Could a risk prediction model based on patient record data improve our understanding of carotid stenosis?

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Research Article

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Abstract

Digitalised patient records represent a large potential source of real-world data. Nevertheless, confidentiality and data protection has made big data extraction from patient records impossible in the past. Future options for artificial intelligence in free text reading might enable data extraction while maintaining confidentiality. In turn this could enable improvement in risk prediction for several disease groups. Still, it is not known if free text record data provides an appropriate data source for this purpose. In this project we have analysed a pilot dataset of patients with carotid stenosis in order to estimate the stroke risk in relation to treatment, and by that to assess the individual risk profile. The pilot dataset is applied to design a statistical model suitable for patient record data analysis. In this article a detailed description of the data set, and the methods behind our model choice will be presented.

Introduction

Atherosclerotic diseases represent a large group of conditions, where demographic changes impact both development and progression. In the same disease group, diagnostics and treatment options are developing quickly, and keeping track of all aspects can be challenging. Improved prevention strategies could slow down progression of the chronic disease, and prevent or postpone life-threatening acute events such as heart attack, stroke or critical limb ischemia. Still, evidence-based tailoring of therapy is necessary for safe and cost-effective prophylaxis, and minimised impact of adverse treatment effects.

Surgical or endovascular treatment of carotid stenosis for stroke prevention is well known for its inevitable risk of periprocedural strokes. Although the stroke risk in association to treatment is reported to be slightly lower today than 20 years ago (1), the risk of a procedure-related stroke is still considerable for both endovascular procedures and open endarterectomy.

Risk prediction tools could provide an aid in determining who are likely to benefit the most, and thereby tailor treatment recommendations for each individual patient. Several risk calculators have been developed(2–4), but none has yet succeeded in significantly challenging the established guidelines for carotid disease(5). In the past, such risk prediction tools have generally been based on the same data material as current guidelines, and the additional value in decision making seems sparse.

Artificial intelligence (AI) is technology with a broad range of applications in medicine(6). The virtual AI branch includes deep learning, which enables data extraction from free text. By harvesting information from free text patient records, large information databases could be established while maintaining confidentiality. If risk prediction models based on patient record data can be verified, AI could be applied to establish large databases, allowing real-time adjusted risk prediction to the current demographic properties of a population.

We present a model for evaluating the risk of stroke in patients with carotid stenosis based on patient record data analysis. The intention of this model is to develop a decision-making aid, by estimating the
individual benefit of treatment. In this article we will describe the background for the model choice, and the method applied in the development.

**Methods**

**Data material**

This analysis is seen as a pilot in evaluating the model potential, where a historical data approach to risk prediction is carried out. A pilot data set was manually established by the use of “all comer” patient record data from the University Hospital of North Norway. 1428 patients registered with the ICD-10 diagnosis “carotid stenosis” since the introduction of an electronic record system in 2003, were invited. Both symptomatic and asymptomatic patients were included. Most of the asymptomatic patients had been referred to the out-patient clinic from the Tromsø Study. This is a large population study that has been taking place since 1974, with seven separate studies performed to date. The study consists of questionnaires for all participants, and various examination studies performed on a smaller selection. In the studies Tromsø4 (1994-95), Tromsø5 (2001) and Tromsø6 (2007–2008), a selection of participants were examined by ultrasound for carotid stenosis by an ultrasound technician. Those who had carotid atherosclerosis, were referred to the neurological out-patient clinic for a more detailed ultrasound evaluation. Advice was given in relation to treatment and follow up, and most of these asymptomatic patients had standard medical therapy prescribed. For most patients with a stenosis of more than 50%, follow-up examination to evaluate disease progression was performed.

**Inclusion by consent**

All participants referred from the Tromsø Study had previously given a broad consent to the use of Tromsø Study data. The Regional Ethical Committee (REC) advised inclusion of these patients without new consent. For all deceased individuals, REC also advised exemption from consent to access patient record data. Written consent was obtained to permit access to patient record data for all other participants.

**Parameters of consideration**

The results from previous carotid studies were used to target patient properties associated with disease progression and/or ischemic events(2, 7–13). We registered previous medical or surgical treatment at the start of follow up, and separately registered therapy initiated at the time of diagnosis. If CEA/CAS was performed at any time during follow up, preceding events, timing of treatment, method and complications, including postoperative strokes, were registered.

