SKALA - Predictive Policing in North Rhine-Westphalia

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Abstract

Predictive Policing (PP) is an umbrella term used to describe methodological processes utilised by law enforcement agencies to predict crimes and to aid in planning operational responses. Essentially, they are computer-assisted, spatially-based, probability calculations of crime. These processes have gained international popularity and have become a frequently discussed topic that has attracted the interest of policymakers and decision-makers in law enforcement circles. This article provides an insider's assessment of the implementation of one such process, SKALA (Crime Analysis and Anticipation System), by the State Office of Criminal Investigation of North Rhine-Westphalia (NRW), Germany. We explain the rationales both for PP and for SKALA and explain how the latter operates in practice. Piloted in six police authorities between 2015 and 2018, the State Office assessed that SKALA was a promising technique that could assist strategic decision-making; particularly, in the allocation of scarce police resources. When it was rolled out across the state, practitioners found the system to lack sufficient detail for their needs and the State Office, in conjunction with a higher education institution and with those practitioners, took steps to generate improvements in the analytical products produced for frontline staff and these have been more readily accepted. We (I) argue that it is too early to present definitive conclusions on SKALA's utility. We can say that as yet there is no statistical evidence to support the hypothesis that crime is reduced in NRW because of SKALA but it is interesting that a decrease in the number of burglaries has been observed in all areas (not just those in the areas where the system was applied). More research would be needed to explain why that is the case.

Key words: *Predictive Policing, SKALA, Crime Analysis,*

Introduction

Over the last decade, Predictive Policing (PP) has gained international popularity and has become a frequently discussed topic in both academic and non-academic literature. This paper is based on the understanding of PP as a computer-assisted method for spatially based probability calculations of crime (Seidensticker, Bode & Stoffel 2018, p.1). By applying PP, possible future crime targets are identified, and the planning of operational police can be determined. This means that PP forecasts where and when an increased risk of crime could probably be observed in the future. Therefore, the term 'prediction' in this paper is defined as spatio-temporal crime forecast.

Predictive Policing methodologies use mathematical algorithms to analyse large datasets to predict when and where crimes may be committed (Willems & Doeleman, 2014). Although the definition of PP is not uniform in science and practice, it is analogous with PP (Pollich & Bode 2017: 3). Predictive Policing utilises a wide range of methods. For example, some methods use perpetrator-related prognoses while others rely upon spatially-related prognoses.

According to Perry et al (2013), there are four broad categories of predictive methods. These methods are focused either on predicting: crime; offenders; victims; or perpetrator identities. The innovative aspect of PP is that it focuses on the prevention of 'future crimes' rather than on combatting 'previous crimes'. We have seen police forces and other actors in the security architecture focus on reinforcing methods of PP (e.g. Ferguson, 2017, pp.63-65; Perry et al, 2013, p.18). At the level of criminal policy, there are also more proposals for the implementation of predictive crime analysis (e.g. Hauber et al., 2017, p.82; Egbert, 2018, p.102). It is therefore not surprising that PP methods are now part of everyday police work in many police forces in many countries. By visualizing areas that pose a high risk of crime in the future (instead of retrospective hot spots), PP aims to stimulate proactive and future-oriented police work. In Germany, which consists of 16 federal states, many different PP solutions are currently running (KLB-operativ in Hessen, KrimPro in Berlin, precobs in Bavaria, PreMap in Lower Saxony and SKALA). The landscape of implementation possibilities in Germany is correspondingly diverse (see Bode & Seidensticker 2020).

Predicting crime

Predictive Policing is predicated on the assumption that criminality is not random, but that it is to some extent predictable because of patterns of crime and their continuation (De Vries & Smit, 2016). By analysing historical data, Predictive Policing systems aim to identify these crime patterns. Therefore, not all types of crime are suitable for predictions. For example, a homicide is not the type of crime to which models can be applied. First, this type of crime is comparatively rare, so models can only be trained with a small sample. However, a sufficiently large sample is needed to train a model that is capable of making accurate predictions. Secondly, this type of crime is strongly influenced by impulsiveness and emotions rather than rational decisions, which rather contradicts the thesis of crime patterns based on rational choice. Technically, it should be noted that crime phenomena cannot be fully modelled in data, which is the main influence of the residual that is part of any predictive model.

