutch 'chemical industry' and 'pharmaceutical industry' in SNAC-EXIOBASE is 1.04 kg CO_2 eq./€, which means that the Dutch 'pharmaceutical industry' has a lower carbon intensity than the average Dutch 'chemical industry'.

The fact that these two sectors have a carbon intensity that differs so much indicates that combining the pharmaceutical industry and the chemical industry into one category 'chemicals n.e.c.' (as is normally done in EXIOBASE) creates an aggregation problem, where expenses on pharmaceutical products are given a too high carbon coefficient. This is because the EXIOBASE carbon intensity of the Dutch 'chemicals n.e.c.' is 1.74 kg CO_2 eq./€, which is 5.6 times the carbon intensity of the SNAC-EXIOBASE category 'pharmaceutical industry'.

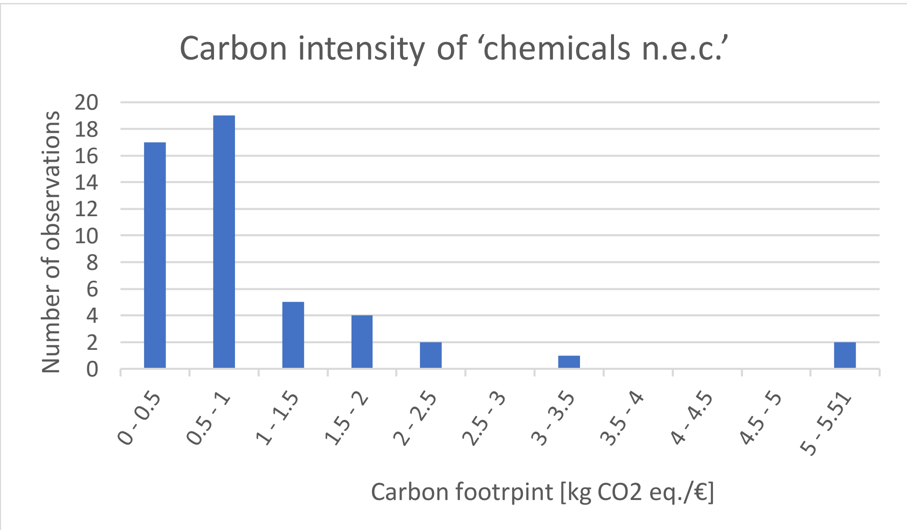

Figure 10: Carbon intensity of 'chemicals n.e.c.' and the Dutch pharmaceutical and chemical industries

Figure 10 shows that the two countries that have the highest carbon intensity are depicted by Slovakia (5.50 kg CO_2 eq./€) and South Africa (5.21 kg CO_2 eq./€) are outliers. Next to this, 'chemicals n.e.c.' of the Rest of the World (RoW) Europe also has a fairly high carbon intensity of 3.12 kg CO_2 eq./€. China has the lowest carbon intensity of 2.11×10^{-1} kg CO_2 equivalents.

Minerals

Figure 11 shows that the outliers are more extreme for the mineral intensity of 'chemicals n.e.c.'. The largest mineral intensity is caused by China, which has a mineral intensity of 12.90 kg of minerals/€. The Dutch 'chemical industry' from the SNAC-EXIOBASE dataset has a high mineral intensity (2.77 kg minerals/€), while the Dutch 'pharmaceutical industry' has a relatively low mineral intensity of 3.89×10^{-1} kg minerals/€. Again, the EXIOBASE Dutch 'chemicals n.e.c.' seems not to depict the 'pharmaceutical industry' that well, as the mineral intensity is 1.30 kg of minerals/€. This can also explain the large differences in the material footprint of this study compared to Steenmeijer et al. (2022), where the Dutch pharmaceutical and chemical industries are combined into the category 'chemicals n.e.c'. This result indicates that at least for the material footprint the aggregation problem influences the results.

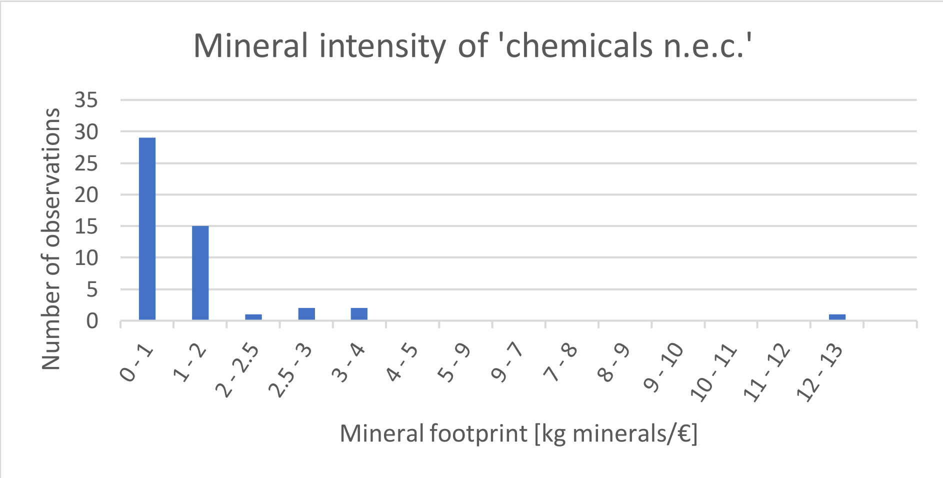

Figure 11: Mineral intensity of 'chemicals n.e.c.' and the Dutch pharmaceutical and chemical industries

The average mineral intensity is 1.33 and the median is 8.84×10^{-1}, which means that the Dutch chemical industry has an above-average mineral intensity, while the Dutch pharmaceutical industry has a below-average mineral intensity when comparing them to the 'chemicals n.e.c.' sectors available in the SNAC-EXIOBASE database.

Metals

Most countries have a metal intensity of 'chemicals n.e.c.' that falls in the 0-2.50×10^{-1} kg of metals/€. The mineral intensities of the Dutch 'chemical industry' (1.37×10^{-1} kg metals/€) and 'pharmaceutical industry' (4.72×10^{-2} kg metals/€) are both below the average of 1.90×10^{-1}, while the Dutch 'chemical industry' is above the median of 1.01×10^{-1}. The metal intensity of the Dutch 'chemical industry' is triple that of the Dutch 'pharmaceutical industry' category in the SNAC-EXIOBASE dataset. The metal intensity of the EXIOBASE Dutch 'chemicals n.e.c.' is 1.96×10^{-1} kg metals/€, which is almost the same as the chemical industry in the SNAC-EXIOBASE. This means that the EXIOBASE category 'chemicals n.e.c.' only depicts the Dutch 'chemical industry' well, however, the extraction of the metals caused by expenditure on pharmaceutical products is again overestimated. India and Mexico have the largest metal intensities of 'chemicals n.e.c.' compared to other countries. This is especially interesting because India is has a large market share in the 'pharmaceutical industry' (WHO, 2021).

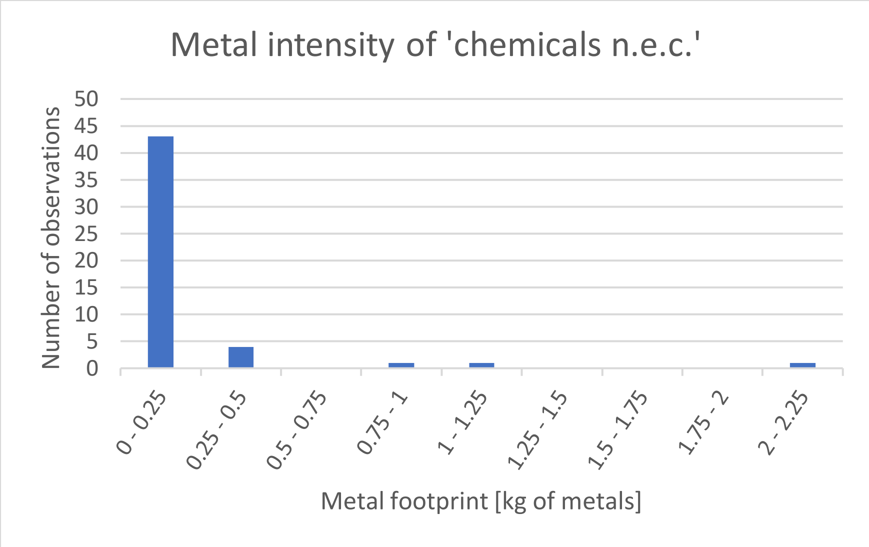

Figure 12: Metal intensity of 'chemicals n.e.c.' and the Dutch pharmaceutical and chemical industries

In conclusion, can be said that there is an aggregation problem in 'chemicals n.e.c.' as was introduced in section 5.3.2. It is especially obvious for the mineral footprint as it is halved when using the SNAC-EXIOBASE dataset. Next to this, the mineral and metal intensity also show that there are aggregation problems. The mineral intensity is 4 times as small for the Dutch pharmaceutical industry as for the original EXIOBASE 'chemicals n.e.c.'. The metal intensity is around 1.5 times smaller for the Dutch chemical industry than for the original EXIOBASE 'chemicals n.e.c.'. For the carbon footprint, the aggregation problem was not immediately obvious when comparing the healthcare carbon footprint of this study with Steenmeijer et al. (2022), however, the carbon intensity analysis showed that there is an aggregation problem in 'chemicals n.e.c.', which is 3 times higher than for the 'pharmaceutical industry'. The aggregation problem mainly arises in the sector itself, while the carbon footprint is caused by every step in the supply chain. This is why the aggregation problem in 'chemicals n.e.c.' has less impact on the total Dutch healthcare sector's carbon footprint.

5.3.4 Structural path analysis

The structural path analysis give insight into the production paths that contribute most to the carbon, mineral and metal footprint of the analysed sector. As the carbon, mineral and metal intensity of the 'pharmaceutical industry' as covered in the SNAC-EXIOBASE dataset is much lower than the 'chemical industry' and the EXIOBASE 'chemicals n.e.c.', the structural path analysis can give insight into why this is the case. The detailed results of the SPA can be found in appendix S.

