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***Assessing a population's need for healthcare***  
***The role of multimorbidity***

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## Abstract (English):

The need for healthcare corresponds to the level of treatable morbidity in a population and is a vital component in healthcare planning to estimate the required number of physicians. As such, the need for healthcare is a complex construct that is ought to be approximated through a robust theoretical concept, considering central indicators. However, a systematic assessment of current methodologies to estimate needs-based supply of physicians using central requirements is missing. In Germany, physician planning follows a supply-based approach using physician-to-population ratios, which are adapted with a demographic factor. In recent years, it was found that multimorbidity (the occurrence of multiple conditions in one individual) is correlated with healthcare utilisation and it has seen a steady increase in prevalence. Thus, multimorbidity as a central driver of need was declared a major challenge for health systems – including Germany – as health systems are centred on single-disease treatment approaches and fragmented in the provision of healthcare. Yet information on the distribution of multimorbid individuals is ambiguous.

This thesis aims to enhance knowledge in both areas: (1) needs-based planning of physicians and (2) necessity to integrate regional multimorbidity in office-based physician planning.

First, a methodological review was conducted to assess current approaches that estimate needs-based supply of physicians through a set of quality criteria while determining the role of multimorbidity. The review highlighted differences in the conceptual frameworks, data bases, modelling approaches and integration of future trends. It was also found that approaches estimating needs-based supply of physicians against quality criteria revealed several weaknesses and methodological gaps, with none of the studies meeting all quality criteria. Importantly, no incorporation of multimorbidity measures in needs-based physician planning was found.

Second, a cross-sectional study was conducted to analyse regional variations of multimorbidity levels in four physician disciplines in Germany: General practitioners (GPs), neurologists, ophthalmologists, and orthopaedic specialists. Bernoulli cluster analysis was applied to detect high-rate and low-rate clusters of multimorbid patients per discipline, with the results tested for robustness through spatial autocorrelation mapping. Additionally, high-rate clusters were compared with the available supply of physicians. The study identified significant variations in the regional distribution of multimorbidity levels. High-rate clusters with varying size and location were predominantly found in central and eastern Germany for all physician groups. The comparison of high-rate clusters with supply demonstrated that almost all high-rate clusters of specialised physicians were met by average supply that exceeded the targeted coverage, but high-rate clusters of GPs were met with average supply below targeted coverage in 5 out of 11 clusters.

To conclude, the methodological weaknesses identified in the systematic review can now be tackled by policymakers and scholars alike to improve future needs-based planning of physicians. Moreover, the variations in regional distribution of multimorbidity clusters highlight the importance of integrating multimorbidity measures when estimating the need for office-based physicians. These findings can be used as an additional resource to reform German physician planning as it will help to direct the planning focus on areas of increased need for healthcare services and care coordination. Given the situation in general practice, improvements in GP care should be targeted most urgently.

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## List of abbreviations

ACG – Adjusted Clinical Groups

AVZ – Angepasste Verhältniszahlen

BW – Baden-Württemberg

BY – Bavaria

BE – Berlin

BB – Brandenburg

CL – Cluster

CIRS – Cumulative Illness Rating Scale

DALY – Disability-adjusted life years

EU – European Union

GP – General practitioner

HB – Bremen

HH – Hamburg

HE – Hessen

ICD – International Classification of Diseases

JBI – The Joanna Briggs Institute

KBV – Kassenärztliche Bundesvereinigung

KR – Kreisregionen

NI – Lower Saxony

MB – Mittelbereich

MMAT – Mixed Methods Appraisal Tool

MV – Mecklenburg-Vorpommern

NW – North Rhine-Westphalia

PRISMA – preferred reporting items for systematic reviews and meta-analyses

RP – Rhineland-Palatinate

SL – Saarland

SN – Saxony

ST – Saxony-Anhalt

SH – Schleswig-Holstein

TH – Thuringia

WHO – World Health Organization

## 1. Introduction

### 1.1 Need for healthcare

#### 1.1.1 Definition

Need is a complex concept without a uniform definition. In his taxonomy of need, Bradshaw [1] defined four types: the normative, the felt, the expressed and the comparative need.

- (I) The *normative need* is the need of an individual as identified by norms laid down by experts and/or administrators. Norms, however, are dependent on the prevailing knowledge and the social values at the time they were laid down, which may be subject to change. An example of normative need in the context of health service planning would be mandatory vaccinations for individuals.
- (II) The *felt need*, also referred to as subjective need, is perceived by the individual and thus, limited to their perceptions which are biased as the individual might not know a service exists or might not be willing to express the need truthfully. Thus, overprediction and underprediction of need in a population might be the result. An example of a felt need would be having stomach-ache.
- (III) The *expressed need*, equal to the demand, is felt need which is acted upon. Thus, under the expressed need all demanded services are considered. A limitation of the expressed need definition is that it includes the bias of felt need and adds the dependency on existing supply. One example which can be applied for health services planning would be to use waiting lists as proxy for unmet need.
- (IV) The *comparative need* is based on characteristics of a population which is receiving certain services and has been used for individual as well as area assessment of need. These services are then compared to the services received by a similar group. If other individuals with resembling characteristics do not receive certain services, then they are assumed to be in need of that service. One example for comparative need is to register risks such as birth trauma of infants who require special care, which are then used to identify infants at risk of special care early.

Bradshaw argues further that the four definitions of need can overlap fully or to only some extent in several variations, with an overlap of all definitions being most reasonable to identify the actual need of a population [1].

After considering the definition of need as a combination of the four types of need, it is vital to distinguish the need for healthcare from the need for health, as the latter entails all shortfalls in health including those that cannot be treated by health services currently available. In turn, the need for healthcare is very specific and refers to a population's capability to profit from healthcare services and interventions [2]. Matthew [3] and Cochrane [4] added to this specification that the healthcare service or intervention needs to be at reasonable costs.

A frequently used definition by Culyer [5] specifies the term 'reasonable costs' further as the least amount of resources needed to fulfil an individual's potential to benefit from healthcare [6]. By doing so, he argues to ensure that need measures are easily interpretable, directly derived from healthcare systems, applicable in the context of horizontal and vertical distribution, person- and services-specific, linked to resources, and are not producing inequitable results [5]. This definition necessitates the accessibility of appropriate treatments and services to improve health outcomes or quality of life [5, 7, 8]. Moreover, Culyer stresses that a treatment should not be classified as appropriate if another identically effective and less resource-intensive treatment is available [5].

Accordingly, the need for healthcare corresponds to treatable morbidity and should be considered a complex construct which cannot be measured directly but must be approximated through a well-grounded theoretical concept, based on central indicators that are related to the need for healthcare [9, 10]. Figure 1 illustrates a systematisation of central indicators that are directly or indirectly related to the need for healthcare for the purpose of this thesis.

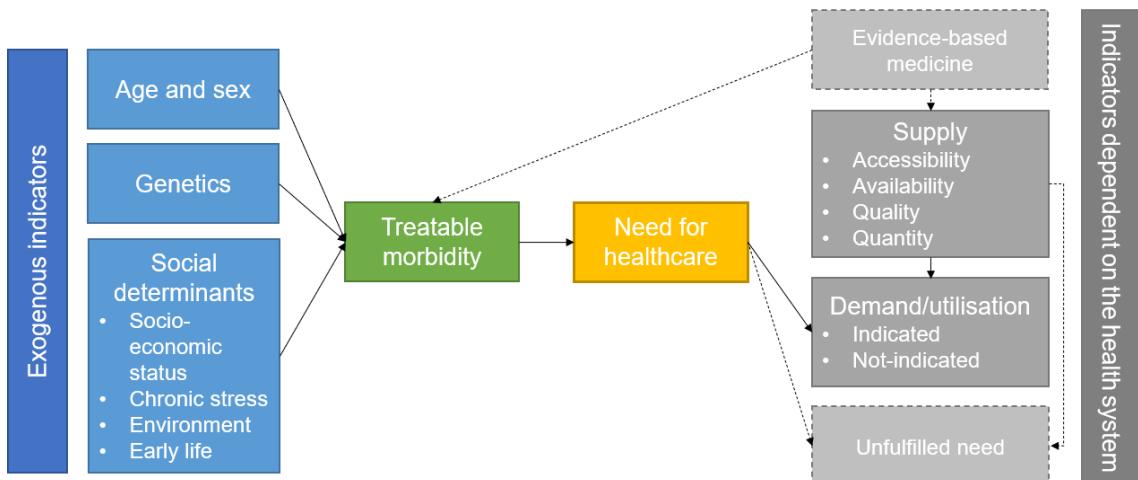


Figure 1 Systematisation of central indicators related to the need for healthcare.

Source: adapted from Sundmacher et al. [10]

### **1.1.2 Indicators related to the need for healthcare**

#### **1.1.2.1 Supply-based indicators**

The need for healthcare matches morbidity that responds to treatments and healthcare services. Thus, it is influenced by supply dependent factors, including the state of evidence-based medicine. Moreover, treatments and services ought to be cost-effective for a disease to correspond to healthcare needs [6]. Therefore, available supply and related factors which are part of the healthcare system may reflect the need for healthcare if the quantity and quality of healthcare services [11] as well as availability and accessibility of appropriate services over space and time is ensured [6].

However, when relying on supply-dependent factors as the main or only indicators of need, existing inequities in access to care and/or availability of treatments (resulting in unfulfilled need or unindicated demand) are carried forward [12–14]. To account for potential biases in supply-based indicators (e.g. due to variable access to care), indicators such as waiting times or missed appointments can be considered in addition to independent variables related to the need to improve the approximation of the need for healthcare [6].

#### **1.1.2.2 Demand/utilisation-based indicators**

The demand for healthcare can be described as the level of utilisation until the conceived marginal benefits of healthcare equal the marginal cost (indirect and direct) of accessing care. Beyond this point, costs offset benefits and an individual will not make use of available healthcare [6]. Thus, demand for healthcare is influenced by healthcare costs to a considerable degree, which are in turn affected by the availability of health insurance, type of health insurance, benefits as well as patient's contributions or out-of-pocket payments [15]. Accordingly, demand-dependent indicators may reflect the need for healthcare if costs do not limit the utilisation of appropriate and cost-effective healthcare services to treat the underlying morbidity.

Nevertheless, relying on utilisation-based indicators to estimate the need for healthcare may lead to overestimation or underestimation of actual need in a population due to patient preferences, availability of care, including affordability of healthcare costs, insurance or time off work, as well as provider incentives such as supply-induced demand [16–19]. Additionally, a recent study found that the availability of health insurances (either private or public) improved access to care but did not promote cost-effective healthcare services [20]. Thus, indicators of healthcare utilisation such as outpatient visits or healthcare expenditure rates reflect the need for healthcare only partially [21]. To account for potential biases from demand-based indicators, which approximate imbalances such as estimates of under detected diseases, uninsurance rates, or uptake rates of routine vaccinations, can be considered conjunct with other factors, including morbidity measures and endogenous indicators [6].

### 1.1.2.3 Exogenous indicators

The need for healthcare correlates with indicators of treatable morbidity independent from the healthcare system, such as demographic variables, individual genetics, and social determinants of health [22–28].

Demographic variables of a person, such as age and sex may significantly influence the likelihood for developing acute and chronic diseases [22–27]. Multimorbidity, for example, appears to be more frequent in women compared to men over all age groups, and both sexes show different disease patterns, with men primarily suffering from several cardiometabolic diseases and women from skeletal and/or mental disorders [29, 30]. Additionally, age and sex may also influence the outcomes and the utilisation of healthcare services [31]. Thus, both indicators are factors to consider when assessing the need for healthcare.

The genetic disposition is known to have an influence on the morbidity of an individual as certain genomes have been associated with specific diseases [28]. Recently, these genetic risk factors were also linked to disability-adjusted life years (DALY) to measure their impact on the quality of life on an individual and population level, which can be used to approximate the need for healthcare [32].

Social determinants of health are social and economic factors that correlate with the need for health services [33]. The socioeconomic status of a person, including education, income, wealth, housing and employment, is associated with the risk of diseases (e.g. obesity) based on factors such as health behaviour (e.g. level of activity) and health literacy [27, 34–37]. Also, chronic stress is known as a risk factor for developing medical conditions, most predominantly cardiometabolic diseases [38]. An individual's health status is also affected by the living and working environment. Regional deprivation (e.g. from air and/or noise pollution) can directly impact health outcomes but also indirectly influences health behaviour such as physical activity levels [27, 39]. Another social determinant which needs to be stressed in this regard are the early life experiences of a person, starting with maternal stress and nutrition during pregnancy, which have a significant influence on the morbidity in later life [40–44]. Maltreatment in childhood (including physical, emotional, sexual abuse, or neglect) was also found to have a significant impact on the development of chronic conditions in adulthood [44]. Additionally, experiencing economic crises in early childhood, like the post-war period in Germany after World War II, was found to be related to an expansion in morbidity in the population when aged 65–71 years [45].

As exogenous factors indirectly approximate the need for healthcare over treatable morbidity, they depend on the accuracy of the relationships between exogenous factors and morbidity levels. Potential inaccuracies due to changes in these relationships may result in over- or underestimations of need. Thus, it is important to regularly reassess established relationships and to combine estimates from exogenous factors with, for instance, other measures of morbidity to ensure that the need for healthcare is accurately predicted [10].

#### 1.1.2.4 Treatable morbidity

Treatable morbidity, including one or several cooccurring diseases directly influences the need for healthcare based on the definition set out in the previous chapter, so it is a central parameter for approximating the need in a population (see Figure 1). Apart from indirectly estimating treatable morbidity by exogenous factors as described above, morbidity levels, morbidity patterns and trends in morbidity can be directly retrieved from incidence and prevalence rates as well as prognoses of diseases from epidemiological studies, medical records, disease registries, or insurance claims data [10, 46, 47].

However, the validity of morbidity estimates may vary depending on the sample size, data collection technique, and data source [46]. As treatable morbidity is amongst other things subject to changes in the current state of evidence-based medicine, it is vital to regularly update estimates to ensure validity and accuracy. Additionally, morbidity measures should be related to exogenous factors, so changes in for instance the demography of a population can be taken into account [10].

## 1.2 Physician planning

### 1.2.1 Overview

Human resources, specifically physicians and their spatial and temporal availability play a central role in meeting the need for healthcare of a population, directly impacting the functionality of healthcare systems. Therefore, the overall objective of physician planning is to guarantee that a sufficient amount of physicians, with an adequate skillset is available to deliver cost-effective health services to the population at the right place and time, making physician planning not only a technical process but also a political topic of interest [48, 49].

Healthcare systems, irrespective of their financing model, experienced difficulties to meet this aim under given resource constraints [4]. In particular, publicly funded healthcare systems seem to struggle with financial sustainability as increased healthcare expenditures are not necessarily linked to increased need, which is why effective planning and management of healthcare resources based on the population's need is required [50].

There are several studies summarising approaches used for physician planning [47, 49, 51]. The three main approaches described in the literature for healthcare planning are the needs-based approach, the supply-based approach, and the utilisation/demand-based approach [48, 52]. Despite being distinct, the approaches may also overlap to various degrees with no uniform classification. Depending on the indicators used in each method as outlined in the previous chapter, every approach is capable of reflecting the need for healthcare under certain assumptions. A short summary of each method and the hypothesis under which it reflects the need for healthcare, can be found in Table 1. Even though several approaches for physician planning exist, a systematic assessment of the application of each approach is yet missing.

Table 1 Short summary of the three main methods applied in physician planning and hypothesis under which they reflect the need for healthcare of a population.

<b>Method</b>	<b>Summary</b>	<b>Hypothesis</b>
Needs-based approach	Needs-based approaches estimate healthcare requirements based on age and sex-specific approximated levels of morbidity in the population, including service norms and trends in morbidity derived from epidemiological, demographic, and sociocultural studies, as well as expert opinions, which are subsequently converted via productivity norms/estimations into workforce requirements.	Needs-based approaches reflect the need of a population, if estimations/predictions of healthcare requirements match actually required healthcare services.
Supply-based approach	Supply-based approaches use indicators derived from existing supply to estimate the need for healthcare. In their basic form, supply-based approaches use workforce-to-population ratios (densities) which are set at a proposed threshold as the main indicator to estimate the health workforce needed. More complex approaches try to account for existing imbalances (e.g., limited availability) in various forms.	Supply-based approaches reflect the need of a population, if access to care as well as availability, quality, and quantity of health services are ensured for everyone and remain constant over time.
Utilisation/demand-based approach	Utilisation-based approaches use actual or estimated utilisation rates, which are related to demographic characteristics of the population and subsequently converted into workforce requirements based on population projections. Similar to supply-based approaches, complex utilisation-based approaches try to account for imbalances such as unmet need and supply-induced demand.	Utilisation-based approaches reflect the need of a population, if utilised services are indicated, remain constant over time, and are not influenced by subjective needs, limited access, or are induced by supply.

Regardless of the selected approach, there are four central requirements for physician planning, which should be considered [10]:

- (I) A strong conceptual basis is required to approximate the need for healthcare and to define appropriate variables, also considering potential biases of each indicator.
- (II) Representative and accurate data sources have to be identified and secured to depict these variables, also considering timeliness and availability of data.
- (III) Suitable models need to be selected and tested to estimate the need for healthcare. Subsequently, these estimates have to be linked to service/time requirements of physicians in order to translate them into physician capacities.
- (IV) The sustainability of these estimates have to be outlined, including the planning horizon and underlying assumptions regarding future trends and developments [10, 47–49].

Following these requirements can help to improve physician planning by reducing imbalances in current supply estimations.

### 1.2.2 Physician planning in Germany

As healthcare in the European Union (EU) is the responsibility of the member state, every country follows its own approach [53]. Physician planning in Germany started in 1977 and was reformed in the 1990s with the aim to cap the number of office-based physicians by introducing a simple supply-based approach (physician-to-population ratios) with a proposed threshold of the physician density of 1990 [10].

On a national level, the number of physicians needed per discipline and planning level are designated by the self-administered German National Association of Statutory Health Insurance Physicians (*Kassenärztliche Bundesvereinigung*, KBV) [10]. In 2012 and 2015, additional laws were passed as a response to new challenges in physician planning, especially demographic changes. Thus, a so-called demographic factor was introduced to correct the physician-to-population ratios for additional service needs of older adults (65+ years of age compared to 64 years and younger). Moreover, Associations of the Statutory Health Insurance Physicians in each state were given the opportunity to demand regional adaptations of the physician-to-population ratios to so-called ‘adapted physician-to-population ratios’ (*angepasste Verhältniszahlen*, AVZ) based on regional characteristics, specifically morbidity and demography, which go beyond the corrections resulting from the demographic factor but have to be in agreement with relevant state administrative bodies [54].

Since 2019, physician-to-population ratios are adapted with a morbidity factor instead of the demographic factor, which accounts for demographic changes, but also for regional morbidity levels according to two categories, namely increased morbidity and no increased morbidity. An individual is thereby classified under ‘increased morbid’, if the records of the statutory health insurance show at least six diseases out of a list of

diseases set by the Federal Insurance Office over a period of two billing quarters. Subsequently, the regional age, gender, and morbidity distribution is compared with the federal level and adapted with a physician-specific requirement factor. No further adaptations to account for potential oversupply or undersupply of services are currently considered. However, the resulting adapted physician-to-population ratios are updated every two years [55].

## 1.3 Multimorbidity

### 1.3.1 Classification

Multimorbidity has been defined in various ways. The World Health Organization (WHO) as the entity responsible for setting international norms and standards, defined multimorbidity as at least two simultaneously occurring chronic health conditions, without further defining the word 'condition' and thus leaving room for interpretation [56–58]. As a consequence, over the last decades researchers have employed several definitions of multimorbidity. The most recent systematic literature review found that multimorbidity is most commonly defined as the occurrence of multiple diseases or conditions (threshold typically set at two and above) in one individual [59], with one included study suggesting that the second disease/condition can also be substituted by a biopsychosocial factor or somatic risk factor [58].

Based on their great extent, methods employed to classify multimorbidity are explained separately in the next chapter.

### 1.3.2 Methods to measure multimorbidity

Similar to the variations in definitions, there is no uniform and internationally accepted method to classify multimorbidity to date. Nevertheless, some methods are more frequently applied than others. The four most commonly applied methods to measure multimorbidity in a population are in alphabetical order the Adjusted Clinical Groups (ACG) system, the Charlson co-morbidity Index, the Cumulative Illness Rating Scale (CIRS), and the disease counts approach [59, 60].

The ACG software matches individuals based on their risk score to one of 100 groupings. The risk scores are calculated through age, sex, and diagnosis groups, which are observed over a certain period of time (usually 12 months). The groupings were used amongst others to estimate the morbidity burden in a certain population [61]. The software, which was designed for data from medical records or insurance claims is available for a fee under several licence types, depending on the area of application [60]. The system is continuously evolving and was previously applied, for example, in the field of population profiling, performance analysis and resource allocation [62].

According to the Charlson's index [63], comorbidities of patients are categorised based on the International Classification of Diseases (ICD) codes, and weights for originally 18

disease categories (chronic and acute) are assigned to each patient, ranging from one to six with six being most severe. If a patient suffers from several diseases, the sum of all weights builds the final score. The Charlson Index was primarily used to assess and predict the effect of comorbidities on mortality [60, 64] but has also been used in its adapted form to predict resource utilisation [65]. Despite the fact that there are variations of the Charlson index, all of them were found to produce similar results [60].

The CIRS is used for measuring chronic comorbidities via 14 categories, rating the person's impairment due to the disease on a scale of 0 (no impairment) to 4 (severe impairment). As the name suggests, the cumulated ratings of the 14 categories are used as final score. CIRS can be recorded during consultations or derived from claims data or medical records. Higher CIRS scores were related to higher mortality and higher healthcare utilisation rates. The CIRS is available in adapted versions which all have been found to obtain similar results [60, 66, 67].

The disease counts approach was most frequently used in the literature to measure multimorbidity. An individual is classified as multimorbid based on simple counts of diseases, disease categories, and/or risk factors from a predefined list. The number of items per list was found to vary between 9 and 40 [60, 68]. Compared to weighted methods, disease counts approaches are applied to detect influences of multimorbidity on multiple health outcomes or for outcomes where no validated measure exists [59, 60].

In general, methods to measure multimorbidity should be chosen according to the objective of the study and based on the validity of the method. Regarding appropriate data sources to measure multimorbidity, no recommendations are found in the literature on preferred data sources. Nevertheless, the selection of the data source is crucial as findings from self-reported surveys may result in different prevalence rates of multimorbidity compared to findings from claims data or medical records (e.g. due to recall biases). Therefore, the selection of the data source has an effect on the outcomes of the study [59].

### 1.3.3 Influence of multimorbidity on healthcare utilisation

Research suggests a strong correlation between multimorbidity and healthcare utilisation of several types [57, 61, 69–73]. The most frequently mentioned uses of healthcare services are summarised below.

Outpatient visits of multimorbid individuals, specifically in older adults, were found to be more than twice as high compared to patients with only one or no chronic condition [69–72, 74]. Additionally, multimorbid patients were found to be frequent emergency department visitors (four or more visits per year), having a significantly increased likelihood when suffering from three to five chronic conditions [72, 75]. Moreover, multimorbid patients are associated with higher hospitalisation rates [72].

The occurrence of certain conditions in multimorbid patients were also found to have an influence on the utilisation of health services. Acute coronary syndromes, for example, in multimorbid patients were less often treated with evidence-based treatments and were found to require longer average hospital stays [76]. Moreover, dementia combined with acute myocardial infarction, chronic kidney diseases, heart failure, or rheumatoid arthritis/osteoarthritis had significantly higher risk ratios for annual hospital visits compared to combinations with other chronic diseases such as hypertension or diabetes [77]. Also, Parkinson's disease and cardiac insufficiency were found to be responsible for the largest share of the healthcare costs for multimorbid patients [78]. In general, mental health conditions in multimorbid patients were associated with an increased use of health services and extended consultation lengths [79]. The precise effect of multimorbidity (with or without mental health conditions) on the consultation lengths in terms of additional minutes, however, remains unknown [70, 80, 81].

Another factor that was found commonly present in multimorbid patients was polypharmacy, which leads to more frequent interactions with health services and makes multimorbid patients vulnerable to safety issues [57, 82]. Moreover, the frequent use of potentially inappropriate medications was found to negatively impact the health outcomes of multimorbid patients [83]. Despite the fact that interventions to reduce inappropriate prescribing and healthcare utilisation exist, there is limited evidence on their effect on clinical and patient-related outcomes [84].

Multimorbidity does not only affect older adults. Research on young adults showed that multimorbidity was common in individuals under 30 years of age [85, 86], with increasing rates specifically among women [87, 88]. Being multimorbid as a young adult was found to be related to an increased number of sick days and impaired health-related quality of life, which further increased the economic burden attributed to multimorbidity [88, 89]. No study was found to describe the healthcare utilisation pattern of multimorbid adolescents or children compared to healthy individuals.

One limitation in multimorbidity studies is that they focused mainly on the influence of multimorbidity on healthcare utilisation in general, irrespective of the physician discipline [74, 90, 91]. Thus, it remains uncertain whether utilisation patterns of multimorbid people affect office-based physicians similarly or whether some physicians are more affected than others [92]. This knowledge, however, is critical to distribute healthcare resources efficiently [10].

As definitions and methods to classify multimorbidity vary, the results need to be treated with caution as they might not be directly comparable (or transferable) to other settings [93]. Moreover, since multimorbidity is associated with general indicators of morbidity such as the socio-economic status [94] which in turn influences healthcare utilisation itself, interactions of multimorbidity and other indicators need to be considered [73, 95].

#### **1.3.4 Trends in multimorbidity**

Multimorbidity was declared a major challenge for national health systems with a steady increase in prevalence over the last decades in varying percentages depending on the underlying population [57, 93, 96–98]. In countries of the EU, for example, average annual percentage change in multimorbidity from 2004 to 2017 found in an ecological survey ranged from 1.0 and 0.9 in France (lowest increase) to 6.9 and 3.3 in Germany (highest increase) for men and women, respectively [98]. Current estimates also suggest that 36% of EU citizens aged  $\geq 65$  are suffering from two or more chronic diseases, with women being more frequently affected than men [53]. In general, the multimorbidity burden was also found to expand over time across all age and sex groups, leading to a greater increase of lifetime spent with multimorbidity than the increase of life expectancy [99] with demographic changes in terms of an aging population believed as main drivers for the increase in multimorbidity [57, 100, 101].

Similar to healthcare utilisation, progression of multimorbidity was found to be dependent on health conditions and the socio-economic background of an individual. For morbidity clusters of metabolic and cardiovascular conditions, for instance, factors such as socio-economic status and related physical activity as well as alcohol/tobacco consumption had a significant effect on the progression of multimorbidity [93, 102]. Additionally, clusters of major mental health conditions such as dementia and bipolar or manic mood disorders have significantly increased over time compared to other chronic diseases like cardiac valve diseases or skin ulcer (including decubitus) [100, 103].

The COVID-19 pandemic also increased the number of people suffering from mental health conditions, such as depression, and thus, may have led to an increase in multimorbidity. Additionally, due to long COVID, which affects young and older adults alike (about 10% of people infected with COVID-19 are estimated to suffer from long COVID), further increases in several chronic conditions are expected in the upcoming years [53].

With a rising number of multimorbid individuals and a case-mix towards more severe diseases, healthcare expenditures are expected to increase substantially, putting health systems that are historically centred on single-disease treatment approaches under additional pressure [93, 99, 100]. Specifically, the fragmentation of care and the lack of integrated care approaches pose major challenges to the treatment of multimorbid patients [93].

#### **1.3.5 Multimorbidity in Germany**

Although international studies defined multimorbidity with at least two diseases/conditions, many studies conducted in Germany set the threshold to three or more chronic diseases. Such studies argue that two chronic diseases were found in almost all older adults, so three chronic diseases would provide a superior depiction of increased disease burden [83, 90, 102, 104–108].

As there is no common definition of multimorbidity in Germany, prevalence rates vary from 17% to 80% [104]. For example, Frank et al. [105] found that between 2007 and 2014 the percentage of multimorbid individuals over at the age of 65 and above increased by 8% (from 68% to 76%) and 9% (from 63% and 72%) for women and men, respectively. In the study, a person was identified as multimorbid if a minimum of three diseases out of a list of 46 chronic conditions were coded in three out of four quarters from claims data from the public health insurance.

In contrast, Souza et al. [98], who used the definition of two or more chronic diseases and classified multimorbidity based on eleven non-communicable diseases that were grouped into five categories, reported an estimated annual average percentage change in multimorbidity from 2004 to 2017 of 6.9% in men and 3.2% in women among people aged 50 and above, starting with multimorbidity levels around 30% for both sexes in 2005 in Germany, with women having slightly higher levels. The data source was obtained by six waves of an ecological study, surveying health, ageing, and retirement across Europe.

No data newer than 2017 and no studies that estimate the multimorbidity burden of people under 50 years across Germany were found.

## 1.4 Aim of the thesis

The aim of this thesis was to systematically assess current approaches that estimate needs-based supply of physicians and to add to the current knowledge where major methodological gaps occur. Furthermore, it intended to test the necessity of integrating regional multimorbidity levels when assessing the need for healthcare, which are hypothesised as proxy for additional healthcare need in a population, in the context of office-based physician planning in Germany. Thus, the following research questions were addressed:

- (I) Do previous studies that estimate needs-based supply of physicians follow quality criteria regarding the conceptual basis, data sources, model selection including translation into provider requirements, and sustainability of the results?
- (II) Do multimorbidity levels vary regionally and between disciplines exemplified by four office-based physician groups in Germany?
- (III) Can the supply of physicians meet the potentially greater need for care and care coordination in areas with significantly higher rates of multimorbid patients exemplified in the case of Germany?

The findings of this thesis can be applied by policymakers and healthcare planners alike to reform current strategies by improving their approaches to estimate needs-based supply of physicians and by strengthening care provision in areas with high multimorbidity levels. The overall objective was to improve the quality of office-based care from both a patient and a provider perspective.

## 2. Material and Methods

### 2.1 Study design

The thesis followed a mixed-method design. First, a systematic, methodological review was performed to evaluate approaches that quantify the need for healthcare in high-resource setting. Second, a cross-sectional study was set up to assess regional variations of multimorbidity levels in selected office-based physicians through cluster analysis in Germany. Additionally, high-rate clusters of multimorbid patients were compared with the current supply of physicians to assess whether the supply could meet potentially greater needs in high-rate areas.

### 2.2 Methodological literature review

As a systematic assessment of approaches to estimate needs-based supply of physicians was yet missing, the main aim of the methodological literature review was to systematically analyse methodologies applied in previous studies that estimated needs-based supply of physicians in high-resource settings. Additionally, the current role of multimorbidity as an emerging driver of healthcare need is determined.

*Disclaimer: Materials and methods from the methodological review have already been published by Geiger et al. ([109]).*

#### 2.2.1 Search strategy and study selection

The preferred reporting items for systematic reviews and meta-analyses (PRISMA) flow diagram and the PRISMA 2020 checklist were used to guide the review (see Figure 2) [110, 111]. First, PubMed, ScienceDirect and Web of Science Core Collection as the largest bibliographic databases were searched in April and October 2017 for peer-reviewed articles that fulfil the predefined selection criteria noted in Table 2 using logical combinations of keywords that included ‘workforce planning’, ‘capacity planning’, ‘health human resource’, ‘service requirement\*’, ‘physician’, ‘need’, ‘demand’. An update search in all databases was performed in March 2020 (before the outbreak of the COVID-19 pandemic) to ensure that recent literature was included. The results were not restricted by filters and the citation manager software Mendeley was used to collate the literature search results. The full list of keywords used and the respective results per bibliographic database can be found in Appendix A. Next, hand searches on international and national internet sites including amongst others WHO (Regional Office for Europe), were performed to detect additional literature. To complement the results obtained from bibliographic databases and hand searches, author searches and mining of sources from retrieved literature were carried out.

Table 2 Overview of inclusion and exclusion criteria.

	<b>Criterion</b>	<b>Meaning</b>
Inclusion	Quantification of need in physician capacities	The need for healthcare had to be quantified and converted into physician capacities.
	Date of publication	The search period was restricted to the timeframe between January 1980 and March 2020.
	Language restrictions	To prevent errors in translation, language was restricted to English and German.
Exclusion	Predicting physicians	Studies were excluded if existing supply was forecasted without using measures relating to healthcare needs.
	Hospital care	The studies included were restricted to office-based physician planning due to differences in resource allocation.
	Other healthcare professionals	To avoid any biases resulting from estimations of other healthcare professionals, only studies estimating physician supply were included.
	Low-resource settings	Due to unique contexts and constraints in data accessibility, only studies in high-resource settings were included.

Source: adapted from Geiger et al. [109]

Screening of the identified literature was conducted by two independent researchers based on the predefined selection criteria in Table: To be included, a study had to quantify a population's need for healthcare and translate it into physician requirements. Moreover, to avoid any translation biases, studies had to be available either in English or German. All studies that primarily forecasted the supply of physicians based on expected changes in age and gender of the population without including any other indicators of need, were excluded from this review, as they do not assess the need for healthcare. Moreover, studies that focused on workforce planning in hospital care or on healthcare professionals other than office-based physicians were disqualified as they lie outside the scope of this review. Additionally, studies that focused on physician planning in low resource settings were also excluded due to significant differences in healthcare provision and different priorities in healthcare.

After removing duplicates, abstracts were examined by each reviewer, independently. If a study fulfilled all selection criteria mentioned above, full texts were acquired. Both parties settled any disagreements until they reached a consensus. A detailed protocol of the reviewing process can be found in Appendix A.

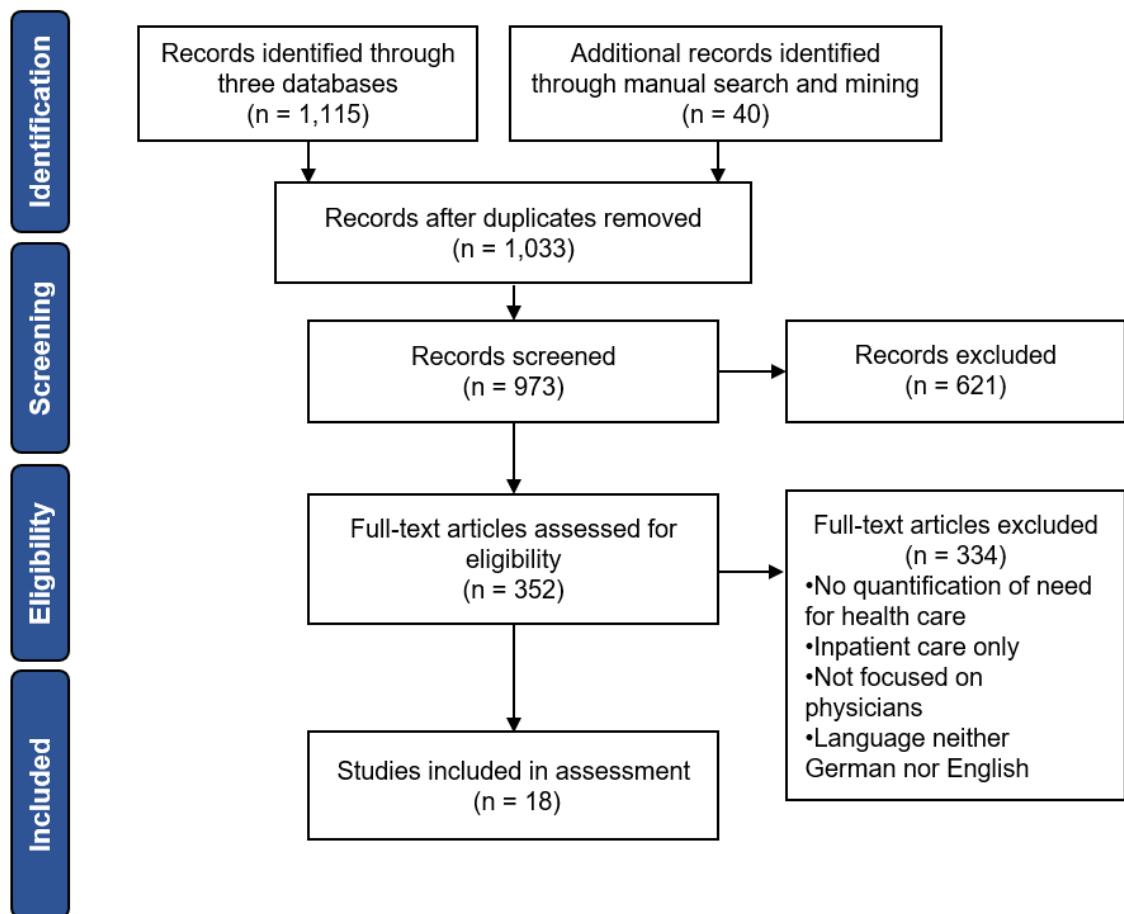


Figure 2 PRISMA flowchart adapted from Moher et al. [111]

Source: Geiger et al. [109]

### 2.2.2 Data collection and synthesis process

For data collection, a matrix with columns representing the four central requirements of physician planning (quality criteria) as defined by Sundmacher et al. [10] was developed. Each requirement was further divided into subcategories, leading to a set of ten criteria which were used to systematically assess each study. An overview of the criteria within the central requirements, including the respective statement to each criterion can be found in Table 3. Also, main characteristics of each study, such as year, planning unit or country of origin were added as columns to the matrix next to the central requirements.