**Cerebral ischemic events**

The primary endpoint was defined as an ischemic stroke caused by the carotid stenosis. All new ischemic cerebral events were registered, until death or censoring at the end of follow up. As carotid strokes can be difficult to objectify, all-cause stroke was explored as the endpoint in separate analyses. TIAs were
defined as ischemic events with full recovery within 24 hours, where no hemorrhagic or ischemic lesion was detected on CT or MRI. TIAs were not considered as endpoints, as no sequelae will follow. These events are still known to increase the risk of stroke, and were included in the model as risk predictors. TIAs accounted for the presentation of symptomatic carotid disease in 156 patients, and by that triggered the indication for surgical treatment in 65 of these.

**Endpoint classification**

The risk of stroke from any cause is obviously higher than the stroke risk solely from carotid stenosis. Less than 20% of all patients with ischemic strokes are found to have carotid stenosis, and the condition is seen as the cause of the event in only about half of these (14). As the stroke risk is shown to depend on the degree of stenosis (8), it is assumed to increase in the presence of traditional risk factors for atherosclerotic progression if the observation time is long enough. A previous study with a median of 13 years of follow-up still fails to prove this(12). Stroke by other causes, such as cardiac thromboembolism, is assumed to have a different risk pattern with different targets of prevention. Thus, endpoint subclassification is desirable, to pinpoint the risk of strokes caused by the carotid stenosis. A clear cause of cerebral ischemia can still be difficult to define in some cases, which calls for a systematic approach where the subclassification is reproducible and standardised. We have chosen the ASCOD score (15).

Ischemic strokes were registered when a new lesion was detected by CT or MRI, or when symptoms suggestive of cerebral ischemia persisted for more than 24 hours and hemorrhage was ruled out. We applied the ASCOD phenotyping to subtype the events (15). The ASCOD phenotype A1-1, when S, C, O and D are 0 or 3, strongly indicates the carotid stenosis as causative of the event. In the case of A1-2 or A2-1, where SCOD grade is 0, the causation is also likely. The phenotype A0 makes other causes of the ischemic event more likely. This also applies to A2 and A3 if S, C, O or D grade is 1. When no ASCOD 1 grade is defined, or two or more grade 1 coexist within the phenotypes, the cause is uncertain. In these cases, the most likely cause is evaluated individually for each patient.

Even after ASCOD classification, there is some uncertainty in relation to the causality of the carotid disease when an ischemic stroke occurs. This can represent a potential source of error, due to a degree of objective endpoint evaluation. To explore this, separate analyses are performed for the endpoints carotid stroke, any ischemic stroke, and any ischemic stroke or death.

**Recurrent events in survival analysis**

In evaluation of the effect of prophylactic therapy, a long observation time is desirable, as ideally, we would like to reveal the lifetime risk. During a decade or more of follow up, some individuals will experience more than one stroke. These patients could have properties making them particularly vulnerable to new events. Therefore, all new events were registered and included in the model.

In traditional risk prediction, survival analysis is most commonly applied. A cox regression analysis can estimate multivariate risk based on the time to an event, or right censoring if no events occur during the observation time. Covariates are measured at baseline. Multiple endpoint analysis is rarely performed.
Recurrent event models in survival analysis was first described in the eighties, and offers statistical methods for evaluating the risk of an event that can occur more than once. Different models exist, and the choice of model depends on whether or not the events are seen as different processes, and on the dependency of risk on the time from entry into the study to the first and recurrent events. In the analysis of stroke, each event is seen as the same process. The time to the first event is assumed to impact the time to a potential recurrent event. A proportional intensity model, as proposed by Andersen and Gill (16) could be fit for this analysis, but does not account for the order of events. The Prentice, Williams, and Peterson Total Time Model (PWP-TT) (17) evaluates this by sequencing events, and is our model of choice.

**Time dependent variables**

Some key variables are known to have a strong impact on the risk of new events, such as carotid stenosis and TIAs. During a long observation time, the degree of stenosis can change, and new TIAs can occur. This is assumed to impact the risk of new events, and we would like to incorporate this in our model.

Medical, surgical or endovascular therapy will affect the risk of new events, and obviously needs to be included in a risk model. This therapy can be initiated at the time of diagnosis, but patients commonly receive their treatment as a result of a new event. As the risk is expected to fall after successful treatment, it is desirable to include this in the model with time dependency.