Predictive models are commonly based on the phenomenon of near repeat victimisation, which has often been empirically proven. Studies show that crime events are often followed by a subsequent crime event in the following days and in the surrounding area. The near-repeat phenomenon has mostly been researched in context of residential burglary (Bernasco, Johnson & Ruiter, 2015). However, the near repeat phenomenon has also been tested in other types of crime such as bicycle theft (Bowers & Johnson, 2004) and shootings (Youstin, Nobles, Ward & Cook, 2011). Researchers have argued that each type of crime has a unique spatio-temporal pattern that determines the actual realisation of near repeat victimisation.

In summary, it can be said that before making spatio-temporal crime predictions, it must be examined whether a crime is, in principle, suitable for prediction (Seidensticker, 2017, p.295). Reviewing the international use of PP solutions, it becomes clear that crime predictions often are made for the offense of residential burglary (LKA NRW, 2018b, p.76-78). This offense is characterised by its almost exact spatial reference and its relatively low number of unreported cases. Furthermore, its spatio-temporal variability makes it particularly suitable for crime predictions (e.g. Albers, 2015, p.141). There is also the possibility of influencing the occurrence of residential burglaries through police measures.

Predictive Policing as a process

Predictive Policing is a method used to create crime predictions that refer to specific areas and to limited, usually short, periods of time. Advocates of PP claim that as a result, crime can be suppressed and consequently reduced. The extant literature suggests that the validity of the predictions must be considered as limited by time and they must be updated at regular intervals (see for example Stoffel et al. 2017; Seidensticker 2017). Predictive Policing must therefore be understood as a continuous process consisting of various steps.

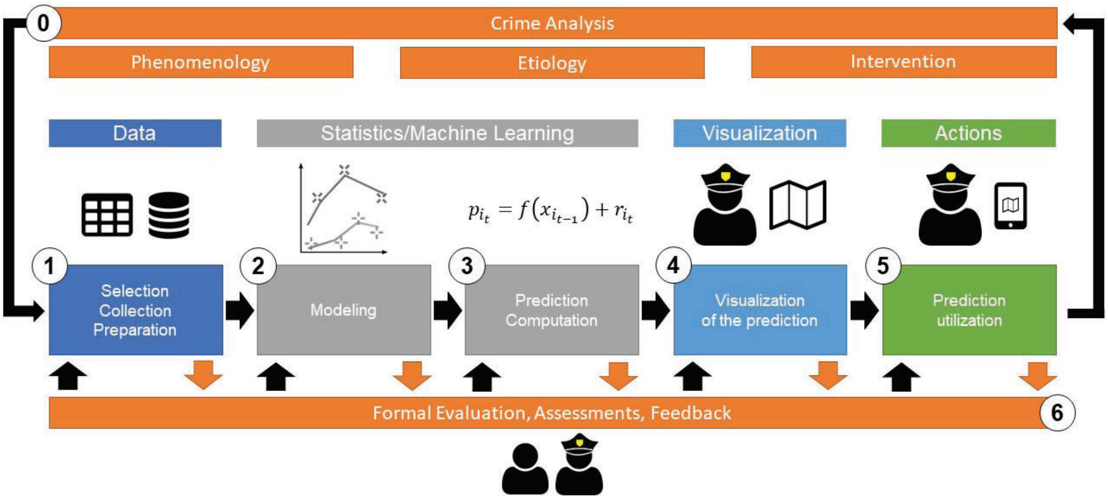
The first step is to collect the data and analyse it using a statistical model. The results of this modelling are called predictions and often are visualised. However, this is only one aspect of PP. Police interventions may be performed as a response to the predictions, which in turn can change or disrupt the environment. Police interventions may change the social situation and therefore new data must be collected in order to make new predictions that take account of those changes. In this way, the data used continuously represent the events of interest and bias in performance measurement is avoided.