To synthesise the results, the realisation of each criterion is indicated with 1 (the criterion is met) or 0 (the criterion is not or only partially met). Moreover, a short description of how the criterion was presented per study is given in the framework. Each study is thereby represented in a single row. However, if a study applied several approaches, each approach was assessed individually, thus having a separate row.

Table 3 Overview of quality criteria for physician planning.

Criteria	Statement
<b>1. Conceptual framework</b>	
1.1 Selection and justification of needs indicators	The selection of indicators is well-founded and, if possible, empirically supported based on the actual context of the study.
1.2 Relationship between supply and need	The conceptual dependency of indicators of need on supply in general regarding unmet need/lack of physicians or overuse/oversupply are explored and, if feasible, accounted for in the analysis.
<b>2. Data basis</b>	
2.1 External validity	The population for which providers are to be planned and the population from which data are used are identical or representative.
2.2 Internal validity	The observed data accurately measures the indicators of interest.
2.3 Timeliness and availability	The timeliness of data and availability of data sources is reported and considered with respect to the intended planning horizon.
<b>3. Modelling and conversion into physician requirements</b>	
3.1 Transformation into provider requirements	The estimated need for healthcare is related to some measure of provider productivity to transfer the estimated service requirement to physician capacities.
3.2 Model selection and validation	The statistical model is appropriate and well-founded, and the validity and the robustness of the findings were established.
3.3 Level of analysis	The level of analysis is defined and discussed regarding the potential for ecological errors.
<b>4. Integration of future trends and developments</b>	
4.1 Projection variables	Projection variables are present that can be modelled according to future changes in the population's need for healthcare.
4.2 Planning horizon	The chosen planning horizon is justified appropriately with respect to future changes.

Source: adapted from Geiger et al. [109]

### 2.2.3 Risk of bias assessment

When defining the quality criteria based on central requirements, appraisal tools such as the Mixed Methods Appraisal Tool (MMAT) [112] and the appraisal tools of The Joanna Briggs Institute (JBI) [113] were consulted to ensure that the framework is in line with other assessment tools. However, as no appraisal tool to assess the risk of bias at the time of writing was found to be suitable for a methodological assessment of different study types, the development of an own matrix was deemed more suitable to the purpose of our study.

## 2.3 Cross-sectional study

The cross-sectional study was used to provide an overview of variations in multimorbidity across Germany and to examine whether regional multimorbidity levels should be considered for needs-based physician planning.

*Disclaimer: Materials and methods from the cross-sectional study have already been published by Geiger et al. [92].*

### 2.3.1 Study population

Physician planning in Germany is responsible for accommodating the healthcare needs of all individuals under the German statutory health insurance. Thus, the study population for this analysis comprised all publicly insured Germans.

The office-based physician groups under study included general practitioners (GPs), neurologists, ophthalmologists, and orthopaedic specialists. GPs and ophthalmologists were selected based on having the highest outpatient rates and thus treat the highest number of patients per year [91]. Moreover, GPs as central contact points for care coordination, may encounter the highest amount of multimorbid patients of all outpatient physician groups. Neurologists and orthopaedic specialists were included in the study as musculoskeletal disorders and diseases of the nervous system account for the largest percentage of chronic illnesses in Germany, apart from cancer and circulatory diseases [114]. Additionally, disease patterns in combination with dementia, Parkinson's disease or rheumatoid arthritis/osteoarthritis, were found to be associated with a significant increase in healthcare utilisation, which may mostly concern neurologists or orthopaedic specialists, respectively [77, 78].

### 2.3.2 Data source

Claims data from all Germans that were insured under the statutory health insurance over all four quarters of 2015, were made accessible by the KBV for the cross-sectional study to classify multimorbidity levels in the population. In addition to the recorded diseases, the area of residency of an individual and the number of patient visits per

physician group were available in the dataset. The dataset was originally used for a report regarding physician planning in Germany [10].

Current numbers of office-based physicians in fulltime equivalents and AVZs per respective planning unit were provided in a survey collected by the KBV in 2016.

### 2.3.3 Measures

#### 2.3.3.1 Multimorbidity

In line with the majority of German studies that examine multimorbidity, individuals suffering from at least three chronic diseases were defined as multimorbid. Following the disease count approach, 40 chronic disease categories as recommended by Barnett et al. [68] were used to classify multimorbidity. The disease count approach was preferred to weighed measures such as the Charlson Co-Morbidity Index, as the purpose was to detect physician-specific variations in multimorbidity levels. Weighted measures were designed for predicting the influence of multimorbidity on particular outcomes such as mortality rather than epidemiological studies (see Chapter 1.3.2.).

One advantage of using the disease categories of Barnett et al. [68] is that they consist of both mental and physical health conditions, and thus represent a great variety of diseases. However, the categories are not linked to the ICD. Thus, ICD-10-GM codes were merged to each category and subsequently validated by two medical specialists. A list of all categories and respective ICD-10-GM codes can be found in Appendix B.

To account for potential errors in coding and to ensure that the coded diseases are manifested in an individual, each category had to be diagnosed in at least two quarters of the year 2015. Finally, the number of multimorbid patients per physician was aggregated to the respective planning unit of each physician discipline, namely the '*Mittelbereich*' (MB) for GPs and the '*Kreisregion*' (KR) for neurologists, ophthalmologist, and orthopaedic specialists.

#### 2.3.3.2 Physician supply

Physician supply per discipline was defined as physician coverage [in percent] per discipline and planning unit: First, the respective AVZ was used to calculate the targeted number of physicians per planning unit. Next, the actual number of physicians available in 2016 were divided by the targeted values and multiplied the results with 100 to receive the physician coverage per physician discipline and planning unit in percent.

Subsequently physician coverage per discipline and planning unit were divided into five levels according to KBV thresholds used for physician planning as outlined in Table 4.

Table 4 Classification for physician coverage

Level and definition	Percentage physician coverage
1 – shortage	<75% for GPs and <50% for specialists
2 – imminent shortage	75 to <100 for GPs and 50 to <100% for specialists
3 – target coverage	100 to <110% for all physicians.
4 – potential excess	110 to <140% for all physicians
5 – excess	≥140% for all physicians

Source: own contribution

### 2.3.4 Statistical methods

#### 2.3.4.1 Descriptive statistics

Multimorbidity levels from claims per physician were descriptively summarised in absolute numbers of multimorbid patients and proportions of multimorbid patients per physician discipline. Moreover, boxplots of multimorbidity shares (in percent) were calculated as measures of dispersion and compared between disciplines. The underlying hypothesis was that substantial variation in multimorbidity shares would support the need to incorporate multimorbidity measures per physician discipline when estimating needs-based physician supply.

#### 2.3.4.2 Bernoulli cluster detection

Spatial scan statistics were selected to measure and test regional variation in multimorbidity between physician disciplines. More specifically, the Bernoulli model was applied to detect high-rate and low-rate clusters of multimorbid patients across Germany.

Based on Kulldorff [115], the spatial point process is expressed as  $N$  with  $N(A)$  being an arbitrary amount of points in the set  $A \subset G$ , and with  $G$  being the geographical area. When the scanning window moves over the study area, it defines a collection ( $\mathcal{Z}$ ) of zones ( $Z$ ) in the subset of the geographical area ( $G$ ). Measures ( $\mu$ ) are only considered so  $\mu(A)$  is an integer of all subsets ( $A \subset G$ ) with each unit of measure corresponding to a patient who is in one of two states ('multimorbid' or 'not multimorbid'). Patients with multimorbidity are defined as points and the respective area constitutes the point process. Within the zone  $Z \subset G$ , each patient has the probability ( $p$ ) of being multimorbid; outside the zone, the probability ( $q$ ). Importantly, the probability of a patient is independent from all others. The null hypothesis for the Bernoulli cluster detection is  $H_0: p = q$ , and the alternative hypothesis is  $H_1: p > q, Z \in \mathcal{Z}$ .

For the likelihood ratio test,  $n_Z$  represents the number of multimorbid patients within the zone ( $Z$ ) and  $n_G$  the total number of multimorbid patients [115].

Thus, the likelihood function (1) can be expressed as:

$$L(Z, p, q) = p^{n_Z} (1-p)^{\mu(Z)-n_Z} q^{n_G-n_Z} (1-q)^{(\mu(G)-\mu(Z))-(n_G-n_Z)} \quad (1)$$

To identify the most likely cluster, the zone ( $\hat{Z}$ ) that maximises the likelihood function needed to be found. In summary, the test statistic (2) can be expressed as:

$$\lambda = \frac{\sup_{Z \in \mathbb{Z}_{p>q}} L(Z, p, q)}{\sup_{p=q} L(Z, p, q)} = \frac{L(\hat{Z})}{L_0} \quad (2)$$

Thus, the denominator is only dependent on the total number of multimorbid patients and not on their spatial distribution. To detect low-rate areas of multimorbid patients, the direction of the underlying equation can be changed (also compare [115]). Finally, Monte Carlo simulations were used to attain the likelihood ratios and the respective p-values.

The centroids (point processes) in the analysis corresponded to the planning units (MBs for GPs and KR for all specialised physicians) and patients with and without multimorbidity area aggregated accordingly. As suggested by Kulldorff [116], the maximum size of a spatial cluster was set to 50% of the study population with a circular shaped scanning window. The Bernoulli cluster detection was used to identify high and low rates of multimorbid patients under the premise that the KBV data recorded in 2015 was representative of all publicly insured. High-rate clusters were hypothesised to correspond to a greater need for healthcare and care coordination, whereas low-rate clusters were presumed to indicate no added need for health services. Significant clusters were outlined and compared descriptively and spatially displayed on maps for each physician discipline. For this study, statistical significance was set to a p-value < 0.01. Scanning statistics were executed via SaTScan (version 9.6).

#### 2.3.4.3 Robustness test

Spatial autocorrelation mapping of high-rate and low-rate clusters was performed in QGIS (version 3.22.4) to estimate the robustness of the results. According to Anselin [117], the local Moran's I (3) can be expressed as:

$$I_i = z_i \sum_j w_{ij} z_j \quad (3)$$

Where observations  $z_i$  and  $z_j$  are variations from the mean with the summation over  $j$  only comprising neighbouring values  $j \in j_i$  [117]. Therefore, spatial autocorrelation is dependent on multimorbidity levels of neighbouring planning units compared to the Bernoulli model, which is dependent only on the total number of multimorbid patients.

### 2.3.4.4 Comparison of high-rate clusters with current physician supply

In a last step, the high-rate areas, which are hypothesised as pointing to greater health- and integrated care needs, are graphically and descriptively compared with levels of physician coverage to estimate whether the current supply can meet the increased needs in these areas. The underlying assumption was that planning units with a higher probability of multimorbid patients require a great(er) number of physicians to adequately meet their healthcare requirements. As the AVZ, which constitutes the basis of the physician coverage, should comprise need requirements per planning unit and due to the lack of other classifications, level 3 and above as outlined in Chapter 2.3.3 were considered suitable to meet the needs of high-rate areas.

All data in this study were analysed and prepared using CRAN R (version 4.0.3). All maps were produced using QGIS (version 3.22.4).

### 3. Results

#### 3.1 Methodologies to estimate needs-based supply of physicians

*Disclaimer: Results from the methodological review have already been published by Geiger et al. ([109]).*

##### 3.1.1 Descriptive summary of studies

As noted in Chapter 2.2.1, the review identified 18 studies out of more than 1,000 records when searching for needs-based supply of office-based physicians. Table 5 descriptively summarises the year of publication, the country in which the study was carried out, and the physician discipline that was estimated.

Most studies ( $n = 12$ ) were published between 2011 and 2017, with the remaining six studies issued between 1995 and 2010. However, there was a gap between 1998 and 2008, where no suitable study was found. Moreover, no suitable study was found between 1980 and 1994.

The country with the highest number of studies identified was Germany ( $n = 7$ ), followed by the USA ( $n = 5$ ) and Canada ( $n = 2$ ). One study each was derived from Australia, Singapore, Spain, and the UK.

The physician disciplines that were estimated in the studies varied extensively, ranging from 1 up to 43. Studies focussing on one physician discipline predominantly assessed eye care professionals, GPs, and mental health professionals, with two studies each. Dental care, oncologists and otolaryngologists were estimated once each.

Most studies ( $n = 15$ ) estimated needs-based supply of physicians based on a single approach. However, three studies were included that applied two [118], three [119], or four approaches [120]. Thus, the overall number of approaches included in the review exceeds the number of studies ( $n = 24$ ).

Table 5 Descriptive overview of studies included in the review.

	<b>Frequency</b>	<b>Reference(s)</b>
Year	1995-2002: n = 3	[118, 119, 121]
	2003-2010: n = 3	[122-124]
	2011-2017: n = 12	[120, 125-135]
Country	Australia: n = 1	[131]
	Canada: n = 2	[124, 129]
	Germany: n = 7	[125-128, 132, 134, 135]
	Singapore: n = 1	[120]
	Spain: n = 1	[122]
	UK: n = 1	[130]
	USA: n = 5	[118, 119, 121, 123, 133]
Physician discipline	Dentists: n = 1	[127]
	Eye care professionals: n = 2	[118, 120]
	GPs: n = 2	[130, 131]
	Mental health professionals: n = 2	[123, 126]
	Multiple professionals: n = 9	[121, 122, 124, 125, 128, 132-135]
	Oncologists: n = 1	[129]
	Otolaryngologists: n = 1	[119]

Source: adapted from Geiger et al. [109]

### 3.1.2 Review against quality criteria

The review against the central requirements, which were used to synthesise the studies and assess the risk of bias, showed that no study was able to meet all appraisal criteria. The study adopting most methodological requirements to estimate needs-based supply was Dall et al. [133]. Apart from the assessment of the accuracy of the data used in the analysis (internal validity) and considerations regarding oversupply/overuse in addition to their consideration of shortages in physicians and underutilisation, all remaining criteria were addressed. An overview of the results per study regarding the assessment against the quality criteria can be found in Appendix C. Moreover, a summary of the findings per criterion can be found in Table 6.

Table 6 Overview of quality criteria to assess methods estimating needs-based supply. Please note that the number of approaches (n = 24) exceeds the number of studies as three studies adopted multiple approaches.

1. Conceptual framework	Findings
1.1 Selection and justification of needs indicators <ul style="list-style-type: none"> <li>Theoretical rationale</li> <li>Empirical validation</li> </ul>	Theoretical rationale for the indicators <ul style="list-style-type: none"> <li>n = 24</li> </ul> Empirical validation of indicators <ul style="list-style-type: none"> <li>n = 5</li> </ul>
1.2 Relationship between supply and need <ul style="list-style-type: none"> <li>Potential influence</li> <li>Potential unmet need or lack of physicians</li> <li>Potential overuse or oversupply</li> </ul>	Discuss potential influence of supply <ul style="list-style-type: none"> <li>n = 9</li> </ul> Adjust potential unmet need or lack of physicians <ul style="list-style-type: none"> <li>n = 6</li> </ul> Adjust potential overuse or oversupply <ul style="list-style-type: none"> <li>None</li> </ul>
2. Data basis	Findings
2.1 External validity <ul style="list-style-type: none"> <li>Representativeness</li> </ul>	Representativeness <ul style="list-style-type: none"> <li>Population data: n = 2</li> <li>Representative sample: n = 2</li> <li>Convenience samples: n = 2</li> <li>Mixed data: n = 18</li> </ul>
2.2 Internal validity <ul style="list-style-type: none"> <li>Accuracy of indicators</li> </ul>	Discuss accuracy of indicators <ul style="list-style-type: none"> <li>n = 14</li> </ul>
2.3 Timeliness and availability <ul style="list-style-type: none"> <li>Survey period</li> </ul>	Survey/recording periods (in years) <ul style="list-style-type: none"> <li>Ranges between 1-20 years</li> </ul>
3. Modelling and conversion into physician requirements	Findings
3.1 Transformation into provider requirements <ul style="list-style-type: none"> <li>Methodology</li> </ul>	Methodology to translate estimated need into supply <ul style="list-style-type: none"> <li>Fulltime equivalents (FTE): n = 14</li> <li>Physician-to-population ratio adjustment: n = 10</li> </ul>
3.2 Model selection and validation <ul style="list-style-type: none"> <li>Type of model</li> <li>Justification and validation</li> </ul>	Type of model <ul style="list-style-type: none"> <li>Regression-based: n = 4</li> <li>Simulations: n = 9</li> <li>Extrapolations: n = 11</li> </ul> Validation of the model <ul style="list-style-type: none"> <li>n = 21</li> </ul>
3.3 Level of analysis <ul style="list-style-type: none"> <li>Aggregated data</li> <li>Individual data</li> </ul>	Model based on aggregated data <ul style="list-style-type: none"> <li>n = 21</li> </ul> Model based on individual data <ul style="list-style-type: none"> <li>n = 3</li> </ul>
4. Integration of future trends and developments	Findings
4.1 Projection variables <ul style="list-style-type: none"> <li>Selection of variables</li> </ul>	Variables for projection models <ul style="list-style-type: none"> <li>Demographics: n = 13</li> <li>Utilisation: n = 5</li> <li>Supply: n = 5</li> <li>Morbidity: n = 3</li> <li>Insurance status: n = 2</li> <li>Health behaviour: n = 1</li> </ul>
4.2 Planning horizon <ul style="list-style-type: none"> <li>Length</li> <li>Validation</li> </ul>	Length of need projections <ul style="list-style-type: none"> <li>Ranges between 10-31 years, <math>\bar{x} = 17</math></li> </ul> Validation of length <ul style="list-style-type: none"> <li>None</li> </ul>

Source: adapted from Geiger et al. [109]

### 3.1.2.1 Conceptual framework

The assessment of the conceptual framework included the selection and justification of need indicators as well as the consideration of the relationship between supply and need. Criterion 1.1 refers to the foundation of the selected indicators according to the context of the study and their empirical evidence base. Although all studies provided a rationale, the depth of the respective foundation and conceptualisation varied significantly.

Some authors, like Stuckless et al. [129], chose variables following theoretical frameworks of other scholars and which they assume to be the main drivers of need with no empirical verification. Also, Laurence and Kannon [131] (Australia) and the Centre for Workforce Intelligence (CfWI) report (UK) [130] relied on existing conceptual frameworks. Despite being from different countries, both studies applied variables selected by Canadian researchers [136, 137]. In fact, most studies mentioned that the used need indicators were based on prior research ( $n = 11$ ) [119–122, 126, 127, 129–131, 133, 135].

In contrast, eight authors developed their own framework [118, 120, 123–125, 128, 132, 134]. By way of example, Lee et al. [118] created a step-based conceptual framework, outlining the most important areas regarding the need for eye care professionals and assigning them to corresponding ICD codes. To confirm their approach, an expert panel was invited to assess the conceptual framework.

Five studies [123, 125, 126, 132, 135] presented empirical validation of the indicators used in the analysis by assessing the relationship between morbidity proxies or mortality measures and socioeconomic status or deprivation [125, 126, 135], conducting either factor analyses [125, 132] or regression models [135]. Moreover, prevalence rates of underlying diseases were empirically derived by two studies [123, 126].

As need can be approximated by several indicators, Figure 3 illustrates all indicators applied in the included studies showing their frequency. Six studies employed supply-based indicators such as the number of available physicians [120, 122, 135] and the ability of physicians to deliver necessary services (productivity) [119, 129, 130]. Another six studies used utilisation-based indicators like the number of cases or in-person visits [120, 130, 131, 133, 134], or the frequency of patient referrals [129].

Exogenous determinants as used by almost all studies ( $n = 17$ ) were the age and sex distribution in the population [118–120, 122–128, 130–135], followed by education and income as part of the social determinants of health, which were applied in eight studies [120, 123, 125, 126, 132, 133]. Other social determinants found in the selected literature were unemployment [125, 126, 132, 135] and environmental factors, such as regional deprivation and place of residency [126, 132, 133, 135] in addition to the risk of passive smoke exposure [124]. Health behaviour such as alcohol intake and obesity levels were included in two studies [124, 133].

Indicators used by more than 80% of studies ( $n = 14$ ) were measures of treatable morbidity [118–120, 123–128, 131–135], with indicators reaching from incidence and/or

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prevalence rates [118, 123, 124, 129, 131] over the reliance on long-term care [125, 127] to certain morbidity patterns [119–122, 127, 128, 130, 134, 135]. No study included measures of multimorbidity.

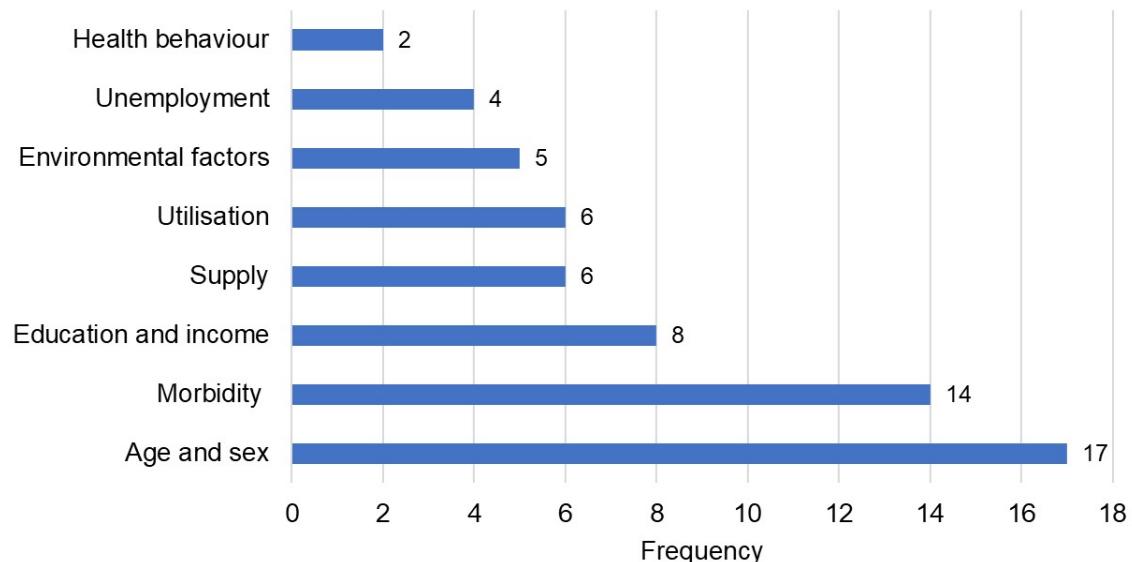


Figure 3 Indicators related to need used in studies estimating needs-based supply of physicians.

Source: adapted from Geiger et al. [109]

Another criterion related to the conceptual framework involves the identification of the relationship between supply and need indicators (Criterion 1.2). Overall, half of the included studies ( $n = 9$ ) explored the impact of available supply on need indicators [119, 120, 122, 124–126, 130, 133, 134], with two studies excluding indicators based on their assumed dependency on supply [125, 126]. Further three studies highlighted that their results might be biased due to regional differences in the availability of supply which might have affected the number of recorded diseases used in their analysis [134] or may be subject to unequal access to healthcare services [120, 125].

While one third of these studies theoretically discussed the dependency of need indicators on supply [125, 126, 134], the remaining two thirds tried to account for possible influences of limited access to healthcare services in terms of physician shortages or unmet need [119, 120, 122, 124, 130, 133]. For example, Anderson et al. [119] tried to account for existing inequities in access by including predictions of uninsured individuals in their model. Also, Dall et al. [133] tried to account for barriers to access based on differences in demand patterns of population groups with different socio-economic backgrounds.

Barber and López-Valcárcel [122] tried to account for shortages by looking for available job openings for physicians in Spain, while Singh et al. [124] incorporated the people that were currently not registered at a GP practice in their reference scenario.

Another method was applied by Ansah et al. [120] who incorporated the projected unfulfilled healthcare needs in one of their approaches by looking at waiting lists, i.e. differences between the day of registration and the day of the actual appointment. In contrast, the CfWI [130] consulted an expert panel to provide estimates and accounted for unfulfilled healthcare needs in the population.

None of the included studies assessed and/or corrected their analysis for overuse of healthcare services, including supply-induced demand, oversupply or demand based on the subjective need for health. Also, empirical assessments of the relationship between supply and indicators related to the need for healthcare were not conducted.

### 3.1.2.2 Assessing the validity of the data basis

To assess the overall validity of the data basis, the external and internal validity of the data was well as the timeliness and availability of the data were examined.

Regarding external validity (Criterion 2.1), it was not feasible to classify the validity of the data sources in the majority of approaches ( $n = 18$ ) included in the review as several data sources with varying representativeness were used. However, population data, which was assumed as the highest level of validity, was applied in two studies with data originating from statistics offices [125] and the statutory health insurance [128]. Another two studies stated that their data basis was derived from representative samples [126, 133]. The lowest classifiable validity level in terms of representativeness were convenience samples, which were utilised in two approaches [119, 134] with both being derived from claims data.

Internal validity (Criterion 2.2) regarding the quality and accuracy of the data to measure indicators of interest were discussed in 14 approaches within 13 studies [118, 119, 121, 123–126, 128, 130–132, 134], also acknowledging potential biases which may affect the internal validity such as changing insurers when relying on claims data or using non-repeated epidemiological studies [126, 131]. Only one study (CfWI) transparently assessed data quality in combination with limitations of the data and provided confidence ratings per model variable, stating underlying assumptions of each data source [130].

About half of the studies ( $n = 6$ ) which discussed their internal validity also attempted to account for biases in their datasets [118, 119, 121, 124, 130, 134], most frequently by consulting expert panels [118, 124, 130], retrieving additional information from literature [118, 124], or using an alternative data source [118, 121, 134].

Conclusively, timeliness and availability of the data source (Criterion 2.3) were assessed. Regarding timeliness, all studies provided at least the year of data collection for the primary data source. However, two studies referenced the year of publication of the underlying epidemiological study, instead of the corresponding year of data collection [120, 127].

When comparing the years of data collection with the year for which the physician disciplines were estimated, ranges of one up to 20 years were found, with just two studies discussing the application of several base years, stating the assumption that included measures are unlikely to change over a timeframe of one or two years [134, 135].

Only one study provided detailed information on the availability of data sources, including access and frequency of reporting [131]. The most frequent argument of data application was that the data used was the newest available [125, 131, 133] and that frequency of reporting was routinely [118, 128, 129, 134].

### 3.1.2.3 Modelling and conversion into physician requirements

Once the approaches for need estimations were identified, transformation of need into provider requirements, model selection and validation as well as considerations regarding the level of analysis were deliberated.

Our results showed that fulltime equivalents (FTE) were most frequently used ( $n = 14$ ) to convert the population need for healthcare into physician requirements (Criterion 3.1) [118–124, 128–131, 133]. To that end, estimated need measures are related to minutes or visits needed to treat a disease in combination with suggested working hours per year or other productivity measures per physician discipline.

The remaining approaches linked need estimates to measures of physician supply such as physician-to-population ratios which were adjusted by estimates of need instead of directly converting estimates into physician requirements [119, 120, 125–127, 132, 134, 135]. Underlying assumptions and limitations of the conversion method were not discussed in detail, with Konrad et al. [123] pointing to the lack of uniform methods.

The included studies used in 46% of approaches extrapolations [118, 119, 121, 123, 127, 129, 132, 134], 37% simulations [120, 122, 124, 130, 131, 133], and 17% regression models [125, 126, 128, 135]. Five authors from studies using extrapolations [125, 126, 132, 134, 135] provided conceptual rationales. Moreover, authors of system dynamic models highlighted the capability of this type of simulation models to process complex relations over time [120, 122, 130], with one author team of simulation models arguing to use the latest microsimulation approaches [133]. No further rationalisations were provided.

Attempts of model validation (Criterion 3.2) were found in varying depth in almost all approaches [118–120, 123, 126, 129–131, 134], including sensitivity analysis [118–120, 122, 123, 125–134], model fitting [125, 127, 128, 132], cross-validation [120, 121, 133], stakeholder, expert, or literature consultations [119–122, 129], and application of international model validation criteria [133].

The level of analysis (criterion 3.3) was individual data in three approaches [126, 128, 133] with the remaining approaches applying aggregated or in the case of two approaches by Ansah et al. [120] partially disaggregated data. A thorough examination of implications arising from the usage of individual vs aggregated data was not found in

any study. However, two studies argued that aggregated data might have concealed correlations due to averaged results [135], highlighting that small-scale models should be preferred over large-scale models [134].

### 3.1.2.4 Integration of future trends and developments

In the course of integrating future trends and developments, projection variables and planning horizons were assessed.

Our review showed that 12 studies [118–122, 124, 125, 127, 129–131, 133] forecasted needs-based supply of physicians (Criterion 4.1) with projection variables mainly consisting of demographic changes, while holding all other variables constant. Three studies also projected trends in morbidity, either through estimations of future disease prevalence (e.g. from average historical increase rates) [124, 129] or through estimations by expert panels [130]. Variables relating to supply (e.g. consultation rates and staffing ratios) [124, 129, 130, 133] and demand (e.g. utilisation patterns and growth rates) [120–122, 131, 133] were included in eight studies. Additionally, insurance coverage [119, 121] and estimated variations in health risk factors [124] were found in the forecasts of the selected studies.

The planning horizon (Criterion 4.2) ranged from 10 years [129, 131] up to 31 years [121] ( $\bar{x} = 17$  years). The main reason for choosing the respective planning horizon was that population projections, which built the foundation of the projection, were provided in that timeframe [118–120, 122, 125, 127, 130]. No well-grounded validation for the planning horizons was found in the included studies.

## 3.2 Regional variation in multimorbidity in Germany

*Disclaimer: Results from the cross-sectional study have already been published by Geiger et al. [92].*

### 3.2.1 Descriptive summary

In 2015, about 89% of German citizens (~70.8M) were insured under the statutory health insurance, out of which approximately 67.2M were seeing a physician and thus were recorded in the dataset.

Table 7 provides an overview of GPs, neurologists, ophthalmologists, and orthopaedic specialists, including their FTE, average number of cases per year and physician, overall count of patients in the study period, and the number of multimorbid patients as classified using the disease count approach described in chapter 2.3.3. While neurologists were found to have the highest percentage of multimorbid patients (60.1%), ophthalmologists on average faced the highest number of multimorbid patients per year and physician ( $n = 1,315$ ), with all GPs together seeing the highest absolute amount of multimorbid

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patients (17.2M) but the lowest proportion (31.5%). Orthopaedic specialists were found to have a lower average number of cases per year ( $n = 3,824$ ) than ophthalmologists ( $n = 5,145$ ) and GPs. However, orthopaedic specialists were seeing on average the second highest number of multimorbid patients per year and physician ( $n = 861$ ) after ophthalmologists.

Table 7 Overview of office-based physician disciplines including fulltime equivalents (FTE), average number of cases per year, patient counts, and multimorbid patients in 2015.

Discipline	FTE*	Ø cases per year	Patients	Multimorbid patients
GPs	52,527	3,940	54,799,570	17,239,488
Neurologists	4,683	2,204	4,386,298	2,637,461
Ophthalmologists	5,434	5,145	16,195,148	7,145,558
Orthopaedic specialists	5,483	3,824	11,659,090	4,722,933

\*FTE were recorded in 2016

Source: adapted from Geiger et al [92]

In order to illustrate overall dispersion, boxplots per physician discipline and planning unit are provided in Figure 4. Neurologists showed the highest median proportion of multimorbid patients (~59%) with an interquartile range (IQR) of ~9.0%, followed by ophthalmologists with a median of 43% and a higher IQR of ~9.5%, orthopaedic specialists with a median of 41% and the highest IQR of ~10.0%, and lastly, GPs with the lowest median (~31%) and lowest IQR (~6.5%).

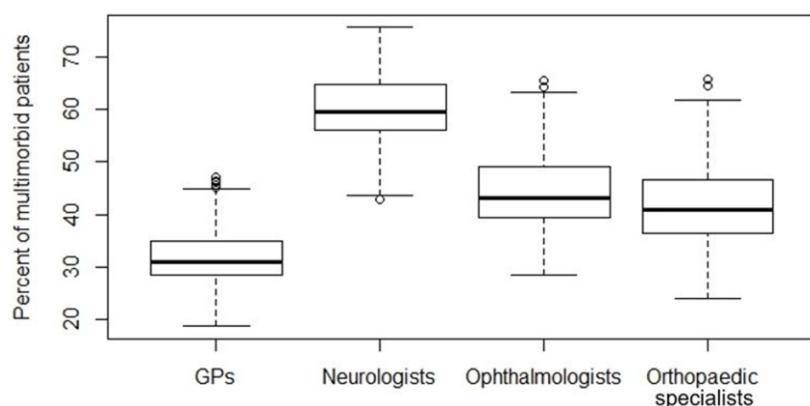


Figure 4 Boxplots of percentages of multimorbid patients seen by GPs, neurologists, ophthalmologists, and orthopaedic specialists in 2015 according to their planning unit.

Source: Geiger et al. [92]

### 3.2.2 Cluster detection and comparison

The Bernoulli spatial scan statistics resulted in eleven high-rate clusters for GPs with relative risks (RR) ranging from 1.04-1.28, eight high-rate clusters for orthopaedic specialists (RR 1.03-1.35), and five high-rate clusters for both neurologists (RR 1.02-1.20) and ophthalmologists (RR 1.04-1.33) as compiled in see Table 8 and Table 10. The clusters are abbreviated as 'CL' in combination with Arabic numerals based on the underlying likelihood ratio, starting with number one for the highest likelihood. CL-1 is situated in eastern Germany in all physician disciplines with varying sizes and covering parts of several states, including parts of northern Bavaria (BY), Brandenburg (BB), Saxony (SN), Saxony-Anhalt (ST) and Thuringia (TH). The largest CL-1 was found in orthopaedic specialists with a radius of 177 km compared to neurologists with the smallest radius of 128 km. Other areas of high-rate clusters over all physician disciplines with varying likelihood ratios were found in parts of Mecklenburg-Vorpommern (MV) and North Rhine-Westphalia (NW).

Cluster detection for low-rate clusters resulted in ten clusters for orthopaedic specialists (RR 0.73-0.94) and nine clusters for GPs (RR 0.82-0.93), neurologists (RR 0.83-0.97), and ophthalmologists (RR 0.75-0.94), with the most likely low-rate clusters (CL-2/CL-3) occurring in southern Germany covering Baden-Württemberg and Bavaria. Other low-rate clusters were detected in parts of Bremen (HB), Hamburg (HH), Hessen (HE), Lower Saxony (NI), North Rhine-Westphalia (NW), Rhineland-Palatinate (RP), and Schleswig-Holstein (SH). A comprehensive overview of detected high-rate and low-rate clusters for all physician disciplines per federal state including the areas covered in each state both overall and per individual cluster is presented in Table 9. The corresponding SaTScan scanning results can be found in Appendix D.

Figure 5a maps the regional variation in multimorbidity levels of GPs, and Figure 5b illustrates the detected high- and low-rate clusters of multimorbid patients including the respective areas. As GPs are planned on a separate planning unit (MBs), no direct comparison of the results between GPs and physicians planned on KRs was feasible. However, looking at the results per federal state in Table 9 and comparing Figures 5-8, the Bernoulli model of GPs apparently detected similar areas as for other physician disciplines, though varying in size and location.

Figures 6a/b, 7a/b, and 8a/b provide an overview of regional variation in multimorbidity levels and significant high- and low-rate clusters of multimorbid patients on KR level for neurologists, ophthalmologists, and orthopaedic specialists, respectively. The analysis of high-rate areas in specialised physicians (neurologists, ophthalmologists, orthopaedic specialists) neglecting differences in RR and likelihoods, resulted in 159 KR<sub>s</sub> found in at least one physician discipline, of which 63 KR<sub>s</sub> (~40%) were found in all, 35 KR<sub>s</sub> (~22%) in two and 61 KR<sub>s</sub> (~38%) in one. In other words, about 62% of high-rate areas were detected for two or more specialists. Neurologists were found to have the highest percentage of overlapping high-rate areas with at least one other discipline (~89%), followed by ophthalmologists and orthopaedic specialists with approximately 78% and 77%, respectively.

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When looking at detected low-rate areas, 198 KRs were found in at least one physician discipline, of which 130 KRs (~66%) were overlapping between two or more disciplines. 78 KRs were detected that were present in all specialised physicians. In contrast to high-rate areas, orthopaedic specialists were found to have the highest share of overlapping areas (~93%) with neurologists and/or ophthalmologists, followed by neurologists with about 83% and, ophthalmologists with about 77%.

Table 8 Summary of significant high- and low-rate clusters per physician discipline based on the spatial Bernoulli cluster analysis. '+' denoting high-rate and '-' denoting low-rate clusters and RR abbreviating the relative risk.

Physician discipline	Clusters +	Covered areas +	RR range +	Clusters -	Covered areas -	RR range -
GPs	11	292 MBs	1.04-1.28	9	324 MBs	0.82-0.93
Neurologists	5	97 KRs	1.02-1.20	9	146 KRs	0.83-0.97
Ophthalmologists	5	101 KRs	1.04-1.33	9	153 KRs	0.75-0.94
Orthopaedic specialists	8	122 KRs	1.03-1.35	10	107 KR	0.73-0.94

Source: own contribution

As high-rate and low-rate areas were detected within clusters, specialised physicians were also compared on a cluster level. The results showed that most high-rate clusters did not fully match with clusters detected in other disciplines, meaning 100% of high-rate clusters for orthopaedic specialists, 80% (n = 4) of high-rate clusters for neurologists (CL-1, CL-3, CL-5, CL-12) and 80% (n = 4) of high-rate clusters for ophthalmologists (CL-1, CL-2, CL-11, CL-12) did not fully match. Only cluster CL-14 in NW was found to completely overlap in terms of radius and site between neurologists and ophthalmologists with RRs of 1.04 and 1.06, respectively. Identical low-rate clusters in Saarland (SL) were found once in CL-7 for both, ophthalmologists (RR 0.75) and orthopaedic specialists (RR 0.83) also matching with CL-6 for neurologists (RR 0.73). Additional three clusters were identical in two disciplines, with two amongst ophthalmologists (CL-5, RR 0.85 and CL-10, RR 0.88) and orthopaedic specialists (CL-4, RR 0.80 and CL-11, RR 0.88) as well as one between orthopaedic specialists (CL-2) and neurologists (CL-2) with RRs of 0.78 and 0.83, respectively.