Carbon

First, the structural paths of the carbon emissions of the three sectors will be discussed. Figure 13 shows that except for direct emissions, 'chemicals n.e.c.' in Belgium (6.12%) and the Dutch energy companies (5.43%) contribute a lot to the total emissions of the 'pharmaceutical industry' as represented in the SNAC-EXIOBASE dataset. The 'chemicals n.e.c.' industries that contribute the most to the total emissions are the Belgian, the Dutch, the German (specifically because of gas extraction in the Netherlands) and the United States industries. Next to this, large shares are found in Dutch waste management, air travel, food industry, agriculture. The extraction of natural gas in Russia also has a large share.

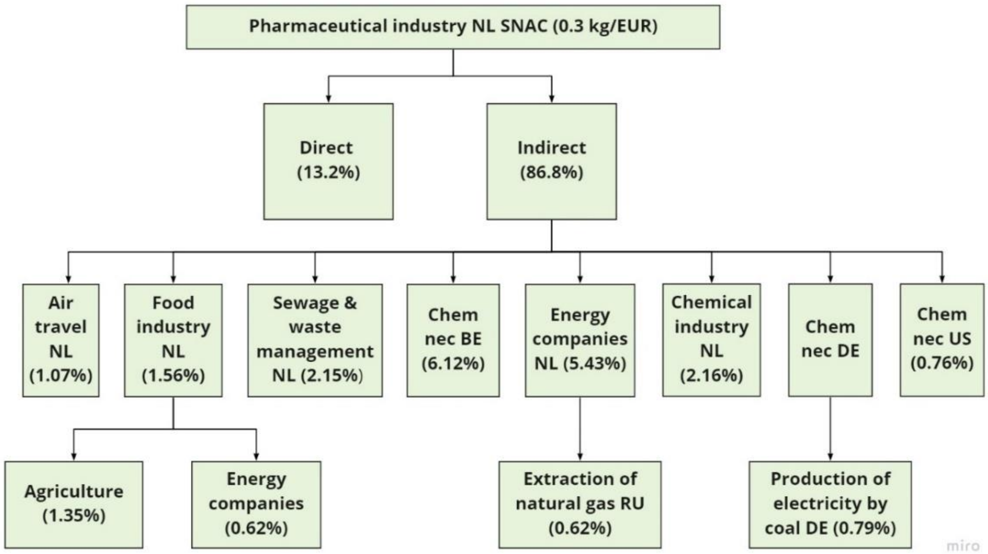

Figure 13: Structural path analysis of the carbon emissions occurring due to the Dutch 'pharmaceutical industry' category from SNAC-EXIOBASE. The figure shows 35.8% of the total impact by different paths (cut-off at 0.6%)

Figure 14 shows that the 'chemical industry' has more large share paths compared to the 'pharmaceutical industry', as with the same cut-off the path of the 'chemical industry' is responsible for almost double the share of the total impact (62.1%) compared to the 'pharmaceutical industry' (35.8%). The Dutch 'chemical industry' is now responsible for a larger share and induces other large paths in the second stage. Next to this, the direct emissions are almost double that of the 'pharmaceutical industry', and the Dutch petroleum industry seems to play a larger role in the Dutch 'chemical industry' than in the Dutch 'pharmaceutical industry'.

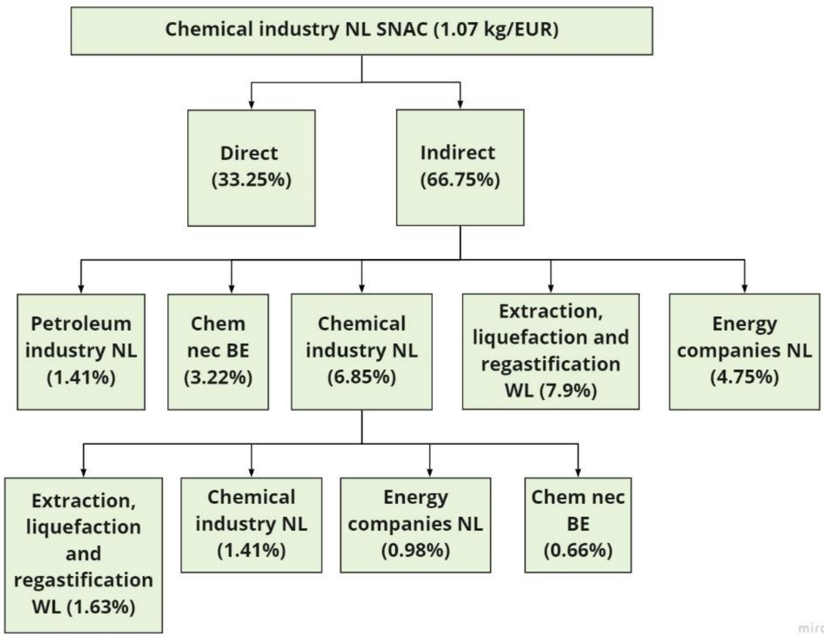

Figure 14: Structural path analysis of the carbon emissions occurring due to the Dutch 'chemical industry' category from SNAC-EXIOBASE. The figure shows 62.1.8% of the total impact by different paths (cut-off at 0.6%

The SPA of the Dutch EXIOBASE 'chemicals n.e.c.' sector shows that almost half of the carbon emissions are caused by direct emissions. Next to this, the extraction and refining of petroleum and natural gas contribute a lot to the first stage of the structural path analysis. Compared to the Dutch 'chemical industry' and the Dutch 'pharmaceutical industry' in (Figures 13 and 14), it is remarkable that Belgium 'chemicals n.e.c.' does not seem to have a path that is larger than 0.6% of the total carbon emissions.

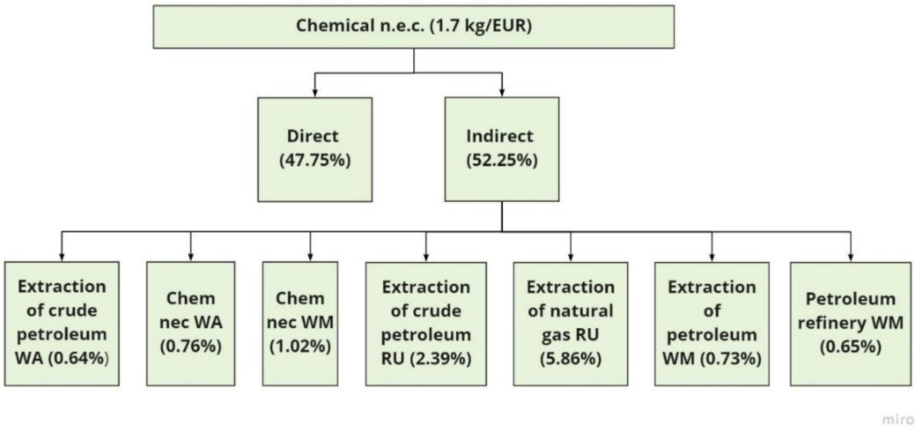

Figure 15: Structural path analysis of the carbon emissions occurring due to the Dutch 'chemicals n.e.c.' category from EXIOBASE. The figure shows 59.8% of the total impact by different paths (cut-off at 0.6%)

Minerals

Mineral extraction only occurs at extracting sectors, which is why we also see more multiple-stage paths in the paths that are above the cut-off of 1% of the total mineral emissions caused by expenditure on the relevant sectors. Figure 16 shows that in the Dutch 'pharmaceutical industry' the direct extraction is smaller than the cut-off of 1%. All extraction paths that are shown in figure 16 trace to the 'quarrying of sand and clay' sectors, which makes sense as the sector 'quarrying of sand and clay' usually cover a large share of material footprints. Next to this, also 'other minerals' are extracted in the 'quarrying of sand and clay' sectors. Large paths are caused by the Dutch, Belgian, Chinese, and France 'chemicals n.e.c'. Remarkable are the 'other services' of Denmark. The sand and clay extraction mainly takes place in India and China.

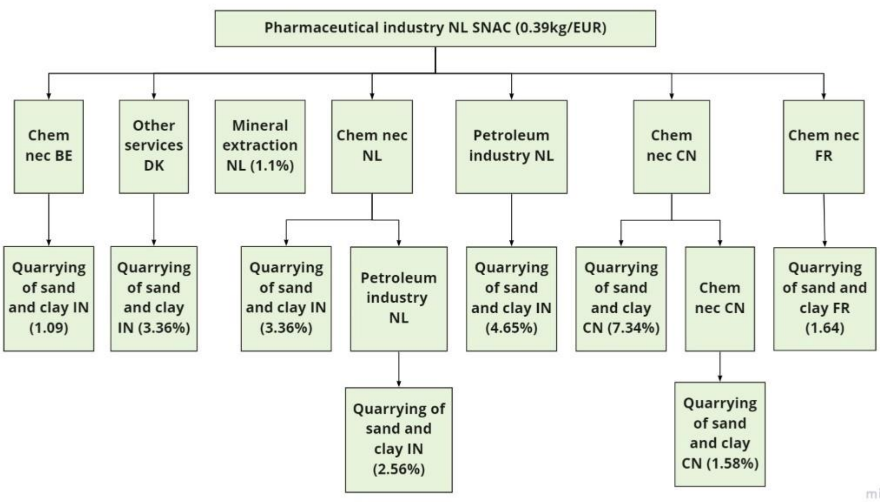

Figure 16: Structural path analysis of mineral use occurring due to the Dutch 'pharmaceutical industry' category from SNAC-EXIOBASE. The figure shows 26.71% of the total impact by different paths (cut-off at 1%)

Figure 16 shows the mineral extraction structural path analysis of the Dutch 'chemical industry' as depicted in the SNAC-EXIOBASE dataset. Here, India seems to dominate the structural path analysis more than in the Dutch 'pharmaceutical industry'. Looking at this SPA and at the SPA of figure 15 can be observed that the Dutch 'pharmaceutical industry' consumes more of the Belgian chemicals than the Dutch 'chemical industry'. The 'chemical industry' causes a lot of extraction in the 'quarrying of sand and clay' sector in India in the first stage, as well as in the second stage caused by the 'petroleum industry', this might be the reason why the mineral intensity of the chemical industry is 7 times as high, however, it still gives very little insight in what induces this extraction.