The process we have described has been visualized by Perry et al as the "Prediction-Led Policing Business Process" (2013, p.12). This is a well-known model that explains the principles of the process and the interactions associated usually with the implementation of PP (figure 1).

Figure 1: Prediction-Led-Policing Business Process (Perry et al., 2013, p. 12).

However, Perry et al have given only limited attention to the methodological approach we address in this paper. Therefore, we have included a second illustration of the PP process, as explained by Stoffel et al, 2017 (see Figure 2). This process provides insight into the steps involved in implementing PP from a police perspective. Deviations from this are of course conceivable, but we argue that similar configurations normatively are used when machine-learning techniques are implemented in law enforcement settings (e.g. Bode et al, 2017). Bode et al.'s model also provides us with a handy framework for explaining the SKALA system.

Figure 2: The Predictive-Policing-Process (Seidensticker, 2017, based on Bode et al., 2017).



Predictive Policing in North Rhine-Westphalia

The NRW police forces currently use PP to predict residential burglaries, commercial burglaries and motor vehicle offences. The application of PP to other offences such as robbery or bicycle theft is the subject of ongoing tests. As mentioned earlier, PP requires sufficient available data to generate accurate predictions. Consequently, it is not possible to provide predictions for all types of crimes requested by the police forces. Rather, PP must be considered as one possible reaction based on crime analysis (Step 0 of the Bode et al model).

From 2015, the State Office of Criminal Investigation NRW (LKA NRW) implemented the SKALA project in six major police authorities. The aim of the project was to investigate the possibilities and limitations of crime prediction and to test the efficiency and effectiveness of police interventions based on these predictions. SKALA focuses on predicting crime risks using spatial data for each residential district in police precincts, ensuring that crime predictions are produced for entire cities. SKALA uses a proprietary in-house programme. Many law enforcement agencies use ready-to-use applications created by private providers but that was not an option that was considered by LKA NRW.

A major advantage of developing such methods in-house is that potentially sensitive police data always remains under the control of the police organisation and not third parties. SKALA was evaluated in cooperation with external scientific consultants by the Gesellschaft für innovative Sozialforschung und Sozialplanung e.V. (GISS). The project ended in February 2018, the evaluation report and the final project report were published online (LKA NRW, 2018a; 2018b). LKA NRW came to the conclusion that PP was a promising technique that could be an important building block for strategic decisions, especially for the allocation of police resources. After the end of the project, SKALA was subsequently taken over into regular service and implemented in 26 of 47 police departments in NRW.

Selection, collection and preparation of data

Using the Bode et al framework (Figure 2), we begin with the data. All components of the PP process depend on the data to be processed, the corresponding data collection and the data preparation for further processing. In addition to the problems of data collection, data uncertainty is a critical factor in data quality. These data uncertainties describe the problem of the unknowns. It usually is not known to what extent errors are contained in the data collected and processed. In this context, problems in data collection, such as measurement uncertainties, also are conceivable. For example, the presumed time of a burglary is usually uncertain (when the householder is absent and no witnesses to the crime are available) and has an interval between the time 'from' and the time 'to' in which the burglary was committed. Another potential source of uncertainty may be the problem that criminal offenses are either legally misjudged by police officers or are reported late or incomplete by victims (not uncommon when reporting burglaries; see Seidensticker, 2019, p.8; Stoffel et al., 2017, p.4f.).