A detailed overview of all scanning results of GPs can be found in Appendix E and the comparison between specialised physicians can be found in Appendix F.

### 3.2.3 Robustness test

Figures 5c to 8c provide a visual comparison between the results of the spatial Bernoulli model as represented by blue (low-rate) and yellow (high-rate) circles with corresponding dots and the results obtained by Moran's I autocorrelation test as represented by filled areas (clusters) or outlined areas (outlier) using the same colour code.

The lowest confirmation rate of high-rate areas was found in GPs, with 146 MBs out of 292 MB detected with Bernoulli confirmed by Moran's I, equalling 50%, followed by orthopaedic specialists with 72 KRs out of 122 KRs (~59%). Neurologists and ophthalmologists were confirmed in 63 KRs of 97 KRs (~65%) and 71 KRs of 101 KRs (~70%), respectively. The robustness test of low-rate areas delivered less conformities with neurologists being confirmed in 33% of detected low-rate areas, GPs and ophthalmologists in 43%, and orthopaedic specialists in 57%.

When looking at the results reversely, most areas detected through Moran's I were also identified using the Bernoulli model, with high-rate areas ranging from ~84% (GPs) to ~88% (orthopaedic specialists) and low-rate areas ranging from ~83% (GPs) to ~97% (ophthalmologists). The comparison of the results through spatial autocorrelation within specialised physicians, showed that between ~86% (ophthalmologists) and ~95% of high-rate areas (neurologists), and between 57% (ophthalmologists) and ~74% of low-rate areas (neurologists) were found in all three specialities. A list of the detected areas per physician group and planning unit by Bernoulli and Moran's I can be found in Appendices E and F.

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Table 9 Comparison of significant high-rate and low-rate clusters for GPs, neurologists, ophthalmologists, and orthopaedic specialists on state level with covered areas on planning level (either MBs or KRs) in brackets. '+' denoting high-rate and '-' denoting low-rate clusters.

State	CLs	GPs (MBs)	Neurologists (KRs)	Ophthalmologists (KRs)	Orthopaedic specialists (KRs)	Sum
BW	+	/	/	/	/	/
	-	CL-2 (71)	CL-2 (28)	CL-3 (24), CL-8 (9)	CL-2 (28)	71 MBs, 89 KR
BY	+	CL-5 (12), CL-18 (9)	CL-5 (7)	CL-1 (2)	CL-1 (6), CL-6 (2)	21 MBs, 17 KR
	-	CL-2 (43), CL-8 (72), CL-14 (6)	CL-2 (4), CL-4 (43)	CL-3 (15), CL-4 (36), CL-8 (5), CL-13 (5)	CL-2 (4), CL-5 (16)	121 MBs, 128 KR
BE	+	/	/	CL-2 (1)	/	1 KR
	-	/	/	/	/	/
BB	+	CL-1 (23), CL-3 (13)	CL-1 (9), CL-3 (6)	CL-2 (14)	CL-1 (9), CL-3 (5)	36 MBs, 43 KR
	-	/	/	/	/	/
HB	+	/	/	/	/	/
	-	CL-4 (2)	CL-7 (2)	CL-5 (1)	CL-4 (1)	2 MBs, 4 KR
HH	+	/	/	/	/	/
	-	CL-4 (1)	CL-7 (1)	CL-5 (1)	CL-4 (1)	1 MB, 3 KR
HE	+	CL-5 (24)	CL-5 (4)	/	CL-6 (13)	24 MBs, 17 KR
	-	CL-6 (16), CL-11 (4)	CL-8 (5), CL-10 (2)	CL-8 (13), CL-9 (2)	CL-9 (4)	20 MBs, 26 KR
NI	+	CL-5 (1), CL-13 (1)	/	CL-11 (17)	CL-6 (3), CL-14 (1)	2 MBs, 21 KR
	-	CL-4 (54), CL-7 (2)	CL-7 (22)	CL-5 (4), CL-6 (5)	CL-4 (4), CL-8 (10)	56 MBs, 45 KR
MV	+	CL-3 (26)	CL-3 (12)	CL-2 (13)	CL-3 (13)	26 MBs, 38 KR
	-	/	/	/	/	/
NW	+	CL-9 (20), CL-15 (38), CL-17 (7)	CL-12 (11), CL-14 (3)	CL-11 (1), CL-12 (1), CL-14 (3)	CL-6 (1), CL-10 (5), CL-13 (5), CL-16 (2), CL-17 (1)	65 MBs, 33 KR
	-	CL-4 (2), CL-7 (20), CL-11 (16), CL-12 (5), CL-16 (1)	CL-7 (1), CL-9 (7), CL-10 (4)	CL-6 (8), CL-9 (4), CL-10 (1), CL-11 (9), CL-13 (1)	CL-8 (15), CL-11 (1), CL-12 (5), CL-15 (2), CL-18 (1)	44 MBs, 59 KR
RP	+	CL-10 (5), CL-19 (1), CL-20 (8)	/	/	CL-17 (4)	14 MBs, 4 KR
	-	CL-6 (6), CL-11 (1)	CL-8 (3), CL-10 (1)	CL-8 (6), CL-9 (1)	CL-9 (1), CL-12 (1)	7 MBs, 12 KR
SL	+	CL-10 (1), CL-20 (2)	/	/	/	3 MBs
	-	/	CL-6 (5)	CL-7 (5)	CL-7 (5)	15 KR
SN	+	CL-1 (47)	CL-1 (24)	CL-1 (18)	CL-1 (25)	47 MBs, 67 KR
	-	/	/	/	/	/
ST	+	CL-1 (20)	CL-1 (6)	CL-1 (10), CL-2 (2)	CL-1 (8)	20 MBs, 26 KR
	-	/	/	/	/	/
SH	+	/	/	/	/	/
	-	CL-4 (16)	CL-7 (8)	CL-5 (8)	CL-4 (8)	16 MBs, 24 KR
TH	+	CL-1 (17), CL-5 (17)	CL-1 (3), CL-5 (12)	CL-1 (19)	CL-1 (8), CL-6 (11)	34 MBs, 53 KR
	-	/	/	/	/	/

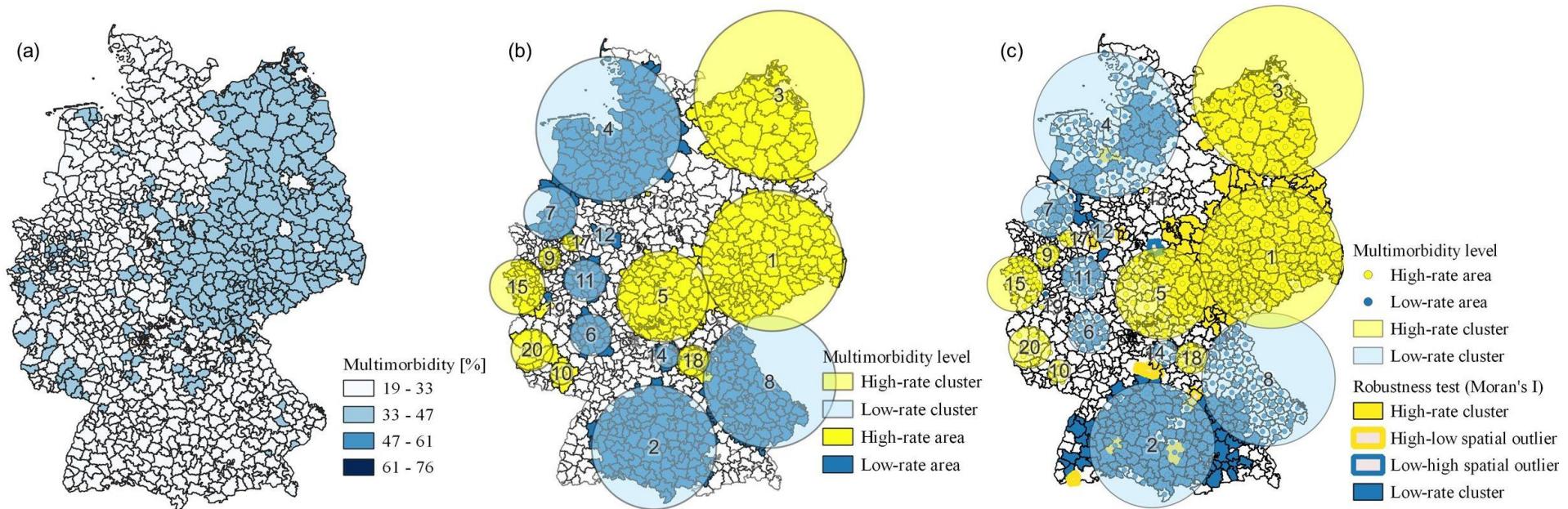


Figure 5 Multimorbidity levels in percentage (a), significant high-rate and low-rate clusters (b) of multimorbid patients numbered consecutively based on the underlying likelihood ratio and comparison of results with Moran's I autocorrelation test (c) for **GPs** in Germany in 2015.

Source: adapted from Geiger et al. [92]

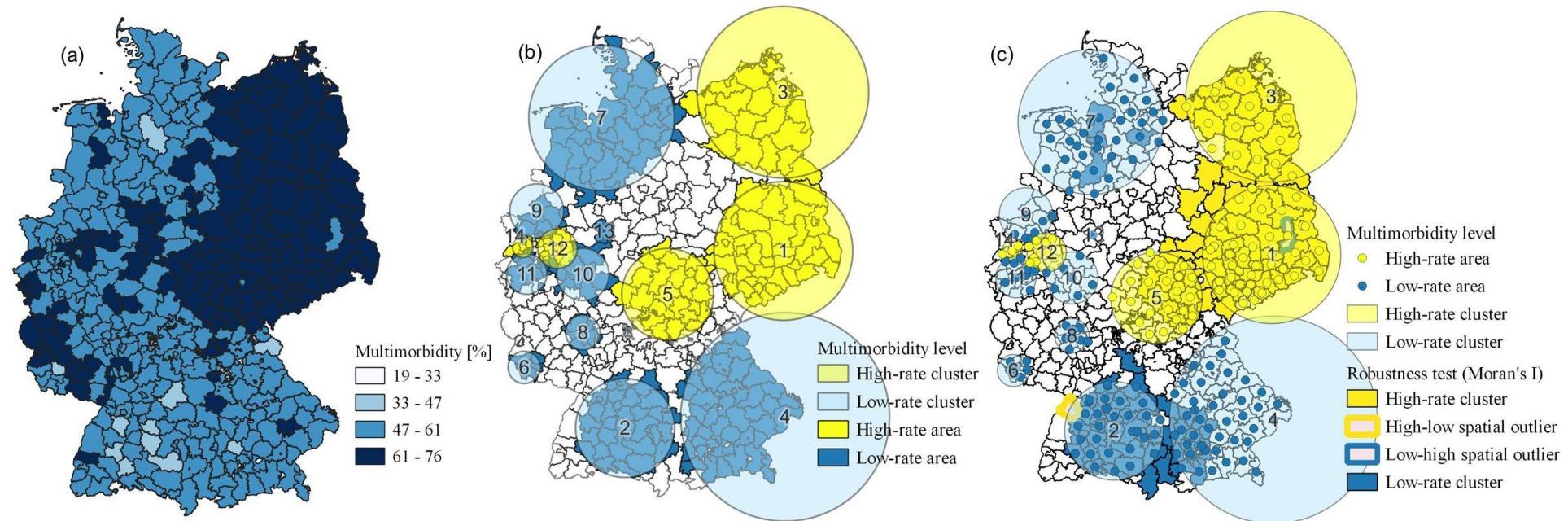


Figure 6 Multimorbidity levels in percentage (a), significant high-rate and low-rate clusters (b) of multimorbid patients numbered consecutively based on the underlying likelihood ratio and comparison of results with Moran's I autocorrelation test (c) for **neurologists** in Germany in 2015.

Source: adapted from Geiger et al. [92]

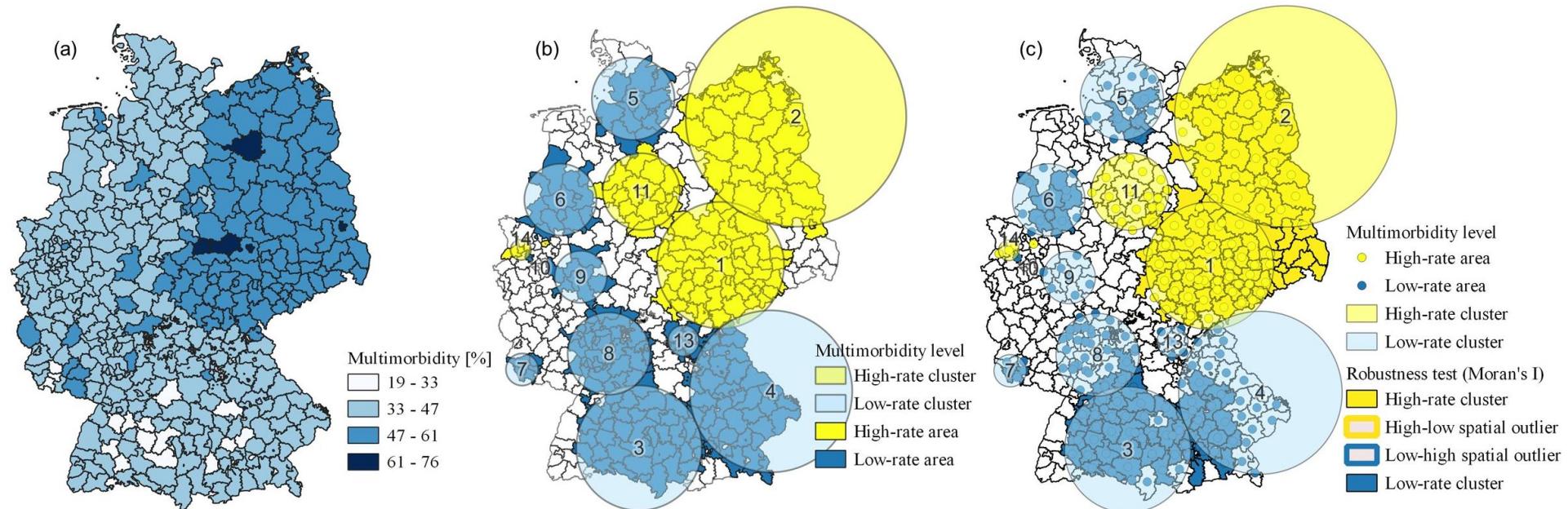


Figure 7 Multimorbidity levels in percentage (a), significant high-rate and low-rate clusters (b) of multimorbid patients numbered consecutively based on the underlying likelihood ratio and comparison of results with Moran's I autocorrelation test (c) for **ophthalmologists** in Germany in 2015.

Source: adapted from Geiger et al. [92]

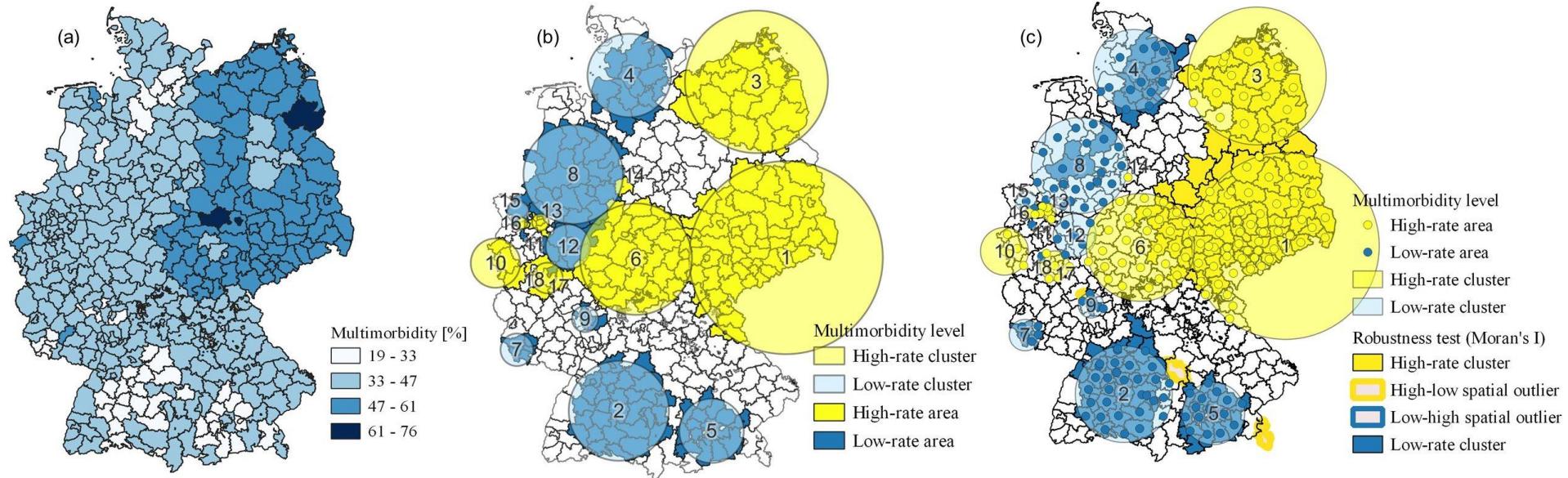


Figure 8 Multimorbidity levels in percentage (a), significant high-rate and low-rate clusters (b) of multimorbid patients numbered consecutively based on the underlying likelihood ratio and comparison of results with Moran's I autocorrelation test (c) for **orthopaedic specialists** in Germany in 2015.

Source: adapted from Geiger et al. [92]

### 3.2.4 Comparison of high-rate clusters with current physician supply

The comparison of detected high-rate clusters of multimorbid patients with the current supply was drawn at cluster level, meaning that the average supply level of all regions within a cluster was used as a measure of cluster supply (see Table 10). It should be noted that Figures 9 and 10 illustrate high-rate clusters mapped on original levels of physician supply per planning unit to provide a better understanding of the supply distribution within a cluster.

In general, the comparison demonstrated that almost all high-rate clusters were met by average supply that exceeded the targeted coverage as defined in Chapter 2.3.3. GPs were the exception, as five clusters (CL-1, CL-3, CL-13, CL-15, CL-20) were met with average supply below targeted coverage, having supply coverage down to 2 which represents imminent shortage in the case of CL-13. Moreover, CL-19 was met exactly by target supply.

Appendices D and E provide an overview of all results of the cross-sectional study including the average supply level per cluster and physician discipline.

Table 10 Juxtaposition of high-rate clusters of multimorbid patients with average ( $\bar{\varnothing}$ ) physician supply on cluster level per physician discipline.

Physician discipline	Below targeted coverage	Above targeted coverage
GPs	CL-1, $\bar{\varnothing} = 2.87$ CL-3, $\bar{\varnothing} = 2.77$ CL-13, $\bar{\varnothing} = 2.00$ CL-15, $\bar{\varnothing} = 2.92$ CL-20, $\bar{\varnothing} = 2.80$	CL-5, $\bar{\varnothing} = 3.46$ CL-9, $\bar{\varnothing} = 3.35$ CL-10, $\bar{\varnothing} = 3.33$ CL-17, $\bar{\varnothing} = 3.57$ CL-18, $\bar{\varnothing} = 3.22$ CL-19, $\bar{\varnothing} = 3.00$
Neurologists		CL-1, $\bar{\varnothing} = 4.51$ CL-3, $\bar{\varnothing} = 4.40$ CL-5, $\bar{\varnothing} = 4.11$ CL-12, $\bar{\varnothing} = 4.60$ CL-14, $\bar{\varnothing} = 4.00$
Ophthalmologists		CL-1, $\bar{\varnothing} = 3.91$ CL-2, $\bar{\varnothing} = 4.04$ CL-11, $\bar{\varnothing} = 3.77$ CL-12, $\bar{\varnothing} = 4.00$ CL-14, $\bar{\varnothing} = 4.00$
Orthopaedic specialists		CL-1, $\bar{\varnothing} = 4.25$ CL-3, $\bar{\varnothing} = 4.28$ CL-6, $\bar{\varnothing} = 4.33$ CL-10, $\bar{\varnothing} = 4.00$ CL-13, $\bar{\varnothing} = 4.40$ CL-14, $\bar{\varnothing} = 4.00$ CL-16, $\bar{\varnothing} = 4.50$ CL-17, $\bar{\varnothing} = 4.40$

Source: own contribution

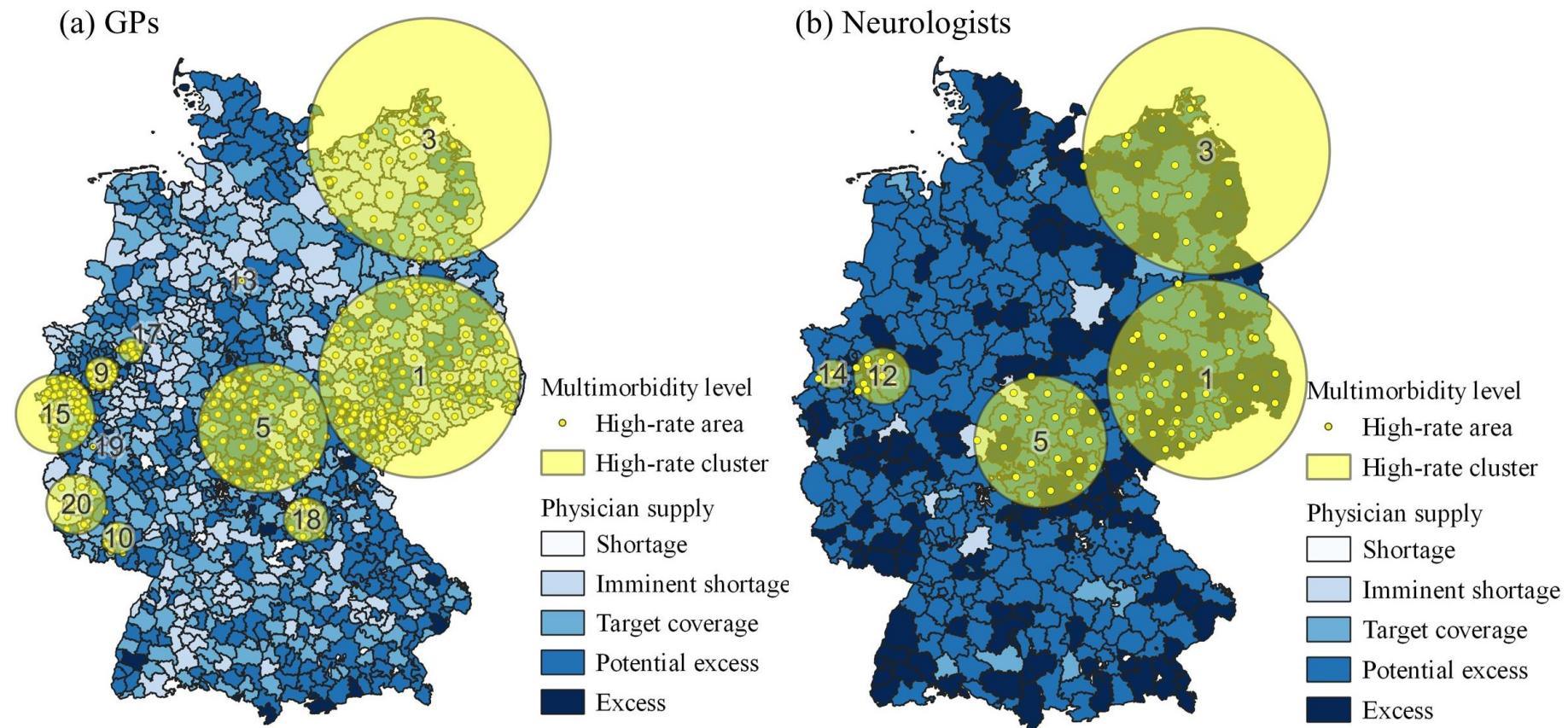
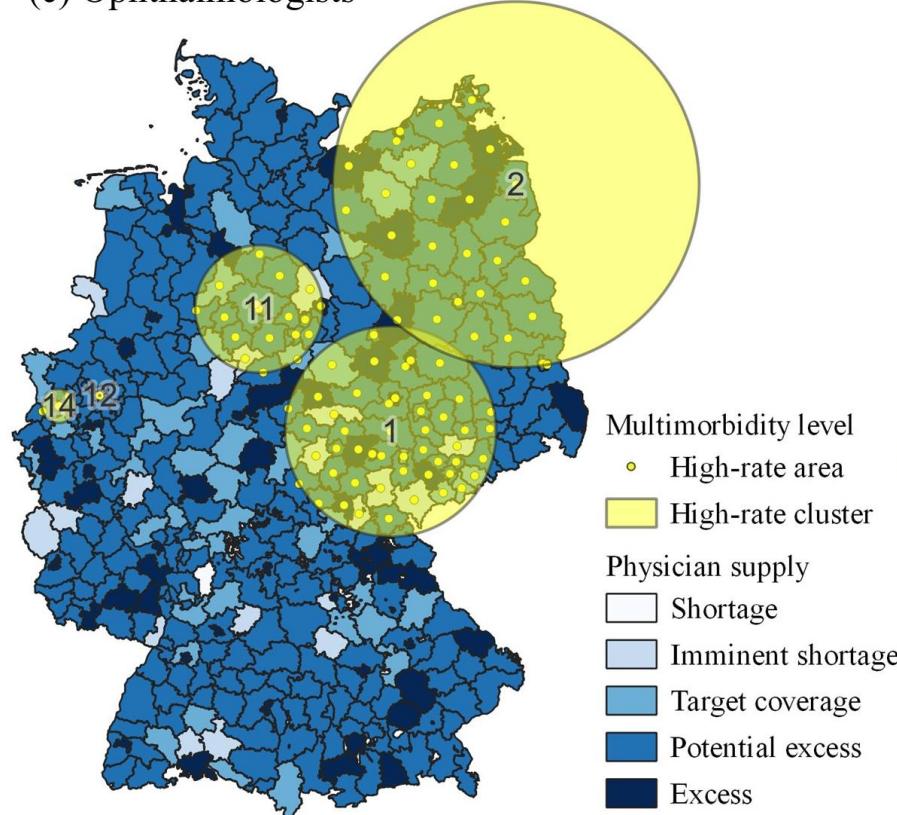


Figure 9 Level of physician supply and significant high-rate clusters of multimorbid patients numbered consecutively based on the underlying likelihood per planning unit for (a) GPs and (b) neurologists in Germany in 2015.

Source: Geiger et al. [92]

(c) Ophthalmologists



(d) Orthopaedic specialists

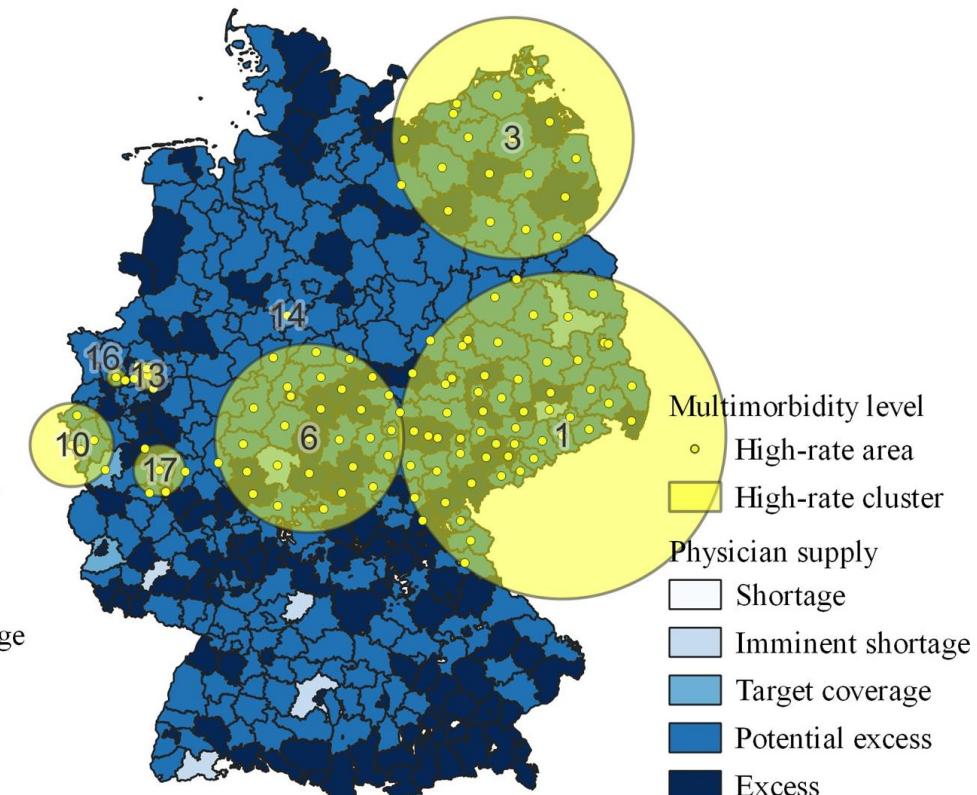


Figure 10 Level of physician supply and significant high-rate clusters of multimorbid patients numbered consecutively based on the underlying likelihood per planning unit for (a) ophthalmologists and (b) orthopaedic specialists in Germany in 2015.

Source: Geiger et al. [92]

## 4. Discussion

Physician planning under consideration of changes in healthcare needs of a population (e.g. the rising number of multimorbid individuals) plays a central role in achieving equitable access to healthcare services. The assessment of approaches estimating needs-based supply of physicians against quality criteria revealed weaknesses and methodological gaps, which should be addressed in future studies. By detecting regional variation in multimorbidity levels within and between office-based physicians, the importance of integrating multimorbidity measures when estimating the need for healthcare was emphasised. Given that almost 50% of the high-rate clusters of multimorbid patients in GPs are met with physician coverage below targeted values, improvements in GP care should be targeted most urgently.

### 4.1 Methodological assessment of studies

The conceptual basis of needs-based physician planning including proxies used to approximate the need for healthcare are governed by underlying assumptions with no uniform standards. Transparently deliberating and reporting these assumptions was missing in the included studies. In particular, when relying on approaches from other scholars [119–122, 126, 127, 129–131, 133, 135], it is important to reflect whether these approaches can be applied in another context or if adaptations are required. For instance, transferability of established approaches especially to other countries may be limited due to differences in healthcare delivery, population structure, and access to care.

When looking at the indicators used to approximate need for healthcare, a comprehensive selection of indicators was revealed. Despite being the most direct measure of need according to the systematisation of healthcare needs in this thesis, four studies did not apply morbidity measures in their analysis, with even fewer studies including social determinants of health. Not drawing from the full range of indicators related to need for healthcare could be a source of biases and thus seems like a passed opportunity as each indicator may add to the validity of the estimates. An example of how several indicators can be integrated when estimating the need for healthcare is provided by Sundmacher et al. [10], who set up several regression-based models to estimate needs-based supply of physicians in Germany.

Indicators related to need can be heavily influenced by physician supply and access to healthcare services (see Chapter 1.1.2). Not reflecting on the effects of supply on need estimations potentially harms the accuracy of the estimates and replicates existing imbalances. With more than every third study (39%) included in the review not discussing these limitations in any of their approaches used to estimate needs-based supply, a major gap was identified. Ways to account for supply dependency in terms of unmet need or lack of physicians provided in the review include waiting lists, unfilled positions, uninsured or unattached individuals, estimates from an expert panel, and accounting for

differences in access by socio-economic background (see 3.1.2.1). Apart from unmet healthcare needs, unindicated healthcare utilisation in terms of supply-sensitive care should also be acknowledged when estimating needs-based supply based on utilisation measures [138], which was not considered in any study included in the review. Resources discovering supply-sensitive care are available for several countries [139], with one prominent example being the Dartmouth Atlas of Health Care (USA) [140].

Requirements regarding the data basis were challenging in two ways; firstly, with regards to the assessment of the studies itself as the transparency of reporting internal and external validity as well as timeliness of the data basis was limited, and secondly, concerning the ability of studies to fulfil these areas. Overall, data availability seemed to be the most limiting factor within the requirements for the data basis. Efforts to improve data availability on a national and international level including the provision of funding to develop a sustainable platform that is made accessible to scholars under adherence of the General Data Protection Regulation are needed. For hospital care, international platforms which can be used for research purposes, such as eNewborn [141] in the field of neonatology, already exist. In Germany, endeavours were undertaken to establish a data centre for research purposes but the data is not yet accessible to researchers [142]. As outlined by the European Parliament, there are still several obstacles preventing the establishment of a European-wide data centre, which need to be addressed by all member states [143].

While assessing the translation of estimated healthcare needs to physician requirements, it became clear that more research is needed to find a uniform conversion method. As direct conversions are the preferred option, some measures of productivity must be employed. Productivity measures, however, may vary over time and between physician disciplines as they are dependent on the availability of physicians in general and the way of service provision [130]. Innovative models of service delivery, for example, which aim to reduce physician contacts through integrated care approaches may have an influence on overall productivity measures [144, 145]. Moreover, researchers showed that changes in income can also lead to alterations in productivity, even having a negative effect on productivity if income is set over a certain limit [146]. Therefore, productivity measures need to be carefully selected bearing in mind their limitations and regularly tested for validity.

The selection of a statistical model should be based on the properties of the included variables, considering the level of analysis to avoid ecological fallacy. Moreover, all models need to be validated to ensure accuracy of the findings. Apart from models using system dynamics or extrapolations based on indices, no explanation for model selection was offered. While most studies provided at least one type of model validation, thorough validation processes were also missing, being limited to three studies [118, 120, 133]. Consulting reports for model validation such as provided by Eddy et al. [147] may help to improve future models.

To incorporate future trends and developments is again a very complex task as medical care is a fast-changing area [148]. Nevertheless, it is important to project estimates of needs-based supply of physicians into the future as sustainable provision of physicians relies on forward planning. Projection variables identified in the review mainly consist of demographic changes (age and sex distribution). However, relying on age and sex as main indicators to forecast need bears the risk of overestimation or underestimation as demographic variables alone may be insufficient to accurately predict need for healthcare. For example, since morbidity seems to be expanding in high-resource countries like Germany [105], need projections based on age and sex alone would lead to underestimation of future healthcare needs. Integrating changes and trends in morbidity may improve predictions as they are directly influencing the need for healthcare [10]. The main challenge with morbidity measures also constitutes their reliability over time. Even if historic datasets are used to estimate a trend in morbidity, outcomes should be additionally validated by expert panels as they may be aware of trends in morbidity that are not yet visible [122, 130].

Given the great range in planning horizons (10-31 years) observed in the methodological review, which were mainly justified by the availability of population data, the need for an evidence-based selection process of planning horizons is stressed. In general, short-term estimations for 3-5 years provide more accurate results with less uncertainty [149, 150]. However, adopting a range-based horizon with an increasing number of scenarios and decreasing certainty over time – such as applied by the WHO when estimating scenarios regarding future pandemics and epidemics [149] – may allow for medium-term and long-term physician planning under considerations of certain assumptions. Importantly, short-term scenarios need to be frequently updated to detect relevant developments, changes, or trends in healthcare needs at an early stage.

The outbreak of the COVID-19 pandemic [151] led to sudden changes in healthcare needs across and within countries, which are not covered under the general needs-based physician planning as infectious disease outbreaks in particular are difficult to predict [152]. The knowledge of such events, however, can be used as a resource to complement findings from needs-based physician planning. Canadian researchers, for example, estimated additional service requirements needed in the case of an outbreak of influenza [153] and during the COVID-19 pandemic [154]. However, before integrating these approaches, their accuracy in predicting additional healthcare needs must be tested more extensively.

## 4.2 Regional variation in multimorbidity in Germany

The results from the cross-sectional study in all of Germany illustrate that levels of multimorbid patients vary significantly between areas and affect physician disciplines to a varying degree. These findings in combination with the increased healthcare utilisation of multimorbid patients as outlined in Chapter 1.3.3 promote the integration of regional multimorbidity levels when estimating needs-based supply of physicians. While regional differences in clusters of multimorbid patients between specialised physicians detected by the Bernoulli model were more prominent, results from the spatial autocorrelation test demonstrate more similar patterns between all three specialities, specifically in high-rate areas. Thus, more research is needed to test whether regional multimorbidity levels should be integrated overall or rather stratified by physician discipline. However, if overall levels are used as they might prove more robust over time, ways to account for the different shares of multimorbid patients between physician disciplines should be considered (e.g. by assigning weights).

The most likely high-rate clusters were found in Eastern Germany. i.e. in areas of the former German Democratic Republic. One reason might be that the old-age dependency ratio in East German area states is higher than in West German area states, with a ratio of 40.9 individuals of pensionable age (to 100 individuals in working age) in East German compared to 33.9 in West German area states in 2015 [155]. Moreover, Eastern Germany also seems to have higher levels of deprivation according to the deprivation index of Kroll et al [156]. This, however, does not hold true for other high-rate clusters found, for example, in North Rhine-Westphalia as their old-age dependency ratio was set at 34.0 in 2015 [155] with varying levels of deprivation [156]. In-depth research regarding the underlying reason for high rates in multimorbidity is required in order to efficiently improve care.