Variables can be analysed as time dependent by the use of an extended Cox model. This allows a variable to change value after a given time interval. It is possible to include both time dependent and time independent variables in the same analysis. The time-independent variables will not change value during the observation time, and is obviously suitable for static properties such as gender. Several of our registered variables in relation to general cardiovascular risk, could be seen as time dependent, such as smoking, blood pressure and antihypertensive treatment. However, to simplify the model, only factors considered to have a strong impact on stroke risk is included with time dependency in the pilot model. In the pilot model, we have chosen to include TIAs, surgical treatment of the carotid stenosis, and degree of stenosis at the time of a new event as time dependent variables.

Most ischemic cerebral events cause little or no disability, but every time a stroke occurs there is a risk of severe disability and death. We approach this by grading stroke severity by use of the modified Rankin scale. This variable is registered for each time interval, and applied to define severe endpoints.

**Sidedness**

Ischemic events can occur in two cerebral hemispheres, each supplied by a separate carotid artery. Intracerebral communications through the Circle of Willis serve as security across the hemispheres, to maintain perfusion if a precerebral artery is compromised. The risk of an embolic stroke affecting one side depend on the degree of carotid stenosis on the ipsilateral side (8, 18). Still, stroke by hypoperfusion can occur in both hemispheres if the total perfusion to watershed areas of the brain is insufficient due to severe stenosis or occlusion of the precerebral arteries. Each side is therefore considered to carry a
separate stroke risk, where the atherosclerotic status of both carotid arteries may contribute to the risk on each side.

If an ischemic event occurs, surgical or endovascular treatment is usually performed on the ipsilateral side. If there is ipsilateral carotid occlusion, treatment might be performed on the contralateral side to prevent hypoperfusion, although there is controversy about this indication for therapy(19). In our data material, the time and side of treatment is registered, and the degree of stenosis on this side drops to zero after successful recanalization.

As previously described TIAs are included in the model as time dependent variables. The TIA variable is also subdivided into right and left sides, or unknown if the symptoms are not side specific. These variables are allowed to “count” if several TIAs occur, which means that the excess risk assumed to be associated with having more than one TIA on the same side can be estimated.

**Software for data analysis**

Redcap was used for data collection, and data was then imported to SPSS. SPSS was used for simple data analysis and some graphics. Data preparation for a matrix set-up with time intervals to new events and/or changes in time dependent variables was also performed in SPSS, and the matrix dataset was then exported to the SAS software 9.4, SAS Institute Inc., Cary, NC, USA for analysis with time dependent variables and time dependency of endpoints.

**Results**

1428 patients were registered with the diagnosis carotid stenosis between 2003 and 2019. Of these, 494 were dead at the time of inclusion, and these were included without consent as advocated by REC. Consent was received from 440 patients, either through the Tromsø Study, or by returning a signed consent form. Patients found to have an incorrect diagnosis of carotid stenosis were excluded. 392 symptomatic and 471 asymptomatic patients were included in the analysis.

The baseline characteristics were comparable to those seen in previous studies, as shown in Table 1.
Table 1
Baseline characteristics for asymptomatic and symptomatic patient with carotid stenosis

<table>
<thead>
<tr>
<th></th>
<th>Asymptomatic N = 471</th>
<th>Symptomatic N = 392</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean age</td>
<td>69.4</td>
<td>68.6</td>
</tr>
<tr>
<td>Sex ratio (F:M)</td>
<td>197:274 (41.8% : 58.2%)</td>
<td>135:258 (34.4% : 65.6%)</td>
</tr>
<tr>
<td>Uncorrected hypertension</td>
<td>60.9%</td>
<td>64.4%</td>
</tr>
<tr>
<td>Uncorrected hypercholesterolemia (total cholesterol &gt; 5)</td>
<td>44.4%</td>
<td>51.1%</td>
</tr>
<tr>
<td>Diabetes mellitus</td>
<td>15.5%</td>
<td>23.9%</td>
</tr>
<tr>
<td>Previous stroke/TIA</td>
<td>33.8%</td>
<td>29.5%</td>
</tr>
<tr>
<td>Coronary heart disease</td>
<td>52.9%</td>
<td>46.1%</td>
</tr>
<tr>
<td>Atrial fibrillation</td>
<td>8.5</td>
<td>9.9%</td>
</tr>
<tr>
<td>Smoking (current smoker or history of smoking)</td>
<td>74.1%</td>
<td>76.6%</td>
</tr>
<tr>
<td>Anticoagulant treatment</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aspirin</td>
<td>58.6%</td>
<td>49.6</td>
</tr>
<tr>
<td>Clopidogrel</td>
<td>4.0%</td>
<td>2.8%</td>
</tr>
<tr>
<td>Dual antiplatelet therapy</td>
<td>3.4%</td>
<td>3.6%</td>
</tr>
<tr>
<td>Warfarin</td>
<td>5.7%</td>
<td>4.8%</td>
</tr>
<tr>
<td>Antihypertensive therapy (any)</td>
<td>67.9%</td>
<td>65.9%</td>
</tr>
</tbody>
</table>