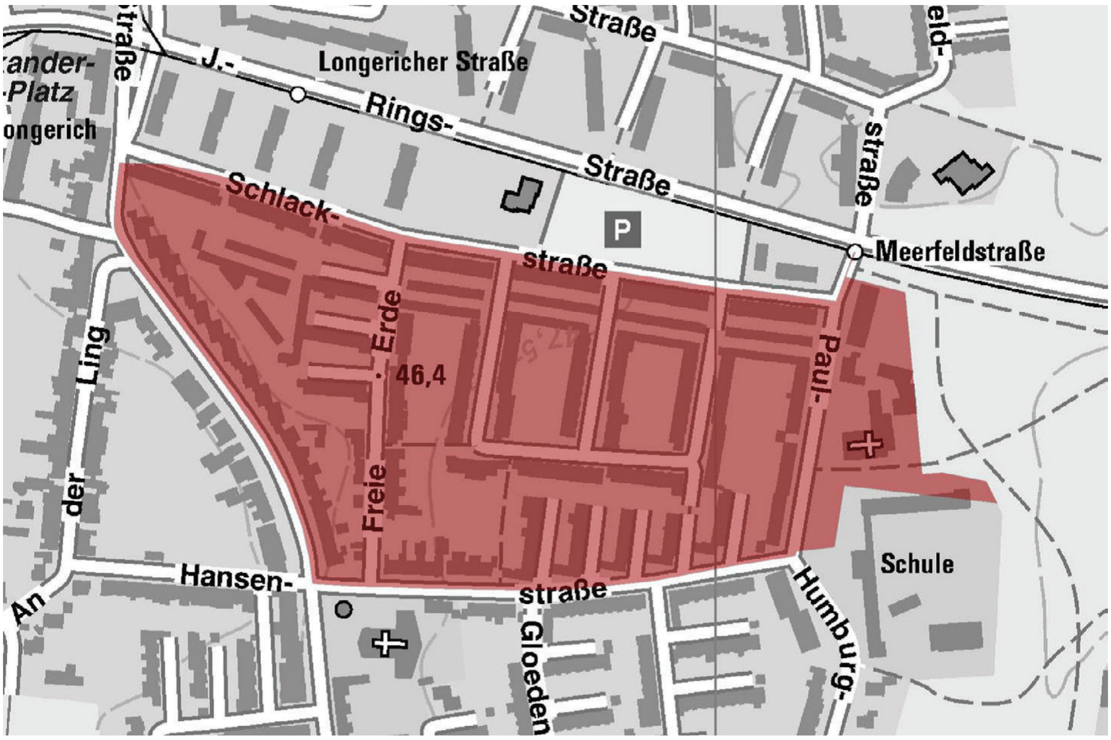
The predictions in SKALA are computed on the basis of a theoretical framework consisting of criminological and socio-scientific theories of crime, empirical evidence and professional knowledge. For example, rational choice theories are used as one approach explaining the spatial and temporal distribution of residential burglary. Many other theories are used to create a foundation that explains specific offenses. The system's programmers take a hypothesis-based approach. According to the relevant indicators for each of the hypotheses, the corresponding data is identified. In contrast to many other models that predict the occurrence of crime, data other than crime data is used for modelling and prediction. The socio-economic data include information on the residential location such as: population structure; building construction; income; infrastructure connections; and mobility indicators. A dataset, which consists of more than 200 variables, is acquired annually. In order to avoid "overfitting" and to avoid the "curse of dimensionality" (Bellman, 1957), only a subset of variables is used for modelling. The subset is created by a feature selection technique based on a random forest procedure, a classification and regression method consisting of several uncorrelated decision trees (LKA NRW, 2018b, 52 ff). The collected crime data mainly includes time and location of the offense, the modus operandi and the proceeds of the crimes (property stolen). Since SKALA follows the German definition of PP (it is defined as a computer-assisted method for spatially based probability calculations of crime and the aim is to identify areas of risk in which suitable measurements are to be used to deal with future police actions) there is no focus on perpetrator or victim data. Consequently, no personal data is collected or included in the computations (Seidensticker et al., 2018).

It is argued that socio-economic data are very stable over time (LKA NRW, 2018b). Only significant changes affect variables (such as average household income) and are even then their effect is expected to be gradual. As a result, such data are quite stable, and updates are required infrequently. In the SKALA process, they are updated annually while historical crime data included in the data set are updated weekly. Data from these different sources must be linked together before any calculations can be made.

Modelling and predictions

Once the data has been collected, amalgamated and processed, a prediction model is computed. In general, the models can be computed using different methods, such as regressions (Box et al., 2015, 305 ff.), decision trees (Kass, 1980) or artificial neural networks (e.g. Zhang & Qi, 2005). In addition, a suitable spatial reference for crime prediction is defined that refers to the specific offense, its occurrence in space and the police interventions intended to prevent its occurrence. In order to be able to create models that incorporate the spatial aspects of crime, SKALA uses so-called 'residential districts' as spatial references when modelling the occurrences of residential burglary (Figure 3). Originally, residential districts were defined by the extent of former constituencies, each district consisting of about 500 households (Nexiga, 2017).