Moran's I was used to validate the findings derived from the Bernoulli model. Although the majority of high-rate areas was confirmed, low-rate areas were only confirmed to a limited extend. One reason for the differences in detected areas may lie in the underlying functions as the Bernoulli model [115] is not influenced by neighbouring areas compared to Moran's I [117]. Researchers testing several spatial clustering approaches confirmed that clusters identified through different methods are likely to differ as they are looking for different types of clusters [157]. In accordance with the aim of the thesis, the Bernoulli model was deemed most appropriate method for cluster detection as the number of multimorbid patients in neighbouring areas was of low relevance.

According to the data used in the cross-sectional study, Germany seems to be well-equipped regarding the provision of neurologists, ophthalmologist, and orthopaedic specialists. Thus, it is unsurprising that average physician coverage even in high-rate clusters of multimorbid patients is exceeding targeted values. The question remains, however, if physician planning in 2015, which was mainly based on physician-to-population ratios from the 1990s adapted with a demographic factor (see Chapter 1.2.2), sufficiently accounted for healthcare needs based on the underlying morbidity. Thus, it

would be essential to repeat the study and test whether the potential excess in specialised physicians, specifically in the identified high-rate areas, remains identical when applying new AVZs as basis, which (since 2019) include measures of morbidity [55]. The integration of morbidity measures might have led to an increased number of targeted physicians, which in turn could lead to a lower level of physician coverage in areas with a greater likelihood of multimorbid patients. Moreover, the morbidity factor itself can be tested against high- and low-rate areas of multimorbid patients to examine whether the estimations of additional care needs are similar.

In contrast to specialised physicians, the physician coverage of GPs varied significantly across Germany. Almost half of the detected high-rate clusters are met with average physician supply below targeted values. Following the above-mentioned hypothesis that physician planning in 2015 might have underestimated the need for healthcare in the population, the suggested shortages in GPs might also be an understatement. Therefore, it is of utmost importance to improve care, specifically in high-rate areas with imminent shortages of GPs.

### 4.3 Strengths and limitations

The assessment of methodologies of studies that quantify needs-based supply was systematically structured and followed clear quality criteria, enabling a coherent and replicable evaluation, which constitutes an advancement to previous studies [49, 158]. While existing appraisal tools failed to grasp the complexity of physician planning, the framework used in the review at hand provides a novel appraisal tool, which encompasses central requirements of needs-based physician planning as defined by Sundmacher et al. [10].

In addition to what has been previously studied, knowledge regarding shortcomings of current studies estimating needs-based supply specifically with regards to the influence of supply on need proxies and in combination with recommendations on how to improve these areas is added. These recommendations can be directly applied by policymakers to improve their current workforce planning.

Given that multimorbidity is found at any age [85, 86], the classification of multimorbidity without age restrictions used in this thesis to assess regional variation of multimorbidity across Germany can be seen as central advancement, providing an overview of multimorbidity burden per physician discipline and planning unit. Other studies conducted in Germany predominantly focussed on older adults [83, 90, 102, 104–108], which limits the explanatory power of the research as trends in multimorbidity in younger age categories would be missed. An important area for future research are age-specific prevalence rates of multimorbid patients and their development over time. Interaction terms between multimorbidity and age could be used to analyse their influence on need for healthcare and to test whether interaction terms or age and multimorbidity as

separate variables are better predictors of healthcare needs under consideration of other variables such as sex [29].

One limitation in the methodological review was the language restriction. Despite including two languages, studies in other languages might have been missed. As workforce planning is a national task, it is reasonable to assume that many countries provide their approaches to estimate need in a population in their national languages and thus were not included in this study. Future studies should be conducted in a large (multinational) team or cooperative research project with a great variety in native languages and ideally also knowledge of various country-specific workforce planning approaches to ensure that as many studies as possible can be considered whilst nevertheless avoiding translation errors.

Moreover, as the aim of the review was to assess models for needs-based supply of physicians, no recommendations regarding supply side modelling were provided. Further research is needed to evaluate whether approaches for supply-side modelling are adequate. Similar to needs-based models, supply-side models also need to take changing productivity of physicians and other factors such as demographic changes and shifting expectations of the health workforce into account to achieve a sustainable provision of physicians [130, 159]. With regards to the COVID-19 pandemic and the considerable potential of similar outbreaks [149], improved preparedness plans including a diverse portfolio of measures to quickly increase available physician capacities in order to meet changing healthcare needs, are needed [152, 160].

The cross-sectional study was based on claims data of the German statutory health insurance. Despite being combined data of all statutory health insurance providers (>100 in Germany), differences in access to care might have influenced the results. For example, uninsured people would not be visible in the data. Based on limitations in data availability, no cross-validation was feasible as only data from a European-wide survey of people aged 50 and above (including 20 disease categories) on low resolution (national level) would have been available [161].

Previous studies showed that age and socio-economic status may correlate with the number of multimorbid patients [162, 163]. Nevertheless, neither variable was used to adjust the results from the cross-sectional study, with the main reason being data restrictions and uncertainties regarding the actual influence of age and socio-economic status on multimorbidity, which can be primarily attributed to differences in definitions of multimorbidity. Sundmacher et al. [10] also found that adding multimorbidity to the analysis when estimating need for healthcare (including variables regarding age and socio-economic status) increases the explanatory power. More research is needed to clarify the underlying relationship between these variables.

Another limitation lies in the timeliness of the data used to identify multimorbidity, specifically as the estimates are pre-dating the onset of the COVID-19 pandemic [151]. Although German estimations of changes in multimorbidity over time are limited to people above 50 years of age [98] or 65 years of age [105], and vary between 1% and

7% increase per year [98, 105], there is reason to assume that the number of multimorbid patients has increased since 2015. Thus, it will be important to update the estimates of this thesis once the consequences from the COVID-19 pandemic are fully unfold, particularly including chronic or secondary conditions such as (or associated with) long COVID.

#### **4.4 Role of multimorbidity in future**

In order to integrate multimorbidity measures sustainably when assessing the need for healthcare in a population, additional research is needed to understand the influence of multimorbidity on healthcare needs, starting with agreeing on a common definition for multimorbidity with regards to the need for healthcare and including an evidence-based threshold of the minimum number of diseases required to be classified as multimorbid. Moreover, a core set of healthcare conditions with international consent would ease the comparability of findings between studies. Research showed that even within one country such as Germany detected prevalence rates of individuals suffering from multimorbidity may vary significantly [104].

Despite the above-mentioned limitations, multimorbidity measures are important proxies of the need for healthcare and should be considered for future estimations of needs-based supply of physicians. This is particularly important with regards to the increase in mental health conditions related to the COVID-19 pandemic [53, 160], as these conditions combined with other diseases were found to be associated with increased healthcare utilisation and consultation lengths [79].

Researchers found that multimorbid patients require continuous care initiatives as they suffer disproportionately from the fragmentation of care, leaving them vulnerable to adverse effects from inadequate medication, which in turn impacts their quality of life [70, 164]. Moreover, challenges arising from multimorbid patients like uncertainties in evidence of treatments, interactions between medications, and undefined responsibilities put an additional burden on the attending physicians [165]. Therefore, policymakers are demanded to strengthen integrated care specifically in areas with high rates of multimorbid individuals, which would support patients and physicians alike. Moreover, these areas are also well-suited to test innovative, integrated care approaches in order to improve the health outcomes for multimorbid patients and relief burden from physicians [166].

In order to decrease the burden of multimorbidity on healthcare systems in general, initiatives decelerating the development and progression of chronic noncommunicable diseases, which account for more than half of the global burden are needed. As shown by the global Burden of Diseases, Injuries, and Risk Factors Study [167], many of the illnesses causing the majority of DALYs concern conditions that may be preventable, such as mental health conditions, low back pain, diabetes, ischaemic heart disease, and stroke with attributed risk factors including (among others) smoking, unhealthy diet including alcohol consumption, air pollution and bullying. These factors in addition to the socio-economic status and the physical activity level were also linked to accelerated progression of multimorbidity [93, 102]. Initiatives promoting physical activity, which was found to improve outcomes of multimorbid patients and does not require many resources [168], can help to lower the burden of multimorbidity. However, more research is needed on how to implement preventive measures and policies sustainably [169] to decrease the number of chronic diseases and thus the number of multimorbidity in the population.

## 5. Conclusion

The methodological review identified weaknesses in almost all central areas in current approaches for workforce planning. These weaknesses can now be tackled by policymakers and scholars alike to improve future needs-based planning of physicians. Despite the fact that the level of multimorbid individuals is constantly rising and associated with increased healthcare needs, its integration into needs-based physician planning is yet missing. Significant differences in regional multimorbidity levels across Germany underline the importance of integrating multimorbidity measures in needs-based physician planning. For an effective integration, empirical studies defining a core set of diseases to classify multimorbidity and information on their influence on healthcare utilisation and consultation lengths are needed. Moreover, data availability must be expanded in order to allow for appropriate estimations of the need for healthcare and to account for potential influences of supply on indicators used to approximate need.

In the meantime, findings from the cross-sectional study, pointing to high-rate clusters of multimorbid individuals predominantly in the central and eastern parts of Germany, can be used as additional resource to reform German physician planning and to strengthen areas with an increased need for healthcare services and care coordination.

The results of the thesis underline that estimating needs-based supply of physicians is a complex task which requires deliberate decision-making under consideration of certain limitations with regards to the conceptual basis, data sources, model selection including translation into provider requirements, and sustainability of the estimates.

## References

1. Bradshaw J. *Taxonomy of social need*. London: Oxford University Press; 1972.
2. Stevens A, Raftery J, Mant J, Simpson S. *Health Care Needs Assessment: The Epidemiologically Based Needs Assessment Reviews*, v. 2, First Series. Boca Raton, FL: Taylor and Francis, an imprint of CRC Press; 2006.
3. Matthew GK. *Measuring need and evaluating services*. portfolio for Health; Problem and Progress in Medical care. 1971.
4. Acheson RM. The definition and identification of need for health care. *J Epidemiol Community Health*. 1978;32:10–5. doi:10.1136/jech.32.1.10.
5. Culyer AJ. Need: the idea won't do -but we still need it. *Soc Sci Med*. 1995;40:727–30. doi:10.1016/0277-9536(94)00307-f.
6. Rodriguez Santana I, Mason A, Gutacker N, Kasteridis P, Santos R, Rice N. Need, demand, supply in health care: working definitions, and their implications for defining access. *Health Econ Policy Law*. 2023;18:1–13. doi:10.1017/S1744133121000293.
7. Donabedian A. *Aspects of medical care administration: Specifying requirements for health care*. 2nd ed. Cambridge, Mass.: Harvard Univ. Press; 1974.
8. Wright J, Williams R, Wilkinson JR. Health needs assessment. Development and importance of health needs assessment. *British Medical Journal* 1998;316: BMJ Publishing Group. doi:10.1136/bmj.316.7140.1310.
9. Mackenbach JP. The persistence of health inequalities in modern welfare states: The explanation of a paradox. *Social Science and Medicine*. 2012;75:761–9. doi:10.1016/j.socscimed.2012.02.031.
10. Sundmacher L, Schang L, Schüttig W, Flemming R, Frank-Tewaag J, Geiger I, et al. *Gutachten zur Weiterentwicklung der Bedarfsplanung iSd §§ 99 ff. SGB V zur Sicherung der vertragsärztlichen Versorgung*; 2018.
11. Goddard M, Smith P. Equity of access to health care services: theory and evidence from the UK. *Soc Sci Med*. 2001;53:1149–62. doi:10.1016/s0277-9536(00)00415-9.
12. Gibson A, Asthana S, Brigham P, Moon G, Dicker J. Geographies of need and the new NHS: methodological issues in the definition and measurement of the health needs of local populations. *Health & Place*. 2002;8:47–60.
13. Bevan G. The search for a proportionate care law by formula funding in the English NHS. *Financial Accountability & Management*. 2009;25:267–4424.
14. Mason T, Sutton M, Whittaker W, Birch S. Exploring the limitations of age-based models for health care planning. *Social Science and Medicine*. 2015;132:11–9. doi:10.1016/j.socscimed.2015.03.005.
15. Gerfin M. Health Insurance and the Demand for Healthcare. In: Hamilton JH, editor. *Oxford Research Encyclopedia of Economics and Finance*. New York: Oxford University Press; 2016. doi:10.1093/acrefore/9780190625979.013.257.
16. Lauterbach KW, Lüngen M, Schrappe M, Schrappe M, editors. *Gesundheitsökonomie, Management und Evidence-based Medicine: Handbuch für Praxis, Politik und Studium*. 3rd ed. Stuttgart: Schattauer; 2012.
17. Allin S, Grignon M, Le Grand J. Subjective unmet need and utilization of health care services in Canada: what are the equity implications? *Soc Sci Med*. 2010;70:465–72. doi:10.1016/j.socscimed.2009.10.027.
18. Rosen R. Meeting need or fuelling demand?: Improved access to primary care and supply-induced demand. London; June 2014.
19. Israel S. How social policies can improve financial accessibility of healthcare: a multi-level analysis of unmet medical need in European countries. *Int J Equity Health*. 2016;15:41. doi:10.1186/s12939-016-0335-7.

## References

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20. Dugan J. Effects of health insurance on patient demand for physician services. *Health Econ Rev.* 2020;10:31. doi:10.1186/s13561-020-00291-y.
21. Smith PC. Formula Funding of Public Services: An Economic Analysis. *Oxford Review of Economic Policy.* 2003;19:301–22. doi:10.1093/oxrep/19.2.301.
22. Barnett R, Malcolm L. Practice and ethnic variations in avoidable hospital admission rates in Christchurch, New Zealand. *Health & Place.* 2010;16:199–208. doi:10.1016/j.healthplace.2009.09.010.
23. Kim H, Helmer DA, Zhao Z, Boockvar K. Potentially preventable hospitalizations among older adults with diabetes. *Am J Manag Care.* 2011;17:e419-26.
24. Longman JM, I Rolfe M, Passey MD, Heathcote KE, Ewald DP, Dunn T, et al. Frequent hospital admission of older people with chronic disease: a cross-sectional survey with telephone follow-up and data linkage. *BMC Health Serv Res.* 2012;12:373. doi:10.1186/1472-6963-12-373.
25. Balogh R, Brownell M, Ouellette-Kuntz H, Colantonio A. Hospitalisation rates for ambulatory care sensitive conditions for persons with and without an intellectual disability-- a population perspective. *J Intellect Disabil Res.* 2010;54:820–32. doi:10.1111/j.1365-2788.2010.01311.x.
26. Walker RL, Chen G, McAlister FA, Campbell NRC, Hemmelgarn BR, Dixon E, et al. Relationship between primary care physician visits and hospital/emergency use for uncomplicated hypertension, an ambulatory care-sensitive condition. *Can J Cardiol.* 2014;30:1640–8. doi:10.1016/j.cjca.2014.09.035.
27. Wilkinson RG, Marmot M. Solid determinants of health: The Solid facts. Copenhagen: World Health Organization, Regional Office for Europe; 1998.
28. Visscher PM, Wray NR, Zhang Q, Sklar P, McCarthy MI, Brown MA, Yang J. 10 Years of GWAS Discovery: Biology, Function, and Translation. *Am J Hum Genet.* 2017;101:5–22. doi:10.1016/j.ajhg.2017.06.005.
29. Abad-Díez JM, Calderón-Larrañaga A, Poncel-Falcó A, Poblador-Plou B, Calderón-Meza JM, Sicras-Mainar A, et al. Age and gender differences in the prevalence and patterns of multimorbidity in the older population. *BMC Geriatr.* 2014;14:75. doi:10.1186/1471-2318-14-75.
30. Agur K, McLean G, Hunt K, Guthrie B, Mercer SW. How Does Sex Influence Multimorbidity? Secondary Analysis of a Large Nationally Representative Dataset. *Int J Environ Res Public Health.* 2016;13:391. doi:10.3390/ijerph13040391.
31. Tarannum S, Widdifield J, Wu CF, Johnson SR, Rochon P, Eder L. Understanding sex-related differences in healthcare utilisation among patients with inflammatory arthritis: a population-based study. *Ann Rheum Dis.* 2023;82:283–91. doi:10.1136/ard-2022-222779.
32. Jukarainen S, Kiiskinen T, Kuitunen S, Havulinna AS, Karjalainen J, Cordioli M, et al. Genetic risk factors have a substantial impact on healthy life years. *Nat Med.* 2022;28:1893–901. doi:10.1038/s41591-022-01957-2.
33. Wilkinson RG, Marmot M, World Health Organization. Regional Office for Europe. The solid facts: social determinants of health; 20.03.2014.
34. Billings J, Zeitel L, Lukomnik J, Carey TS, Blank AE, Newman L. Impact of socioeconomic status on hospital use in New York City. *Health Aff (Millwood).* 1993;12:162–73. doi:10.1377/hlthaff.12.1.162.
35. Giuffrida A, Gravelle H, Roland M. Measuring quality of care with routine data: avoiding confusion between performance indicators and health outcomes. *BMJ.* 1999;319:94–8. doi:10.1136/bmj.319.7202.94.
36. Mackenbach JP, Stirbu I, Roskam A-JR, Schaap MM, Menvielle G, Leinsalu M, Kunst AE. Socioeconomic inequalities in health in 22 European countries. *N Engl J Med.* 2008;358:2468–81. doi:10.1056/NEJMsa0707519.

## References

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37. Ansari Z, Laditka JN, Laditka SB. Access to health care and hospitalization for ambulatory care sensitive conditions. *Med Care Res Rev.* 2006;63:719–41. doi:10.1177/1077558706293637.
38. Marmot MG, Bosma H, Hemingway H, Brunner E, Stansfeld S. Contribution of job control and other risk factors to social variations in coronary heart disease incidence. *Lancet.* 1997;350:235–9. doi:10.1016/s0140-6736(97)04244-x.
39. Stamatakis E, Hillsdon M, Mishra G, Hamer M, Marmot M. Television viewing and other screen-based entertainment in relation to multiple socioeconomic status indicators and area deprivation: the Scottish Health Survey 2003. *J Epidemiol Community Health.* 2009;63:734–40. doi:10.1136/jech.2008.085902.
40. Luo Y, Waite LJ. The impact of childhood and adult SES on physical, mental, and cognitive well-being in later life. *J Gerontol B Psychol Sci Soc Sci.* 2005;60:S93-S101. doi:10.1093/geronb/60.2.s93.
41. Pudrovska T, Anikputa B. Early-life socioeconomic status and mortality in later life: an integration of four life-course mechanisms. *J Gerontol B Psychol Sci Soc Sci.* 2014;69:451–60. doi:10.1093/geronb/gbt122.
42. Barker DJ. Mothers, babies and health in later life. 2nd ed. Edinburgh u.a.: Churchill Livingstone; 1998.
43. Forty L. Chapter 2 - How early childhood events impact upon adult health. In: Short E, editor. *A prescription for healthy living: A guide to lifestyle medicine.* London, England: Academic Press; 2021. p. 17–29. doi:10.1016/B978-0-12-821573-9.00002-3.
44. Hanlon P, McCallum M, Jani BD, McQueenie R, Lee D, Mair FS. Association between childhood maltreatment and the prevalence and complexity of multimorbidity: A cross-sectional analysis of 157,357 UK Biobank participants. *J Comorb.* 2020;10:2235042X10944344. doi:10.1177/2235042X10944344.
45. Stephan AJ, Strobl R, Schwettmann L, Meisinger C, Ladwig KH, Linkohr B, et al. Being born in the aftermath of World War II increases the risk for health deficit accumulation in older age: results from the KORA-Age study. *European Journal of Epidemiology* 2019. doi:10.1007/s10654-019-00515-4.
46. Bahr J, van den Berg N, Kraywinkel K, Stentzel U, Radicke F, Baumann W, Hoffmann W. Deutschlandweite, regionalisierte Prognose der bevölkerungsbezogenen Morbidität für häufige Krebserkrankungen--Auswirkungen auf die Versorgung. [Prognosis of population-related morbidity for common cancers in Germany--Effects on health care]. *Dtsch Med Wochenschr.* 2015;140:e80-8. doi:10.1055/s-0041-101356.
47. WHO. Models and tools for health workforce planning and projections. Geneva: World Health Organization; 2010.
48. Dreesch N, Dolea C, Dal Poz MR, Goubarev A, Adams O, Aregawi M, et al. An approach to estimating human resource requirements to achieve the Millennium Development Goals. *Health Policy Plan.* 2005;20:267–76. doi:10.1093/heapol/czi036.
49. Tomblin Murphy G, Birch S, MacKenzie A, Bradish S, Elliott Rose A. A synthesis of recent analyses of human resources for health requirements and labour market dynamics in high-income OECD countries. *Human Resources for Health.* 2016;14:59. doi:10.1186/s12960-016-0155-2.
50. Birch S, Murphy GT, MacKenzie A, Cumming J. In place of fear: aligning health care planning with system objectives to achieve financial sustainability. *J Health Serv Res Policy.* 2015;20:109–14. doi:10.1177/1355819614562053.
51. Ono T, Lafourture G, Schoenstein M. Health workforce planning in OECD countries: a review of 26 projection models from 18 countries. *OECD Health Working Papers.* 2013;No. 62:8–11. doi:10.1787/5k44t787zcwb-en.
52. MacKenzie A, Tomblin Murphy G, Audas R. A dynamic, multi-professional, needs-based simulation model to inform human resources for health planning. *Human Resources for Health.* 2019;17:42. doi:10.1186/s12960-019-0376-2.

## References

---

53. OECD/EU. Health at a Glance: Europe 2022: State of Health in the EU Cycle. Paris: OECD Publishing; 2022.
54. §99 Bedarfsplan. In: SGB V; 12/20/1988.
55. Gemeinsamer Bundesausschuss. Richtlinie des Gemeinsamen Bundesausschusses über die Bedarfsplanung sowie die Maßstäbe zur Feststellung von Überversorgung und Unterversorgung in der vertragsärztlichen Versorgung: Bedarfsplanungs-Richtlinie. 2022. [https://www.g-ba.de/downloads/62-492-2937/BPL-RL\\_2022-04-21\\_iK-2022-08-19.pdf](https://www.g-ba.de/downloads/62-492-2937/BPL-RL_2022-04-21_iK-2022-08-19.pdf). Accessed 1 Jan 2023.
56. WHO. The World Health Report 2008: Primary Health Care - Now More Than Ever. Geneva: World Health Organization; 2008.
57. Mercer S, Furler J, Moffat K, Fischbacher-Smith D, Sanci LA. Multimorbidity. Geneva: World Health Organization; 2016.
58. Le Reste JY, Nabbe P, Rivet C, Lygidakis C, Doerr C, Czachowski S, et al. The European general practice research network presents the translations of its comprehensive definition of multimorbidity in family medicine in ten European languages. *PLoS ONE*. 2015;10:e0115796. doi:10.1371/journal.pone.0115796.
59. Johnston MC, Crilly M, Black C, Prescott GJ, Mercer SW. Defining and measuring multimorbidity: a systematic review of systematic reviews. *Eur J Public Health*. 2019;29:182–9. doi:10.1093/eurpub/cky098.
60. Huntley AL, Johnson R, Purdy S, Valderas JM, Salisbury C. Measures of multimorbidity and morbidity burden for use in primary care and community settings: a systematic review and guide. *Ann Fam Med*. 2012;10:134–41. doi:10.1370/afm.1363.
61. Starfield B, Kinder K. Multimorbidity and its measurement. *Health Policy*. 2011;103:3–8. doi:10.1016/j.healthpol.2011.09.004.
62. Johns Hopkins ACG® System. Johns Hopkins ACG® System. 03.02.2023. <https://www.hopkinsacg.org/>. Accessed 13 Apr 2023.
63. Charlson ME, Pompei P, Ales KL, MacKenzie CR. A new method of classifying prognostic comorbidity in longitudinal studies: development and validation. *J Chronic Dis*. 1987;40:373–83. doi:10.1016/0021-9681(87)90171-8.
64. Yurkovich M, Avina-Zubieta JA, Thomas J, Gorenstein M, Lacaille D. A systematic review identifies valid comorbidity indices derived from administrative health data. *J Clin Epidemiol*. 2015;68:3–14. doi:10.1016/j.jclinepi.2014.09.010.
65. Charlson ME, Charlson RE, Peterson JC, Marinopoulos SS, Briggs WM, Hollenberg JP. The Charlson comorbidity index is adapted to predict costs of chronic disease in primary care patients. *J Clin Epidemiol*. 2008;61:1234–40. doi:10.1016/j.jclinepi.2008.01.006.
66. Parmelee PA, Thuras PD, Katz IR, Lawton MP. Validation of the Cumulative Illness Rating Scale in a geriatric residential population. *J Am Geriatr Soc*. 1995;43:130–7. doi:10.1111/j.1532-5415.1995.tb06377.x.
67. Salvi F, Miller MD, Grilli A, Giorgi R, Towers AL, Morichi V, et al. A manual of guidelines to score the modified cumulative illness rating scale and its validation in acute hospitalized elderly patients. *J Am Geriatr Soc*. 2008;56:1926–31. doi:10.1111/j.1532-5415.2008.01935.x.
68. Barnett K, Mercer SW, Norbury M, Watt G, Wyke S, Guthrie B. Epidemiology of multimorbidity and implications for health care, research, and medical education: a cross-sectional study. *The Lancet*. 2012;380:37–43. doi:10.1016/S0140-6736(12)60240-2.
69. Glynn LG, Valderas JM, Healy P, Burke E, Newell J, Gillespie P, Murphy AW. The prevalence of multimorbidity in primary care and its effect on health care utilization and cost. *Fam Pract*. 2011;28:516–23. doi:10.1093/fampra/cmr013.
70. Wallace E, Salisbury C, Guthrie B, Lewis C, Fahey T, Smith SM. Managing patients with multimorbidity in primary care. *BMJ*. 2015;350:h176. doi:10.1136/bmj.h176.

## References

---

71. Lehnert T, König H-H. Auswirkungen von Multimorbidität auf die Inanspruchnahme medizinischer Versorgungsleistungen und die Versorgungskosten. [Effects of multimorbidity on health care utilization and costs]. *Bundesgesundheitsblatt, Gesundheitsforschung, Gesundheitsschutz*. 2012;55:685–92. doi:10.1007/s00103-012-1475-6.
72. Soley-Bori M, Ashworth M, Bisquera A, Dodhia H, Lynch R, Wang Y, Fox-Rushby J. Impact of multimorbidity on healthcare costs and utilisation: a systematic review of the UK literature. *The British journal of general practice : the journal of the Royal College of General Practitioners*. 2021;71:e39-e46. doi:10.3399/bjgp20X713897.
73. Sum G, Ishida M, Koh GC-H, Singh A, Oldenburg B, Lee JT. Implications of multimorbidity on healthcare utilisation and work productivity by socioeconomic groups: Cross-sectional analyses of Australia and Japan. *PLoS ONE*. 2020;15:e0232281. doi:10.1371/journal.pone.0232281.
74. Bähler C, Huber CA, Brüniger B, Reich O. Multimorbidity, health care utilization and costs in an elderly community-dwelling population: a claims data based observational study. *BMC Health Serv Res*. 2015;15:23. doi:10.1186/s12913-015-0698-2.
75. Giannouchos TV, Kum H-C, Foster MJ, Ohsfeldt RL. Characteristics and predictors of adult frequent emergency department users in the United States: A systematic literature review. *Journal of Evaluation in Clinical Practice*. 2019;25:420–33. doi:10.1111/jep.13137.
76. Breen K, Finnegan L, Vuckovic K, Fink A, Rosamond W, DeVon HA. Multimorbidity in Patients With Acute Coronary Syndrome Is Associated With Greater Mortality, Higher Readmission Rates, and Increased Length of Stay: A Systematic Review. *J Cardiovasc Nurs*. 2020;35:E99-E110. doi:10.1097/JCN.0000000000000748.
77. MacNeil-Vroomen JL, Thompson M, Leo-Summers L, Marottoli RA, Tai-Seale M, Allore HG. Health-care use and cost for multimorbid persons with dementia in the National Health and Aging Trends Study. *Alzheimers Dement*. 2020;16:1224–33. doi:10.1002/alz.12094.
78. König H-H, Leicht H, Bickel H, Fuchs A, Gensichen J, Maier W, et al. Effects of multiple chronic conditions on health care costs: an analysis based on an advanced tree-based regression model. *BMC Health Serv Res*. 2013;13:219. doi:10.1186/1472-6963-13-219.
79. Scheidt-Nave C, Richter S, Fuchs J, Kuhlmeier A. Herausforderungen an die Gesundheitsforschung für eine alternde Gesellschaft am Beispiel "Multimorbidität". [Challenges to health research for aging populations using the example of "multimorbidity"]. *Bundesgesundheitsblatt, Gesundheitsforschung, Gesundheitsschutz*. 2010;53:441–50. doi:10.1007/s00103-010-1052-9.
80. Tadeu ACR, E Silva Caetano IRC, Figueiredo IJ de, Santiago LM. Multimorbidity and consultation time: a systematic review. *BMC Fam Pract*. 2020;21:152. doi:10.1186/s12875-020-01219-5.
81. McPhail SM. Multimorbidity in chronic disease: impact on health care resources and costs. *Risk Manag Healthc Policy*. 2016;9:143–56. doi:10.2147/RMHP.S97248.
82. Davies LE, Spiers G, Kingston A, Todd A, Adamson J, Hanratty B. Adverse Outcomes of Polypharmacy in Older People: Systematic Review of Reviews. *J Am Med Dir Assoc*. 2020;21:181–7. doi:10.1016/j.jamda.2019.10.022.
83. Krüger C, Schäfer I, van den Bussche H, Bickel H, Dreischulte T, Fuchs A, et al. Comparison of FORTA, PRISCUS and EU(7)-PIM lists on identifying potentially inappropriate medication and its impact on cognitive function in multimorbid elderly German people in primary care: a multicentre observational study. *BMJ Open*. 2021;11:e050344. doi:10.1136/bmjopen-2021-050344.
84. Ali MU, Sherifali D, Fitzpatrick-Lewis D, Kenny M, Lamarche L, Raina P, Mangin D. Interventions to address polypharmacy in older adults living with multimorbidity: Review of reviews. *Can Fam Physician*. 2022;68:e215-e226. doi:10.46747/cfp.6807e215.
85. Crespo PA, Nunes BP, Barros FC, Gonçalves H, Menezes AMB, Wehrmeister FC. Multimorbidity and simultaneity of health risk factors, from adolescence to early adulthood: 1993 Pelotas Birth Cohort. *Prev Med*. 2022;155:106932. doi:10.1016/j.ypmed.2021.106932.

## References

---

86. Chau K, Baumann M, Chau N. Socioeconomic inequities patterns of multi-morbidity in early adolescence. *Int J Equity Health.* 2013;12:65. doi:10.1186/1475-9276-12-65.
87. Harris ML, Egan N, Forder PM, Loxton D. Increased chronic disease prevalence among the younger generation: Findings from a population-based data linkage study to inform chronic disease ascertainment among reproductive-aged Australian women. *PLoS ONE.* 2021;16:e0254668. doi:10.1371/journal.pone.0254668.
88. Troelstra SA, Straker L, Harris M, Brown S, van der Beek AJ, Coenen P. Multimorbidity is common among young workers and related to increased work absenteeism and presenteeism: results from the population-based Raine Study cohort. *Scand J Work Environ Health.* 2020;46:218–27. doi:10.5271/sjweh.3858.
89. Ge L, Ong R, Yap CW, Heng BH. Effects of chronic diseases on health-related quality of life and self-rated health among three adult age groups. *Nurs Health Sci.* 2019;21:214–22. doi:10.1111/nhs.12585.
90. van den Bussche H, Koller D, Kolonko T, Hansen H, Wegscheider K, Glaeske G, et al. Which chronic diseases and disease combinations are specific to multimorbidity in the elderly? Results of a claims data based cross-sectional study in Germany. *BMC Public Health.* 2011;11:101. doi:10.1186/1471-2458-11-101.
91. Nagl A, Witte J, Hodek JM, Greiner W. Relationship between multimorbidity and direct healthcare costs in an advanced elderly population. Results of the PRISCUS trial. *Z Gerontol Geriatr.* 2012;45:146–54. doi:10.1007/s00391-011-0266-2.
92. Geiger I, Flemming R, Schüttig W, Sundmacher L. Regional variations in multimorbidity burden among office-based physicians in Germany. *Eur J Public Health* 2023. doi:10.1093/eurpub/ckad039.
93. Siah KW, Wong CH, Gupta J, Lo AW. Multimorbidity and mortality: A data science perspective. *J Multimorb Comorb.* 2022;12:26335565221105431. doi:10.1177/26335565221105431.
94. Álvarez-Gálvez J, Ortega-Martín E, Carretero-Bravo J, Pérez-Muñoz C, Suárez-Lledó V, Ramos-Fiol B. Social determinants of multimorbidity patterns: A systematic review. *Front Public Health.* 2023;11:1081518. doi:10.3389/fpubh.2023.1081518.
95. Doheny M, Agerholm J, Orsini N, Schön P, Burström B. Socio-demographic differences in the frequent use of emergency department care by older persons: a population-based study in Stockholm County. *BMC Health Serv Res.* 2019;19:202. doi:10.1186/s12913-019-4029-x.
96. Uijen AA, van de Lisdonk EH. Multimorbidity in primary care: prevalence and trend over the last 20 years. *Eur J Gen Pract.* 2008;14 Suppl 1:28–32. doi:10.1080/13814780802436093.
97. Kwon I, Shin O, Park S, Kwon G. Multi-Morbid Health Profiles and Specialty Healthcare Service Use: A Moderating Role of Poverty. *Int J Environ Res Public Health* 2019. doi:10.3390/ijerph16111956.
98. Souza DLB, Oliveras-Fabregas A, Minobes-Molina E, Camargo Cancela M de, Galbany-Estragués P, Jerez-Roig J. Trends of multimorbidity in 15 European countries: a population-based study in community-dwelling adults aged 50 and over. *BMC Public Health.* 2021;21:76. doi:10.1186/s12889-020-10084-x.
99. Geyer S, Eberhard S. Compression and Expansion of Morbidity. *Dtsch Arztebl Int.* 2022;119:810–5. doi:10.3238/ärztebl.m2022.0324.
100. Steffler M, Li Y, Weir S, Shaikh S, Murtada F, Wright JG, Kantarevic J. Trends in prevalence of chronic disease and multimorbidity in Ontario, Canada. *CMAJ.* 2021;193:E270-E277. doi:10.1503/cmaj.201473.
101. Nowossadeck E. Demografische Alterung und Folgen für das Gesundheitswesen: Robert Koch-Institut; 2012.
102. Schäfer I, Hansen H, Kaduszkiewicz H, Bickel H, Fuchs A, Gensichen J, et al. Health behaviour, social support, socio-economic status and the 5-year progression of

## References

---

- multimorbidity: Results from the MultiCare Cohort Study. *J Comorb.* 2019;9:2235042X19883560. doi:10.1177/2235042X19883560.
103. Beerten SG, Helsen A, Lepeleire J de, Waldorff FB, Vaes B. Trends in prevalence and incidence of registered dementia and trends in multimorbidity among patients with dementia in general practice in Flanders, Belgium, 2000-2021: a registry-based, retrospective, longitudinal cohort study. *BMJ Open.* 2022;12:e063891. doi:10.1136/bmjopen-2022-063891.
104. Tiemann M, Mohokum M. Demografischer Wandel, Krankheitspanorama, Multimorbidität und Mortalität in Deutschland. In: Tiemann M, Mohokum M, editors. *Prävention und Gesundheitsförderung: Mit 169 Abbildungen und 117 Tabellen.* Berlin: Springer; 2021. p. 3–11. doi:10.1007/978-3-662-62426-5\_1.
105. Frank J, Babitsch B. Kompression oder Expansion der Morbidität in der ambulanten Versorgung? : Die Generation 65plus in 2007 und 2014. [Compression or expansion of morbidity in outpatient healthcare? : Generation 65plus in 2007 and 2014]. *Z Gerontol Geriatr.* 2018;51:557–66. doi:10.1007/s00391-017-1291-6.
106. van den Bussche H, Schön G, Kolonko T, Hansen H, Wegscheider K, Glaeske G, Koller D. Patterns of ambulatory medical care utilization in elderly patients with special reference to chronic diseases and multimorbidity--results from a claims data based observational study in Germany. *BMC Geriatr.* 2011;11:54. doi:10.1186/1471-2318-11-54.
107. Schäfer I, Hansen H, Schön G, Maier W, Höfels S, Altiner A, et al. The German MultiCare-study: Patterns of multimorbidity in primary health care - protocol of a prospective cohort study. *BMC Health Serv Res.* 2009;9:145. doi:10.1186/1472-6963-9-145.
108. Breckner A, Glassen K, Schulze J, Lühmann D, Schaefer I, Szecsenyi J, et al. Experiences of patients with multimorbidity with primary care and the association with patient activation: a cross-sectional study in Germany. *BMJ Open.* 2022;12:e059100. doi:10.1136/bmjopen-2021-059100.
109. Geiger I, Schang L, Sundmacher L. Assessing needs-based supply of physicians: A criteria-led methodological review of international studies in high-resource settings. 2023. doi: 10.1186/s12913-023-09461-0
110. Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ.* 2021;372:n71. doi:10.1136/bmj.n71.
111. Moher D, Liberati A, Tetzlaff J, Altman DG. Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. *BMJ.* 2009;339:b2535. doi:10.1136/bmj.b2535.
112. Hong QN, Fàbregues S, Bartlett G, Boardman F, Cargo M, Dagenais P, et al. The Mixed Methods Appraisal Tool (MMAT) version 2018 for information professionals and researchers. *EFI.* 2018;34:285–91. doi:10.3233/EFI-180221.
113. Munn Z, Stone JC, Aromataris E, Klugar M, Sears K, Leonardi-Bee J, Barker TH. Assessing the risk of bias of quantitative analytical studies: introducing the vision for critical appraisal within JBI systematic reviews. *JBI Evidence Synthesis.* 2023;21:467–71. doi:10.11124/JBIES-22-00224.
114. Redaktion Deutsches Ärzteblatt. Mehr als die Hälfte der deutschen Bevölkerung ist chronisch krank. 2020. <https://www.aerzteblatt.de/nachrichten/116897/Mehr-als-die-Haelfte-der-deutschen-Bevoelkerung-ist-chronisch-krank>. Accessed 26 Mar 2022.
115. Kulldorff M. A spatial scan statistic. *Communications in Statistics - Theory and Methods.* 1997;26:1481–96. doi:10.1080/03610929708831995.
116. Kulldorff M, Nagarwalla N. Spatial disease clusters: detection and inference. *Statistics in Medicine.* 1995;14:799–810. doi:10.1002/sim.4780140809.
117. Anselin L. Local Indicators of Spatial Association-LISA. *Geographical Analysis.* 1995;27:93–115. doi:10.1111/j.1538-4632.1995.tb00338.x.