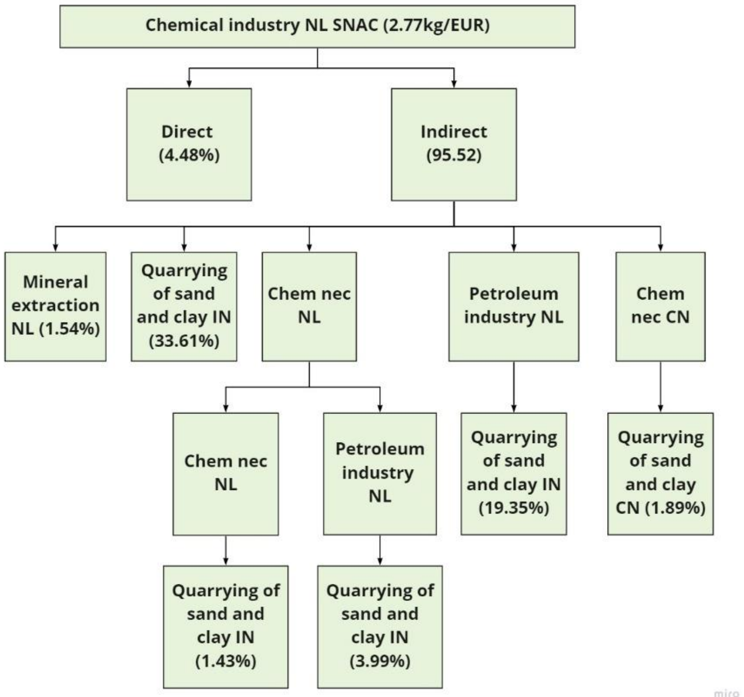

Figure 17: Structural path analysis of mineral use occurring due to the Dutch 'chemical industry' category from SNAC-EXIOBASE. The figure shows 66.29% of the total impact by different paths (cut-off at 1%)

The mineral structural path analysis of the EXIOBASE 'chemicals n.e.c.' shows a lot of large paths that end in the quarrying of sand and clay sector in RoW Africa, RoW Middle East and China, while India has a smaller contribution compared to figure 16 and 17. The large contribution of RoW Africa and RoW Middle East are not visible in the SPA of the Dutch 'chemical industry' and the Dutch 'pharmaceutical industry'. The sector 'mining of chemicals and fertilizer minerals, the production of salt and other mining' in the Netherlands is responsible for a large share (6.42%) of the minerals extracted by expenditure on the Dutch 'chemicals n.e.c.'. This category did not pop up in the other SPA results. As this study assumes that the SNAC-EXIOBASE data is more accurate, the above-mentioned differences could indicate errors in the EXIOBASE data, specifically where extraction is induced.

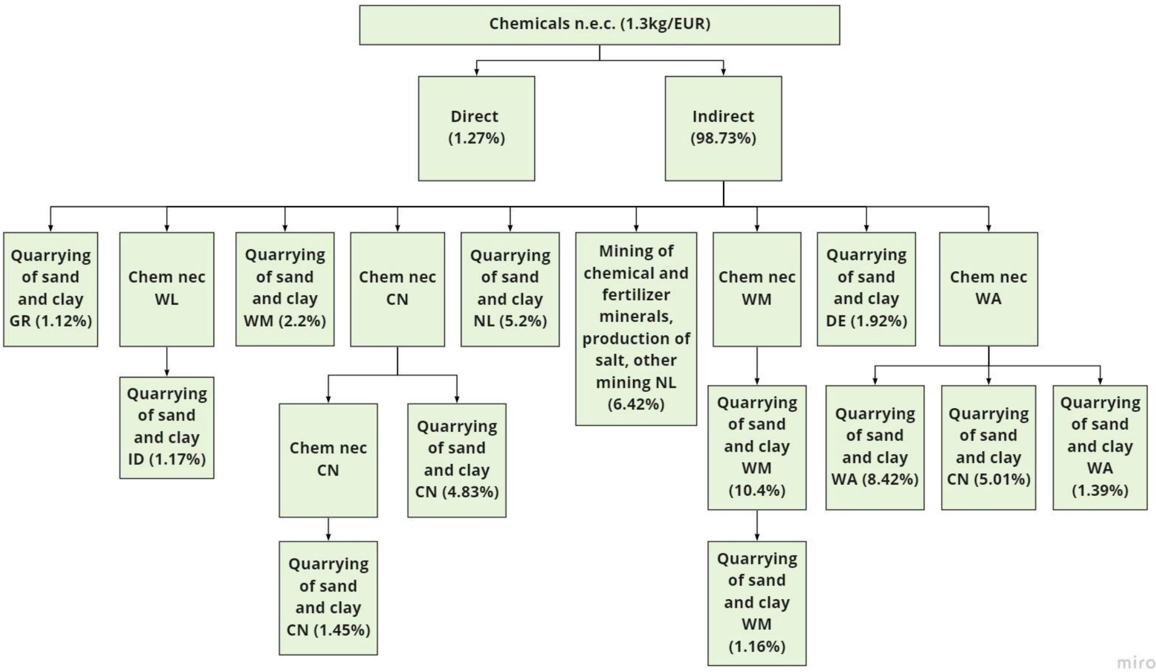

Figure 18: Structural path analysis of mineral use occurring due to the Dutch 'chemicals n.e.c.' category from EXIOBASE. The figure shows 50.69% of the total impact by different paths (cut-off at 1%)

Metals

The structural path analysis of metal used caused by the Dutch 'pharmaceutical industry' (figure 19) shows that most metal extraction occurs in the RoW Latin America (WL), Sweden, Indonesia, and the United States. This matches the hotspot analysis results. Interestingly, the Dutch 'food industry' is again responsible for 2 large paths, which was also the case for the carbon extension. This is only the case for the 'pharmaceutical industry' and not for 'chemicals n.e.c.' and the 'chemical industry'.

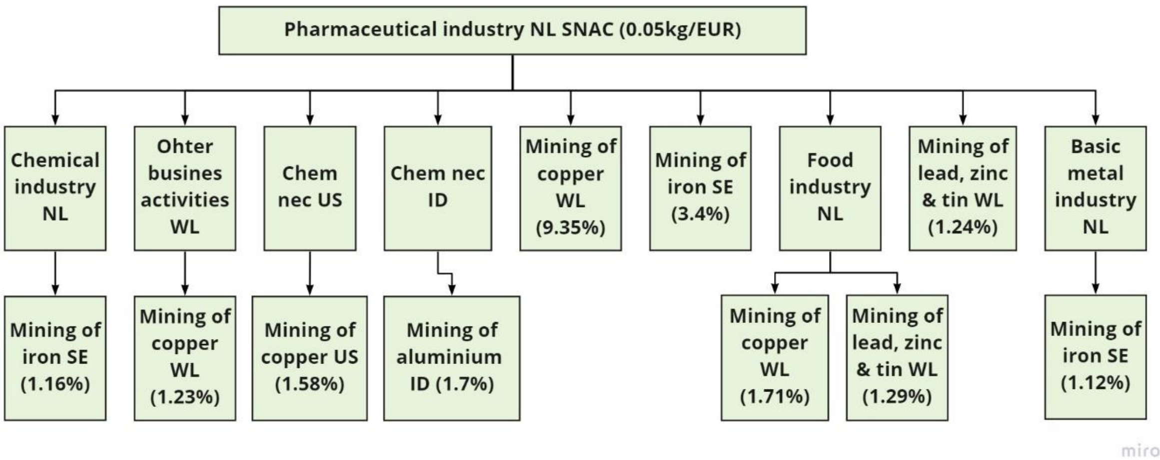

Figure 19: Structural path analysis of metal use occurring due to the Dutch 'pharmaceutical industry' category from SNAC-EXIOBASE. The figure shows 23.78% of the total impact by different paths (cut-off at 1%)

The metal structural path analysis of the 'chemical industry' (figure 20) is quite similar to the 'pharmaceutical industry' in figure 19. Only, the Dutch 'food industry' and the Dutch 'basic metal industry' does not occur in the SPA of the 'chemical industry'. The mining of iron in Britain is a large path for the 'chemical industry' (2.04%) while it is not for the 'pharmaceutical industry'.

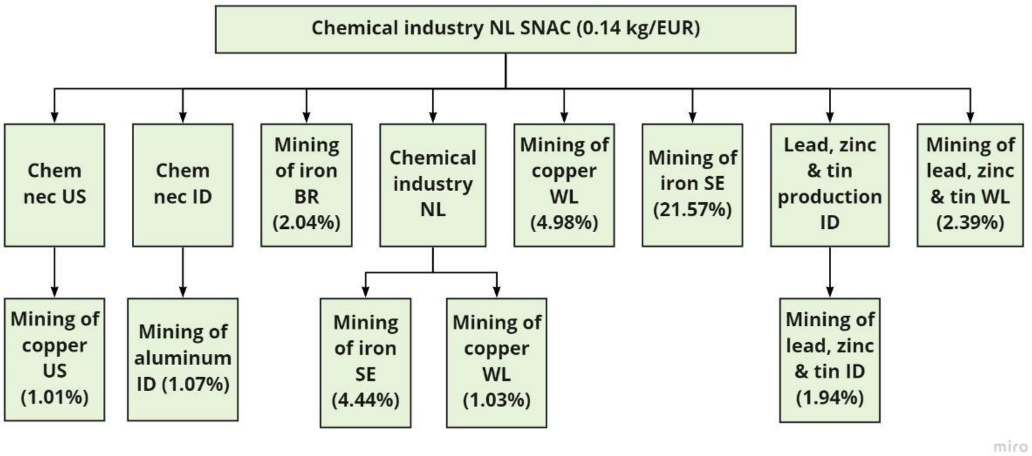

Figure 20: Structural path analysis of metal use occurring due to the Dutch 'chemical industry' category from SNAC-EXIOBASE. The figure shows 40.47% of the total impact by different paths (cut-off at 1%)

Figure 21 shows that the metal structural path analysis of 'chemicals n.e.c.' shows more differences. The 'mining of chemical and fertilizers minerals, salt and other chemicals' sector in RoW Africa and the Middle East cause large shares of extraction in the 'mining of aluminium' sector (4.2%) and the 'mining of lead, zinc and tin sector (1.32%). The 'mining of uranium and thorium' sector is a large path that occurs due to the Dutch 'chemicals n.e.c.' in RoW Africa, while it does not occur in the 'pharmaceutical industry' and 'chemical industry' categories.