Distribution of carotid stenosis

At the time of presentation, symptomatic patients had a distribution of carotid disease heavily skewed towards high degree ipsilateral stenosis. The distribution of ipsilateral and contralateral carotid stenosis is shown in Figs. 1 and 2.

For the asymptomatic patients, the distribution of right and left sided carotid stenosis was quite similar for the two sides, with the distribution as shown in the Figs. 3 and 4.

Effect of surgical treatment

A traditional cox regression is performed, with survival time to the first ipsilateral stroke for symptomatic patients, and time to first event for asymptomatic patients. As shown in Table 2, very little impact on the
risk of stroke is seen by individual variables, but a strong risk improvement occurred in patients who had carotid surgery performed after the index event. This is illustrated for the symptomatic group in Fig. 5.
Table 2
Cox regression analysis of risk predictor variables for the time to an ischemic stroke after the diagnosis of carotid stenosis for patients without symptoms at presentation, and time from the presenting ischemic event to a new ipsilateral stroke for symptomatic patients.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Asymptomatic at diagnosis, time to first event</th>
<th>Included after symptoms of a cerebral ischemic event, time to first new ipsilateral event</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age, years (at time of diagnosis)</td>
<td>HR (95% CI)</td>
<td>p</td>
</tr>
<tr>
<td>Sex (f)</td>
<td>1.02 (0.98, 1.06)</td>
<td>0.35</td>
</tr>
<tr>
<td>Systolic blood pressure at time of diagnosis, 10 mmHg</td>
<td>1.10 (0.99, 1.02)</td>
<td>0.34</td>
</tr>
<tr>
<td>Diabetes mellitus</td>
<td>0.67 (0.32, 1.39)</td>
<td>0.28</td>
</tr>
<tr>
<td>Current smoker</td>
<td>0.82 (0.46, 1.45)</td>
<td>0.49</td>
</tr>
<tr>
<td>No statin therapy after diagnosis</td>
<td>1.27 (0.64, 2.50)</td>
<td>0.50</td>
</tr>
<tr>
<td>No anticoagulation after diagnosis</td>
<td>2.26 (0.85, 6.06)</td>
<td>0.10</td>
</tr>
<tr>
<td>No antihypertensive treatment</td>
<td>0.52 (0.28, 0.98)</td>
<td>0.05</td>
</tr>
<tr>
<td>Carotid stenosis by side</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Right side:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt; 50%</td>
<td>ref</td>
<td></td>
</tr>
<tr>
<td>50–69%</td>
<td>1.24 (0.60, 2.55)</td>
<td>0.57</td>
</tr>
<tr>
<td>70–99%</td>
<td>2.40 (1.18, 4.89)</td>
<td>0.16</td>
</tr>
<tr>
<td>100%</td>
<td>2.4 (0.96, 5.88)</td>
<td>0.62</td>
</tr>
<tr>
<td>Left side:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt; 50%</td>
<td>ref</td>
<td></td>
</tr>
<tr>
<td>50–69%</td>
<td>2.00 (0.97, 4.12)</td>
<td>0.06</td>
</tr>
<tr>
<td>70–99%</td>
<td>2.08 (1.01, 4.28)</td>
<td>0.46</td>
</tr>
</tbody>
</table>
Asymptomatic at diagnosis, time to first event | Included after symptoms of a cerebral ischemic event, time to first new ipsilateral event
---|---
100% | 1.89 (0.67, 5.34) 0.23 | 0.41 (0.06, 3.22) 0.41
CEA | 2.04 (0.75, 5.55) 0.16 | 0.32 (0.14, 0.71) 0.01

A similar result is seen if the endpoint is defined as any ipsilateral stroke (i.e. ischemic stroke from any cause), but with a weaker effect of the carotid surgery, illustrated in Fig. 6.