## References

---

118. Lee PP, Jackson CA, Relles DA. Estimating eye care workforce supply and requirements. *Ophthalmology*. 1995;102:1964-71; discussion 1971-2. doi:10.1016/s0161-6420(95)30767-1.
119. Anderson GF, Han KC, Miller RH, Johns ME. A comparison of three methods for estimating the requirements for medical specialists: the case of otolaryngologists. *Health Services Research*. 1997;32:139-53.
120. Ansah JP, Koh V, Korne D de, Bayer S, Pan C, Thiagarajan J, et al. Comparing health workforce forecasting approaches for healthcare planning: The case for ophthalmologists. *IJH*. 2016;3:84. doi:10.5430/ijh.v3n1p84.
121. Greenberg L, Cultice JM. Forecasting the need for physicians in the United States: the Health Resources and Services Administration's physician requirements model. *Health Services Research*. 1997;31:723-37.
122. Barber P, López-Valcárcel BG. Forecasting the need for medical specialists in Spain: application of a system dynamics model. *Human Resources for Health*. 2010;8:24. doi:10.1186/1478-4491-8-24.
123. Konrad TR, Ellis AR, Thomas KC, Holzer CE, Morrissey JP. County-level estimates of need for mental health professionals in the United States. *Psychiatr Serv*. 2009;60:1307-14. doi:10.1176/ps.2009.60.10.1307.
124. Singh D, Lalani H, Kralj B, Newman E, Goodyear J, Hellyer D, Tepper J. Ontario population needs-based physician simulation model: Final Report. Toronto; October 2010.
125. Albrecht M, Nolting H-D, Schliwen A, Schwinger A. Neuordnung der ärztlichen Bedarfsplanung, Wissenschaftliches Gutachten im Auftrag der Patientenvertretung im Gemeinsamen Bundesausschuss. Berlin; 2012.
126. Albrecht M, Ochmann R, Jacobi F, Bretschneider J, Thom J, Müllender S, Becker M. Bedarfsplanung Psychotherapeuten - Konzept für eine bedarfsoorientierte Planung der Psychotherapeutenstätte: IGES Institut, Psychologische Hochschule Berlin; 2016.
127. Jäger R, van den Berg N, Hoffmann W, Jordan RA, Schwendicke F. Estimating future dental services' demand and supply: A model for Northern Germany. *Community Dentistry and Oral Epidemiology*. 2016;44:169-79. doi:10.1111/cdoe.12202.
128. Stillfried D von, Czihal T. Möglichkeiten der fachgruppenspezifischen Risikoadjustierung der Verhältniszahlen für einezeitgemäße Versorgungsplanung. *GuS*. 2011;65:26-33. doi:10.5771/1611-5821-2011-2-26.
129. Stuckless T, Milosevic M, Metz C de, Parliament M, Tompkins B, Brundage M. Managing a national radiation oncologist workforce: a workforce planning model. *Radiother Oncol*. 2012;103:123-9. doi:10.1016/j.radonc.2011.12.025.
130. CfWI. In-depth review of the general practitioner workforce: Final report. London; July 2014.
131. Laurence CO, Karon J. Improving the planning of the GP workforce in Australia: a simulation model incorporating work transitions, health need and service usage. *Human Resources for Health*. 2016;14:13. doi:10.1186/s12960-016-0110-2.
132. Czaja M, Meinlschmidt G, Bettge S. Sozialindikative Planung der regionalen ärztlichen Versorgung. *GuS*. 2012;66:34-43. doi:10.5771/1611-5821-2012-3-34.
133. Dall TM, West T, Chakrabarti R, Iacobucci W. The Complexities of Physician Supply and Demand: Projections from 2014 to 2025: Final Report: Association of American Medical Colleges; 2016.
134. Ozegowski S, Sundmacher L. Wie "bedarfsgerecht" ist die Bedarfsplanung? Eine Analyse der regionalen Verteilung der vertragsärztlichen Versorgung. [Is the needs-based planning mechanism effectively needs-based? An analysis of the regional distribution of outpatient care providers]. *Gesundheitswesen*. 2012;74:618-26. doi:10.1055/s-0032-1321748.
135. Kopetsch T, Maier W. Analyse des Zusammenhangs zwischen regionaler Deprivation und Inanspruchnahme – Ein Diskussionsbeitrag zur Ermittlung des Arztbedarfes in Deutschland. *Das Gesundheitswesen*. 2016;80:27-33. doi:10.1055/s-0042-100622.

## References

---

136. Birch S., Kephart G., Tomblin-Murphy G., O'Brien-Pallas L., Alder R. and MacKenzie A. Human Resources Planning and the Production of Health: A Needs-Based Analytical Framework on JSTOR. University of Toronto Press. 2007:1–16.
137. Birch S, Kephart G, Murphy GT, O'Brien-Pallas L, Alder R, MacKenzie A. Health human resources planning and the production of health: development of an extended analytical framework for needs-based health human resources planning. *Journal of public health management and practice : JPHMP* 2009. doi:10.1097/PHH.0b013e3181b1ec0e.
138. Wennberg JE. Time to tackle unwarranted variations in practice. *BMJ*. 2011;342:d1513. doi:10.1136/bmj.d1513.
139. Organisation for Economic Co-operation and Development. *Geographic variations in health care: what do we know and what can be done to improve health system performance?* Paris: OECD Publishing; 2014.
140. Bronner K, Eliassen S, King A, Leggett C, Punjasthitkul S, Skinner J. *The Dartmouth Atlas of Health Care: 2018 Data Update*: The Trustees of Dartmouth College; 2021.
141. Haumont D, Modi N, Saugstad OD, Antetere R, NguyenBa C, Turner M, et al. Evaluating preterm care across Europe using the eNewborn European Network database. *Pediatr Res*. 2020;88:484–95. doi:10.1038/s41390-020-0769-x.
142. BfArM. Das FDZ | FDZ Gesundheit. 2023. <https://www.forschungsdatenzentrum-gesundheit.de/das-fdz>. Accessed 20 Jan 2023.
143. Martins H. EU Health data centre and a common data strategy for public health. 2021. [https://www.europarl.europa.eu/RegData/etudes/STUD/2021/690009/EPRS\\_STU\(2021\)690009\\_EN.pdf](https://www.europarl.europa.eu/RegData/etudes/STUD/2021/690009/EPRS_STU(2021)690009_EN.pdf). Accessed 10 Mar 2023.
144. Geiger I, Reber KC, Darius H, Holzgreve A, Karmann S, Liersch S, et al. Improving care coordination for patients with cardiac disease: Study protocol of the randomised controlled new healthcare programme (Cardiolotse). *Contemporary Clinical Trials*. 2021;103:106297. doi:10.1016/j.cct.2021.106297.
145. Geiger I, Kammerlander C, Höfer C, Volland R, Trinemeier J, Henschelchen M, et al. Implementation of an integrated care programme to avoid fragility fractures of the hip in older adults in 18 Bavarian hospitals - study protocol for the cluster-randomised controlled fracture liaison service FLS-CARE. *BMC Geriatr*. 2021;21:43. doi:10.1186/s12877-020-01966-1.
146. Lee SK, Mahl SK, Rowe BH. The Induced Productivity Decline Hypothesis: More Physicians, Higher Compensation and Fewer Services. *Healthc Policy*. 2021;17:90–104. doi:10.12927/hcpol.2021.26655.
147. Eddy DM, Hollingsworth W, Caro JJ, Tsevat J, McDonald KM, Wong JB. Model transparency and validation: A report of the ISPOR-SMDM modeling good research practices task force-7. *Medical Decision Making*. 2012;32:733–43. doi:10.1177/0272989X12454579.
148. Laiteerapong N, Huang ES. The pace of change in medical practice and health policy: collision or coexistence? *J Gen Intern Med*. 2015;30:848–52. doi:10.1007/s11606-015-3182-0.
149. WHO. *Imagining the future of pandemics and epidemics: a 2022 perspective*. Geneva: World Health Organization; 2022.
150. van Greuningen M, Batenburg RS, van der Velden LF. The accuracy of general practitioner workforce projections. *Human Resources for Health*. 2013;11:31. doi:10.1186/1478-4491-11-31.
151. World Health Organization. WHO Director-General's opening remarks at the media briefing on COVID-19. Geneva; 03/11/2020.
152. Bertozzi AL, Franco E, Mohler G, Short MB, Sledge D. The challenges of modeling and forecasting the spread of COVID-19. *Proc Natl Acad Sci U S A*. 2020;117:16732–8. doi:10.1073/pnas.2006520117.

## References

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153. Murphy GT, Birch S, MacKenzie A, Rigby J, Langley J. Démarche axée sur les besoins intégrés pour les services de santé et la planification de la main-d'œuvre en santé : application à une pandémie d'influenza. [An Integrated Needs-Based Approach to Health Service and Health Workforce Planning: Applications for Pandemic Influenza]. *Healthc Policy*. 2017;13:28–42. doi:10.12927/hcpol.2017.25193.
154. MacKenzie A, MacQuarrie C, Murphy M, Piers G, Philopoulos K, Carrigan S, et al. Operationalizing integrated needs-based workforce planning at Nova Scotia Health in response to the COVID-19 pandemic. *Healthc Manage Forum*. 2022;35:222–30. doi:10.1177/08404704221093982.
155. Statistisches Bundesamt. Demographischer Wandel. 13.12.2022. [https://www.destatis.de/DE/Home/\\_inhalt.html](https://www.destatis.de/DE/Home/_inhalt.html). Accessed 1 May 2023.
156. Kroll LE, Lampert T. Regionalisierung von Gesundheitsindikatoren: Ergebnisse aus der GEDA-Studie 2009. *Bundesgesundheitsbl*. 2012;55:129–40. doi:10.1007/s00103-011-1403-1.
157. Wheeler DC. A comparison of spatial clustering and cluster detection techniques for childhood leukemia incidence in Ohio, 1996–2003. *Int J Health Geogr*. 2007;6:13. doi:10.1186/1476-072X-6-13.
158. O’Malley L, Macey R, Allen T, Brocklehurst P, Thomson F, Rigby J, et al. Workforce Planning Models for Oral Health Care: A Scoping Review. *JDR Clinical & Translational Research*. 2022;7:16–24. doi:10.1177/2380084420979585.
159. Anderson M, O’Neill C, Macleod Clark J, Street A, Woods M, Johnston-Webber C, et al. Securing a sustainable and fit-for-purpose UK health and care workforce. *Lancet*. 2021;397:1992–2011. doi:10.1016/S0140-6736(21)00231-2.
160. Bourgeault IL, Maier CB, Dieleman M, Ball J, MacKenzie A, Nancarrow S, et al. The COVID-19 pandemic presents an opportunity to develop more sustainable health workforces. *Human Resources for Health*. 2020;18:83. doi:10.1186/s12960-020-00529-0.
161. Börsch-Supan A. Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 6: SHARE-ERIC; 2022.
162. Puth M-T, Weckbecker K, Schmid M, Münster E. Prevalence of multimorbidity in Germany: impact of age and educational level in a cross-sectional study on 19,294 adults. *BMC Public Health*. 2017;17:826. doi:10.1186/s12889-017-4833-3.
163. Schäfer I, Hansen H, Schön G, Höfels S, Altiner A, Dahlhaus A, et al. The influence of age, gender and socio-economic status on multimorbidity patterns in primary care. First results from the multicare cohort study. *BMC Health Serv Res*. 2012;12:89. doi:10.1186/1472-6963-12-89.
164. Dodel R. Multimorbidität: Konzept, Epidemiologie, Versorgung. [Multimorbidity: concept, epidemiology and treatment]. *Nervenarzt*. 2014;85:401–8. doi:10.1007/s00115-013-3937-y.
165. Damarell RA, Morgan DD, Tieman JJ. General practitioner strategies for managing patients with multimorbidity: a systematic review and thematic synthesis of qualitative research. *BMC Fam Pract*. 2020;21:131. doi:10.1186/s12875-020-01197-8.
166. Baker JM, Grant RW, Gopalan A. A systematic review of care management interventions targeting multimorbidity and high care utilization. *BMC Health Serv Res*. 2018;18:65. doi:10.1186/s12913-018-2881-8.
167. GBD 2019 Human Resources for Health Collaborators. Measuring the availability of human resources for health and its relationship to universal health coverage for 204 countries and territories from 1990 to 2019: a systematic analysis for the Global Burden of Disease Study 2019. *2022;399:2129–54*. doi:10.1016/S0140-6736(22)00532-3.
168. Barker K, Holland AE, Skinner EH, Lee AL. Clinical Outcomes Following Exercise Rehabilitation in People with Multimorbidity: A Systematic Review. *J Rehabil Med*. 2023;55:jrm00377. doi:10.2340/jrm.v55.2551.

## References

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169. Oh A, Abazeed A, Chambers DA. Policy Implementation Science to Advance Population Health: The Potential for Learning Health Policy Systems. *Front Public Health*. 2021;9:681602. doi:10.3389/fpubh.2021.681602.

## Appendix A: Review protocol

### 1. Search history

#### a. Electronic database

Database, provider		Web of Science Core Collection, Thomson Reuters	Update
Search date (dd/mm/yyyy)		05/04/2017	09/03/2020
Period or update status		1963-05/04/2017	05/04/2017-09/03/2020
#	Search	Results	Results
1	TOPIC: ("workforce planning")	680	/
2	TOPIC: ("capacity planning")	2,024	/
3	TOPIC: ("human resource*")	27,379	/
4	TOPIC: ("planning")	343,331	/
5	TOPIC: ("service requirement*")	2,857	/
6	TOPIC: ("health")	1,545,733	/
7	TOPIC: ("physician*")	252,153	/
8	#7 AND #6	80,602	/
9	#8 AND #5	8	/
10	#8 AND #1	66	/
11	#8 AND #2	7	/
12	#8 AND #4 AND #3	70	/
14	#13 OR #12 OR #11 OR #10 OR #9	<b>132</b>	<b>91</b>

Source: Geiger et al. [109]

Database, provider		PubMed, U.S. National Library of Medicine	Update
Search date (dd/mm/yyyy)		16/05/2017	09/03/2020
Period or update status		1980-16/05/2017	16/05/2017-09/03/2020
#	Search	Results	Results
1	TOPIC: ("need")	391,069	/
2	TOPIC: ("capacity planning")	83	/
3	TOPIC: ("health human resource")	104	/
4	TOPIC: ("demand")	67427	/
5	TOPIC: ("healthcare")	166,724	/
6	TOPIC: ("workforce planning")	511	/
7	TOPIC: ("forecast") / ("projection")	4,400 / 48,535	/
8	#6 AND #5	85	/
9	#6 AND #5 AND #1	25	/
10	#6 AND #5 AND #4	24	/
11	#6 AND #5 AND #7	2	/
12	#6 AND #3	4	/
13	#6 AND #7	8	/
14	#3 AND #1	25	/
15	#3 AND #4	13	/
16	#9 OR #10 OR #11 OR #12 #13 OR #14 OR #15	<b>186</b>	<b>3</b>

Source: Geiger et al. [109]

## Appendix A: Review protocol

Database, provider		Science Direct, Elsevier	Update
Search date (dd/mm/yyyy)		20/09/2017	09/03/2020
Period or update status		1980-20/09/2017	20/09/2017-09/03/2020
#	Search	Results	Results
1	TOPIC: ("need")	6,016,181	/
2	TOPIC: ("capacity planning")	5,326	/
3	TOPIC: ("health human resource")	403	/
4	TOPIC: ("demand")	1,537,913	/
5	TOPIC: ("healthcare")	392,618	/
6	TOPIC: ("workforce planning")	1,344	/
7	TOPIC: ("forecast") / ("projection")	244,797 / 698,167	/
8	#6 AND #3	26	/
9	#6 AND #5 AND #4 AND #1	298	/
10	#6 AND #7 AND #5 AND #4 AND #1	65	/
11	#6 AND #7 AND #3	10	/
12	#2 AND 5 AND #7	117	/
13	#8 OR #9 OR #10 OR #11 OR #12	<b>516</b>	<b>187</b>

Source: Geiger et al. [109]

### Summary of search history

Database, provider	Search date (dd/mm/yyyy)	Period or update status	Results	Update
Web of Science Core Collection, Thomson Reuters	04/04/2017	1963 – 05/04/2017	132	91
PubMed, U/S/ National Library of Medicine	16/05/2017	1980 – 16/05/2017	186	3
Science Direct, Elsevier	16/05/2017	1980 – 20/09/2017	516	187
Overall including duplicates			834	281
Overall no duplicates			<b>790</b>	<b>203</b>

Source: Geiger et al. [109]

- b. List of websites included in the identification process [109]
- International
    - GHWA <http://www/who/int/workforcealliance/>
      - NOW transitioned into: <http://www/who/int/hrh/network/en/>
    - WHO Health Workforce <http://www/who/int/hrh/resources/en/>
    - OECD <http://www/oecd.org/>
    - World Bank <http://www/worldbank.org/>
    - Andean network of Observatories for human resources for health <http://www/observatoriorth.org/andino/?q=taxonomy/term/23>
    - European Observatory on Health Systems and Policies <http://www/euro/who/int/en/about-us/partners/observatory>
    - WHO EURO Health Evidence Network (HEN)
    - <http://www/euro/who/int/en/data-and-evidence/evidence-informed-policy-making/health-evidence-network-hen>
    - The Health Systems and Policy Monitor
    - <http://www/hspm.org/mainpage.aspx>
    - European Commission on Public Health, health workforce [http://ec.europa.eu/health/workforce/policy/index\\_en.htm](http://ec.europa.eu/health/workforce/policy/index_en.htm)
    - Joint Action on Health Workforce Planning and Forecasting <http://www/euhwforce/eu/>
    - HRH Global Resource Centre <http://www/hrhresourcecenter/org/>
    - KIT <http://www/kit/nl/kit/en/>
    - Health Cluster EU <http://healthclusternet/eu>
    - WHO Collaborating Centers focusing on HRH
      - University of Western Cape <http://www/uwc/ac/za/Faculties/CHS/soph/Pages/WHO-Collaborating-Center-aspx>
      - University of Illinois at Rockford <http://ncrhp/uic/edu/index.cfm?id=1031&b=1003&page=World%20Health%20Organization%20%28WHO%29%20Collaborating%20Centre>
      - McMaster University [http://nursing/mcmaster/ca/WHO\\_collaborating\\_centre/html](http://nursing/mcmaster/ca/WHO_collaborating_centre/html)

## Appendix A: Review protocol

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- WHO Collaborating Center on Health Workforce Policy and Planning -  
<http://whoccworkforce/hmt/unl/pt/>
- ii. Country specific
- Canada
  - Health Canada (human resources strategy) <http://www/hc-sc/gc/ca/hcs-sss/hhr-rhs/strateg/index-eng.php>
  - CHHRN <http://www/hhr-rhs/ca/>
- Netherlands
  - NIVEL <http://www/nivel/nl/en>
  - Advisory Committee on Medical Manpower Planning  
<http://www/capaciteitsorgaan.nl/Publicaties/tabid/68/language/en-US/Default.aspx>
- Austria
  - Gesundheitsportal <https://www/gesundheit/gv/at/Portal/Node/ghp/public>
  - Hauptverband der österreichischen Sozialversicherungsträger  
<http://www/hauptverband/at/portal27/hvbportal/content?contentid=10007/752050&viewmode=content>
- Sweden
  - Ministry of Health and Social Affairs <http://www/government/se/sb/d/2061>
  - National Board of Health and Welfare <http://www/socialstyrelsen/se/english>
- UK
  - Centre for Workforce Intelligence <http://www/cfwi/org/uk/>
  - Department of Health  
[https://www/gov/uk/government/publications?departments\[\]&=department-of-health](https://www/gov/uk/government/publications?departments[]&=department-of-health)
  - Health Education England <https://hee/nhs/uk/>
- Germany
  - IGES Institut GmbH <https://www/iges/com/>
  - Zentralinstitut für die kassenärztliche Versorgung <http://www/zi/de/>
  - GKV Spitzenverband <https://www/gkv-spitzenverband/de/>
  - Wissenschaftliches Institut für Gesundheitsökonomie und Gesundheitssystemforschung <http://www/wig2/de/>

## Appendix B: Multimorbidity categories according to Barnett et al. [68]

Disease categories	ICD-10-GM codes		
	1-digit code	3-digit code	4/5-digit code
Hypertension		I10 - I11	
		O11	
Depression		F33	F41.2
		F32	F20.4
		F34	
Painful condition		M54	F62.80
		N23	F45.40
		R51, R52	H57.1
		R10	K14.6
			K08.88
			M25.5
			M79.6
			N64.4
			H92.0
			R10.2
			R07.0, R07.1
Asthma (currently treated)		J45, J46	
Coronary heart disease		I20 - I25	
Treated dyspepsia		K29 - K31	F45.31
			R10.1
Diabetes		E10 - E14	
Thyroid disorders		E00 - E07	
Rheumatoid arthritis, other inflammatory polyarthropathies & systematic connective tissue disorders		M05 - M14	
		M20 - M25	
Hearing loss		H90	H83.3
		H93	H91.0, H91.2, H91.3, H91.9
Chronic obstructive pulmonary disease		J44	
Anxiety & other neurotic, stress related & somatoform disorders		F40 - F48	
Irritable bowel syndrome		K58	
New diagnosis of cancer in last 5a	C, D (48)		
Alcohol problems		F10	
Other psychoactive substance misuse		F11 - F19	
Treated constipation			K59.0
Stroke & transient ischaemic attack		I60 - I62	
		I63	
		I65 - I67	
		G45, G46	
Chronic kidney disease		N18	
Diverticular disease of intestine		K57	
Atrial fibrillation		I47 - I49	
Peripheral vascular disease		I70 - I89	
Heart failure		I50	
Prostate disorders		N40 - N42	
Glaucoma		H40	
Epilepsy (currently treated)		G40, G41	
Dementia		F00 - F03	
Schizophrenia (and related non-organic psychosis) or bipolar disorder		F20, F21, F25	F23.3
			F20.4
Psoriasis or eczema		L40	
		L20, L21	
Inflammatory bowel disease		K50 - K52	
Migraine		G43, G44	
Blindness & low vision		H53, H54	
Chronic sinusitis		J32	
Learning disability		F80, F81, F83, F84	
Anorexia or bulimia		F50	
Bronchiectasis		J47	Q33.4
		A15, A16	
Parkinson's disease		G20, G22	
		G21	
Multiple sclerosis		G35	R63.0
Viral Hepatitis		B15 - B19	
Chronic liver disease		K70-77	

Source: Geiger et al. [92]

## Appendix C: Overview of assessment against the quality criteria

ID	First author	Year	Country	Physician group
1	Albrecht, M	2012	Germany	outpatient care physicians
2	Ansah, J	2017	Singapore	eyecare workforce
3	Anderson, G	1997	USA	otolaryngologist
4	Barber, P	2010	Spain	medical specialists
5	Greenberg, L	1997	USA	primary care physicians
6	Jäger, R	2016	Germany	dentists
7	Konrad, T	2009	USA	mental health professionals
8	Lee, P	1995	USA	eyecare workforce
9	von Stillfried, D	2011	Germany	office-based physicians
10	CFWI	2014	UK	general practitioner
11	Stuckless, T	2012	Canada	oncologists
12	Singh, D	2010	Canada	primary care physicians
13	Laurence, C	2016	Australia	general practitioner
14	Albrecht, M	2016	Germany	psychotherapists
15	Ozegowski, S	2012	Germany	office-based physicians
16	Kopetsch, T	2016	Germany	office-based physicians
17	Czaja, M	2012	Germany	psychotherapists and GPs
18	Dall, T	2015	USA	physician workforce (primary care, medical specialties, surgical specialties and "other" specialties)

Source: Geiger et al. [109]

## Appendix C: Overview of assessment against the quality criteria

ID	Conceptual framework						
	1.1 Rationale of indicators of need and empirical justification	Description	1.2 Influence of supply on need	Description	1.2.1 Accounting for potential unmet need or lack of physicians	Description	1.2.2 Accounting for potential overuse or oversupply
	0/ 1		0/ 1		0/1		0/1
1	1	individual framework and factor analysis	1	target variables that are statistically independent from supply	0		0
2	1	prior research	0	supply based model, unequal distribution of healthcare workforce	0		0
	1	prior research	0		0		0
	1	prior research	0		0		0
	1	individual framework	1		1	unmet care needs (waitlists)	0
3	1	prior research	1		1	adjusted for uninsured	0
	1	prior research	0		0		0
	1	prior research	0		0		0
4	1	prior research	1	supply based model	1	positions unfilled	0
5	1	prior research	0	highlight the effects of under- and oversupply in introduction (lacking access to services and supply induced demand)	0		0
6	1	prior research	0	try to establish association between need/demand and access using the Gini coefficient and regression models	0		0
7	1	individual framework and regression model (logit) to estimate prevalence	0		0		0
8	1	individual framework			0		0
	1	individual framework			0		0
9	1	individual framework	0		0		0
10	1	prior research	1	qualitative discussion of unmet need	1	panel estimates unmet	0
11	1	prior research	0		0	no	0
12	1	individual framework	1	acknowledge importance of needs-based models instead of utilisation/pop-physician-ratio	1	limited access, different estimates on physician shortages (people unattached to GP)	0
13	1	prior research	0		0		0
14	1	(update of) prior research and individual data analysis to estimate prevalence	1	measure morbidity via epidemiological study to get data independent of supply (find more need for older people than utilisation data suggested)	0		0
15	1	individual framework	1	utilisation is influenced by e.g. supply-induced demand; however assumption that over and under supply cancel each other out throughout Germany, additionally argue only publicly funded utilisation for less influence	0		0

## Appendix C: Overview of assessment against the quality criteria

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16	1	prior research and regression model (GIMD ~ morbidity, utilisation, mortality)	0		0		0
17	1	individual framework and factor analysis	0	mention that demand might be supply-driven, neglect potential oversupply or undersupply	0		0
18	1	(update of) prior research	1	assumption supply and demand roughly in equilibrium (conservative), however no systematic study to quantify current shortfalls/excess of supply, thus demand projections are extrapolated from 2014 -> take imbalance (shortfalls or excess) into the future	1	account for shortages in GPs and psychiatrists; include utilization equity scenario to account for underutilisation (inadequate access)	0

Source: Geiger et al. [109]

## Appendix C: Overview of assessment against the quality criteria

ID	Validity of data basis					
	2.1 External validity	Description	2.2 Internal validity	Description	2.3 Timeliness and availability	Description
	0/ 1		0/ 1		0/ 1	
1	1	population data	1	discuss potential limitations	1	2007/8, latest data available
2	0	mixed data (population data - statistics, data from medical council, limitations not discussed)	0	unclear	1	2012, further years not mentioned just referenced, assumed numbers to remain constant, not further disclosed
	0	mixed data (population data - statistics, SEED study limitations not discussed, ministry of health)	0	unclear	1	2012, further years not mentioned just referenced, assumed numbers to remain constant to remain constant, not further disclosed
	0	mixed data (population data - statistics, SEED study limitations not discussed, ministry of health)	0	unclear	1	2012, further years not mentioned just referenced, assumed numbers to remain constant to remain constant, not further disclosed
	0	mixed data (population data - statistics, SEED study limitations not discussed, literature, expert opinions)	0	unclear	1	2012, further years not mentioned just referenced, assumed numbers to remain constant to remain constant, not further disclosed
3	0	convenience sample (three largest HMOs, use adjustments to make extrapolations possible)	1	try to enhance (based on limitations adjustments were applied; sensitivity analysis of adjustments)	1	1992-4, not further disclosed
	0	mixed data (numbers from Bureau of Health Professionals)	0	unclear (final estimations given from external source (not further discussed))	1	1993, not further disclosed
	0	mixed data (estimates of Delphi panel, utilisation data)	1	discuss potential limitations (acknowledge that only limited to people that have access to care and office-based care, subject to bias)	1	1992, 1994, not further disclosed
4	0	mixed data (population data, data of Health Ministry on physicians, estimation of private doctors, data from autonomous community health service and internet searches)	0	unclear, no discussion	1	1990-2008, not further disclosed
5	0	mixed data (population and survey data (representativeness not discussed))	1	try to enhance (use additional dataset to adjust unsystematically reported data)	1	1980, 1985, 1989, not further disclosed
6	0	mixed data (population data, insurance claims data, cross-sectional data)	0	used repeated cross-sectional data (not discussed further)	1	2011, 2014, year of cross-sectional study not mentioned just referenced, not further disclosed
7	0	mixed data (population data, survey (nationally representative), survey data adjusted for utilisation estimates)	1	discuss potential limitation and try to enhance (sampling error, repeated replications utilisation based on self-reported data)	1	2001, 1990, 2003, 1993, 2006, not further disclosed

## Appendix C: Overview of assessment against the quality criteria

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8	0	mixed data (epidemiological data, smaller studies, population data, current utilisation rescaled), state non representative sample	1	try to enhance indicator validity (validate with utilisation numbers, advisory panel, adjust incidents rates downward based on experts/literature, check for response bias)	1	1989-1991, 1993, state survey is periodically conducted
	0	mixed data (epidemiological data, smaller studies (scientific literature), population data (census), current utilisation rescaled), state non representative sample	1	try to enhance indicator validity (validate with utilisation numbers, advisory panel, adjust incidents rates downward based on experts/literature and check for response bias)	1	1989-1991, 1993, state survey is periodically conducted
9	1	population data (all publicly ensured patients)	1	discuss (potential limitation if patients change insurance)	1	2008, routinely collected data
10	0	mixed data (national statistics, literature, NHS data)	1	try to enhance (used Delphi panel exercise to estimate uncertain/poor quality data and state limitations of approach, data confidence rating, validation approaches, state assumptions)	1	2012, 2011, 2010, updated in march 2013, not further disclosed
11	0	mixed data (various datasets, e.g. cancer registries and survey (complete response rates), validity of data checked when possible, claim robust dataset)	0	unclear, no discussion	1	1989–2009, state possibility to recalculate annually (collected annually)
12	0	mixed data (literature reviews, statistic bureau, survey - low response rate)	1	try to enhance (weighted variables based on expert opinion, complementary literature)	1	2001-2005, 2008, not further disclosed
13	0	mixed data (bureau of statistics, claims data, acknowledge limitation based on sample size and selection bias)	1	discuss (unrepeated cross-sectional data, use reference group of experts for additional info on trends)	1	2003, 2004, 2007, detailed description and scope of dataset, latest data available
14	1	representative sample (survey data (country-wide, stratified, representative sample), but limitations)	1	discuss (using prevalence data from surveys is more precise than claims data)	1	2004, 2014, latest data available
15	0	convenience sample (claims data from one sickness fund, not validated if representative)	1	discuss and try to enhance (excluded utilisation data outside home area, discuss accuracy of claims data)	1	2007, 2008, discuss transferability
16	0	mixed data (public health insurance claims, national statistics, GIMD)	0	unclear, no discussion	1	2006, 2008, 2010, mention potential to update, discuss transferability
17	0	mixed data (insurance claims data (KV Berlin), indices, national statistics)	1	discuss potential limitations (morbidity index with diseases corresponding to physicians)	1	2007, 2007, 2010, not further disclosed
18	1	representative sample (i.e. derived through matching and re-sampling)	0	unclear, state that some data based on telephone interviews	1	2004, 2008-2013; numbers assumed to remain constant, latest data available

Source: Geiger et al. [109]

## Appendix C: Overview of assessment against the quality criteria

ID	Modelling							Integration of future trends and developments		
	3.1 Conversion into FTE	Description	3.2 Model (description)	Validation	Description	3.3 Level of analysis	Description	4.1 Projection variable	Description	4.2 Planning horizon
	0/ 1			0/ 1		0/ 1		0/ 1		
1	0	(adaptation/adjustment of) physician-population ratio	regression analysis and adjustments	1	used R <sup>2</sup>	0	aggregated	1	population projection (change size and age)	2010-2025 (15a)
2	0	physician-population ratio	System Dynamics	1	compare results with historical data, stakeholder validation, sensitivity analysis of outcome parameter (sensitivity bounds)	0	aggregated	1	population projection (change size and age)	2010-2040 (30a)
	1	FTE - average demand for eye service divided per average patient visit per ophthalmologist	System Dynamics	1	compare results with historical data, stakeholder validation, sensitivity analysis of outcome parameter (sensitivity bounds)	0	aggregated	1	population projection (change size and age)	2010-2040 (30a)
	1	FTE - expected patient visits divided by average patient visit per ophthalmologist (including uptake rate)	System Dynamics	1	compare results with historical data, stakeholder validation, sensitivity analysis of outcome parameter (sensitivity bounds)	0	aggregated (partially)	1	population projection (change size and age)	2010-2040 (30a)
	1	FTE - expected patient visits divided by average patient visit per ophthalmologist (changes in uptake rates among different populations included)	System Dynamics	1	compare results with historical data, stakeholder validation, sensitivity analysis of outcome parameter (sensitivity bounds)	0	aggregated (partially)	1	population projection (change size and aging, use of service), differences in disease treatment duration	2010-2040 (30a)
3	0	(adaptation/adjustment of) physician-population ratio	descriptive analyses and extrapolations	1	sensitivity analyses	0	aggregated	1	population projection	1994-2010 (16a)
	1	FTE - physician productivity over minutes required for service, then dividing required total patient-care minutes by average number of minutes worked per physician	Delphi survey, descriptive analyses and extrapolations	0		0	aggregated	1	population projection, based on demographics, insurance coverage projections	1994-2010 (16a)
	0	visits per population (translation not explained)	descriptive analyses and extrapolations	1	suggest that other method (Delphi panel) not suitable	0	aggregated		new estimations of physician Delphi panel	1994-2010 (16a)

## Appendix C: Overview of assessment against the quality criteria

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4	0	adjusted ratios to FTE	System Dynamics, Delphi survey	1	argue method is frequently used and adapted for planning purposes	0	aggregated	1	population growth, four potential variations in demand - demographics and Delphi panel (growth-rate of demand)	2008-2025 (17a)
5	1	FTE - through translation of minutes (total number of minutes devoted by physicians divided by total number of physicians)	extrapolations	1	highlight advantages to simpler approaches, cross-validation	0	aggregated	1	six different scenarios, change in demographics, insurance status, utilisation pattern	1989-2020 (31a)
6	0	no direct translation: comparison of relative regional need (in terms of morbidity estimated in demand-time) and relative physician supply	extrapolations	1	mention in discussion: established model (model fit estimate using $R^2$ )	0	aggregated	1	population growth scenarios, morbidity based on age, changing pattern per scenario	2011-2030 (19a)
7	1	FTE - conversion of minutes of services needed, yearly hours of direct patient contact	adjusted extrapolation model	1	replications + CI for prevalence, acceptable fit, might be subject to prediction error and sampling error	0	aggregated	0		
8	1	FTE - based on work time (minutes) associated with disease divided by patient care minutes available per FTE, conversion factor	adjusted extrapolation model	1	sensitivity analysis	0	aggregated	1	population projections (demographic changes)	1994-2010 (16a)
	1	FTE - based on work time (minutes) associated with disease divided by patient care minutes available per FTE, conversion factor	adjusted extrapolation models, bootstrapped data	1	sensitivity analysis	0	aggregated		population projections (demographic changes)	1994-2010 (16a)
9	1	FTE - averaged need (in points) of a region divided by average number of points a physician group performs	linear regression analysis, descriptive analyses	1	more variation explained after adding morbidity ( $R^2$ )	1	individual	0	projection (in 5a intervals) mentioned in discussion	
10	1	FTE - staffing patterns are used to convert to FTE: national volume of services divided by number of physicians	System Dynamics	1	sensitivity analyses	0	aggregated	1	population growth and changing composition, increased morbidity, increased workload, increased consultations per age and gender	2013-2030 (17a)
11	1	FTE - estimated demand in patient referrals is divided by the amount of new patients seen per FTE	forward calculation (prediction) model	1	expert panel and literature review, predictive validation, sensitivity analysis	0	aggregated	1	incident growth annually recalculated, ratio of new cases per FTE, 5a baseline data	2010-2020 (10a)

## Appendix C: Overview of assessment against the quality criteria

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12	1	FTE - based on work time associated with disease (survey data), variance is converted by average number of hours work per year per speciality	simulation model (state transition cohort model, different base cases)	0		0	aggregated	1	change in demographics, increase in disease prevalence, health risk factors based on gender, productivity	2008-2030 (22a)
13	1	FTE - Estimated number of consultations per year (+ average length by gender/age) were translated into FTE with 40 hour working week and 44-week working year (allow for CME, holiday etc)	simulation model (two sub-modules)	1	sensitivity analyses, predictive validity	0	aggregated	1	three scenarios change in demographics and different utilisation rates or increasing prevalence	2003-2013 to compare with real numbers (10a)
14	0	(adaptation/adjustment of) physician-population ratio	regression analysis for prevalence predictions, small area estimations	1	sensitivity analyses, variation coefficient, area under the curve	1	individual	0	mentioned possibility in discussion	
15	0	no direct translation: comparison of relative regional need (in terms of expected physician contacts) and relative physician supply	extrapolations model	1	rationalise usage of concentration index in context, sensitivity analyses	0	aggregated	0		
16	0	(adaptation/adjustment of) physician-population ratio	regression based linear additive model	0		0	aggregated	0		
17	0	(adaptation/adjustment of) physician-population ratio	linear additive model using weighting	1	weight both indices equally	0	aggregated	0		
18	1	FTE - demand for physicians is linked to demand for healthcare services, accounting for portion of time that physicians spend providing care in different delivery settings. FTE is the average weekly patient care hours (per specialty) 35.3 hours up to 54.3 hours	microsimulation of individual utilisation and regression models, model calibration	1	full validation based on ISPOR guidelines	1	individual	1	demographics (age, gender, race/ethnicity), utilisation pattern - extrapolated, staffing	2014-2025 (11a)

Source: Geiger et al. [109]

## Appendix D: SaTScan scanning results from the Bernoulli purely spatial analysis [92]

### General information:

#### Data Checking

Temporal Data Check: Check to ensure that all cases and controls are within the specified temporal study period.  
Geographical Data Check: Check to ensure that all observations (cases, controls and populations) are within the specified geographical area.