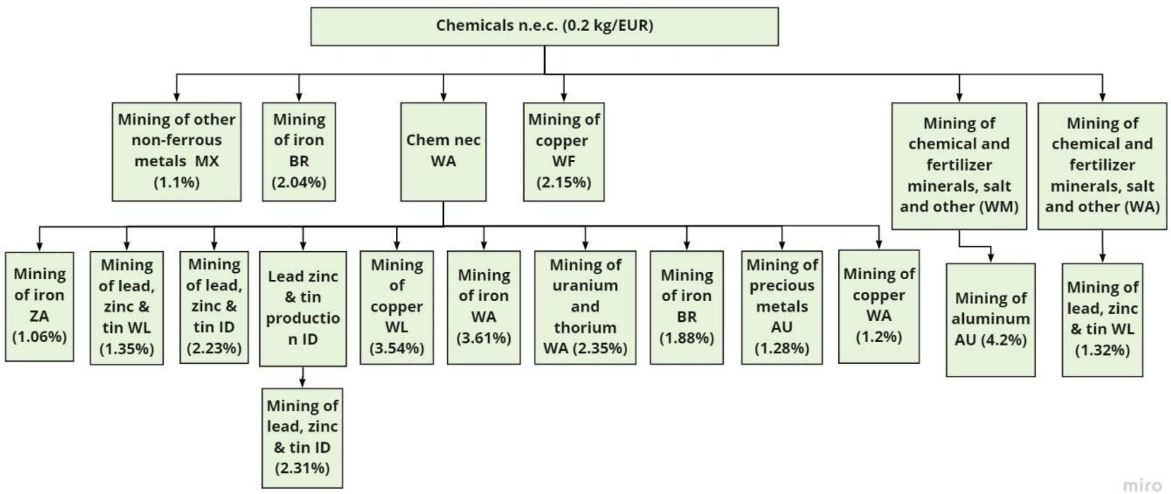

Figure 21: Structural path analysis of metal use occurring due to the Dutch 'chemicals n.e.c.' category from EXIOBASE. The figure shows 31.58% of the total impact by different paths (cut-off at 1%)

In conclusion, the SPA seems to give little insight into why the carbon, mineral, and metal intensities differ so much between the different categories. The SPA could provide more insight if the paths were aggregated and did not have to be cut-off for representing the results. The most remarkable insight for the carbon extension is that the direct emissions of 'chemicals n.e.c.' and the chemical industry are larger than the 'pharmaceutical industry'. Also, Belgium 'chemicals n.e.c.' does not have a large path in the SPA of the Dutch 'chemical n.e.c.'. An interesting finding for the material extensions is that the ‘chemical industry’ induces large paths towards the ‘quarrying of sand and clay’ sector in India (33.61%) in the first stage. This might be the reason why the mineral intensity of the ‘chemical industry’ is 7 times as high, however, it still gives very little insight into what induces this extraction. Next to this, ‘mining of chemicals and fertilizer minerals, the production of salt and other mining’ in the Netherlands are responsible for a large share (6.42%) of the minerals extracted by expenditure on the Dutch ‘chemicals n.e.c.’. This category did not pop up in the largest paths in SNAC-EXIOBASE categories. Lastly, for the metal extension, an interesting finding is the path ‘mining of thorium and uranium’ induced by the Dutch ‘chemicals n.e.c.’. Also, the ‘mining of chemical and fertilizers minerals, salt and other chemicals’ pops up in the Dutch ‘chemicals n.e.c’.

5.4 The carbon and material footprint of individual pharmaceutical products in comparison to IOA aggregated products of 'chemicals n.e.c.'

Based on chapter 5.3 there seems to be an aggregation problem in 'chemicals n.e.c.' which is especially evident in the material footprint results. This chapter dives deeper into this possible aggregation problem by identifying the carbon and material footprint of individual pharmaceuticals (sub-question 4).

First, a small literature review was conducted to find out if there are already scientific papers and reports that researched the carbon and material footprint of individual pharmaceutical products and their contribution to the total healthcare footprint. No relevant studies for the material footprint were found. Several studies investigate the carbon footprint. The National Health Service (NHS) (2014) published a report aimed to identify prescription pharmaceuticals with high GHG intensities for the English healthcare sector. This study identified pharmaceuticals of interest for further study based on yearly costs, the quantity of API used, and GHG emissions. This list is shown in table 26.

Table 26: Priority list of prescription pharmaceuticals for future research identified by the NHS (2014) in alphabetical order.

Priority prescription pharmaceuticals	
Adalimumab	Gabapentin
Amoxicillin	Ibuprofen
Atorvastatin	Metformin Hydrochloride
Beclometasone Dipropionate	Naproxen
Budesonide	Paracetamol
Co-Codramol (Codeine Phos/Paracetamol)	Salbutamol
Co-Dydramol (Dihydrocodeine /Paracet)	Simvastatin
Enteral Nutrition	Sodium Valproate
Etanercept	Sulfasalazine
Fluticasone Propionate (Inhaler)	Tiotropium

Unfortunately, these GHG intensities are not available in the report. The report also mentions, that several GHG intensities are based on pharmaceutical manufacturers expert guidance, which means there is a large uncertainty on the GHG intensities and therefore on the priority list (NHS, 2014). It does, however, give an initial insight into prescription pharmaceuticals that can have a large contribution to the total pharmaceutical carbon footprint.

Belkhir & Elmeligi (2019) calculated the carbon intensities of major pharmaceutical companies for the years 2012 and 2015. Excluding outliers, the study showed a range of carbon intensities from 1.40×10^{-2} kg CO_2/\$ for Roche to 7.70×10^{-2} kg CO_2 eq./\$ for Elli Lilly for the year 2015. Of 9 of the 15 major companies, the carbon intensity was below 3.30×10^{-2} kg CO_2 eq./\$. All industries except for TEVA showed a decrease in emissions between 2012 and 2015. Weisz et al. (2020) is the only study that calculates a national healthcare carbon footprint and also calculates the carbon footprint of several commonly used pharmaceuticals like paracetamol and naproxen. However, Weisz (2020) investigated too few pharmaceutical products to answer sub-question 4.

Therefore, an LCA literature review on the carbon and material footprint of individual pharmaceuticals was conducted.

5.4.1 Literature review of LCA studies on pharmaceutical products

The literature study shows that there is a lack of LCA studies on pharmaceuticals, as only 17 relevant articles were found of which 11 were suitable for this study. Most of these studies have a cradle-to-gate scope, making it difficult to use these for input-output analysis in the future since input-output analysis takes a cradle-to-grave approach.

Of all reviewed articles, only 2 studies included an indicator that somewhat resembled a material footprint, namely an abiotic depletion potential, a metal depletion potential and net mass of materials used (Henderson et al., 2008; Ott et al., 2014). This shows that a very limited number of LCA studies on pharmaceuticals take material use into account. The review of the LCA studies on pharmaceuticals also shows that often different impact assessment methods are used. Owsianiak et al. (2014) show that converting the impact scores of different impact assessment methods (IMPACT 2002+, ReCiPe 2008, and ILCD's recommended practice) to a common metric can lead to large discrepancies for the mineral and metal depletion categories. This means that even if in the future more studies would include mineral and metal depletion in their LCA on pharmaceuticals it would be difficult to compare these to a material footprint calculated using IOA. Not to forget, LCA impact assessment methods often express metal or mineral depletion into one equivalent, for example, the CML 3.02 method expresses it in Sb-eq. (antimony equivalents). This means that the materials that are extracted to produce the product are multiplied with the characterisation factor (which is in kg antimony/kg extraction) to get to the indicator result (van Oers et al., 2020). The problem of calculating a material footprint of an individual pharmaceutical product lies in the unavailability of the data behind this conversion. This makes it difficult to uncover which metals were extracted to produce 1 kg of API.

The information in the reviewed articles allowed us to calculate the physical carbon footprint (kg CO_2 eq. per kg API or chemical) and the monetary carbon footprint (kg CO_2 eq./€) of 44 substances. This highlights that the carbon footprint of many pharmaceutical products is not known Table 27 shows the identified articles and the substances documented in them. It also shows the physical and monetary carbon footprint of the substances. A more detailed version of the comparison can be found in appendix T. As these carbon footprints are per 1 kg or 1 euro, from now on they are referred to as carbon intensity in the same way as was done in chapter 5.3.3. Calculating the carbon intensity of individual pharmaceutical and chemical products used to produce pharmaceuticals gives a first impression of the range in carbon intensities. This chapter tries to get a better understanding of the product category 'pharmaceutical industry' as depicted in the SNAC-EXIOBASE dataset by comparing it to the range of carbon intensities of the individual pharmaceutical based on LCA studies.

The LCA studies on pharmaceuticals are mainly dominated by studies on anaesthetics, which makes sense as anaesthetics are known for their high GHG emissions during release (Hu et al., 2021; Sherman et al., 2012), and because these are commonly used pharmaceuticals. The study of Goulet et al. (2017) focussed on pressurised metered-dose inhalers (pMDI). The use emissions of pMDI are important to mention in this study since Steenmeijer et al. (2022) include 19 kt CO2 eq. for pMDI use in the Dutch healthcare sector's carbon footprint (0.47%). The emissions of using pMDI are difficult to include in the standard IOA framework because they occur in households, which in most healthcare carbon footprint studies are not included. Therefore, extra attention should be paid to including pMDI use emissions in the carbon footprint calculations of the healthcare sector.

Table 27 only shows the physical carbon intensity of the Proventil inhaler and the electric nebulizer because they are not sold in the Netherlands, which is why the monetary carbon intensity could not be calculated. The LCA study by McAlister (2019) is the only cradle-to-grave study shown in table 27.