If the endpoint is defined as any stroke (any side, any cause) or death, the protective effect of surgery after the index stroke is still evident, but less pronounced, as shown in Fig. 7.

When patient record data is being analysed, the total protective effect of CEA is suspected to be overestimated in comparison to an RCT analysis, as patients selected for surgery are believed to have less comorbidity, better life expectancy and a lower stroke severity. To illustrate this, we explore the Modified Rankin Scale (mRS) after the index event for those with an index stroke (i.e. Not TIA).

As shown in Fig. 8, a larger percentage of those who did not undergo carotid surgery had a major index stroke with mRS > 2.

**Surgical risk**

In the 392 patients who were symptomatic at presentation, 194 received surgical treatment for the carotid stenosis at some stage. Of these, 10 suffered a postoperative ipsilateral stroke (4.9%).

In the 471 patients who were asymptomatic at the time of diagnosis of the carotid stenosis, 40 underwent surgery for asymptomatic disease, of which four had bilateral surgery. In 44 procedures, two postoperative strokes occurred, one ipsilateral and one contralateral (4.5%, or 2.3% if only ipsilateral strokes are considered). The patient with a contralateral stroke had 80% ICA stenosis and vertebral artery occlusion on the non-operated side.

In the asymptomatic group, 60 patients received treatment for symptomatic disease which occurred during the observation time. Of these, 56 had one procedure, three had two procedures and one had three procedures, of which the last was a CAS. In a total of 65 procedures, seven strokes occurred (10.8%). This incidence is higher than expected. The CAS for a second procedure on the same side resulted in a stroke, but even with this procedure eliminated, the stroke incidence after surgery is 9.4% which is surprisingly high. If both the patients which were symptomatic at presentation and those who became symptomatic during follow-up are considered, the total number of procedures for symptomatic disease is 258 (excluding the CAS redo). Thus, a total of 16 postoperative strokes (6.2%) occurred after treatment of symptomatic disease.
Discussion

In the establishment of new risk prediction tools, a large data source is desirable in order to develop a reliable and stable model. The lower the event frequency and the higher the number of variables, the larger the desired data material. The power of our data material is not considered to have a strong enough power for an applicable risk prediction tool, and the intention of this study was to explore the model potential.

With the standard use of digitalised patient record systems world-wide, data derived from this gold mine of information is expected by the authors to play an increasingly important role in prognostic models. Extraction of data from free text information by the use of machine learning could make anonymised data collection possible. Regardless, even for anonymised data, ethical considerations about ownership, data protection and confidentiality represent a controversy for the use of this information in research. The European Data Protection Regulation (GDPR) of 2018 serves to protect the data subject, and by that intensify the responsibility of the processors. By article 11 of GDPR, processing which does not require identification can still be performed as long as adherence to these regulations is fulfilled. Anonymised data collection is thus regarded as having a large potential in future research.

In free text patient records, the lack of uniformity of information and tests represent a challenge. This can be exemplified by spot measurement of blood pressure: In RCTs, resting blood pressure is normally measured in accordance to a certain protocol. In our patient selection, most blood pressure measurements were performed only once, and usually in only one arm. The method, positioning, and arm side of the measurement is rarely described. "White-coat hypertension" is likely to overestimate the resting blood pressure in some individuals. If the prognostic model is to be applied in a clinical setting, the patient record derived data could still be postulated to resemble that of real-life observations in a representative way. Furthermore, occult stenoses of the subclavian or brachial arteries could be present in some of these patients with established atherosclerosis, underestimating the systemic blood pressure, which could represent a source of error. This type of “free text error” could be present in several other variables, and is a disadvantage in the use of patient records as data source.