#### Spatial Neighbours

Use Non-Euclidian Neighbours file: No

Use Meta Locations File: No

Multiple Coordinates Type: Allow only one set of coordinates per location ID.

#### Spatial Window

Maximum Spatial Cluster Size 50 percent of population at risk

Window Shape: Circular

Isotonic Scan: No

#### Inference

P-Value Reporting: Standard Monte Carlo

Report Gumbel Based P-Values: No

Number of Replications: 999

Adjusting for More Likely Clusters: No

#### Spatial Output

Report Hierarchical Clusters: Yes

Criteria for Reporting Secondary Clusters: No Geographical Overlap

Report Gini Optimized Cluster Collection: No

Restrict Reporting to Smaller Clusters: Yes

Reported Clusters: Only clusters smaller than 10 percent of population at risk reported.

### 1. GPs

#### SUMMARY OF DATA

Study period: 2015/1/1 to 2015/12/31

Number of locations: 959

Total population: 54,799,570

Total number of cases: 17,239,488

Percent cases in area: 31.5

#### CLUSTERS DETECTED

1. Location IDs included.: 3400200, 3400196, 3400407, 3400207, 3400201, 3400206, 3400194, 1204120, 3400164, 3400202, 3400409, 1204070, 3400321, 3400198, 3400204, 1503070, 3400208, 3400165, 3400203, 3400193, 1204080, 1204110, 3400166, 1603000, 3400167, 3400209, 3400190, 1503010, 3400178, 1503020, 3400172, 3400189, 3400188, 1603100, 1205080, 3400192, 3400171, 1504020, 1504030, 3400168, 1204100, 3400177, 3500161, 3500159, 1503060, 3400173, 3400191, 1204040, 3400176, 3400199, 3600522, 3400169, 3400197, 3400187, 1503040, 1504040, 3600526, 1205070, 1204020, 1602600, 3400170, 1204090, 3400408, 1205110, 1602900, 1504010, 1204050, 1205050, 1602700, 3400186, 1503030, 3600527, 1503050, 3400174, 1603500, 1602500, 1204010, 1602000, 3600524, 1205120, 1504060, 1502020, 1205130, 3400181, 3400179, 1204060, 3400185, 1205040, 1205100, 1603400, 3600528, 1204030, 1204130, 1502050, 1203040, 3400182, 3400180, 1505050, 1505060, 1600200, 1603200, 1205030, 3400184, 1505040, 1601900, 3400183, 3500162

Coordinates / radius.: (51.319400 N, 13.053642 E) / 131.52 km

Population.....: 5428136

Number of cases.....: 2117537

Expected cases.....: 1709101.26

Observed / expected...: 1.24

Relative risk.....: 1.27

Percent cases in area.: 39.0

Log likelihood ratio.: 76489.133840

Monte Carlo rank.....: 1/1000

P-value.....: 0.001

## Appendix D: SaTScan scanning results from the Bernoulli purely spatial analysis [92]

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2. Location IDs included.: 811050, 811020, 915030, 811040, 915020, 811030, 2900144, 811060, 811010, 812080, 915040, 915010, 2900145, 810060, 812040, 915050, 812020, 801140, 810030, 812030, 803040, 812010, 2900143, 812070, 915060, 801130, 2900352, 801100, 2900391, 810020, 916030, 916010, 801120, 812090, 2900123, 812060, 916020, 916050, 810080, 803030, 812050, 801090, 2900343, 916060, 810050, 810010, 803020, 801070, 2900142, 916070, 2900371, 809060, 2900309, 2900373, 2900122, 801060, 810040, 809090, 810070, 801080, 801110, 909050, 2900303, 803010, 808040, 916040, 917010, 801150, 809080, 801030, 914050, 909040, 2900302, 2900310, 916080, 806070, 801040, 809070, 802090, 801050, 808020, 917020, 914080, 2900124, 806050, 910030, 806040, 801010, 801020, 914030, 2900152, 910040, 917080, 802050, 808050, 2900132, 808010, 802080, 917040, 806060
- Coordinates / radius.: (48.212343 N, 9.925358 E) / 115.75 km
- Population.....: 5329548
- Number of cases.....: 1404320
- Expected cases.....: 1678059.87
- Observed / expected....: 0.84
- Relative risk.....: 0.82
- Percent cases in area.: 26.3
- Log likelihood ratio.: 37164.729538
- Monte Carlo rank.....: 1/1000
- P-value.....: 0.001
3. Location IDs included.: 3300503, 3300501, 3300511, 3300502, 3300505, 3300520, 3300509, 3300510, 3300506, 3300514, 3300516, 1302050, 1303070, 3300513, 1303080, 3300517, 3300515, 3300518, 1302040, 3300507, 1202010, 1202020, 1201080, 1301060, 1202030, 3300508, 1201010, 1201040, 3300155, 1202040, 3300519, 1201050, 1201060, 1202050, 1203060, 1201030, 3300512, 1201070, 3300504
- Coordinates / radius.: (54.088914 N, 13.414215 E) / 157.82 km
- Population.....: 1665881
- Number of cases.....: 656200
- Expected cases.....: 524518.79
- Observed / expected....: 1.25
- Relative risk.....: 1.26
- Percent cases in area.: 39.4
- Log likelihood ratio.: 23961.215522
- Monte Carlo rank.....: 1/1000
- P-value.....: 0.001
4. Location IDs included.: 2400001, 339010, 2300429, 2300434, 2300087, 2300107, 2300112, 333020, 314020, 319010, 2300108, 2300100, 2300103, 2400000, 2300105, 321010, 2300099, 319020, 329010, 2300086, 2300115, 2300090, 104030, 2300085, 321020, 2300111, 330020, 2300101, 104020, 331010, 319030, 104040, 2300442, 323020, 2100083, 104010, 330010, 2300102, 338010, 315010, 105070, 331020, 2300096, 2200000, 307020, 325010, 332010, 320010, 2300437, 307030, 103020, 103040, 320030, 338020, 2300113, 2100080, 337010, 2300441, 2100084, 320020, 105050, 332020, 101120, 504010, 306010, 101110, 337020, 504020, 2300004, 103010, 2300114, 2300432, 2100082, 306030, 101090
- Coordinates / radius.: (53.542867 N, 8.576513 E) / 134.61 km
- Population.....: 5401922
- Number of cases.....: 1531117
- Expected cases.....: 1700847.53
- Observed / expected....: 0.90
- Relative risk.....: 0.89
- Percent cases in area.: 28.3
- Log likelihood ratio.: 13948.338567
- Monte Carlo rank.....: 1/1000
- P-value.....: 0.001
5. Location IDs included.: 1600900, 601200, 1601100, 601210, 1600800, 1601000, 2900372, 601190, 601180, 601220, 601170, 2900346, 3600523, 1601200, 601130, 903020, 601150, 602080, 2900345, 1601800, 1600500, 1601300, 2600270, 601120, 903030, 1600400, 603060, 2600272, 1601500, 1600600, 602070, 601050, 3600521, 903040, 2600271, 2900148, 601100, 2600274, 603090, 602060, 2900127, 2900304, 2900149, 904020, 602120, 2600273, 1602300, 1600700, 1600300, 603070, 2300095, 1602200, 904010, 601090
- Coordinates / radius.: (50.745283 N, 10.128848 E) / 84.64 km
- Population.....: 2197553
- Number of cases.....: 773317
- Expected cases.....: 691920.87
- Observed / expected....: 1.12
- Relative risk.....: 1.12
- Percent cases in area.: 35.2
- Log likelihood ratio.: 7143.345783
- Monte Carlo rank.....: 1/1000
- P-value.....: 0.001

## Appendix D: SaTScan scanning results from the Bernoulli purely spatial analysis [92]

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6. Location IDs included.: 603130, 603110, 603160, 603170, 603140, 603100, 603120, 703030, 603190, 603260, 703020, 603150, 603200, 603180, 703010, 603250, 603020, 701110, 2700116, 703050, 602150, 603270  
Coordinates / radius...: (50.079149 N, 8.260376 E) / 38.74 km  
Population.....: 1974684  
Number of cases.....: 550963  
Expected cases.....: 621748.41  
Observed / expected...: 0.89  
Relative risk.....: 0.88  
Percent cases in area.: 27.9  
Log likelihood ratio.: 6231.632185  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
7. Location IDs included.: 503060, 503050, 503120, 503040, 503110, 503130, 503070, 503140, 503170, 503010, 503080, 503160, 503090, 503150, 503100, 503230, 2300438, 503180, 503240, 332030, 503020, 503270  
Coordinates / radius...: (52.093125 N, 7.058568 E) / 49.60 km  
Population.....: 1137345  
Number of cases.....: 319570  
Expected cases.....: 358104.10  
Observed / expected...: 0.89  
Relative risk.....: 0.89  
Percent cases in area.: 28.1  
Log likelihood ratio.: 3153.444098  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
8. Location IDs included.: 911050, 911060, 2900350, 912010, 2900386, 2900401, 2900406, 2900377, 912090, 2900383, 2900351, 2900400, 2900392, 2900397, 2900394, 2900375, 911030, 912100, 2900362, 906070, 2900379, 2900384, 2900357, 2900141, 2900398, 2900385, 2900344, 2900341, 912050, 912060, 2900396, 906020, 913030, 2900367, 2900128, 2900353, 911070, 911090, 2900380, 906010, 2900359, 906040, 911080, 2900368, 2900356, 2900361, 2900146, 2900129, 2900370, 912080, 913080, 2900358, 913010, 911010, 2900402, 907060, 2900393, 913070, 905040, 905080, 2900136, 914010, 2900399, 2900138, 918010, 907050, 2900342, 2900348, 2900135, 2900130, 918020, 2900137  
Coordinates / radius...: (49.285830 N, 12.880936 E) / 123.30 km  
Population.....: 2243965  
Number of cases.....: 659238  
Expected cases.....: 706534.14  
Observed / expected...: 0.93  
Relative risk.....: 0.93  
Percent cases in area.: 29.4  
Log likelihood ratio.: 2438.324057  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
9. Location IDs included.: 501430, 501400, 505360, 501420, 501440, 505340, 501390, 501160, 501410, 505350, 501380, 501170, 501370, 505390, 505320, 505330, 501460, 505370, 501450, 501360  
Coordinates / radius...: (51.337479 N, 7.088029 E) / 21.23 km  
Population.....: 1573763  
Number of cases.....: 533963  
Expected cases.....: 495514.54  
Observed / expected...: 1.08  
Relative risk.....: 1.08  
Percent cases in area.: 33.9  
Log likelihood ratio.: 2212.714316  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
10. Location IDs included.: 705030, 705020, 705040, 1000080, 705050, 705060  
Coordinates / radius...: (49.413043 N, 7.526107 E) / 20.80 km  
Population.....: 340205  
Number of cases.....: 125115  
Expected cases.....: 107116.84  
Observed / expected...: 1.17  
Relative risk.....: 1.17  
Percent cases in area.: 36.8  
Log likelihood ratio.: 2161.111783  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001

## Appendix D: SaTScan scanning results from the Bernoulli purely spatial analysis [92]

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11. Location IDs included.: 505160, 505170, 505130, 505190, 505200, 505150, 505140, 505180, 701010, 602020, 505120, 505230, 505210, 502300, 602010, 502330, 505090, 505240, 602090, 601070, 505070  
Coordinates / radius...: (50.984411 N, 8.061247 E) / 38.92 km  
Population.....: 754396  
Number of cases.....: 212675  
Expected cases.....: 237528.90  
Observed / expected...: 0.90  
Relative risk.....: 0.89  
Percent cases in area.: 28.2  
Log likelihood ratio.: 1962.870483  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
12. Location IDs included.: 504220, 504210, 505020, 504230, 504200  
Coordinates / radius...: (51.765423 N, 8.540728 E) / 20.21 km  
Population.....: 266785  
Number of cases.....: 70591  
Expected cases.....: 83999.84  
Observed / expected...: 0.84  
Relative risk.....: 0.84  
Percent cases in area.: 26.5  
Log likelihood ratio.: 1620.065221  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
13. Location IDs included.: 306050  
Coordinates / radius...: (52.465977 N, 9.704680 E) / 0 km  
Population.....: 37589  
Number of cases.....: 15180  
Expected cases.....: 11835.26  
Observed / expected...: 1.28  
Relative risk.....: 1.28  
Percent cases in area.: 40.4  
Log likelihood ratio.: 661.230403  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
14. Location IDs included.: 902050, 2900389, 903070, 2900403, 2900313, 2900404  
Coordinates / radius...: (49.753176 N, 10.256027 E) / 22.89 km  
Population.....: 227996  
Number of cases.....: 64713  
Expected cases.....: 71786.75  
Observed / expected...: 0.90  
Relative risk.....: 0.90  
Percent cases in area.: 28.4  
Log likelihood ratio.: 520.489293  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
15. Location IDs included.: 502120, 502080, 502110, 502220, 502070, 502100, 502230, 502130, 502060, 502180, 502050, 502030, 502140, 502240, 502020, 502170, 502040, 502160, 502010, 502190, 501320, 502380, 502260, 501260, 502150, 502390, 501250, 502200, 502400, 501270, 502250, 501330, 502420, 501230, 501290, 501280, 502410, 501240  
Coordinates / radius...: (50.828460 N, 6.269418 E) / 51.32 km  
Population.....: 1742905  
Number of cases.....: 568218  
Expected cases.....: 548770.54  
Observed / expected...: 1.04  
Relative risk.....: 1.04  
Percent cases in area.: 32.6  
Log likelihood ratio.: 516.342800  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
16. Location IDs included.: 502430  
Coordinates / radius...: (50.688724 N, 7.095696 E) / 0 km  
Population.....: 199568  
Number of cases.....: 56252  
Expected cases.....: 62835.92  
Observed / expected...: 0.90  
Relative risk.....: 0.89  
Percent cases in area.: 28.2  
Log likelihood ratio.: 515.520854  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001

## Appendix D: SaTScan scanning results from the Bernoulli purely spatial analysis [92]

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17. Location IDs included.: 505430, 505420, 505460, 505450, 505400, 505440, 503290  
Coordinates / radius.: (51.622922 N, 7.629610 E) / 15.89 km  
Population.....: 374967  
Number of cases.....: 126716  
Expected cases.....: 118062.00  
Observed / expected.....: 1.07  
Relative risk.....: 1.07  
Percent cases in area.: 33.8  
Log likelihood ratio.: 460.306138  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
18. Location IDs included.: 907010, 907020, 2900364, 904060, 907030, 2900378, 2900347, 2900349, 907040  
Coordinates / radius.: (49.666190 N, 10.914525 E) / 28.93 km  
Population.....: 927128  
Number of cases.....: 304870  
Expected cases.....: 291915.24  
Observed / expected.....: 1.04  
Relative risk.....: 1.05  
Percent cases in area.: 32.9  
Log likelihood ratio.: 423.526710  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
19. Location IDs included.: 701050  
Coordinates / radius.: (50.471370 N, 6.999173 E) / 0 km  
Population.....: 63772  
Number of cases.....: 22953  
Expected cases.....: 20079.23  
Observed / expected.....: 1.14  
Relative risk.....: 1.14  
Percent cases in area.: 36.0  
Log likelihood ratio.: 293.484437  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
20. Location IDs included.: 2700283, 2700281, 702080, 2700282, 702050, 1000010, 702060, 702040, 1000020, 703080  
Coordinates / radius.: (49.786803 N, 6.746398 E) / 39.02 km  
Population.....: 377791  
Number of cases.....: 125826  
Expected cases.....: 118951.16  
Observed / expected.....: 1.06  
Relative risk.....: 1.06  
Percent cases in area.: 33.3  
Log likelihood ratio.: 289.077760  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001

### 2. Ophthalmologists

#### SUMMARY OF DATA

Study period: 2015/1/1 to 2015/12/31  
Number of locations: 385  
Total population: 16,195,148  
Total number of cases: 7,145,558  
Percent cases in area: 44.1

#### CLUSTERS DETECTED

1. Location IDs included.: 150840, 160740, 150880, 160520, 160530, 150020, 340061, 340021, 160710, 160770, 160760, 160680, 150870, 340033, 340035, 340024, 160510, 340039, 160750, 160650, 160730, 350017, 340027, 160700, 150890, 340019, 340083, 340028, 350018, 340081, 340036, 160670, 160620, 340038, 160640, 150910, 160720, 94750, 94760, 150850, 340023, 340026, 340037, 150030, 340022, 160690, 340082, 160610, 160660  
Coordinates / radius.: (51.147303 N, 11.883881 E) / 117.24 km  
Population.....: 1556108  
Number of cases.....: 883094  
Expected cases.....: 686579.75  
Observed / expected.....: 1.29  
Relative risk.....: 1.33  
Percent cases in area.: 56.8  
Log likelihood ratio.: 55229.122868  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001

## Appendix D: SaTScan scanning results from the Bernoulli purely spatial analysis [92]

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2. Location IDs included.: 130620, 120730, 130590, 130550, 130520, 120600, 120650, 130560, 130610, 120640, 130570, 120680, 130530, 310016, 130510, 130030, 120630, 130600, 120540, 120670, 120700, 120610, 120690, 120720, 150900, 130580, 130540, 150860, 120520, 120710  
Coordinates / radius.: (53.574148 N, 14.069925 E) / 203.26 km  
Population.....: 1604093  
Number of cases.....: 845977  
Expected cases.....: 707751.50  
Observed / expected....: 1.20  
Relative risk.....: 1.22  
Percent cases in area.: 52.7  
Log likelihood ratio.: 26608.229601  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
3. Location IDs included.: 84260, 84360, 84250, 84210, 97750, 84370, 84150, 97780, 84350, 97740, 97760, 81170, 84170, 81160, 81350, 97800, 84160, 83350, 83270, 97770, 97720, 97730, 81110, 97610, 91810, 81150, 81360, 81190, 83250, 97710, 91900, 83260, 97790, 81180, 82370, 82350, 91790, 91880, 81270  
Coordinates / radius.: (48.107673 N, 9.774403 E) / 115.62 km  
Population.....: 1532075  
Number of cases.....: 546811  
Expected cases.....: 675976.01  
Observed / expected....: 0.81  
Relative risk.....: 0.79  
Percent cases in area.: 35.7  
Log likelihood ratio.: 24803.581092  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
4. Location IDs included.: 92760, 92710, 92720, 93720, 92780, 92750, 92790, 92770, 93750, 93620, 93760, 92740, 92730, 91710, 91830, 93740, 93710, 93730, 91770, 93770, 91780, 91860, 91760, 91610, 91890, 95740, 91750, 94790, 91850, 91870, 95760, 94720, 91720, 91740, 91620, 91840  
Coordinates / radius.: (49.022814 N, 13.099907 E) / 149.87 km  
Population.....: 1180312  
Number of cases.....: 455320  
Expected cases.....: 520772.54  
Observed / expected....: 0.87  
Relative risk.....: 0.87  
Percent cases in area.: 38.6  
Log likelihood ratio.: 8020.783563  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
5. Location IDs included.: 10610, 10560, 10510, 33590, 10600, 10580, 20000, 33520, 10620, 10020, 10570, 33530, 40120, 33570  
Coordinates / radius.: (53.924334 N, 9.514041 E) / 76.12 km  
Population.....: 897025  
Number of cases.....: 340739  
Expected cases.....: 395781.78  
Observed / expected....: 0.86  
Relative risk.....: 0.85  
Percent cases in area.: 38.0  
Log likelihood ratio.: 7337.090564  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
6. Location IDs included.: 55660, 55150, 34040, 34590, 55580, 55700, 34560, 55540, 34540, 57540, 59150, 34600, 55620  
Coordinates / radius.: (52.211514 N, 7.579225 E) / 66.45 km  
Population.....: 761920  
Number of cases.....: 286515  
Expected cases.....: 336171.30  
Observed / expected....: 0.85  
Relative risk.....: 0.85  
Percent cases in area.: 37.6  
Log likelihood ratio.: 6975.807202  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001

## Appendix D: SaTScan scanning results from the Bernoulli purely spatial analysis [92]

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7. Location IDs included.: 100440, 100420, 100410, 100430, 100460  
Coordinates / radius.: (49.355298 N, 6.775427 E) / 29.75 km  
Population.....: 161830  
Number of cases.....: 54027  
Expected cases.....: 71401.99  
Observed / expected...: 0.76  
Relative risk.....: 0.75  
Percent cases in area.: 33.4  
Log likelihood ratio.: 3919.720863  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
8. Location IDs included.: 64370, 96760, 64310, 64320, 82250, 64110, 82210, 82260, 82220, 96710, 64380, 64330, 73140, 64130, 73380, 81280, 64120, 81250, 73310, 81210, 96770, 64360, 73150, 81260, 64350, 73320, 64140, 96790, 96630, 73390, 82150, 64340, 64400  
Coordinates / radius.: (49.671448 N, 8.979515 E) / 76.11 km  
Population.....: 1581231  
Number of cases.....: 656609  
Expected cases.....: 697664.42  
Observed / expected...: 0.94  
Relative risk.....: 0.94  
Percent cases in area.: 41.5  
Log likelihood ratio.: 2405.610518  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
9. Location IDs included.: 59700, 59660, 65320, 71320, 65340, 59580, 53740  
Coordinates / radius.: (50.937659 N, 8.194734 E) / 48.15 km  
Population.....: 282308  
Number of cases.....: 113798  
Expected cases.....: 124558.81  
Observed / expected...: 0.91  
Relative risk.....: 0.91  
Percent cases in area.: 40.3  
Log likelihood ratio.: 852.522449  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
10. Location IDs included.: 51110  
Coordinates / radius.: (51.235418 N, 6.810261 E) / 0 km  
Population.....: 105254  
Number of cases.....: 40695  
Expected cases.....: 46439.75  
Observed / expected...: 0.88  
Relative risk.....: 0.88  
Percent cases in area.: 38.7  
Log likelihood ratio.: 646.961954  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
11. Location IDs included.: 32411, 32412, 31570, 32540, 32570, 32520, 33510, 31020, 32560, 31010, 32550, 31510, 33580, 31580, 31030, 57700, 31530, 31550  
Coordinates / radius.: (52.379486 N, 9.769642 E) / 70.98 km  
Population.....: 790463  
Number of cases.....: 362014  
Expected cases.....: 348764.92  
Observed / expected...: 1.04  
Relative risk.....: 1.04  
Percent cases in area.: 45.8  
Log likelihood ratio.: 472.367233  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
12. Location IDs included.: 59110  
Coordinates / radius.: (51.469928 N, 7.224923 E) / 0 km  
Population.....: 82982  
Number of cases.....: 40225  
Expected cases.....: 36612.99  
Observed / expected...: 1.10  
Relative risk.....: 1.10  
Percent cases in area.: 48.5  
Log likelihood ratio.: 318.710764  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001

## Appendix D: SaTScan scanning results from the Bernoulli purely spatial analysis [92]

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13. Location IDs included.: 94710, 95720, 96740, 94740, 94780  
Coordinates / radius.: (49.894622 N, 10.893297 E) / 28.70 km  
Population.....: 117407  
Number of cases.....: 47664  
Expected cases.....: 51801.85  
Observed / expected....: 0.92  
Relative risk.....: 0.92  
Percent cases in area.: 40.6  
Log likelihood ratio.: 299.837851  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
14. Location IDs included.: 51140, 51120, 51660  
Coordinates / radius.: (51.345236 N, 6.579665 E) / 18.94 km  
Population.....: 183259  
Number of cases.....: 85623  
Expected cases.....: 80856.80  
Observed / expected....: 1.06  
Relative risk.....: 1.06  
Percent cases in area.: 46.7  
Log likelihood ratio.: 253.351019  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001

### 3. Orthopaedic specialist

#### SUMMARY OF DATA

Study period.....: 2015/1/1 to 2015/12/31  
Number of locations.....: 385  
Total population.....: 11,659,090  
Total number of cases.....: 4,722,933  
Percent cases in area.....: 40.5

#### CLUSTERS DETECTED

1. Location IDs included.: 340032, 340020, 340037, 340031, 340022, 340026, 340082, 340081, 340027, 340019, 340029, 340023, 340042, 340028, 340024, 340043, 340035, 340036, 340038, 120620, 120660, 340039, 160770, 340061, 340041, 340021, 340033, 160520, 120520, 340083, 120710, 160760, 150910, 150840, 120610, 120720, 150020, 160740, 150880, 160750, 94790, 160530, 350017, 350018, 94750, 93770, 120670, 160710, 120690, 160730, 94760, 93740, 150870, 150890, 120540, 94770  
Coordinates / radius.: (50.890262 N, 13.650447 E) / 176.50 km  
Population.....: 1138830  
Number of cases.....: 600906  
Expected cases.....: 461324.02  
Observed / expected....: 1.30  
Relative risk.....: 1.35  
Percent cases in area.: 52.8  
Log likelihood ratio.: 38598.865331  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
2. Location IDs included.: 84150, 81160, 84160, 84250, 84170, 81170, 84370, 84210, 81110, 81150, 84260, 81190, 97750, 83270, 82350, 81180, 83250, 81350, 82370, 82310, 84360, 82360, 81360, 84350, 97740, 83350, 83260, 81210, 97780, 81250, 97730, 81270  
Coordinates / radius.: (48.406387 N, 9.365822 E) / 91.13 km  
Population.....: 1062119  
Number of cases.....: 344208  
Expected cases.....: 430249.47  
Observed / expected....: 0.80  
Relative risk.....: 0.78  
Percent cases in area.: 32.4  
Log likelihood ratio.: 16297.499237  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001

## Appendix D: SaTScan scanning results from the Bernoulli purely spatial analysis [92]

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3. Location IDs included.: 130520, 130550, 130590, 130560, 130530, 130570, 130510, 130030, 130620, 130610, 130600, 120730, 120680, 120650, 120700, 120600, 130580, 130540  
Coordinates / radius.: (53.797036 N, 13.041971 E) / 130.09 km  
Population.....: 322937  
Number of cases.....: 174974  
Expected cases.....: 130817.24  
Observed / expected....: 1.34  
Relative risk.....: 1.35  
Percent cases in area.: 54.2  
Log likelihood ratio.: 12604.469461  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
4. Location IDs included.: 10610, 10560, 10510, 33590, 10600, 10580, 20000, 33520, 10620, 10020, 10570, 33530, 40120, 33570  
Coordinates / radius.: (53.924334 N, 9.514041 E) / 76.12 km  
Population.....: 630204  
Number of cases.....: 205382  
Expected cases.....: 255286.78  
Observed / expected....: 0.80  
Relative risk.....: 0.80  
Percent cases in area.: 32.6  
Log likelihood ratio.: 8881.998704  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
5. Location IDs included.: 91840, 91620, 91750, 91880, 91790, 91740, 91770, 91820, 91730, 91780, 91870, 91810, 91900, 91830, 91860, 97710  
Coordinates / radius.: (48.077661 N, 11.646389 E) / 58.65 km  
Population.....: 569294  
Number of cases.....: 189205  
Expected cases.....: 230612.99  
Observed / expected....: 0.82  
Relative risk.....: 0.81  
Percent cases in area.: 33.2  
Log likelihood ratio.: 6716.969712  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
6. Location IDs included.: 66320, 66340, 160630, 66360, 66310, 65350, 66110, 160660, 66330, 160610, 160640, 160670, 31520, 66350, 96730, 65340, 65310, 96720, 64350, 64400, 160690, 160700, 160510, 31550, 160620, 57620, 31560, 160650, 65320, 160680  
Coordinates / radius.: (50.906127 N, 9.752800 E) / 101.88 km  
Population.....: 623733  
Number of cases.....: 285133  
Expected cases.....: 252665.47  
Observed / expected....: 1.13  
Relative risk.....: 1.14  
Percent cases in area.: 45.7  
Log likelihood ratio.: 3664.122625  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
7. Location IDs included.: 100440, 100420, 100410, 100430, 100460  
Coordinates / radius.: (49.355298 N, 6.775427 E) / 29.75 km  
Population.....: 138825  
Number of cases.....: 41446  
Expected cases.....: 56236.06  
Observed / expected....: 0.74  
Relative risk.....: 0.73  
Percent cases in area.: 29.9  
Log likelihood ratio.: 3433.147290  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
8. Location IDs included.: 34040, 34590, 55660, 57580, 57540, 34600, 57110, 55700, 55150, 57700, 55580, 34540, 32510, 59150, 57660, 34530, 34560, 32570, 59740, 32560, 34580, 57740, 59780, 55540, 55620  
Coordinates / radius.: (52.277683 N, 8.047039 E) / 90.64 km  
Population.....: 1113903  
Number of cases.....: 416396  
Expected cases.....: 451226.44  
Observed / expected....: 0.92  
Relative risk.....: 0.92  
Percent cases in area.: 37.4  
Log likelihood ratio.: 2518.484320  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001

## Appendix D: SaTScan scanning results from the Bernoulli purely spatial analysis [92]

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9. Location IDs included.: 64330, 64110, 73150, 64360, 64320  
Coordinates / radius.: (49.904380 N, 8.470254 E) / 23.90 km  
Population.....: 139233  
Number of cases.....: 47073  
Expected cases.....: 56401.33  
Observed / expected...: 0.83  
Relative risk.....: 0.83  
Percent cases in area.: 33.8  
Log likelihood ratio.: 1340.113758  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
10. Location IDs included.: 53341, 53342, 53580, 53700, 53660  
Coordinates / radius.: (50.759551 N, 6.109727 E) / 45.08 km  
Population.....: 194072  
Number of cases.....: 87073  
Expected cases.....: 78615.84  
Observed / expected...: 1.11  
Relative risk.....: 1.11  
Percent cases in area.: 44.9  
Log likelihood ratio.: 769.947620  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
11. Location IDs included.: 51110  
Coordinates / radius.: (51.235418 N, 6.810261 E) / 0 km  
Population.....: 114573  
Number of cases.....: 41097  
Expected cases.....: 46411.91  
Observed / expected...: 0.89  
Relative risk.....: 0.88  
Percent cases in area.: 35.9  
Log likelihood ratio.: 523.760529  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
12. Location IDs included.: 59660, 59700, 59620, 53740, 59580, 71320  
Coordinates / radius.: (51.086125 N, 7.976392 E) / 40.68 km  
Population.....: 226743  
Number of cases.....: 86407  
Expected cases.....: 91850.40  
Observed / expected...: 0.94  
Relative risk.....: 0.94  
Percent cases in area.: 38.1  
Log likelihood ratio.: 278.341399  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
13. Location IDs included.: 59110, 59160, 55130, 51130, 59540  
Coordinates / radius.: (51.469928 N, 7.224923 E) / 15.31 km  
Population.....: 292449  
Number of cases.....: 123359  
Expected cases.....: 118466.98  
Observed / expected...: 1.04  
Relative risk.....: 1.04  
Percent cases in area.: 42.2  
Log likelihood ratio.: 173.443781  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
14. Location IDs included.: 32520  
Coordinates / radius.: (52.095088 N, 9.389877 E) / 0 km  
Population.....: 18239  
Number of cases.....: 8530  
Expected cases.....: 7388.36  
Observed / expected...: 1.15  
Relative risk.....: 1.15  
Percent cases in area.: 46.8  
Log likelihood ratio.: 146.495503  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001

## Appendix D: SaTScan scanning results from the Bernoulli purely spatial analysis [92]

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15. Location IDs included.: 51700, 51190  
Coordinates / radius.: (51.626927 N, 6.618260 E) / 20.24 km  
Population.....: 85248  
Number of cases.....: 32292  
Expected cases.....: 34532.77  
Observed / expected....: 0.94  
Relative risk.....: 0.93  
Percent cases in area.: 37.9  
Log likelihood ratio.: 124.013962  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
16. Location IDs included.: 51120, 51170  
Coordinates / radius.: (51.439558 N, 6.734696 E) / 10.36 km  
Population.....: 103466  
Number of cases.....: 44183  
Expected cases.....: 41912.62  
Observed / expected....: 1.05  
Relative risk.....: 1.05  
Percent cases in area.: 42.7  
Log likelihood ratio.: 103.732396  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
17. Location IDs included.: 71380, 71110, 71370, 53820, 71430  
Coordinates / radius.: (50.557667 N, 7.469048 E) / 28.00 km  
Population.....: 192062  
Number of cases.....: 80337  
Expected cases.....: 77801.62  
Observed / expected....: 1.03  
Relative risk.....: 1.03  
Percent cases in area.: 41.8  
Log likelihood ratio.: 70.372784  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
18. Location IDs included.: 53140  
Coordinates / radius.: (50.705774 N, 7.109870 E) / 0 km  
Population.....: 49345  
Number of cases.....: 18739  
Expected cases.....: 19988.97  
Observed / expected....: 0.94  
Relative risk.....: 0.94  
Percent cases in area.: 38.0  
Log likelihood ratio.: 66.443825  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001

### 4. Neurologists

#### SUMMARY OF DATA

Study period: 2015/1/1 to 2015/12/31  
Number of locations: 385  
Total population: 4,386,298  
Total number of cases: 2,637,461  
Percent cases in area: 60.1

#### CLUSTERS DETECTED

1. Location IDs included.: 340082, 340022, 120620, 340020, 340081, 340036, 340029, 120660, 340032, 340037, 340035, 340027, 340031, 340042, 340019, 340026, 340033, 340061, 340021, 150910, 120520, 340024, 120710, 340028, 120610, 120720, 160770, 340041, 340023, 340043, 340039, 340038, 350018, 150020, 350017, 160520, 150840, 150880, 120670, 160760, 120690, 120540  
Coordinates / radius.: (51.311954 N, 13.494769 E) / 127.88 km  
Population.....: 437064  
Number of cases.....: 305521  
Expected cases.....: 262804.59  
Observed / expected....: 1.16  
Relative risk.....: 1.18  
Percent cases in area.: 69.9  
Log likelihood ratio.: 9983.240277  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001

## Appendix D: SaTScan scanning results from the Bernoulli purely spatial analysis [92]

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2. Location IDs included.: 84150, 81160, 84160, 84250, 84170, 81170, 84370, 84210, 81110, 81150, 84260, 81190, 97750, 83270, 82350, 81180, 83250, 81350, 82370, 82310, 84360, 82360, 81360, 84350, 97740, 83350, 83260, 81210, 97780, 81250, 97730, 81270  
Coordinates / radius.: (48.406387 N, 9.365822 E) / 91.13 km  
Population.....: 392866  
Number of cases.....: 198564  
Expected cases.....: 236228.54  
Observed / expected....: 0.84  
Relative risk.....: 0.83  
Percent cases in area.: 50.5  
Log likelihood ratio.: 8122.802459  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
3. Location IDs included.: 130590, 130520, 130620, 130610, 130550, 130570, 120730, 130560, 130530, 130030, 130510, 120650, 120600, 120680, 130600, 120700, 120640, 130580  
Coordinates / radius.: (53.940993 N, 13.662774 E) / 157.99 km  
Population.....: 175232  
Number of cases.....: 125088  
Expected cases.....: 105366.20  
Observed / expected....: 1.19  
Relative risk.....: 1.20  
Percent cases in area.: 71.4  
Log likelihood ratio.: 5022.797305  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
4. Location IDs included.: 92750, 92720, 92710, 92770, 92760, 92790, 91710, 92780, 91830, 92740, 93720, 91890, 91720, 93620, 91770, 93750, 92730, 91870, 91780, 91750, 93760, 91860, 91840, 91620, 91610, 91820, 91740, 93730, 91760, 93710, 93740, 91850, 91790, 91880, 91730, 97710, 93770, 95740, 95760, 97610, 95770, 91810, 91900  
Coordinates / radius.: (48.559606 N, 13.368473 E) / 192.15 km  
Population.....: 424221  
Number of cases.....: 236621  
Expected cases.....: 255082.15  
Observed / expected....: 0.93  
Relative risk.....: 0.92  
Percent cases in area.: 55.8  
Log likelihood ratio.: 1837.135196  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
5. Location IDs included.: 160660, 96730, 160690, 160630, 160670, 160700, 66310, 94730, 160720, 96720, 66320, 160510, 160730, 160640, 96740, 96780, 66360, 94760, 94780, 160710, 160680, 65350, 160610  
Coordinates / radius.: (50.629134 N, 10.427062 E) / 84.72 km  
Population.....: 141416  
Number of cases.....: 94606  
Expected cases.....: 85032.80  
Observed / expected....: 1.11  
Relative risk.....: 1.12  
Percent cases in area.: 66.9  
Log likelihood ratio.: 1427.789132  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
6. Location IDs included.: 100440, 100420, 100410, 100430, 100460  
Coordinates / radius.: (49.355298 N, 6.775427 E) / 29.75 km  
Population.....: 61262  
Number of cases.....: 30707  
Expected cases.....: 36836.56  
Observed / expected....: 0.83  
Relative risk.....: 0.83  
Percent cases in area.: 50.1  
Log likelihood ratio.: 1270.805666  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001