Table 27: A literature review of LCA studies into pharmaceutical products and the calculation of physical and monetary carbon intensities (all cradle-to-gate studies except for McAlister, 2019)

Article	**Type**	**Product**	**kg CO_2 eq./ kg**	**kg CO_2 eq./ €**
Goulet et al. (2017)	Inhalers	Proventil® HFA inhaler	1.02×10^{2}	N/A
		Electric nebulizer, specifically the DeVilbiss Pulmo-Aide® nebulizer	4.68×10^{2}	N/A
Jiménez-Gonzales (2000)	Antidepressant	Sertraline	2.14×10^{3}	3.26
Ott et al. (2014)	Tumour treatment	Z-isomeric compound (Sanofi)	2.25×10^{3}	N/A
Parvatker et al. (2019)	Anaesthetics	Dexmedetomidine	3.01×10^{3}	3.78×10^{-5}
		Morphine	1.51×10^{3}	1.72×10^{-1}
		Hydromorphone	7.99×10^{2}	6.84×10^{-3}
		Midazolam	4.44×10^{2}	4.34×10^{-2}
		Phenylephrine hydrochloride	1.71×10^{2}	3.29×10^{-4}
		Rocuronium Bromide	1.44×10^{2}	1.07×10^{-3}
		Ketamine	1.40×10^{2}	5.87×10^{-4}
		Remifentanil	1.03×10^{2}	3.54×10^{-5}
		Fentanyl	9.58×10^{1}	3.45×10^{-5}
		Ephedrine Hydrochloride	8.20×10^{1}	1.92×10^{-3}
		Glycopyrrolate	7.60×10^{1}	2.00×10^{-5}
		Ondansetron	3.67×10^{1}	1.32×10^{-3}
		Ropivacaine HCl	3.56×10^{1}	2.24×10^{-3}
		Epinephrine	3.38×10^{1}	2.53×10^{-5}
		Lidocaine	2.86×10^{1}	8.00×10^{-3}
		Bupivacaine HCl	2.33×10^{1}	2.46×10^{-3}
		Neostigmine methylsulfate	2.18×10^{1}	5.60×10^{-6}
		Propofol	2.10×10^{1}	2.31×10^{-3}
		Sugammadex	1.16×10^{1}	3.73×10^{-5}
		Succinylcholine	1.12×10^{1}	4.33×10^{-4}
Raymond et al. (2010)	Solvents	Acetone	1.86	5.44×10^{-2}
		Acetonitrile	1.95	3.15×10^{-2}
		Diethyl ether	1.08	4.55×10^{-2}
		Ethanol	1.08	3.80×10^{-2}
		Hexane	8.55×10^{-1}	1.33
		2-propanol (IPA)	1.63	1.01×10^{-1}
		Methanol	6.44×10^{-1}	6.24×10^{-2}
		Tetrahydrofuran	5.46	1.45×10^{-1}
		Toluene	1.19	1.85
		Generic solvent	1.75	N/A
	Commodity chemicals	Ammonia	2.02	1.28×10^{-2}
		50 wt % Sulfuric acid	1.35×10^{-1}	8.73×10^{-3}
		Titanium dioxide	4.26	3.26×10^{-1}
Henderson et al. (2008)	Pharmaceutical intermediate	7-ACA - chemical synthesis process route	3.87×10^{2}	5.33×10^{-1}
		7-ACA - two enzymes catalysed process	2.05×10^{2}	2.82×10^{-1}

Renteria Gamiz et al. (2019)	Anti-inflammatory drugs	Infliximab	8.00×10^{2}-1.24×10^{3}	3.00×10^{-4} - 5.00×10^{-4}
MacAlister et al. (2016)	Analgesics	Morphine	2.04×10^{3}	1.97×10^{-2}
Weisz et al. (2020)		Paracetamol	7.80	2.29×10^{-1}
		Acetylsalicylic acid	4.90	3.25×10^{-2}
		Ibuprofen	3.10	3.40×10^{-2}
		Naproxen	2.30	1.31×10^{-2}
	Antibiotics	Antibiotics	1.43×10^{1}	N/A
	Amoxicillin	Amoxicillin	1.43×10^{1}	8.63×10^{-2}

A very large range of physical carbon intensities (2.30–3.01×10^{3} kg CO_2 eq./kg) monetary carbon intensities (5.60×10^{-6}-3.36 kg CO_2 eq./€.) of the pharmaceuticals can be observed in figure 22. The median lies at 2.24×10^{-3} kg CO_2 eq./€. In this range, sertraline is an outlier with a carbon intensity of 3.26 kg CO_2 eq./€. When looking at the physical carbon intensity of sertraline it is not an outlier, meaning that sertraline is an outlier mainly because of its relatively low price compared to pharmaceuticals with similar physical carbon intensities.

The large range in carbon intensities indicates that the pharmaceutical industry is heterogeneous. When comparing this range in carbon intensity of individual pharmaceutical products to the weighted carbon intensity of the 'pharmaceutical industry' category as available in the SNAC-EXIOBASE dataset (3.05×10^{-1} kg CO_2 eq./€), the carbon intensity of the SNAC-EXIOBASE 'pharmaceutical industry' is a bit above this range, when neglecting the outlier. As mentioned in the methods section, the prices gathered for this analysis might be on the high side, as no reliable industry price could be found. When lower prices would be used, the carbon intensities would increase because the carbon footprint would be divided by a smaller number. In this line of reasoning, the fact that the weighted SNAC-EXIOBASE pharmaceutical industry's carbon intensity is a bit above the range of carbon intensities of individual pharmaceuticals does not mean that this carbon intensity is erroneous. Also, when taking into account that only 28 different pharmaceuticals have been analysed, we could say that the represented range is not complete. More information on how the prices of pharmaceuticals change when using Sigma-Aldrich, the Farmacotherapeutics Kompas and the PharmaCompass can be found in appendix U.

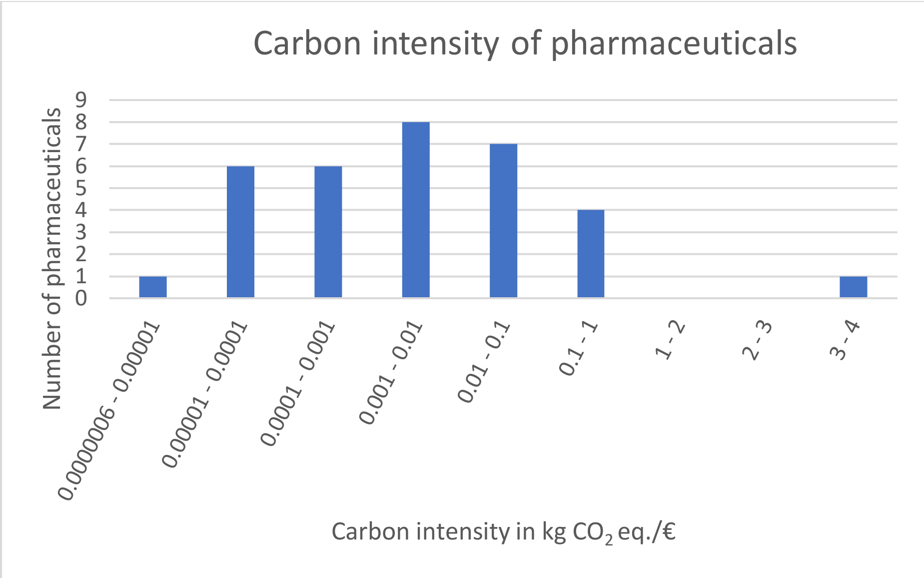

Figure 22: Monetary carbon intensity of pharmaceuticals calculated from LCA studies (also including propofol which is an intravenous anaesthetic and therefore not an anaesthetic gas)

Figure 23 shows the range of monetary carbon intensities of the chemicals studied by Raymond et al. (2010). These chemicals are mainly solvents, that are often used in the production of pharmaceuticals, however, also the commodity chemicals ammonia, sulfuric acid, and titanium oxide were included for comparison. Both the physical and monetary carbon intensities of the commodity chemicals match the solvents (also see table 27). The range of the physical carbon intensities of chemicals is between 1.35×10^{-1}-5.46 kg CO_2eq./kg and for the monetary carbon intensities, it is between 8.73×10^{-3}-1.56 kg CO_2 eq./€ are smaller than compared to pharmaceuticals. This smaller range could be caused by the fact that only 12 substances are compared in the same LCA study. The median lies at lower 5.84×10^{-2} kg CO_2 eq./€. The outliers are hexane (1.33 kg CO_2 eq./€.), and toluene (1.85 kg CO_2 eq./€.), which is probably because lower prices were used for the conversion of these substances. The prices of hexane and toluene were taken from PharmaCompass, an online marketplace for APIs, while the prices of the other chemicals were taken from Sigma-Aldrich, which are generally a lot higher as these are not industry prices as explained in the methods section. The range of the carbon intensities of chemicals used in pharmaceutical products (excluding the outliers) seems to match the range in pharmaceutical carbon intensities as shown in table 22.

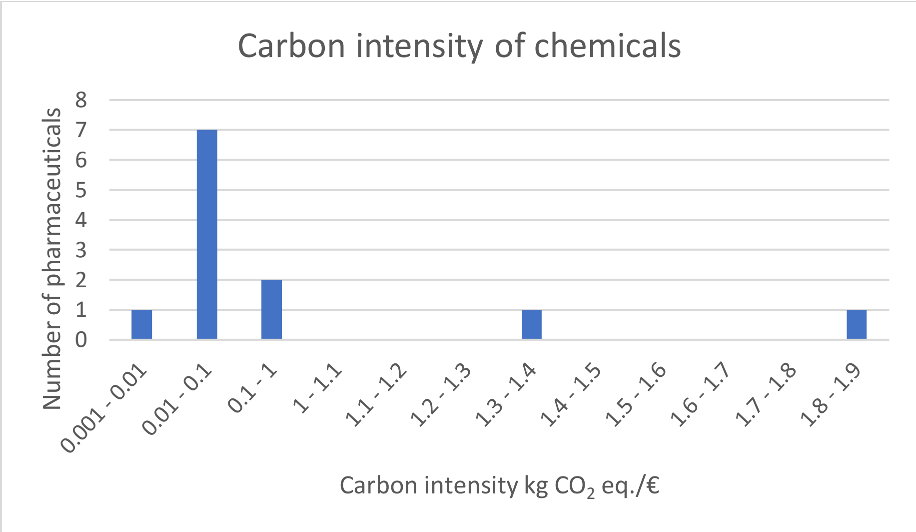

Figure 23: Monetary carbon intensity of chemicals (solvents often used in pharmaceuticals and 3 commodity chemicals) calculated from LCA studies.

Table 28 shows the physical carbon intensity per litre of anaesthetic gasses and propofol and their corresponding monetary carbon footprint. These LCA studies are in a separate table because the physical carbon intensity is per litre, the studies are cradle-to-grave, and they have the unique character that the emissions mainly occur during the use phase and are quite high. The high carbon footprint of anaesthetic gasses can be observed in both the physical carbon intensity and monetary carbon intensity. Both are lower in Hu et al. (2021) compared to Sherman et al. (2012), which can be explained by the fact that scenarios 2 and 3 of Hu et al. (2021) do not include N_2O release, while in Sherman et al. (2012) they do. Scenario 3 of Hu et al. (2021) matches the advice that is given to Dutch anaesthesiologists as the use of N_2O is discouraged and the use of either intravenous anaesthetics or sevoflurane with low gas flows of 0.5 L/minute is advised (Nederlandse Vereniging voor Anesthesiologie, n.d.). The use of desflurane and isoflurane is also discouraged by the association of Dutch anaesthesiologists. However, this advice is not yet fully followed, which is why scenario 2 is also relevant. Table 28 shows that depending on the assumptions made on the gas flows a large difference in the monetary and physical carbon intensities occurs.