The different causes of cerebral ischemia represent an issue of uncertainty when working with stroke risk. Despite of this, numerous carotid stenosis studies present their results without commenting on their endpoint management. The easiest approach would be to include all ischemic strokes as endpoints, and assume an even distribution of strokes from other causes. This seems contra intuitive in cases where the stroke is obviously caused by i.e. cardiac embolization, such as in the presence of bilateral shower embolies. Knowing from previous studies that a stroke is caused by the carotid stenosis in only about half of those who has the condition (14), at the very least an opinion on stroke subclassification is considered appropriate. Our emphasis is a best possible effort of standardising stroke subclassification, to predict the true risk of “carotid strokes”, but to complement this by additionally performing an all cause ischemic stroke analysis. We still consider it a challenge which is not yet overcome in stroke research.
Including multiple endpoints and time dependency of key variables is considered to be a valuable supplement to traditional survival analyses in cardiovascular risk prediction. In any prophylactic treatment, a long observation time is considered of utmost importance to evaluate the effect of the prevention strategy. For any cardiovascular disease, repeat events are common, and expected to be frequently encountered in data material where the observation time is long. Still, the application of recurrent event analysis in cardiovascular research is quite uncommon. The same applies for time dependent variables, which are expected to particularly impact risk in relation to recurrent events, i.e. stroke risk reduction after CEA. We have not found any other studies describing the combination of time dependent variables and recurrent event analysis in the same model. Recurrent event analysis is known to carry a risk of type I error, where a false positive result occurs due to overestimation of risk. It is not known if this can be corrected by the introduction of time dependent variables. Thorough model testing is considered necessary to evaluate model performance, and this is the basis for establishing a pilot model.

By machine learning and automatic data registration, a patient record-based risk predictor could continuously be updated, making such models self-learning and self-improving. The suggested model is emphasised to be a small step in the direction of this approach to risk prediction. We consider this to be relevant also in risk prediction for other cardiovascular diseases. As a start, model testing will be performed to explore the potential for carotid stenosis patients.

**Conclusion**

We consider the data material as representative, and although the power is estimated to be too low for an applicable risk prediction tool, it appears suitable and sufficient for a pilot study of model performance.

**Declarations**

**Ethics approval and consent to participate**

The main intention with this study has been to explore real life patient records as a data source, and public availability of our data is not provided due to confidentiality. The study protocol was approved by the Regional Ethical Committee of North Norway (ref. 2018/161/REK nord). Written informed consent was taken from participants to participate in the study. For deceased individuals with the given diagnosis, waiver for consent to participate was given by the Regional Ethical Committee of North Norway. All methods were performed in accordance with the Declaration of Helsinki.

**Consent to publish**

NA

**Availability of data and materials**
The dataset analysed during the current study can be available from the corresponding author on reasonable request, after removal of person identifiable data such as date of events, procedures and death for deceased individuals.

Competing interests

The authors have no competing interests to report.

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The statistical model is developed in close cooperation with statisticians at the Department of Clinical Research at The University of North-Norway.

Authors’ contributions

Hervik and Kjørstad wrote the main manuscript text, and Wilsgaard significantly contributed in development of the statistical model and model testing. Myrmel has contributed through valuable advice and guidance throughout the process of the project. All authors have reviewed the manuscript.

References


Figures
Figure 1

Distribution of ipsilateral stenosis for patients with carotid atherosclerosis presenting with an ischemic event
Figure 2

Distribution of contralateral stenosis for patients with carotid atherosclerosis presenting with an ischemic event

![Graph showing distribution of contralateral stenosis](image)

Figure 3

Distribution of right sided stenosis for patients with an incidental finding of carotid atherosclerosis
Figure 4

Distribution of left sided stenosis for patients with an incidental finding of carotid atherosclerosis
Figure 5

Kaplan-Meier plot of time in days to the first stroke where the carotid disease is considered causative for symptomatic patients with carotid stenosis, with or without surgery after the index event.
Figure 6

Kaplan-Meier plot of time in days to any new ipsilateral ischemic stroke for symptomatic patients with carotid stenosis, with or without surgery after the index event.
Figure 7

Kaplan-Meier plot of time in days to any new ischemic stroke affecting any hemisphere and vascular territory for symptomatic patients with carotid stenosis, with or without surgery after the index event.
Figure 8

The figure shows the mRS score after an index stroke, in percent of the total number of patients who did and did not received carotid surgery. The bar chart shows that a higher percentage of patients with a high mRS score did not receive operative treatment.