## Appendix D: SaTScan scanning results from the Bernoulli purely spatial analysis [92]

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7. Location IDs included.: 40120, 33520, 34610, 33560, 34550, 40110, 34030, 34510, 33590, 34620, 33570, 34580, 10510, 33610, 10610, 10560, 34570, 34520, 34530, 32510, 20000, 33530, 34600, 33580, 32560, 10600, 10580, 10620, 34540, 10540, 33550, 57700, 10530, 34590  
Coordinates / radius.: (53.542867 N, 8.576513 E) / 133.89 km  
Population.....: 392262  
Number of cases.....: 223428  
Expected cases.....: 235865.35  
Observed / expected...: 0.95  
Relative risk.....: 0.94  
Percent cases in area.: 57.0  
Log likelihood ratio.: 896.607212  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
8. Location IDs included.: 73150, 64140, 73390, 64330, 64360, 64390, 73310, 64110  
Coordinates / radius.: (49.974177 N, 8.241514 E) / 31.98 km  
Population.....: 71887  
Number of cases.....: 39273  
Expected cases.....: 43225.33  
Observed / expected...: 0.91  
Relative risk.....: 0.91  
Percent cases in area.: 54.6  
Log likelihood ratio.: 454.795093  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
9. Location IDs included.: 55540, 55580, 55620, 51700, 55120, 55130, 55150  
Coordinates / radius.: (51.961076 N, 6.899097 E) / 49.62 km  
Population.....: 95062  
Number of cases.....: 53214  
Expected cases.....: 57160.35  
Observed / expected...: 0.93  
Relative risk.....: 0.93  
Percent cases in area.: 56.0  
Log likelihood ratio.: 345.714083  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
10. Location IDs included.: 59700, 59660, 65320, 71320, 65340, 59580, 53740  
Coordinates / radius.: (50.937659 N, 8.194734 E) / 48.15 km  
Population.....: 74261  
Number of cases.....: 41353  
Expected cases.....: 44652.80  
Observed / expected...: 0.93  
Relative risk.....: 0.92  
Percent cases in area.: 55.7  
Log likelihood ratio.: 307.718816  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
11. Location IDs included.: 53620, 53150, 53580, 53160, 51620, 53140, 53780, 51160, 51110  
Coordinates / radius.: (50.904871 N, 6.716684 E) / 37.31 km  
Population.....: 205435  
Number of cases.....: 120299  
Expected cases.....: 123527.13  
Observed / expected...: 0.97  
Relative risk.....: 0.97  
Percent cases in area.: 58.6  
Log likelihood ratio.: 110.545535  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
12. Location IDs included.: 59140, 59540, 59620, 59130, 59110, 51240, 51200, 59780, 59160, 51130, 51220  
Coordinates / radius.: (51.348029 N, 7.497563 E) / 36.41 km  
Population.....: 201707  
Number of cases.....: 124156  
Expected cases.....: 121285.50  
Observed / expected...: 1.02  
Relative risk.....: 1.02  
Percent cases in area.: 61.6  
Log likelihood ratio.: 89.658819  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001

## Appendix D: SaTScan scanning results from the Bernoulli purely spatial analysis [92]

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13. Location IDs included.: 57740  
Coordinates / radius...: (51.664034 N, 8.719670 E) / 0 km  
Population.....: 17805  
Number of cases.....: 10003  
Expected cases.....: 10706.07  
Observed / expected...: 0.93  
Relative risk.....: 0.93  
Percent cases in area.: 56.2  
Log likelihood ratio.: 57.563240  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001
  
14. Location IDs included.: 51140, 51120, 51660  
Coordinates / radius...: (51.345236 N, 6.579665 E) / 18.94 km  
Population.....: 47701  
Number of cases.....: 29723  
Expected cases.....: 28682.39  
Observed / expected...: 1.04  
Relative risk.....: 1.04  
Percent cases in area.: 62.3  
Log likelihood ratio.: 48.175398  
Monte Carlo rank.....: 1/1000  
P-value.....: 0.001“

## Appendix E: Bernoulli model and Moran's I results of GPs

State	Region (MB)	Cluster GP	Low rate	High rate	Average cluster supply	Moran's I p-value	Moran's I q-value
Brandenburg	1203040	1		1	2.87	0.002	1
Brandenburg	1204010	1		1	2.87	0.002	1
Brandenburg	1204020	1		1	2.87	0.002	1
Brandenburg	1204030	1		1	2.87	0.002	1
Brandenburg	1204040	1		1	2.87	0.002	1
Brandenburg	1204050	1		1	2.87	0.002	1
Brandenburg	1204060	1		1	2.87	0.002	1
Brandenburg	1204070	1		1	2.87	0.004	1
Brandenburg	1204080	1		1	2.87	0.002	1
Brandenburg	1204090	1		1	2.87	0.002	1
Brandenburg	1204100	1		1	2.87	0.002	1
Brandenburg	1204110	1		1	2.87	0.002	1
Brandenburg	1204120	1		1	2.87	0.002	1
Brandenburg	1204130	1		1	2.87	0.048	1
Brandenburg	1205030	1		1	2.87	0.026	1
Brandenburg	1205040	1		1	2.87		
Brandenburg	1205050	1		1	2.87	0.002	1
Brandenburg	1205070	1		1	2.87	0.01	1
Brandenburg	1205080	1		1	2.87	0.004	1
Brandenburg	1205100	1		1	2.87		
Brandenburg	1205110	1		1	2.87	0.002	1
Brandenburg	1205120	1		1	2.87	0.016	1
Brandenburg	1205130	1		1	2.87	0.002	1
Saxony-Anhalt	1502020	1		1	2.87	0.002	1
Saxony-Anhalt	1502050	1		1	2.87	0.002	1
Saxony-Anhalt	1503010	1		1	2.87	0.002	1
Saxony-Anhalt	1503020	1		1	2.87	0.002	1
Saxony-Anhalt	1503030	1		1	2.87	0.002	1
Saxony-Anhalt	1503040	1		1	2.87	0.002	1
Saxony-Anhalt	1503050	1		1	2.87	0.002	1
Saxony-Anhalt	1503060	1		1	2.87	0.002	1
Saxony-Anhalt	1503070	1		1	2.87	0.004	1
Saxony-Anhalt	1504010	1		1	2.87	0.002	1
Saxony-Anhalt	1504020	1		1	2.87	0.002	1
Saxony-Anhalt	1504030	1		1	2.87	0.004	1
Saxony-Anhalt	1504040	1		1	2.87	0.002	1
Saxony-Anhalt	1504060	1		1	2.87	0.002	1
Saxony-Anhalt	1505040	1		1	2.87	0.002	1
Saxony-Anhalt	1505050	1		1	2.87	0.004	1
Saxony-Anhalt	1505060	1		1	2.87	0.004	1
Thuringia	1600200	1		1	2.87	0.002	1
Thuringia	1601900	1		1	2.87	0.002	1
Thuringia	1602000	1		1	2.87	0.008	1
Thuringia	1602500	1		1	2.87	0.004	1
Thuringia	1602600	1		1	2.87	0.002	1
Thuringia	1602700	1		1	2.87	0.004	1
Thuringia	1602900	1		1	2.87	0.002	1
Thuringia	1603000	1		1	2.87	0.002	1
Thuringia	1603100	1		1	2.87	0.002	1
Thuringia	1603200	1		1	2.87	0.002	1
Thuringia	1603400	1		1	2.87	0.004	1
Thuringia	1603500	1		1	2.87	0.002	1
Saxony	3400164	1		1	2.87	0.004	1
Saxony	3400165	1		1	2.87	0.002	1
Saxony	3400166	1		1	2.87	0.01	1
Saxony	3400167	1		1	2.87	0.01	1
Saxony	3400168	1		1	2.87	0.04	1
Saxony	3400169	1		1	2.87	0.044	1
Saxony	3400170	1		1	2.87		
Saxony	3400171	1		1	2.87	0.012	1
Saxony	3400172	1		1	2.87	0.024	1
Saxony	3400173	1		1	2.87	0.006	1
Saxony	3400174	1		1	2.87		

Appendix E: Bernoulli model and Moran's I results of GPs

State	Region (MB)	Cluster GP	Low rate	High rate	Average cluster supply	Moran's I p-value	Moran's I q-value
Saxony	3400176	1		1	2.87	0.002	1
Saxony	3400177	1		1	2.87	0.004	1
Saxony	3400178	1		1	2.87	0.004	1
Saxony	3400179	1		1	2.87	0.006	1
Saxony	3400180	1		1	2.87		
Saxony	3400181	1		1	2.87	0.002	1
Saxony	3400182	1		1	2.87	0.004	1
Saxony	3400183	1		1	2.87	0.002	1
Saxony	3400184	1		1	2.87	0.006	1
Saxony	3400185	1		1	2.87	0.014	1
Saxony	3400186	1		1	2.87	0.002	1
Saxony	3400187	1		1	2.87	0.002	1
Saxony	3400188	1		1	2.87	0.004	1
Saxony	3400189	1		1	2.87	0.016	1
Saxony	3400190	1		1	2.87	0.01	1
Saxony	3400191	1		1	2.87	0.044	1
Saxony	3400192	1		1	2.87		
Saxony	3400193	1		1	2.87	0.032	1
Saxony	3400194	1		1	2.87	0.006	1
Saxony	3400196	1		1	2.87	0.006	1
Saxony	3400197	1		1	2.87	0.022	1
Saxony	3400198	1		1	2.87	0.032	1
Saxony	3400199	1		1	2.87	0.008	1
Saxony	3400200	1		1	2.87	0.004	1
Saxony	3400201	1		1	2.87	0.002	1
Saxony	3400202	1		1	2.87	0.008	1
Saxony	3400203	1		1	2.87	0.002	1
Saxony	3400204	1		1	2.87	0.022	1
Saxony	3400206	1		1	2.87	0.004	1
Saxony	3400207	1		1	2.87	0.002	1
Saxony	3400208	1		1	2.87	0.006	1
Saxony	3400209	1		1	2.87	0.002	1
Saxony	3400321	1		1	2.87	0.004	1
Saxony	3400407	1		1	2.87	0.012	1
Saxony	3400408	1		1	2.87	0.006	1
Saxony	3400409	1		1	2.87	0.002	1
Saxony-Anhalt	3500159	1		1	2.87	0.002	1
Saxony-Anhalt	3500161	1		1	2.87		
Saxony-Anhalt	3500162	1		1	2.87	0.018	1
Thuringia	3600522	1		1	2.87	0.002	1
Thuringia	3600524	1		1	2.87	0.008	1
Thuringia	3600526	1		1	2.87	0.002	1
Thuringia	3600527	1		1	2.87	0.004	1
Thuringia	3600528	1		1	2.87	0.006	1
Baden-Württemberg	801010	2	1		3.07		
Baden-Württemberg	801020	2	1		3.07	0.02	3
Baden-Württemberg	801030	2	1		3.07	0.004	3
Baden-Württemberg	801040	2	1		3.07	0.008	3
Baden-Württemberg	801050	2	1		3.07	0.002	3
Baden-Württemberg	801060	2	1		3.07	0.012	3
Baden-Württemberg	801070	2	1		3.07	0.008	3
Baden-Württemberg	801080	2	1		3.07	0.002	3
Baden-Württemberg	801090	2	1		3.07	0.018	3
Baden-Württemberg	801100	2	1		3.07	0.006	3
Baden-Württemberg	801110	2	1		3.07	0.002	3
Baden-Württemberg	801120	2	1		3.07	0.002	3
Baden-Württemberg	801130	2	1		3.07	0.006	3
Baden-Württemberg	801140	2	1		3.07	0.006	3
Baden-Württemberg	801150	2	1		3.07	0.002	3
Baden-Württemberg	802050	2	1		3.07	0.01	3
Baden-Württemberg	802080	2	1		3.07	0.006	3
Baden-Württemberg	802090	2	1		3.07	0.002	3
Baden-Württemberg	803010	2	1		3.07	0.004	3
Baden-Württemberg	803020	2	1		3.07	0.01	3
Baden-Württemberg	803030	2	1		3.07	0.006	3
Baden-Württemberg	803040	2	1		3.07	0.01	3
Baden-Württemberg	806040	2	1		3.07	0.018	3
Baden-Württemberg	806050	2	1		3.07	0.002	3
Baden-Württemberg	806060	2	1		3.07	0.002	3
Baden-Württemberg	806070	2	1		3.07	0.002	3

Appendix E: Bernoulli model and Moran's I results of GPs

State	Region (MB)	Cluster GP	Low rate	High rate	Average cluster supply	Moran's I p-value	Moran's I q-value
Baden-Württemberg	808010	2	1		3.07	0.044	3
Baden-Württemberg	808020	2	1		3.07	0.002	3
Baden-Württemberg	808040	2	1		3.07	0.014	3
Baden-Württemberg	808050	2	1		3.07	0.006	3
Baden-Württemberg	809060	2	1		3.07	0.018	3
Baden-Württemberg	809070	2	1		3.07	0.032	3
Baden-Württemberg	809080	2	1		3.07	0.038	3
Baden-Württemberg	809090	2	1		3.07		
Baden-Württemberg	810010	2	1		3.07	0.002	3
Baden-Württemberg	810020	2	1		3.07	0.002	3
Baden-Württemberg	810030	2	1		3.07	0.002	3
Baden-Württemberg	810040	2	1		3.07	0.002	3
Baden-Württemberg	810050	2	1		3.07	0.002	3
Baden-Württemberg	810060	2	1		3.07	0.002	3
Baden-Württemberg	810070	2	1		3.07	0.004	3
Baden-Württemberg	810080	2	1		3.07	0.006	4
Baden-Württemberg	811010	2	1		3.07	0.002	3
Baden-Württemberg	811020	2	1		3.07	0.002	3
Baden-Württemberg	811030	2	1		3.07	0.002	3
Baden-Württemberg	811040	2	1		3.07	0.002	3
Baden-Württemberg	811050	2	1		3.07	0.008	3
Baden-Württemberg	811060	2	1		3.07	0.002	3
Baden-Württemberg	812010	2	1		3.07	0.002	3
Baden-Württemberg	812020	2	1		3.07	0.006	3
Baden-Württemberg	812030	2	1		3.07	0.02	3
Baden-Württemberg	812040	2	1		3.07	0.004	3
Baden-Württemberg	812050	2	1		3.07		
Baden-Württemberg	812060	2	1		3.07		
Baden-Württemberg	812070	2	1		3.07	0.018	3
Baden-Württemberg	812080	2	1		3.07	0.012	3
Baden-Württemberg	812090	2	1		3.07	0.002	3
Bavaria	909040	2	1		3.07	0.002	3
Bavaria	909050	2	1		3.07	0.01	3
Bavaria	910030	2	1		3.07	0.002	3
Bavaria	910040	2	1		3.07	0.002	3
Bavaria	914030	2	1		3.07	0.002	3
Bavaria	914050	2	1		3.07	0.004	3
Bavaria	914080	2	1		3.07	0.002	3
Bavaria	915010	2	1		3.07	0.004	3
Bavaria	915020	2	1		3.07		
Bavaria	915030	2	1		3.07	0.006	3
Bavaria	915040	2	1		3.07		
Bavaria	915050	2	1		3.07	0.006	4
Bavaria	915060	2	1		3.07		
Bavaria	916010	2	1		3.07	0.004	3
Bavaria	916020	2	1		3.07	0.024	3
Bavaria	916030	2	1		3.07	0.002	3
Bavaria	916040	2	1		3.07	0.008	3
Bavaria	916050	2	1		3.07	0.042	3
Bavaria	916060	2	1		3.07	0.032	3
Bavaria	916070	2	1		3.07	0.038	3
Bavaria	916080	2	1		3.07		
Bavaria	917010	2	1		3.07	0.002	3
Bavaria	917020	2	1		3.07	0.004	3
Bavaria	917040	2	1		3.07	0.012	3
Bavaria	917080	2	1		3.07	0.002	3
Bavaria	2900122	2	1		3.07	0.004	3
Bavaria	2900123	2	1		3.07		
Bavaria	2900124	2	1		3.07	0.008	3
Bavaria	2900132	2	1		3.07		
Bavaria	2900142	2	1		3.07	0.01	3
Bavaria	2900143	2	1		3.07		
Bavaria	2900144	2	1		3.07	0.004	3
Bavaria	2900145	2	1		3.07	0.016	3
Bavaria	2900152	2	1		3.07		
Bavaria	2900302	2	1		3.07		
Bavaria	2900303	2	1		3.07	0.024	3
Bavaria	2900309	2	1		3.07	0.022	3
Bavaria	2900310	2	1		3.07	0.046	3
Bavaria	2900343	2	1		3.07	0.014	3

Appendix E: Bernoulli model and Moran's I results of GPs

State	Region (MB)	Cluster GP	Low rate	High rate	Average cluster supply	Moran's I p-value	Moran's I q-value
Bavaria	2900352	2	1		3.07	0.002	3
Bavaria	2900371	2	1		3.07	0.016	3
Bavaria	2900373	2	1		3.07	0.002	3
Bavaria	2900391	2	1		3.07	0.036	3
Brandenburg	1201010	3		1	2.77	0.002	1
Brandenburg	1201030	3		1	2.77		
Brandenburg	1201040	3		1	2.77	0.026	1
Brandenburg	1201050	3		1	2.77	0.006	1
Brandenburg	1201060	3		1	2.77	0.016	1
Brandenburg	1201070	3		1	2.77		
Brandenburg	1201080	3		1	2.77	0.01	1
Brandenburg	1202010	3		1	2.77	0.002	1
Brandenburg	1202020	3		1	2.77	0.002	1
Brandenburg	1202030	3		1	2.77	0.002	1
Brandenburg	1202040	3		1	2.77	0.004	1
Brandenburg	1202050	3		1	2.77	0.002	1
Brandenburg	1203060	3		1	2.77	0.004	1
Mecklenburg-Western Pomerania	1301060	3		1	2.77	0.002	1
Mecklenburg-Western Pomerania	1302040	3		1	2.77	0.002	1
Mecklenburg-Western Pomerania	1302050	3		1	2.77	0.004	1
Mecklenburg-Western Pomerania	1303070	3		1	2.77	0.002	1
Mecklenburg-Western Pomerania	1303080	3		1	2.77	0.002	1
Mecklenburg-Western Pomerania	3300155	3		1	2.77	0.004	1
Mecklenburg-Western Pomerania	3300501	3		1	2.77	0.002	1
Mecklenburg-Western Pomerania	3300502	3		1	2.77	0.002	1
Mecklenburg-Western Pomerania	3300503	3		1	2.77		
Mecklenburg-Western Pomerania	3300504	3		1	2.77		
Mecklenburg-Western Pomerania	3300505	3		1	2.77		
Mecklenburg-Western Pomerania	3300506	3		1	2.77	0.006	1
Mecklenburg-Western Pomerania	3300507	3		1	2.77	0.002	1
Mecklenburg-Western Pomerania	3300508	3		1	2.77	0.014	1
Mecklenburg-Western Pomerania	3300509	3		1	2.77	0.002	1
Mecklenburg-Western Pomerania	3300510	3		1	2.77		
Mecklenburg-Western Pomerania	3300511	3		1	2.77	0.002	1
Mecklenburg-Western Pomerania	3300512	3		1	2.77	0.012	1
Mecklenburg-Western Pomerania	3300513	3		1	2.77		
Mecklenburg-Western Pomerania	3300514	3		1	2.77	0.002	1
Mecklenburg-Western Pomerania	3300515	3		1	2.77	0.002	1
Mecklenburg-Western Pomerania	3300516	3		1	2.77	0.002	1
Mecklenburg-Western Pomerania	3300517	3		1	2.77		
Mecklenburg-Western Pomerania	3300518	3		1	2.77	0.004	1
Mecklenburg-Western Pomerania	3300519	3		1	2.77		
Mecklenburg-Western Pomerania	3300520	3		1	2.77		
Schleswig-Holstein	101090	4	1		2.97		
Schleswig-Holstein	101110	4	1		2.97		
Schleswig-Holstein	101120	4	1		2.97		
Schleswig-Holstein	103010	4	1		2.97		
Schleswig-Holstein	103020	4	1		2.97	0.048	3
Schleswig-Holstein	103040	4	1		2.97		
Schleswig-Holstein	104010	4	1		2.97		
Schleswig-Holstein	104020	4	1		2.97		
Schleswig-Holstein	104030	4	1		2.97		
Schleswig-Holstein	104040	4	1		2.97	0.046	3
Schleswig-Holstein	105050	4	1		2.97		
Schleswig-Holstein	105070	4	1		2.97		
Lower Saxony	306010	4	1		2.97		
Lower Saxony	306030	4	1		2.97		
Lower Saxony	307020	4	1		2.97		
Lower Saxony	307030	4	1		2.97		
Lower Saxony	314020	4	1		2.97		
Lower Saxony	315010	4	1		2.97	0.002	3
Lower Saxony	319010	4	1		2.97	0.016	3
Lower Saxony	319020	4	1		2.97	0.02	3
Lower Saxony	319030	4	1		2.97	0.022	3
Lower Saxony	320010	4	1		2.97	0.03	3
Lower Saxony	320020	4	1		2.97		
Lower Saxony	320030	4	1		2.97		
Lower Saxony	321010	4	1		2.97	0.028	3
Lower Saxony	321020	4	1		2.97	0.002	3
Lower Saxony	323020	4	1		2.97		

Appendix E: Bernoulli model and Moran's I results of GPs

State	Region (MB)	Cluster GP	Low rate	High rate	Average cluster supply	Moran's I p-value	Moran's I q-value
Lower Saxony	325010	4	1		2.97		
Lower Saxony	329010	4	1		2.97		
Lower Saxony	330010	4	1		2.97		
Lower Saxony	330020	4	1		2.97		
Lower Saxony	331010	4	1		2.97		
Lower Saxony	331020	4	1		2.97	0.012	3
Lower Saxony	332010	4	1		2.97		
Lower Saxony	332020	4	1		2.97	0.048	3
Lower Saxony	333020	4	1		2.97		
Lower Saxony	337010	4	1		2.97	0.018	3
Lower Saxony	337020	4	1		2.97	0.038	3
Lower Saxony	338010	4	1		2.97	0.018	3
Lower Saxony	338020	4	1		2.97	0.014	3
Lower Saxony	339010	4	1		2.97		
Nordrhein-Westfalen	504010	4	1		2.97		
Nordrhein-Westfalen	504020	4	1		2.97		
Schleswig-Holstein	2100080	4	1		2.97		
Schleswig-Holstein	2100082	4	1		2.97		
Schleswig-Holstein	2100083	4	1		2.97	0.014	3
Schleswig-Holstein	2100084	4	1		2.97	0.028	3
Hamburg	2200000	4	1		2.97	0.014	3
Lower Saxony	2300004	4	1		2.97		
Lower Saxony	2300085	4	1		2.97	0.018	3
Lower Saxony	2300086	4	1		2.97		
Lower Saxony	2300087	4	1		2.97		
Lower Saxony	2300090	4	1		2.97	0.034	4
Lower Saxony	2300096	4	1		2.97	0.024	3
Lower Saxony	2300099	4	1		2.97		
Lower Saxony	2300100	4	1		2.97		
Lower Saxony	2300101	4	1		2.97		
Lower Saxony	2300102	4	1		2.97	0.028	3
Lower Saxony	2300103	4	1		2.97	0.02	3
Lower Saxony	2300105	4	1		2.97		
Lower Saxony	2300107	4	1		2.97		
Lower Saxony	2300108	4	1		2.97		
Lower Saxony	2300111	4	1		2.97		
Lower Saxony	2300112	4	1		2.97		
Lower Saxony	2300113	4	1		2.97	0.008	3
Lower Saxony	2300114	4	1		2.97	0.02	3
Lower Saxony	2300115	4	1		2.97		
Lower Saxony	2300429	4	1		2.97		
Lower Saxony	2300432	4	1		2.97		
Lower Saxony	2300434	4	1		2.97		
Lower Saxony	2300437	4	1		2.97		
Lower Saxony	2300441	4	1		2.97		
Lower Saxony	2300442	4	1		2.97	0.042	3
Bremen	2400000	4	1		2.97		
Bremen	2400001	4	1		2.97		
Hessen	601050	5		1	3.46		
Hessen	601090	5		1	3.46		
Hessen	601100	5		1	3.46		
Hessen	601120	5		1	3.46		
Hessen	601130	5		1	3.46		
Hessen	601150	5		1	3.46		
Hessen	601170	5		1	3.46		
Hessen	601180	5		1	3.46		
Hessen	601190	5		1	3.46		
Hessen	601200	5		1	3.46		
Hessen	601210	5		1	3.46		
Hessen	601220	5		1	3.46		
Hessen	602060	5		1	3.46		
Hessen	602070	5		1	3.46		
Hessen	602080	5		1	3.46		
Hessen	602120	5		1	3.46		
Hessen	603060	5		1	3.46		
Hessen	603070	5		1	3.46		
Hessen	603090	5		1	3.46		
Bavaria	903020	5		1	3.46		
Bavaria	903030	5		1	3.46		
Bavaria	903040	5		1	3.46		

Appendix E: Bernoulli model and Moran's I results of GPs

State	Region (MB)	Cluster GP	Low rate	High rate	Average cluster supply	Moran's I p-value	Moran's I q-value
Bavaria	904010	5		1	3.46		
Bavaria	904020	5		1	3.46		
Thuringia	1600300	5		1	3.46	0.002	1
Thuringia	1600400	5		1	3.46	0.012	1
Thuringia	1600500	5		1	3.46	0.004	1
Thuringia	1600600	5		1	3.46	0.044	1
Thuringia	1600700	5		1	3.46	0.014	1
Thuringia	1600800	5		1	3.46	0.008	1
Thuringia	1600900	5		1	3.46		
Thuringia	1601000	5		1	3.46	0.026	1
Thuringia	1601100	5		1	3.46	0.004	1
Thuringia	1601200	5		1	3.46	0.002	1
Thuringia	1601300	5		1	3.46	0.002	1
Thuringia	1601500	5		1	3.46	0.004	1
Thuringia	1601800	5		1	3.46	0.004	1
Thuringia	1602200	5		1	3.46	0.002	1
Thuringia	1602300	5		1	3.46	0.006	1
Lower Saxony	2300095	5		1	3.46		
Hessen	2600270	5		1	3.46		
Hessen	2600271	5		1	3.46		
Hessen	2600272	5		1	3.46		
Hessen	2600273	5		1	3.46		
Hessen	2600274	5		1	3.46		
Bavaria	2900127	5		1	3.46		
Bavaria	2900148	5		1	3.46		
Bavaria	2900149	5		1	3.46		
Bavaria	2900304	5		1	3.46		
Bavaria	2900345	5		1	3.46		
Bavaria	2900346	5		1	3.46		
Bavaria	2900372	5		1	3.46		
Thuringia	3600521	5		1	3.46	0.032	1
Thuringia	3600523	5		1	3.46	0.002	1
Hessen	602150	6	1		3.32		
Hessen	603020	6	1		3.32		
Hessen	603100	6	1		3.32		
Hessen	603110	6	1		3.32		
Hessen	603120	6	1		3.32		
Hessen	603130	6	1		3.32		
Hessen	603140	6	1		3.32		
Hessen	603150	6	1		3.32		
Hessen	603160	6	1		3.32		
Hessen	603170	6	1		3.32		
Hessen	603180	6	1		3.32		
Hessen	603190	6	1		3.32		
Hessen	603200	6	1		3.32		
Hessen	603250	6	1		3.32		
Hessen	603260	6	1		3.32	0.032	3
Hessen	603270	6	1		3.32		
Rhineland-Palatinate	701110	6	1		3.32		
Rhineland-Palatinate	703010	6	1		3.32		
Rhineland-Palatinate	703020	6	1		3.32	0.038	3
Rhineland-Palatinate	703030	6	1		3.32	0.046	3
Rhineland-Palatinate	703050	6	1		3.32		
Rhineland-Palatinate	2700116	6	1		3.32		
Lower Saxony	332030	7	1		3.18		
Nordrhein-Westfalen	503010	7	1		3.18	0.046	3
Nordrhein-Westfalen	503020	7	1		3.18		
Nordrhein-Westfalen	503040	7	1		3.18	0.034	3
Nordrhein-Westfalen	503050	7	1		3.18		
Nordrhein-Westfalen	503060	7	1		3.18	0.05	3
Nordrhein-Westfalen	503070	7	1		3.18	0.008	3
Nordrhein-Westfalen	503080	7	1		3.18		
Nordrhein-Westfalen	503090	7	1		3.18		
Nordrhein-Westfalen	503100	7	1		3.18		
Nordrhein-Westfalen	503110	7	1		3.18		
Nordrhein-Westfalen	503120	7	1		3.18		
Nordrhein-Westfalen	503130	7	1		3.18	0.014	3
Nordrhein-Westfalen	503140	7	1		3.18		
Nordrhein-Westfalen	503150	7	1		3.18		
Nordrhein-Westfalen	503160	7	1		3.18		

Appendix E: Bernoulli model and Moran's I results of GPs

State	Region (MB)	Cluster GP	Low rate	High rate	Average cluster supply	Moran's I p-value	Moran's I q-value
Nordrhein-Westfalen	503170	7	1		3.18		
Nordrhein-Westfalen	503180	7	1		3.18		
Nordrhein-Westfalen	503230	7	1		3.18		
Nordrhein-Westfalen	503240	7	1		3.18		
Nordrhein-Westfalen	503270	7	1		3.18		
Lower Saxony	2300438	7	1		3.18		
Bavaria	905040	8	1		3.40		
Bavaria	905080	8	1		3.40		
Bavaria	906010	8	1		3.40		
Bavaria	906020	8	1		3.40		
Bavaria	906040	8	1		3.40		
Bavaria	906070	8	1		3.40		
Bavaria	907050	8	1		3.40		
Bavaria	907060	8	1		3.40		
Bavaria	911010	8	1		3.40		
Bavaria	911030	8	1		3.40		
Bavaria	911050	8	1		3.40		
Bavaria	911060	8	1		3.40		
Bavaria	911070	8	1		3.40	0.014	3
Bavaria	911080	8	1		3.40	0.022	3
Bavaria	911090	8	1		3.40		
Bavaria	912010	8	1		3.40		
Bavaria	912050	8	1		3.40		
Bavaria	912060	8	1		3.40		
Bavaria	912080	8	1		3.40		
Bavaria	912090	8	1		3.40		
Bavaria	912100	8	1		3.40		
Bavaria	913010	8	1		3.40	0.002	3
Bavaria	913030	8	1		3.40		
Bavaria	913070	8	1		3.40		
Bavaria	913080	8	1		3.40		
Bavaria	914010	8	1		3.40	0.004	3
Bavaria	918010	8	1		3.40	0.004	3
Bavaria	918020	8	1		3.40		
Bavaria	2900128	8	1		3.40		
Bavaria	2900129	8	1		3.40		
Bavaria	2900130	8	1		3.40	0.002	3
Bavaria	2900135	8	1		3.40		
Bavaria	2900136	8	1		3.40	0.002	3
Bavaria	2900137	8	1		3.40	0.006	3
Bavaria	2900138	8	1		3.40	0.002	3
Bavaria	2900141	8	1		3.40		
Bavaria	2900146	8	1		3.40		
Bavaria	2900341	8	1		3.40		
Bavaria	2900342	8	1		3.40	0.004	3
Bavaria	2900344	8	1		3.40	0.032	3
Bavaria	2900348	8	1		3.40		
Bavaria	2900350	8	1		3.40		
Bavaria	2900351	8	1		3.40		
Bavaria	2900353	8	1		3.40	0.036	3
Bavaria	2900356	8	1		3.40		
Bavaria	2900357	8	1		3.40		
Bavaria	2900358	8	1		3.40	0.016	3
Bavaria	2900359	8	1		3.40		
Bavaria	2900361	8	1		3.40		
Bavaria	2900362	8	1		3.40		
Bavaria	2900367	8	1		3.40		
Bavaria	2900368	8	1		3.40		
Bavaria	2900370	8	1		3.40		
Bavaria	2900375	8	1		3.40		
Bavaria	2900377	8	1		3.40		
Bavaria	2900379	8	1		3.40		
Bavaria	2900380	8	1		3.40		
Bavaria	2900383	8	1		3.40		
Bavaria	2900384	8	1		3.40		
Bavaria	2900385	8	1		3.40		
Bavaria	2900386	8	1		3.40		
Bavaria	2900392	8	1		3.40		
Bavaria	2900393	8	1		3.40		
Bavaria	2900394	8	1		3.40		

Appendix E: Bernoulli model and Moran's I results of GPs

State	Region (MB)	Cluster GP	Low rate	High rate	Average cluster supply	Moran's I p-value	Moran's I q-value
Bavaria	2900396	8	1		3.40		
Bavaria	2900397	8	1		3.40		
Bavaria	2900398	8	1		3.40		
Bavaria	2900399	8	1		3.40		
Bavaria	2900400	8	1		3.40		
Bavaria	2900401	8	1		3.40		
Bavaria	2900402	8	1		3.40		
Bavaria	2900406	8	1		3.40		
Nordrhein-Westfalen	501160	9		1	3.35		
Nordrhein-Westfalen	501170	9		1	3.35		
Nordrhein-Westfalen	501360	9		1	3.35		
Nordrhein-Westfalen	501370	9		1	3.35		
Nordrhein-Westfalen	501380	9		1	3.35		
Nordrhein-Westfalen	501390	9		1	3.35		
Nordrhein-Westfalen	501400	9		1	3.35		
Nordrhein-Westfalen	501410	9		1	3.35		
Nordrhein-Westfalen	501420	9		1	3.35		
Nordrhein-Westfalen	501430	9		1	3.35		
Nordrhein-Westfalen	501440	9		1	3.35		
Nordrhein-Westfalen	501450	9		1	3.35		
Nordrhein-Westfalen	501460	9		1	3.35		
Nordrhein-Westfalen	505320	9		1	3.35		
Nordrhein-Westfalen	505330	9		1	3.35		
Nordrhein-Westfalen	505340	9		1	3.35		
Nordrhein-Westfalen	505350	9		1	3.35		
Nordrhein-Westfalen	505360	9		1	3.35		
Nordrhein-Westfalen	505370	9		1	3.35		
Nordrhein-Westfalen	505390	9		1	3.35		
Rhineland-Palatinate	705020	10		1	3.33		
Rhineland-Palatinate	705030	10		1	3.33	0.028	1
Rhineland-Palatinate	705040	10		1	3.33		
Rhineland-Palatinate	705050	10		1	3.33		
Rhineland-Palatinate	705060	10		1	3.33		
Saarland	1000080	10		1	3.33		
Nordrhein-Westfalen	502300	11	1		2.48	0.038	3
Nordrhein-Westfalen	502330	11	1		2.48		
Nordrhein-Westfalen	505070	11	1		2.48		
Nordrhein-Westfalen	505090	11	1		2.48		
Nordrhein-Westfalen	505120	11	1		2.48	0.01	3
Nordrhein-Westfalen	505130	11	1		2.48		
Nordrhein-Westfalen	505140	11	1		2.48	0.006	3
Nordrhein-Westfalen	505150	11	1		2.48		
Nordrhein-Westfalen	505160	11	1		2.48	0.01	3
Nordrhein-Westfalen	505170	11	1		2.48	0.016	3
Nordrhein-Westfalen	505180	11	1		2.48		
Nordrhein-Westfalen	505190	11	1		2.48	0.006	3
Nordrhein-Westfalen	505200	11	1		2.48		
Nordrhein-Westfalen	505210	11	1		2.48		
Nordrhein-Westfalen	505230	11	1		2.48		
Nordrhein-Westfalen	505240	11	1		2.48		
Hessen	601070	11	1		2.48		
Hessen	602010	11	1		2.48		
Hessen	602020	11	1		2.48		
Hessen	602090	11	1		2.48		
Rhineland-Palatinate	701010	11	1		2.48		
Nordrhein-Westfalen	504200	12	1		2.40		
Nordrhein-Westfalen	504210	12	1		2.40		
Nordrhein-Westfalen	504220	12	1		2.40		
Nordrhein-Westfalen	504230	12	1		2.40		
Nordrhein-Westfalen	505020	12	1		2.40		
Lower Saxony	306050	13		1	2.00		
Bavaria	902050	14	1		4.00		
Bavaria	903070	14	1		4.00		
Bavaria	2900313	14	1		4.00		
Bavaria	2900389	14	1		4.00		
Bavaria	2900403	14	1		4.00		
Bavaria	2900404	14	1		4.00		
Nordrhein-Westfalen	501230	15		1	2.92		
Nordrhein-Westfalen	501240	15		1	2.92		
Nordrhein-Westfalen	501250	15		1	2.92		