It does not make sense to compare the carbon footprints of anaesthetic gasses to the carbon intensity of the pharmaceutical industry in the SNAC-EXIOBASE dataset. This is because emissions in anaesthetic gasses occur during the use phase as direct emissions (Hu et al., 2021; Sherman et al. 2012). In IOA usually are not documented in the carbon extension but are added on top of the indirect emissions.

Table 28: Literature review of cradle-to-grave LCA studies of anaesthetic gasses (CO_2 eq./L)

Article	Type	Product	kg CO_2 eq./L	kg CO_2 eq./ €
Sherman et al. (2012)	Anaesthetics	Desflurane	8.12×10^{3}	1.65×10^{1}
		Isoflurane	1.85×10^{4}	3.10×10^{1}
		Sevoflurane	6.97×10^{3}	1.19×10^{1}
	Intravenous anaesthetics	Propofol	1.50×10^{4}	5.43×10^{-2}
Hu et al. (2021)	Anaesthetics scenario 2	Sevoflurane UK_A	9.78×10^{2}	1.66
		Sevoflurane UK_B	1.78×10^{2}	2.21×10^{-1}
		Sevoflurane USA_A	1.02×10^{3}	1.27
		Sevoflurane USA_B	2.67×10^{2}	3.31×10^{-1}
		Isoflurane_A	7.14×10^{2}	8.76×10^{-1}
		Isoflurane_B	5.36×10^{2}	6.57×10^{-1}
		Desflurane_A	2.82×10^{3}	4.18
		Desflurane_B	2.67×10^{3}	3.96
	Anaesthetics scenario 3	Sevoflurane UK_A	8.90×10^{2}	1.11
		Sevoflurane UK_B	3.56×10^{2}	4.42×10^{-1}
		Isoflurane_A	1.07×10^{3}	1.31
		Isoflurane_B	7.14×10^{2}	8.76×10^{-1}
		Desflurane_A	2.85×10^{3}	4.23
		Desflurane_B	2.69×10^{3}	3.99
	Intravenous anaesthetics	Propofol	1.78×10^{1}	3.266×10^{-4}

We can conclude that there are only a few studies that analyse the healthcare carbon footprint by integrating top-down and bottom-up data in their calculation. Only Weisz et al. (2020) considers this approach. Additionally, almost no studies on pharmaceuticals exist that include material extraction or depletion, which indicates that there is more interest in the carbon footprint than in the material footprint of pharmaceuticals. Most studies take a cradle-to-gate approach, which means that the emissions in the use-phase and end-of-life stages are missing in these studies. For better comparison of LCA and IOA studies, but also a better description of the pharmaceutical industry in input-output tables, cradle-to-grave studies are needed. The emissions of anaesthetic gasses during the use phase should be included in the direct emissions from the healthcare sector as reported by Statistics Netherlands. The SNAC-EXIOBASE data currently published by Statistics Netherlands does not provide enough information to assess if the emissions of anaesthetic gasses have been properly accounted for. The large range in the carbon intensity of pharmaceuticals indicates that the pharmaceutical industry is heterogeneous. When comparing the observed ranges to the SNAC-EXIOBASE pharmaceutical industry's carbon intensity to the range of pharmaceuticals there is not yet a reason to think the SNAC-EXIOBASE carbon intensity is very erroneous.

5.5 Improving the calculation of the carbon and material footprint of the Dutch healthcare sector

As became clear in chapter 5.3, calculating the Dutch healthcare carbon and material footprint, an aggregation problem arises in the EXIOBASE 'chemicals n.e.c.' sector that is commonly used to depict the pharmaceutical industry. The comparison of EXIOBASE versus SNAC-EXIOBASE also gives clear indications of how this problem could be solved. This chapter answers the third knowledge gap: "To what extent is EE-IOA a suitable tool to analyse the carbon and material footprint of the Dutch healthcare sector?". Two possibilities to improve the calculation of the carbon and material footprint of the healthcare sector are:

1. A hybrid input-output analysis that connects LCA data to the input-output table.
2. A better depiction of the healthcare sectors in the standard input-output table.

As it is not in the scope of this study to explain how these options work and how the new models should be constructed, only a small introduction to the two possible improvements will be given.

5.5.1 A hybrid input-output-analysis

Hybrid input-output analysis is not a new method, the methodology already originates from the energy analysis studies of the 1970s (Bullard et al., 1978; Wright, 1974). In hybrid input-output analysis the IOA background system is connected with a foreground system. Using process-based LCA (PLCA) as a background system for input-output analysis is often called hybrid input-output analysis (Wiedmann, 2011). Hybrid IOA is used to get more detail in input-output sectors. Even though detail is added, the economy-wide view is preserved, which is why Minx et al. (2008), argue that hybrid IOA is the best option for carbon footprint analysis. This is also the reason why this method can improve the calculation of the carbon and material footprint of the healthcare sector. Using a hybrid IOA can solve the aggregation issue in 'chemicals n.e.c.' by including life cycle inventory data (LCI as a background system.

There are also several disadvantages to using hybrid IOA:

1. Hybridization is still evolving and is not yet a standardised approach (Wiedmann et al., 2011)
2. Constructing a hybrid IOT is, time-consuming, more computing power demanding and complex.
3. IOTs are commonly expressed in monetary value, as a common physical unit for the services and products expressed in IOTs is difficult to conceive (Wiedmann, 2009. In contrast, LCI data is expressed in physical units. Therefore, bridge matrices are needed.
4. It requires additional data needs. Next to LCI data also emission factors for specific processes are needed. LCI data on pharmaceuticals is lacking, and also very difficult to gain due to trade secrets (Jiménez-González & Overcash 2014). Also, specific emission factors are missing. The literature study on the carbon and material footprints of pharmaceuticals already showed that a limited amount of LCA studies were performed on pharmaceuticals. Especially for calculating the material footprint, where the aggregation problem is largest, there is a lack of LCA studies

Especially due to the additional data needs, and the lack of data availability this improvement option is very time-consuming and not feasible.

5.5.2 A better depiction of the healthcare sectors in the standard input-output table

The second option is to use a dataset that better depicts the healthcare sector. Ideally, this dataset should distinguish a separate pharmaceutical sector for every country in the dataset in the same way as is done for the Dutch sectors in the SNAC-EXIOBASE 2014. In this way, there is less of an aggregation problem for pharmaceuticals, as shown in chapter 5.3.3. EXIOBASE does not include a separate pharmaceutical industry sector because it is based on the economical classification NACE Rev. 1.1. In 2021, the Organisation for Economic Co-operation and Development (OECD) published the Inter-Country Input-Output tables (ICIO) based on the ISIC Rev. 4 classification (NACE Rev. 2). The ICIO, therefore, includes a separate pharmaceutical sector for all 66 countries (Organisation for Economic Co-operation and Development [OECD], 2021). The ICIO consists of 45 industries and includes no environmental extensions as the OECD is mainly focused on economic analyses (OECD, 2021). This IOT is available from the years 1998 to 2018 (OECD, 2021). Another advantage of the ICIO is that it is developed by the OED, which as an international statistical organization has an ongoing budget to keep improving and updating these tables. The OECD is also able to comprehensively collect national statistical data. Statistical institutions are better at collecting economic and environmental data of their country, as they use data that is often restricted to the public, and companies are compulsory to share data with these institutions by law (Wiedmann et al., 2011). Where hybrid IOA increases the complexity of the analyses performed, the solution of this section does not increase the complexity. This means that more input-output practitioners will be able to perform analyses.

The main limitations of using the ICIO to calculate the carbon and material footprint of the healthcare sector:

1. The ICIO does not include environmental extensions yet, and it is unlikely that the OECD will add these to the ICIO because it is mainly focused on economic analysis. Therefore, environmental extensions still need to be added.
2. So far, the ICIO has a low resolution (45 industries), which especially for the calculation of the material footprint is a bottleneck. The primary industries resolution is low, as it only differentiates between the mining of energy and non-energy products.
3. Due to the large range of carbon intensities observed in chapter 5.4, there is still a chance there will still be an aggregation problem when using a separate pharmaceutical industry sector, due to the heterogeneous character of these pharmaceutical products.

Creating environmental extensions for the ICIO is time-consuming, however, as these can be based on national accounts it is deemed to be less time consuming than performing all LCA's necessary to be able to make a proper hybrid input-output table. The second improvement option is also in line with recommendations of other studies, that GMRIOs should be more robust, by being based on statistical data (Tukker et al., 2018).

In both options, the direct emissions of the healthcare sector should be considered carefully. In the Dutch situation, more clarity is needed on what emissions are included in the sectoral direct emissions that are documented by the Statistics Netherlands. As shown in section 5.4, anaesthetic gasses are responsible for a very a lot of direct emissions. These should be included in the carbon footprint of the healthcare sector. Preferably, also use emissions (e.g. pMDI use) at households should be included in the healthcare sector's carbon footprint.

Previous chapters showed that there are data limitations and that there is an aggregation problem in 'chemical n.e.c.'. This chapter showed that there are possible solutions for solving these problems.

Both of them involve IOA as the backbone of the analysis. While a hybrid analysis is not feasible due to the lack of LCA data, the use of MRIOs that include a separate pharmaceutical industry seems more feasible. The ICIO can be the basis for future analyses of the carbon and material footprint of the Dutch healthcare sector, especially because the demand for an environmentally-extended high ICIO resolution already exists in the scientific debate, which makes it likely these extensions will be developed. However, the main limitation of input-output analysis; the assumption of homogenous product groups will still have an impact on the results of future studies of the carbon and material footprint of the (Dutch) healthcare sector as the pharmaceutical sector seems to be quite heterogeneous. In conclusion, can be said that IOA is so far the only suitable tool that can analyse the carbon and material footprint of the healthcare sector, however, it comes with a lot of limitations, and therefore should not be seen as a representation of reality.

6. Discussion

In this study, we have analysed the contribution of the consumption of pharmaceuticals to the Dutch carbon and material footprint and the suitability of EE-IOA for this analysis. Step by step possible reasons that could cause the previously observed high contribution of the consumption of pharmaceuticals to the Dutch healthcare sector's carbon and material footprint were investigated.

Analysis of previous studies

First, the previous studies of De Koning (2020) and Steenmeijer et al. (2022) were checked on conceptual and calculation errors. Even though Steenmeijer et al. (2022) use better healthcare expenditure data in the IOA compared to De Koning (2020), the product category 'chemicals n.e.c.' still dominates the carbon and material footprint. This indicates that the high contribution of the consumption of pharmaceuticals to the Dutch healthcare sector's carbon and material footprint cannot be explained by the different data used in the construction of the final demand stimulus. After this, the total Dutch carbon footprint calculated by Steenmeijer et al. (2022) was compared to other studies that also calculated the carbon footprint of the Dutch healthcare sector and with the SNAC-EXIOBASE carbon footprint. This showed a large range in the Dutch carbon footprint, which can be explained by the use of different datasets, as identified by previous studies (Tukker et al., 2020; Wood et al., 2019). This large range can be caused by the difference in sectoral resolution in these datasets. However, when extreme aggregations are avoided (e.g., level of 17 sectors) the errors are below 10% (Tukker et al., 2020). The value of a national carbon footprint also depends on if a residential or territorial approach is used to calculate a carbon footprint, which for small countries like the Netherlands can lead to large deviations (20-70%) (Tukker et al., 2020). Based on the large differences in national carbon footprints between using datasets, Tukker et al. (2020) advise using a SNAC approach when calculating national footprints. The main reason for this is that SNAC IOTs are based on national statistical data. The study of Steenmeijer et al. (2022) falls in the middle to the higher range of observed Dutch carbon footprints, which is to be expected when using EXIOBASE data (Tukker et al., 2020; Wood et al., 2019). Lastly, the investigation into 'chemicals n.e.c.' showed that the EXIOBASE category 'chemicals n.e.c.' is a heterogeneous sector that next to pharmaceuticals also includes products like inks, paints, make-up, soaps, and bulk chemicals. Based on these results, the large contribution of 'chemicals n.e.c.' to the carbon and material footprint of the Dutch healthcare sector cannot be dismissed by conceptual or calculation errors in previous studies. It is either a correct observation or it is caused by the EE-IO model or EE-IO dataset used to calculate the carbon and material footprint of the Dutch healthcare sector.

The Dutch healthcare sector's carbon and material footprint

The comparisons in the first sub-question showed that using different datasets influences the calculation of the Dutch carbon footprint. Therefore, it is to be expected that using SNAC-EXIOBASE inherently changes the Dutch healthcare sector's carbon and material footprint. The Dutch healthcare sector's carbon footprint calculated in this study is 14.26 Mt CO_2 eq., of which 1.65 Mt CO_2 eq. are direct emissions. Mainly energy-related sectors are high contributors to the Dutch healthcare sector's carbon footprint, which is to be expected. Also, 'chemicals n.e.c.' (of all countries except the Netherlands is responsible for a large share (8%). The material footprint of the healthcare sector calculated in this study consists of 15.05 Mt of materials and is dominated by mineral use (89%). The hotspot analysis of the mineral footprint showed a large share of 'other mineral' use (69%). This large share may be explained by the healthcare products that are made of the minerals that fall under 'other minerals', however, this is not quantitatively checked. The hotspot analysis of the metal footprint shows a remarkably high share of gold (11%) and silver (6%). This could be caused by the disaggregation of the material footprint with the use of the EXIOBASE extensions on which the SNAC-

EXIOBASE extensions are based. There is a difference in the total amount of materials extracted per sector between SNAC-EXIOBASE and EXIOBASE, which could cause this high share of gold and silver observed in the metal footprint. As no information is available on this difference between these datasets, and how the SNAC-EXIOBASE table was constructed, the hotspot analysis per mineral and metal group cannot be deemed to be entirely correct.

Identification of aggregation problems

Using SNAC-EXIOBASE compared to EXIOBASE data showed that the indirect carbon footprint diminished by 11% and the material footprint by 61%. This decrease shows that it is likely there is an aggregation problem in the EXIOBASE category 'chemicals n.e.c.'. The total Dutch carbon footprint diminished by 20% when using SNAC-EXIOBASE data compared to EXIOBASE data. This shows that the Dutch healthcare sector's carbon footprint decreases less compared to the total Dutch carbon footprint when using SNAC-EXIOBASE data. In both studies, the share of the Dutch healthcare sector's carbon footprint as a share of the national carbon footprint remains the same (8%). However, the share of the consumption of pharmaceuticals to the total carbon footprint does diminish. The extramural demand for pharmaceuticals attributes to 9% of the carbon footprint, while, for Steenmeijer et al. (2022) (for the year 2014) this is 25%. The Dutch healthcare sector's carbon footprint calculated in this study falls in the middle range of all studies compared (ARUP & Health Care Without Harm, 2019; Gupta Strategists, 2019; Pichler et al., 2016; Steenmeijer et al., 2022.). The fact that the material footprint decreases more than the carbon footprint is in line with previous studies that find that aggregation problems have a larger influence on the material footprint compared to the carbon footprint (De Koning, 2015).

Comparing the carbon, mineral and metal intensities of the Dutch 'pharmaceutical industry' and the Dutch 'chemical industry' in the SNAC-EXIOBASE dataset, with the Dutch 'chemicals n.e.c.' EXIOBASE category showed that the Dutch 'pharmaceutical industry' in all cases had lower intensities. The largest difference can be seen in the mineral intensity, which is 7 times smaller for the Dutch 'pharmaceutical industry' category of SNAC-EXIOBASE than for the original EXIOBASE 'chemicals n.e.c.'. For the metal intensity, this is 4 times smaller and for the carbon intensity, it is 3 times smaller. The carbon, mineral, and metal intensities confirm the aggregation problem in the EXIOBASE category 'chemicals n.e.c.' which initially became clear due to decreases in carbon and material footprint. The relatively high carbon and material footprint of the Dutch consumption of pharmaceuticals can, therefore, reasonably be explained by the aggregation problems in 'chemicals n.e.c.' which is used to depict the pharmaceutical industry, which mainly is a data limitation.

Next to this, a SPA was conducted to identify what causes the carbon, mineral, and metal intensities to differ between the EXIOBASE category 'chemicals n.e.c.' and the Dutch 'pharmaceutical industry' and 'chemical industry' categories in the SNAC-EXIOBASE dataset. The large paths mainly are in the same countries as in the hotspot analyses. The sector quarrying of sand and clay shows to cause large paths in the mineral extension SPA. This seems counter-intuitive when considering that the mineral footprint is dominated by 'other minerals', however, important to note is that multiple mineral extensions are linked to one sector. In the case of quarrying of sand and clay, this includes the mineral extensions 'other minerals, 'sand and gravel', and 'clays and kaolin'. The SPA results also show that there are clear differences in the largest paths between the 3 categories compared, which again confirms the aggregation problem in the EXIOBASE 'chemicals n.e.c.' category.

Literature review on LCA studies

Because of the observed aggregation problem in the EXIOBASE category 'chemicals n.e.c.', a literature review was conducted to find the carbon and material footprint of individual pharmaceuticals. LCA studies on the carbon and material footprint of pharmaceuticals are lacking. There especially is a very limited number of LCA studies on pharmaceuticals that take material use into account. This study found 44 substances that could be compared in both physical and monetary carbon footprints, which is very little. Most studies take a cradle-to-gate approach. Since the studies use different assessment methods and scopes, they are more difficult to compare. For a better comparison of LCA and IOA studies, and a better description of the pharmaceutical industry in input-output tables, cradle-to-grave studies are needed. The studies of Hu et al. (2021) and Sherman et al. (2012) showed that anaesthetic gasses have a high impact during the use phase, which means these emissions should be included as the direct emissions in input-output calculations. Also, the emissions occurring during the use of pressurised metered-dose inhalers should be included in IOA studies through bottom-up approaches.

A large range in both physical (2.30–3.01×10^{3} kg CO_2 eq./kg) and monetary (5.60×10^{-6}-3.36 kg CO_2 eq./€) carbon intensities could be found for pharmaceuticals. Comparing the range of monetary carbon intensities of pharmaceuticals to the range in monetary carbon intensities of pharmaceutical companies (1.40×10^{-2}-7.70×10^{-2} kg CO_2 eq./$) of Belkhir & & Elmeligi (2019), these range ranges seem to match. When comparing the range of carbon intensities of individual pharmaceutical products to the weighted carbon intensity of the SNAC-EXIOBASE Dutch 'pharmaceutical industry' category (3.05×10^{-1} kg CO_2 eq./€), the carbon intensity of the 'pharmaceutical industry' category is a bit above this range, when neglecting the outlier sertraline. The range of carbon intensities of the chemicals used in pharmaceuticals falls in the range of the individual pharmaceutical industries. As mentioned, the prices gathered for this analysis might be on the high side because no reliable industry price could be found. When lower prices would be used, the carbon intensities would increase, because the carbon footprint would be divided by a smaller number. In this line of reasoning, the fact that the weighted SNAC-EXIOBASE pharmaceutical industry's carbon intensity lies a bit above the range of carbon intensities of individual pharmaceuticals does not indicate that this carbon intensity is erroneous. When taking into account that only limited pharmaceuticals have been analysed, however, we also have to mention that the observed range of carbon intensities is far from complete.