Appendix E: Bernoulli model and Moran's I results of GPs

State	Region (MB)	Cluster GP	Low rate	High rate	Average cluster supply	Moran's I p-value	Moran's I q-value
Nordrhein-Westfalen	501260	15		1	2.92		
Nordrhein-Westfalen	501270	15		1	2.92		
Nordrhein-Westfalen	501280	15		1	2.92		
Nordrhein-Westfalen	501290	15		1	2.92		
Nordrhein-Westfalen	501320	15		1	2.92		
Nordrhein-Westfalen	501330	15		1	2.92		
Nordrhein-Westfalen	502010	15		1	2.92		
Nordrhein-Westfalen	502020	15		1	2.92		
Nordrhein-Westfalen	502030	15		1	2.92		
Nordrhein-Westfalen	502040	15		1	2.92		
Nordrhein-Westfalen	502050	15		1	2.92		
Nordrhein-Westfalen	502060	15		1	2.92		
Nordrhein-Westfalen	502070	15		1	2.92		
Nordrhein-Westfalen	502080	15		1	2.92		
Nordrhein-Westfalen	502100	15		1	2.92		
Nordrhein-Westfalen	502110	15		1	2.92		
Nordrhein-Westfalen	502120	15		1	2.92		
Nordrhein-Westfalen	502130	15		1	2.92		
Nordrhein-Westfalen	502140	15		1	2.92		
Nordrhein-Westfalen	502150	15		1	2.92		
Nordrhein-Westfalen	502160	15		1	2.92		
Nordrhein-Westfalen	502170	15		1	2.92		
Nordrhein-Westfalen	502180	15		1	2.92		
Nordrhein-Westfalen	502190	15		1	2.92		
Nordrhein-Westfalen	502200	15		1	2.92		
Nordrhein-Westfalen	502220	15		1	2.92		
Nordrhein-Westfalen	502230	15		1	2.92		
Nordrhein-Westfalen	502240	15		1	2.92		
Nordrhein-Westfalen	502250	15		1	2.92		
Nordrhein-Westfalen	502260	15		1	2.92		
Nordrhein-Westfalen	502380	15		1	2.92		
Nordrhein-Westfalen	502390	15		1	2.92		
Nordrhein-Westfalen	502400	15		1	2.92		
Nordrhein-Westfalen	502410	15		1	2.92		
Nordrhein-Westfalen	502420	15		1	2.92		
Nordrhein-Westfalen	502430	16	1		4.00		
Nordrhein-Westfalen	503290	17		1	3.57		
Nordrhein-Westfalen	505400	17		1	3.57		
Nordrhein-Westfalen	505420	17		1	3.57		
Nordrhein-Westfalen	505430	17		1	3.57		
Nordrhein-Westfalen	505440	17		1	3.57		
Nordrhein-Westfalen	505450	17		1	3.57		
Nordrhein-Westfalen	505460	17		1	3.57		
Bavaria	904060	18		1	3.22		
Bavaria	907010	18		1	3.22		
Bavaria	907020	18		1	3.22		
Bavaria	907030	18		1	3.22		
Bavaria	907040	18		1	3.22		
Bavaria	2900347	18		1	3.22		
Bavaria	2900349	18		1	3.22		
Bavaria	2900364	18		1	3.22		
Bavaria	2900378	18		1	3.22		
Rhineland-Palatinate	701050	19		1	3.00		
Rhineland-Palatinate	702040	20		1	2.80		
Rhineland-Palatinate	702050	20		1	2.80		
Rhineland-Palatinate	702060	20		1	2.80		
Rhineland-Palatinate	702080	20		1	2.80		
Rhineland-Palatinate	703080	20		1	2.80		
Saarland	1000010	20		1	2.80		
Saarland	1000020	20		1	2.80		
Rhineland-Palatinate	2700281	20		1	2.80		
Rhineland-Palatinate	2700282	20		1	2.80		
Rhineland-Palatinate	2700283	20		1	2.80		
Lower Saxony	301110					0.002	1
Nordrhein-Westfalen	503030					0.016	3
Nordrhein-Westfalen	503190					0.034	3
Nordrhein-Westfalen	504190					0.026	3
Nordrhein-Westfalen	504270					0.044	4
Nordrhein-Westfalen	505010					0.012	4
Nordrhein-Westfalen	505050					0.02	3

Appendix E: Bernoulli model and Moran's I results of GPs

State	Region (MB)	Cluster GP	Low rate	High rate	Average cluster supply	Moran's I p-value	Moran's I q-value
Baden-Württemberg	802030					0.03	4
Baden-Württemberg	802040					0.002	3
Baden-Württemberg	802070					0.008	3
Baden-Württemberg	806010					0.04	3
Baden-Württemberg	807010					0.018	3
Baden-Württemberg	807020					0.02	3
Baden-Württemberg	807030					0.026	3
Baden-Württemberg	807050					0.016	3
Baden-Württemberg	807080					0.04	3
Baden-Württemberg	807100					0.042	3
Baden-Württemberg	807110					0.038	3
Baden-Württemberg	808030					0.004	3
Baden-Württemberg	809020					0.01	3
Baden-Württemberg	809030					0.036	4
Bavaria	908070					0.022	4
Bavaria	910010					0.05	3
Bavaria	910050					0.002	3
Bavaria	914060					0.002	3
Bavaria	914090					0.026	3
Bavaria	917030					0.032	3
Bavaria	917050					0.004	3
Bavaria	918120					0.004	3
Berlin	1100000					0.002	1
Brandenburg	1203010					0.002	1
Brandenburg	1203020					0.002	1
Brandenburg	1203030					0.002	1
Brandenburg	1203050					0.006	1
Brandenburg	1203070					0.01	1
Brandenburg	1203080					0.022	1
Brandenburg	1205010					0.038	1
Brandenburg	1205020					0.002	1
Saxony-Anhalt	1501010					0.008	1
Saxony-Anhalt	1501040					0.018	1
Saxony-Anhalt	1502060					0.004	1
Saxony-Anhalt	1505010					0.008	1
Saxony-Anhalt	1505020					0.006	1
Saxony-Anhalt	1505030					0.002	1
Thuringia	1600100					0.002	1
Thuringia	1603300					0.01	1
Lower Saxony	2300094					0.044	2
Lower Saxony	2300433					0.03	1
Lower Saxony	2300435					0.018	1
Lower Saxony	2300439					0.034	1
Bavaria	2900131					0.002	3
Bavaria	2900140					0.014	1
Bavaria	2900305					0.028	3
Bavaria	2900306					0.004	1
Bavaria	2900308					0.042	3
Bavaria	2900355					0.002	3
Bavaria	2900363					0.018	1
Bavaria	2900365					0.02	1
Bavaria	2900376					0.006	1
Bavaria	2900381					0.034	3
Saxony-Anhalt	3500160					0.006	1
Thuringia	3600525					0.002	1

Source: Geiger et al. [92]

## Appendix F: Bernoulli model and Moran's I results of specialised physicians

State	KR	Cluster ophthalmologist	Low rate	High rate	Average cluster supply	Moran's I q-value	Cluster neurologist	Low rate	High rate	Average cluster supply	Moran's I q-value	Cluster orthopaedics	Low rate	High rate	Average cluster supply	Moran's I q-value
BY	94760	1		1	3.91	1	5		1	4.11	1	1		1	4.25	1
BY	94750	1		1	3.91						1		1	4.25	1	
SN	340019	1		1	3.91	1	1		1	4.51	1	1		1	4.25	1
SN	340021	1		1	3.91	1	1		1	4.51	1	1		1	4.25	1
SN	340022	1		1	3.91	1	1		1	4.51	1	1		1	4.25	1
SN	340023	1		1	3.91	1	1		1	4.51		1		1	4.25	
SN	340024	1		1	3.91	1	1		1	4.51	1	1		1	4.25	1
SN	340026	1		1	3.91	1	1		1	4.51	1	1		1	4.25	1
SN	340027	1		1	3.91	1	1		1	4.51	1	1		1	4.25	1
SN	340028	1		1	3.91	1	1		1	4.51	1	1		1	4.25	1
SN	340033	1		1	3.91	1	1		1	4.51	1	1		1	4.25	1
SN	340035	1		1	3.91	1	1		1	4.51	1	1		1	4.25	1
SN	340036	1		1	3.91	1	1		1	4.51	1	1		1	4.25	1
SN	340037	1		1	3.91	1	1		1	4.51	1	1		1	4.25	1
SN	340038	1		1	3.91	1	1		1	4.51		1		1	4.25	1
SN	340039	1		1	3.91	1	1		1	4.51	1	1		1	4.25	1
SN	340061	1		1	3.91	1	1		1	4.51	1	1		1	4.25	1
SN	340081	1		1	3.91	1	1		1	4.51	1	1		1	4.25	1
SN	340082	1		1	3.91	1	1		1	4.51	1	1		1	4.25	1
SN	340083	1		1	3.91	1					1	1		1	4.25	
ST	150020	1		1	3.91		1		1	4.51		1		1	4.25	1
ST	150840	1		1	3.91	1	1		1	4.51	1	1		1	4.25	1
ST	150880	1		1	3.91	1	1		1	4.51	1	1		1	4.25	1
ST	150910	1		1	3.91	1	1		1	4.51	1	1		1	4.25	1
ST	350017	1		1	3.91	1	1		1	4.51	1	1		1	4.25	1
ST	350018	1		1	3.91	1	1		1	4.51		1		1	4.25	1
ST	150870	1		1	3.91	1					1	1		1	4.25	1
ST	150890	1		1	3.91	1					1	1		1	4.25	1
ST	150030	1		1	3.91	1										1
ST	150850	1		1	3.91	1										1
TH	160520	1		1	3.91	1	1		1	4.51	1	1		1	4.25	1
TH	160760	1		1	3.91	1	1		1	4.51	1	1		1	4.25	1
TH	160770	1		1	3.91	1	1		1	4.51	1	1		1	4.25	1
TH	160710	1		1	3.91	1	5		1	4.11	1	1		1	4.25	1
TH	160730	1		1	3.91	1	5		1	4.11	1	1		1	4.25	1
TH	160530	1		1	3.91							1		1	4.25	
TH	160740	1		1	3.91	1					1	1		1	4.25	1
TH	160750	1		1	3.91	1					1	1		1	4.25	1
TH	160510	1		1	3.91	1	5		1	4.11	1	6		1	4.33	

Appendix F: Bernoulli model and Moran's I results of specialised physicians

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State	KR	Cluster ophthalmologist	Low rate	High rate	Average cluster supply	Moran's I q-value	Cluster neurologist	Low rate	High rate	Average cluster supply	Moran's I q-value	Cluster orthopaedics	Low rate	High rate	Average cluster supply	Moran's I q-value
TH	160610	1		1	3.91	1	5		1	4.11		6		1	4.33	1
TH	160640	1		1	3.91	1	5		1	4.11	1	6		1	4.33	1
TH	160660	1		1	3.91		5		1	4.11	1	6		1	4.33	
TH	160670	1		1	3.91	1	5		1	4.11	1	6		1	4.33	1
TH	160680	1		1	3.91	1	5		1	4.11	1	6		1	4.33	1
TH	160690	1		1	3.91	1	5		1	4.11	1	6		1	4.33	1
TH	160700	1		1	3.91	1	5		1	4.11	1	6		1	4.33	1
TH	160620	1		1	3.91	1					1	6		1	4.33	1
TH	160650	1		1	3.91	1					1	6		1	4.33	1
TH	160720	1		1	3.91	1	5		1	4.11	1					1
BE	310016	2		1	4.04	1					1					1
BB	120520	2		1	4.04		1		1	4.51		1		1	4.25	
BB	120540	2		1	4.04		1		1	4.51		1		1	4.25	
BB	120610	2		1	4.04	1	1		1	4.51	1	1		1	4.25	1
BB	120670	2		1	4.04	1	1		1	4.51	1	1		1	4.25	1
BB	120690	2		1	4.04	1	1		1	4.51	1	1		1	4.25	1
BB	120710	2		1	4.04	1	1		1	4.51	1	1		1	4.25	1
BB	120720	2		1	4.04	1	1		1	4.51	1	1		1	4.25	1
BB	120600	2		1	4.04	1	3		1	4.40	1	3		1	4.28	1
BB	120650	2		1	4.04	1	3		1	4.40	1	3		1	4.28	1
BB	120680	2		1	4.04	1	3		1	4.40	1	3		1	4.28	1
BB	120700	2		1	4.04	1	3		1	4.40		3		1	4.28	
BB	120730	2		1	4.04	1	3		1	4.40	1	3		1	4.28	1
BB	120640	2		1	4.04	1	3		1	4.40	1					1
BB	120630	2		1	4.04	1					1					1
MV	130030	2		1	4.04		3		1	4.40		3		1	4.28	
MV	130510	2		1	4.04	1	3		1	4.40	1	3		1	4.28	1
MV	130520	2		1	4.04	1	3		1	4.40	1	3		1	4.28	1
MV	130530	2		1	4.04	1	3		1	4.40	1	3		1	4.28	1
MV	130550	2		1	4.04	1	3		1	4.40	1	3		1	4.28	1
MV	130560	2		1	4.04	1	3		1	4.40	1	3		1	4.28	1
MV	130570	2		1	4.04	1	3		1	4.40	1	3		1	4.28	1
MV	130580	2		1	4.04	1	3		1	4.40	1	3		1	4.28	1
MV	130590	2		1	4.04	1	3		1	4.40	1	3		1	4.28	1
MV	130600	2		1	4.04	1	3		1	4.40	1	3		1	4.28	1
MV	130610	2		1	4.04		3		1	4.40		3		1	4.28	
MV	130620	2		1	4.04	1	3		1	4.40	1	3		1	4.28	1
MV	130540	2		1	4.04							3		1	4.28	
ST	150860	2		1	4.04	1					1					1
ST	150900	2		1	4.04	1					1					1
BW	81110	3	1		3.90	3	2	1		4.23	3	2	1		4.16	3
BW	81150	3	1		3.90	3	2	1		4.23	3	2	1		4.16	3
BW	81160	3	1		3.90	3	2	1		4.23	3	2	1		4.16	3

Appendix F: Bernoulli model and Moran's I results of specialised physicians

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State	KR	Cluster ophthalmologist	Low rate	High rate	Average cluster supply	Moran's I q-value	Cluster neurologist	Low rate	High rate	Average cluster supply	Moran's I q-value	Cluster orthopaedics	Low rate	High rate	Average cluster supply	Moran's I q-value
BW	81170	3	1		3.90	3	2	1		4.23	3	2	1		4.16	3
BW	81180	3	1		3.90	3	2	1		4.23	3	2	1		4.16	3
BW	81190	3	1		3.90	3	2	1		4.23	3	2	1		4.16	3
BW	81270	3	1		3.90	3	2	1		4.23	3	2	1		4.16	3
BW	81350	3	1		3.90	3	2	1		4.23	3	2	1		4.16	3
BW	81360	3	1		3.90	3	2	1		4.23	3	2	1		4.16	3
BW	82350	3	1		3.90	3	2	1		4.23	3	2	1		4.16	3
BW	82370	3	1		3.90	3	2	1		4.23	3	2	1		4.16	3
BW	83250	3	1		3.90	3	2	1		4.23	3	2	1		4.16	3
BW	83260	3	1		3.90	3	2	1		4.23	3	2	1		4.16	3
BW	83270	3	1		3.90	3	2	1		4.23	3	2	1		4.16	3
BW	83350	3	1		3.90	3	2	1		4.23	3	2	1		4.16	3
BW	84150	3	1		3.90	3	2	1		4.23	3	2	1		4.16	3
BW	84160	3	1		3.90	3	2	1		4.23	3	2	1		4.16	3
BW	84170	3	1		3.90	3	2	1		4.23	3	2	1		4.16	3
BW	84210	3	1		3.90		2	1		4.23	3	2	1		4.16	
BW	84250	3	1		3.90	3	2	1		4.23	3	2	1		4.16	3
BW	84260	3	1		3.90	3	2	1		4.23	3	2	1		4.16	3
BW	84350	3	1		3.90	3	2	1		4.23	3	2	1		4.16	3
BW	84360	3	1		3.90	3	2	1		4.23	3	2	1		4.16	3
BW	84370	3	1		3.90	3	2	1		4.23	3	2	1		4.16	3
BY	97730	3	1		3.90		2	1		4.23		2	1		4.16	
BY	97740	3	1		3.90	3	2	1		4.23	3	2	1		4.16	
BY	97750	3	1		3.90	3	2	1		4.23	3	2	1		4.16	3
BY	97780	3	1		3.90	3	2	1		4.23	3	2	1		4.16	
BY	91790	3	1		3.90	3	4	1		4.25	3	5	1		4.75	3
BY	91810	3	1		3.90	3	4	1		4.25	3	5	1		4.75	3
BY	91880	3	1		3.90	3	4	1		4.25	3	5	1		4.75	3
BY	91900	3	1		3.90		4	1		4.25	3	5	1		4.75	3
BY	97710	3	1		3.90	3	4	1		4.25	3	5	1		4.75	3
BY	97610	3	1		3.90		4	1		4.25						
BY	97720	3	1		3.90	3					3					
BY	97760	3	1		3.90											
BY	97770	3	1		3.90	3					3					
BY	97790	3	1		3.90	3					3					4
BY	97800	3	1		3.90						3					
BY	93740	4	1		4.05		4	1		4.25		1	1		4.25	
BY	93770	4	1		4.05		4	1		4.25		1	1		4.25	
BY	94790	4	1		4.05							1			4.25	
BY	91620	4	1		4.05	3	4	1		4.25	3	5	1		4.75	3
BY	91740	4	1		4.05	3	4	1		4.25	3	5	1		4.75	3
BY	91750	4	1		4.05	3	4	1		4.25		5	1		4.75	3
BY	91770	4	1		4.05	3	4	1		4.25		5	1		4.75	3

Appendix F: Bernoulli model and Moran's I results of specialised physicians

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State	KR	Cluster ophthalmologist	Low rate	High rate	Average cluster supply	Moran's I q-value	Cluster neurologist	Low rate	High rate	Average cluster supply	Moran's I q-value	Cluster orthopaedics	Low rate	High rate	Average cluster supply	Moran's I q-value
BY	91780	4	1		4.05	3	4	1		4.25	3	5	1		4.75	3
BY	91830	4	1		4.05	3	4	1		4.25		5	1		4.75	3
BY	91840	4	1		4.05	3	4	1		4.25	3	5	1		4.75	3
BY	91860	4	1		4.05	3	4	1		4.25	3	5	1		4.75	3
BY	91870	4	1		4.05	3	4	1		4.25		5	1		4.75	3
BY	91610	4	1		4.05	3	4	1		4.25	3					
BY	91710	4	1		4.05		4	1		4.25						
BY	91720	4	1		4.05		4	1		4.25						4
BY	91760	4	1		4.05	3	4	1		4.25						
BY	91850	4	1		4.05	3	4	1		4.25	3					
BY	91890	4	1		4.05		4	1		4.25						
BY	92710	4	1		4.05		4	1		4.25						
BY	92720	4	1		4.05		4	1		4.25						
BY	92730	4	1		4.05	3	4	1		4.25						
BY	92740	4	1		4.05	3	4	1		4.25						
BY	92750	4	1		4.05		4	1		4.25						
BY	92760	4	1		4.05		4	1		4.25						
BY	92770	4	1		4.05		4	1		4.25						
BY	92780	4	1		4.05		4	1		4.25						
BY	92790	4	1		4.05		4	1		4.25						
BY	93620	4	1		4.05		4	1		4.25						
BY	93710	4	1		4.05		4	1		4.25						
BY	93720	4	1		4.05		4	1		4.25						
BY	93730	4	1		4.05	3	4	1		4.25						
BY	93750	4	1		4.05	3	4	1		4.25						
BY	93760	4	1		4.05		4	1		4.25						
BY	95740	4	1		4.05		4	1		4.25						
BY	95760	4	1		4.05		4	1		4.25						
BY	94720	4	1		4.05											
HB	40120	5	1		3.94		7	1		4.20		4	1		4.36	
HH	20000	5	1		3.94	3	7	1		4.20		4	1		4.36	3
NI	33520	5	1		3.94		7	1		4.20	3	4	1		4.36	
NI	33530	5	1		3.94	3	7	1		4.20	3	4	1		4.36	3
NI	33570	5	1		3.94		7	1		4.20		4	1		4.36	3
NI	33590	5	1		3.94	3	7	1		4.20		4	1		4.36	3
SH	10510	5	1		3.94		7	1		4.20		4	1		4.36	
SH	10560	5	1		3.94		7	1		4.20		4	1		4.36	3
SH	10580	5	1		3.94		7	1		4.20		4	1		4.36	3
SH	10600	5	1		3.94	3	7	1		4.20		4	1		4.36	3
SH	10610	5	1		3.94		7	1		4.20		4	1		4.36	3
SH	10620	5	1		3.94		7	1		4.20		4	1		4.36	3
SH	10020	5	1		3.94							4	1		4.36	
SH	10570	5	1		3.94							4	1		4.36	3

Appendix F: Bernoulli model and Moran's I results of specialised physicians

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State	KR	Cluster ophthalmologist	Low rate	High rate	Average cluster supply	Moran's I q-value	Cluster neurologist	Low rate	High rate	Average cluster supply	Moran's I q-value	Cluster orthopaedics	Low rate	High rate	Average cluster supply	Moran's I q-value
NI	34540	6	1		4.00		7	1		4.20		8	1		4.20	
NI	34590	6	1		4.00	3	7	1		4.20		8	1		4.20	3
NI	34600	6	1		4.00		7	1		4.20		8	1		4.20	
NI	34040	6	1		4.00							8	1		4.20	
NI	34560	6	1		4.00	3						8	1		4.20	
NW	55150	6	1		4.00	3	9	1		4.09		8	1		4.20	
NW	55540	6	1		4.00		9	1		4.09		8	1		4.20	
NW	55580	6	1		4.00	3	9	1		4.09		8	1		4.20	
NW	55620	6	1		4.00		9	1		4.09		8	1		4.20	
NW	55660	6	1		4.00	3						8	1		4.20	3
NW	55700	6	1		4.00	3						8	1		4.20	
NW	57540	6	1		4.00							8	1		4.20	
NW	59150	6	1		4.00							8	1		4.20	
SL	100410	7	1		4.00	3	6	1		4.40		7	1		4.60	3
SL	100420	7	1		4.00		6	1		4.40		7	1		4.60	3
SL	100430	7	1		4.00	3	6	1		4.40		7	1		4.60	3
SL	100440	7	1		4.00	3	6	1		4.40	3	7	1		4.60	3
SL	100460	7	1		4.00		6	1		4.40		7	1		4.60	
BW	81210	8	1		3.82		2	1		4.23		2	1		4.16	
BW	81250	8	1		3.82	3	2	1		4.23	3	2	1		4.16	3
BW	81260	8	1		3.82	3										3
BW	81280	8	1		3.82	3					3					3
BW	82150	8	1		3.82											3
BW	82210	8	1		3.82											
BW	82220	8	1		3.82											
BW	82250	8	1		3.82											
BW	82260	8	1		3.82											
BY	96630	8	1		3.82											
BY	96710	8	1		3.82											
BY	96760	8	1		3.82											
BY	96770	8	1		3.82											
BY	96790	8	1		3.82											
HE	64350	8	1		3.82							6		1	4.33	
HE	64400	8	1		3.82							6		1	4.33	
HE	64110	8	1		3.82		8	1		3.92		9	1		4.60	
HE	64330	8	1		3.82		8	1		3.92		9	1		4.60	3
HE	64360	8	1		3.82		8	1		3.92		9	1		4.60	
HE	64320	8	1		3.82							9	1		4.60	
HE	64140	8	1		3.82	3	8	1		3.92	3					4
HE	64120	8	1		3.82											
HE	64130	8	1		3.82											
HE	64310	8	1		3.82											
HE	64340	8	1		3.82											

Appendix F: Bernoulli model and Moran's I results of specialised physicians

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State	KR	Cluster ophthalmologist	Low rate	High rate	Average cluster supply	Moran's I q-value	Cluster neurologist	Low rate	High rate	Average cluster supply	Moran's I q-value	Cluster orthopaedics	Low rate	High rate	Average cluster supply	Moran's I q-value	
HE	64370	8		1	3.82												
HE	64380	8		1	3.82												
RP	73150	8		1	3.82		8		1	3.92		9		1		4.60	
RP	73310	8		1	3.82		8		1	3.92							
RP	73390	8		1	3.82		8		1	3.92							
RP	73140	8		1	3.82												
RP	73320	8		1	3.82												
RP	73380	8		1	3.82												
HE	65320	9		1	3.43		10		1	4.00		6		1	4.33		
HE	65340	9		1	3.43		10		1	4.00		6		1	4.33		
NW	53740	9		1	3.43		10		1	4.00		12		1	4.17		
NW	59580	9		1	3.43		10		1	4.00		12		1	4.17		
NW	59660	9		1	3.43		10		1	4.00		12		1	4.17		
NW	59700	9		1	3.43		10		1	4.00		12		1	4.17		
RP	71320	9		1	3.43		10		1	4.00		12		1	4.17		
NW	51110	10		1	4.00		11		1	4.12		11		1	4.00		
NI	31550	11			1	3.77						6		1	4.33		
NI	32560	11			1	3.77		7		1	4.20		8		1	4.20	
NI	32570	11			1	3.77						8		1	4.20		
NI	32520	11			1	3.77						14		1	4.00		
NI	33580	11			1	3.77		7		1	4.20						
NI	31010	11			1	3.77											
NI	31020	11			1	3.77											
NI	31030	11			1	3.77											
NI	31510	11			1	3.77											
NI	31530	11			1	3.77	1								1		
NI	31570	11			1	3.77											
NI	31580	11			1	3.77											
NI	32411	11			1	3.77											
NI	32412	11			1	3.77											
NI	32540	11			1	3.77											
NI	32550	11			1	3.77											
NI	33510	11			1	3.77											
NW	57700	11			1	3.77		7		1	4.20		8		1	4.20	
NW	59110	12			1	4.00		12		1	4.60		13		1	4.40	
BY	94780	13		1		4.00		5		1	4.11						
BY	96740	13		1		4.00		5		1	4.11						
BY	94710	13		1		4.00											
BY	94740	13		1		4.00											
BY	95720	13		1		4.00											
NW	51120	14			1	4.00		14		1	4.00		16		1	4.50	
NW	51140	14			1	4.00		14		1	4.00						
NW	51660	14			1	4.00		14		1	4.00						

Appendix F: Bernoulli model and Moran's I results of specialised physicians

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State	KR	Cluster ophthalmologist	Low rate	High rate	Average cluster supply	Moran's I q-value	Cluster neurologist	Low rate	High rate	Average cluster supply	Moran's I q-value	Cluster orthopaedics	Low rate	High rate	Average cluster supply	Moran's I q-value
BW	82310					2	1		4.23		2	1		4.16	3	
BW	82360				3	2	1		4.23	3	2	1		4.16	3	
BW	82160									4					3	
BY	94770										1			1	4.25	
BY	91730				3	4	1		4.25	3	5	1		4.75	3	
BY	91820					4	1		4.25		5	1		4.75	3	
BY	96720					5		1	4.11		6		1	4.33		
BY	96730					5		1	4.11		6		1	4.33		
BY	95770					4	1		4.25							
BY	94730					5		1	4.11	1						
BY	96780					5		1	4.11							
BY	91800														3	
BB	120620				1	1		1	4.51	1	1		1	4.25	1	
BB	120660				1	1		1	4.51	2	1		1	4.25	1	
HB	40110				7		1		4.20							
HE	65350					5		1	4.11		6		1	4.33		
HE	66310					5		1	4.11		6		1	4.33		
HE	66320					5		1	4.11		6		1	4.33		
HE	66360					5		1	4.11		6		1	4.33		
HE	65310										6		1	4.33		
HE	66110										6		1	4.33		
HE	66330										6		1	4.33		
HE	66340										6		1	4.33		
HE	66350										6		1	4.33		
HE	64390					8	1		3.92							
NI	31520										6		1	4.33	1	
NI	31560										6		1	4.33	1	
NI	32510					7	1		4.20	3	8	1		4.20	3	
NI	34530					7	1		4.20		8	1		4.20		
NI	34580					7	1		4.20		8	1		4.20		
NI	33550					7	1		4.20							
NI	33560					7	1		4.20	3						
NI	33610					7	1		4.20							
NI	34030					7	1		4.20							
NI	34510					7	1		4.20							
NI	34520					7	1		4.20							
NI	34550					7	1		4.20							
NI	34570					7	1		4.20							
NI	34610					7	1		4.20							
NI	34620					7	1		4.20							
NI	33540				1											
NW	57620							12		1	4.60		6	1	4.33	
NW	59780											8	1	4.20		

Appendix F: Bernoulli model and Moran's I results of specialised physicians

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State	KR	Cluster ophthalmologist	Low rate	High rate	Average cluster supply	Moran's I q-value	Cluster neurologist	Low rate	High rate	Average cluster supply	Moran's I q-value	Cluster orthopaedics	Low rate	High rate	Average cluster supply	Moran's I q-value
NW	57740						13	1		4.00		8	1		4.20	
NW	57110											8	1		4.20	
NW	57580											8	1		4.20	
NW	57660											8	1		4.20	
NW	59740											8	1		4.20	
NW	53580						11	1		4.12		10		1	4.00	
NW	53341											10		1	4.00	
NW	53342											10		1	4.00	
NW	53660											10		1	4.00	
NW	53700											10		1	4.00	
NW	59620						12		1	4.60		12		1	4.17	
NW	55130						9		1	4.09		13		1	4.40	
NW	51130						12		1	4.60		13		1	4.40	
NW	59160						12		1	4.60		13		1	4.40	
NW	59540						12		1	4.60		13		1	4.40	
NW	51700						9		1	4.09		15		1	4.00	
NW	51190											15		1	4.00	
NW	51170											16		1	4.50	
NW	53820											17		1	4.40	
NW	53140						11		1	4.12		18		1	5.00	
NW	55120						9		1	4.09						
NW	51160						11		1	4.12						
NW	51620						11		1	4.12						
NW	53150						11		1	4.12						
NW	53160						11		1	4.12						
NW	53620						11		1	4.12						
NW	53780						11		1	4.12						
NW	51200						12		1	4.60						
NW	51220						12		1	4.60						
NW	51240						12		1	4.60						
NW	59130						12		1	4.60						
NW	59140						12		1	4.60						
RP	71110											17		1	4.40	
RP	71370											17		1	4.40	
RP	71380											17		1	4.40	
RP	71430											17		1	4.40	
SN	340020					1	1		1	4.51	1	1		1	4.25	1
SN	340029					1	1		1	4.51	1	1		1	4.25	1
SN	340031					1	1		1	4.51	1	1		1	4.25	1
SN	340032					1	1		1	4.51	1	1		1	4.25	1
SN	340041					1	1		1	4.51	1	1		1	4.25	1
SN	340042					1	1		1	4.51	1	1		1	4.25	1
SN	340043					1	1		1	4.51	1	1		1	4.25	1

## Appendix F: Bernoulli model and Moran's I results of specialised physicians

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State	KR	Cluster ophthalmologist	Low rate	High rate	Average cluster supply	Moran's I q-value	Cluster neurologist	Low rate	High rate	Average cluster supply	Moran's I q-value	Cluster orthopaedics	Low rate	High rate	Average cluster supply	Moran's I q-value
ST	150830				1					1						1
SH	10530					7	1		4.20							
SH	10540					7	1		4.20							
SH	10550							1		4.11	1					3
TH	160630				1	5		1			6		1	4.33	1	

Source: Geiger et al. [92]

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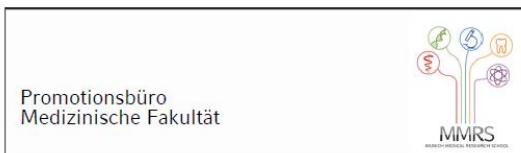
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## Affidavit



### Affidavit

Geiger Isabel

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Surname, first name

I hereby declare, that the submitted thesis entitled:

**Assessing a population's need for healthcare**  
The role of multimorbidity

is my own work. I have only used the sources indicated and have not made unauthorised use of services of a third party. Where the work of others has been quoted or reproduced, the source is always given.

I further declare that the dissertation presented here has not been submitted in the same or similar form to any other institution for the purpose of obtaining an academic degree.

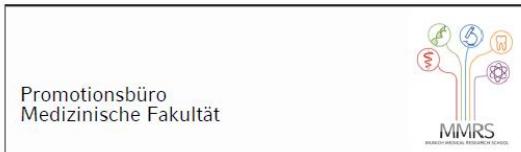
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place, date

Isabel Geiger  
Signature doctoral candidate

## Confirmation of congruency



**Confirmation of congruency between printed and electronic version of  
the doctoral thesis**

Geiger Isabel

Surname, first name

I hereby declare, that the submitted thesis entitled:

**Assessing a population's need for healthcare**  
The role of multimorbidity

is congruent with the printed version both in content and format.

Munich, 30.10.2023

place, date

Isabel Geiger

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# Curriculum vitae

## Education

2018 – present	<b>Ludwig-Maximilians-University (LMU)</b>
Munich, Germany	Ph.D. Medical Research in Epidemiology & Public Health
2016 – 2020	<b>University of Liverpool</b>
Liverpool, UK	M.Phil. in Epidemiology
2014 – 2016	<b>Management Center Innsbruck (MCI)</b>
Innsbruck, Austria	M.A. in International Health and Social Management
2013 – 2014	<b>International Academy of Osteopathy (IAO)</b>
Vienna, Austria	Training in Osteopathy
2010 – 2013	<b>University of Applied Sciences Vienna (FH Campus)</b>
Vienna, Austria	B.Sc. in Physiotherapy

## Professional experience

2021 – present	<b>Senior Project Manager at the European Foundation for the Care of Newborn Infants (EFCNI)</b>
Munich, Germany	Project manager of the European Standards of Care for Newborn Health
2017 – 2021	<b>Research Associate at LMU, Department of Health Services Management</b>
Munich, Germany	Statistical and economic analysis of primary and secondary data, project management of new healthcare programmes and grant submissions
2016 – 2016	<b>Research writer at the Ludwig Boltzmann Institute for Health Technology Assessment</b>
Vienna, Austria	Qualitative analysis of integrated care projects and a literature review
2013 – 2014	<b>Physiotherapist at Reha-Klinik Montafon</b>
Schrüns, Austria	Individual and group therapy in the field of orthopaedics, neurology, and cardiology

## List of publications

- (1) **Geiger I**, Schang L & Sundmacher L. Assessing needs-based supply of physicians: A criteria-led methodological review of international studies in high-resource settings. *BMC Health Service Research*, 2023. doi: 10.1186/s12913-023-09461-0
- (2) **Geiger I**, Flemming R, Schüttig W, & Sundmacher L. Regional variations in multimorbidity burden among office-based physicians in Germany. *European Journal of Public Health*, 2023;ckad039. doi:10.1093/eurpub/ckad039
- (3) Sundmacher L, Flemming R, Leve V, **Geiger I**, Franke S, Czihal T, et al. Improving the continuity and coordination of ambulatory care through feedback and facilitated dialogue-a study protocol for a cluster-randomised trial to evaluate the ACD study (Accountable Care in Germany). *Trials*. 2021;22:624. doi:10.1186/s13063-021-05584-z.
- (4) **Geiger I**, Kammerlander C, Höfer C, Volland R, Trinemeier J, Henschelchen M, ... & Sundmacher L. Implementation of an integrated care programme to avoid fragility fractures of the hip in older adults in 18 Bavarian hospitals—study protocol for the cluster-randomised controlled fracture liaison service FLS-CARE. *BMC geriatrics*, 2021;21:43. doi: 10.1186/s12877-020-01966-1.
- (5) **Geiger I**, Reber KC, Darius H, Holzgreve A, Karmann S, Liersch S, et al. Improving care coordination for patients with cardiac disease: Study protocol of the randomised controlled new healthcare programme (Cardiolotse). *Contemporary Clinical Trials*. 2021;103:106297. doi:10.1016/j.cct.2021.106297.
- (6) Sundmacher L, Schang L, Schüttig W, Flemming R, Frank-Tewaag J, **Geiger I**, Franke S, Wende D, Weinhold I, Höser C, Kistemann T, Kemen J, van den Berg N, Hoffmann W, Kleinke F, Becker U, Brechtel T. Gutachten zur Weiterentwicklung der Bedarfsplanung iSd §§ 99 ff. SGB V zur Sicherung der vertragsärztlichen Versorgung [Internet]. Im Auftrag des Gemeinsamen Bundesausschusses. 2018. Available from: [https://www.g-ba.de/downloads/39-261-3493/2018-09-20\\_Endbericht-Gutachten-Weiterentwicklung-Bedarfsplanung.pdf](https://www.g-ba.de/downloads/39-261-3493/2018-09-20_Endbericht-Gutachten-Weiterentwicklung-Bedarfsplanung.pdf).