Discussion on the approach of this study

The use of SNAC-EXIOBASE for calculating the carbon and material footprint of the Dutch healthcare sector has pros and cons. The main limitations of EE-MRIO analysis also apply to this study. One of these limitations is incomplete data which means that data entries are the result of balancing and reconciliation of the available data (Tukker et al., 2018). A pro of using SNAC-EXIOBASE is that at least for the Netherlands the data entries are based on the official national statistics. However, for the rest of the world, this is still based on reconciliation. Especially for low-income countries, where little detailed data is available this reconciliation can lead to large assumptions. SNAC-EXIOBASE even divides these countries into the Rest of the World (Row) countries. In the case of the metal footprint of the Dutch healthcare sector, RoW America contributes (66%) to the metal footprint. This is not very insightful, and this large share could be a result of the reconciliation. The Dutch part in SNAC-EXIOBASE has a low resolution of only 76 sectors, compared to 163 sectors in EXIOBASE. Lower resolutions can be problematic for the calculation of material footprints (Giljum et al., 2019). All other countries have a higher resolution, which means that this effect is not that large. However, it could still influence the mineral footprint results because 5% of the mineral extraction caused by the Dutch healthcare sector takes place in the Netherlands. Next to this, the SNAC-EXIOBASE dataset is only available for 3 years and is not public, which makes it difficult to compare analyses performed with this data to other studies

Due to the different approaches of the distribution of product supply among countries of origin in this study compared to Steenmeijer et al. (2022), it is difficult to assign the decrease of the healthcare sector's carbon and material footprint completely to the use of different data. For the SNAC-EXIOBASE carbon and material footprint, we assumed all the pharmaceuticals and medical appliances are sourced domestically. There is a trade-off between a better depiction of the pharmaceutical industry and, therefore, assuming the Dutch SNAC-EXIOBASE ‘pharmaceutical industry’ category to be representative for all pharmaceuticals bought in the Netherlands. While Steenmeijer et al (2022) assumed the sourcing to be proportional to the sourcing distribution of the Dutch EXIOBASE ‘chemicals n.e.c.’ category in the total final demand (for national consumption) but uses ‘chemicals n.e.c.’ to depict the pharmaceutical industry which is a downside. Since the SNAC-EXIOBASE dataset only provides the separate pharmaceutical industry for the Netherlands, we cannot derive any import/sourcing distribution as is done in Steenmeijer et al. (2022). While we do not know that the distribution of ‘chemicals n.e.c.’ is representative of pharmaceuticals, it is also unlikely that they are sourced completely domestically.

Due to the limited number of studies on the material footprint of healthcare sectors, the lack of information on how the SNAC-EXIOBASE dataset is constructed, and the not completely explainable domination of ‘other minerals’ in the material footprint, it is difficult to value the material footprint results of the Dutch healthcare sector as calculated in this study. Giljum et al. (2019) also showed that national material footprints differ a lot between calculations when using the same material extension but different IO datasets. This difference is mainly caused by the different sectoral resolutions in the primary industries. For the Netherlands, when using ICIO the material footprint per capita is 13.9, while it is 23.5 tons per capita when using Eora (Giljum et al, 2019). This is almost a doubling, indicating that usage of different datasets has a larger influence on the material footprint compared to the carbon footprint.

Lastly, the carbon footprint calculated in this study does not include commuting emissions and anaesthetic gasses as direct emissions, because including them surpassed the goal of this study. As there is little clarity on if Statistics Netherlands includes the direct emissions of anaesthetic gasses in their documentation, we did not include it to avoid double counting. However, as also shown in chapter 5.4 anaesthetic gasses have a large impact during their use phase. Steenmeijer et al. (2022) estimate the direct emissions of anaesthetics to be 1.6% in 2016. The commuting emissions usually are not included in the carbon footprint of a sector, while several studies analysing the Dutch healthcare sector’s carbon footprint do include them (Gupta Strategists, 2019; Steenmeijer et al., 2022). Steenmeijer et al. (2022) show these to be 11% of the Dutch healthcare carbon footprint.

Suggested improvements

Lastly, even though the limitations mentioned in the previous chapters, IOA is a suitable tool to calculate the carbon and material footprints of the Dutch healthcare sector. It is even essential for it can cover direct and indirect emissions that the healthcare sector triggers along the supply chain, which other tools are not capable of. This study suggested two options for improving the calculation of the carbon and material footprint of the Dutch healthcare sector:

1. A hybrid input-output analysis that connects LCA data to the input-output table.
2. A better depiction of the healthcare sectors in the standard input-output table.

Both options are time-consuming and data demanding. The hybrid-IOA improvement is deemed to be not feasible due to the lack of LCA data. For a better depiction of the pharmaceutical industry in IOTs, the 2021 version of the ICIO developed by the OECD is promising because it includes a separate pharmaceutical industry for all countries in the IOT due to the use of the ISIC Rev. 4 economic classification. Before the 2021 ICIO version by the OECD can be used to calculate the Dutch healthcare sector’s carbon and material footprint it first needs environmental extensions and a higher sectoral resolution. However, we still see this solution as the best option because the use of IOTs developed by international statistical organisations has also been seen as the way forward for EE-IOA by other studies (Tukker et al., 2018). Based on the advice of Tukker et al. (2018), the Netherlands Environmental Assessment Agency (PBL) already included environmental extensions to the 2018 ICIO version based on ISIC Rev. 3 (Wilting, 2021). This showcases the willingness of organisations to use the ICIO for environmental footprint calculations.

Until there is an actual high-resolution MRIO that includes a pharmaceutical industry in all countries and has environmental extensions exists, a SNAC approach including a pharmaceutical industry in the country of interest could be preferred for national analyses, because it is based on official national statistical data. It would be really interesting if a similar analysis would be performed for other countries because it offers opportunities to compare the Dutch 'pharmaceutical industry' category in the SNAC-EXIOBASE dataset to other countries' pharmaceutical industry categories. Until then, using a SNAC approach has limited possibilities because of the lack of pharmaceutical industry categories in the other countries in the IOT. A downside of using a SNAC approach or an MRIO that includes the pharmaceutical industry category for all countries is that even with a dedicated pharmaceutical industry in the IOT, aggregation problems can arise due to the heterogeneous character of the pharmaceutical industry itself, as shown in the LCA review of chapter 4. It is important to still use LCA's as a way to identify hotspots in the healthcare sector to be able to improve the carbon and material footprint of the healthcare sector.

7. Conclusion and future studies

This study dived deep into the calculation of the carbon and the material footprint of the Dutch healthcare sector. The research question to be answered was: *How can the relatively large contribution of the product category 'chemicals n.e.c.' to the carbon and material footprints of the Dutch healthcare sector be explained?*

In conclusion, the main research question is difficult to answer as many different aspects influence the observed decrease in the carbon and material footprint of the Dutch healthcare sector. The observed decrease of the carbon footprint by 11% and material footprint by 61% in combination with the multiplier analysis, and the SPA showed that there is an aggregation problem in the EXIOBASE 'chemicals n.e.c.'. This shows that the results observed in previous studies are subject to a substantial aggregation problem, which also makes sense due to the heterogeneity of the products that fall under 'chemicals n.e.c'. Even though there is a decrease in the carbon and material footprint of the Dutch healthcare sector, it is still reasonable to say that the consumption of pharmaceuticals is a large share of the carbon and material footprint. This can be observed by the contribution analysis, where the pharmaceutical industry has the highest carbon, mineral and metal intensity of all four healthcare-related sectors.

This study contributes to the knowledge on the material footprint of the Dutch healthcare sector, which was an identified knowledge gap. It also provides a comparison to Steenmeijer et al. (2022), which was the only study that calculated the Dutch healthcare sector's material footprint. However, we recommend that the results of the material footprint of the healthcare sector are used carefully because this is a new area of research in which we are not yet sure if it represents reality well enough. Especially the hotspot analysis of the material footprint calculated in this study showed that the large share of 'other minerals' is hard to explain. Also, the total minerals extracted per sector in the SNAC-EXIOBASE extension differs compared to the EXIOBASE extension. Without knowing why these values differ, it is unwise to value these results. Therefore, the knowledge gap: "What is the material footprint of the Dutch healthcare sector?" remains a knowledge gap.

This study showcases that the homogeneity assumption of the product group ‘chemicals n.e.c.’ does not hold. It can be seen as a case study that shows the limitations of assuming homogenous product groups in IOA. This study can, therefore, be used as a roadmap for future studies that want to identify possible aggregation problems in IO categories.

The research field of calculating environmental footprints for the healthcare sector of a nation or globally is still relatively new. So far, all studies have used GMRIOs, while none have used a SNAC approach. This study contributes to the field by taking a SNAC approach and by showing that aggregation problems in the EXIOBASE category ‘chemicals n.e.c.’ are an issue when calculating the carbon and material footprint of the healthcare sector. Also, few studies have focussed on the material footprint of the healthcare sector which means there is almost no frame of reference for this study. Therefore, it would be beneficial if future studies (of other countries) focussed on calculating a national healthcare sectors´ environmental footprint also use a SNAC approach with a separate pharmaceutical sector and include a material footprint analysis. It would be interesting to compare default MRIO healthcare studies of other countries to a SNAC approach study, as was done in this study. It would be interesting to see how the results change when using a SNAC approach based on other datasets (SNAC-Eora or SNAC-WIOD). This study also showcased the importance of more detailed information on the direct emissions registered by Statistics Netherlands because in the current situation it is unclear if anaesthetic gasses are included in this.

The motivation of this study originates in the Green Deal Sustainable Healthcare in the Netherlands (GDDZ) in which RIVM (Steenmeijer et al., 2022) is creating a knowledge base for the environmental impacts of the Dutch healthcare sector. We advise RIVM to be careful to use the material footprint results for policy advice since the results of this study and Steenmeijer et al. (2022) differ so much, and relatively little research has been done on this subject, which makes it hard to value these findings. RIVM is also advised to not base their knowledge base too much on the analysis of one year as creating a knowledge base on the environmental impacts of a healthcare sector benefits from trends over the years. The EXIOBASE dataset is available for many different years and the SNAC-EXIOBASE dataset is available for 2010, 2014 and 2016.

We suggest that future studies on the Dutch healthcare sector should focus on using MRIOs that have a separate pharmaceutical industry as this could solve some of these aggregation issues. The 2021 version of the ICIO by the OECD already apply this because they base their IOT on the ISIC Rev. 4 classification. Before the ICIO can be used for healthcare footprint analyses, environmental extensions should be added and the resolution of sectors in these tables should be increased. Due to the economic analysis focus of the OECD, this study recommends that international statistically organisations take the responsibility to increase the resolution of these tables, while research groups or consultancy firms could focus on adding environmental extensions. As this ICIO table by the OECD is a very recent development we advise RIVM to take these developments into account for future studies as studies based on older economic classification systems (like EXIOBASE) will become outdated. Partnering with PBL could be an option since they have experience in working with the ICIO tables. Lastly, LCA studies can be still very useful to indicate hotspots of emissions or material extraction caused by the healthcare sector. Mitigation measures should be based on low-hanging fruit which can better be found by using LCA.

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