Figure 3: Example of a residential district (LKA NRW, 2018b).



Generally, SKALA can be divided into two phases. First the project phase and second the transition to regular operation, which began in 2018. During the project phase, IBM SPSS Modeler was used for data processing, model training and prediction computations. The models were based on decision trees because they performed well and offered a high degree of comprehensibility. As an effect of testing the models, the same prediction model was used for all police authorities that were part of the project phase. It quickly became clear that the model performance was not appropriate for all urban environments, mainly because it did not consider the characteristics of different cities, e.g. the different infrastructure, density and interconnection of the street network and urban transport networks or the different peripheral areas of the cities. To address this problem, different configurations and methods were tested during the project phase. Today, in the second phase, SKALA uses a combination of spatio-temporal cluster analysis (STCA), random forests and regression models, which are trained independently for each police authority that is part of SKALA. More precisely, the current model consists of a spatio-temporal clustering of criminal offenses, strongly inspired by the near repeat phenomenon (Bernasco, 2008; Pease, 1998), followed by a regression analysis of the socio-economic data of the area to which the model refers. For performance reasons, data processing, model training and predictions are implemented with Python and R.

The trained models are used with historical and potential future data to compute the likelihood of the occurrence of an offense within the observed area, which is the most crucial part of the PP process. As a result, SKALA identifies areas that are likely to have a higher risk of future offenses than other areas during the time span the prediction is computed for. Since the computed crime risk is only valid for a defined time span and a specific prediction area, it can be labelled as a 'spatio-temporal predisposition factor' for the occurrence of a specific offense (Stoffel et al., 2017, p.4). Predictions by SKALA refer to a time span of seven days, Monday till Sunday, for residential and commercial burglaries and vehicle offenses. In principle, the methodology used allows shorter prediction periods. However, the following necessary steps, which include an individual rating by local crime analysts and the planning of appropriate interventions by the police, set a lower bound for the prediction period, which is currently one week.

Visualisation

After modelling crime occurrences in space and time and computing the prediction, it is necessary to effectively communicate the predictions to the subsequent actors, i.e. the local police departments. It is obvious to use geospatial visualisation for this purpose, since the predictions have a primary geographical reference. Therefore, the requirements of the addressed user group and their tasks in implementing the prediction in practice must be clear. Furthermore, it is essential to think about the effects of different visualisation techniques and their (un)intended effect on the user. For example, in SKALA, different data are combined to visualise predictions. As crime risks are computed for all residential districts of cities, it was decided to highlight 1.5 to 2 percent of the areas with the highest crime risks in a single view layer. First, the three residential areas with the highest likelihood were filled with red, the remaining areas with yellow, without giving any information about the concrete risk level. Unfortunately, this visual coding influenced the selection of residential districts in the unintended way that only the red areas were considered relevant for police actions. In order to prevent these effects, it was decided to visualise the predictions in uniform yellow colour. Another unintended effect could be observed using residential areas that cover the entire area of a city: Since forests and lakes were also included in these areas, police forces expressed a low comprehensibility of the predictions, as it was not clear to them why they should prevent residential burglaries e.g. in an area partly covered with forests.

The LKA NRW sends all residential districts with a specific risk factor to the police authorities involved in SKALA and also highlights the top 1.5 percent with the highest risks for the week. The local police authorities themselves decide whether these 1.5 percent is visualised for the operational forces or whether a higher or lower number of districts is included in the map. In the beginning, the predictions in SKALA were mainly communicated as pdf files. While this seemed to be a suitable choice in the beginning, the users involved demanded a more sophisticated method. Crime analysts of the police authorities asked for a possibility to combine the predictions with local analyses in an interactive way. Therefore, in cooperation with the Chair of Data Analysis and Visualization at the University of Konstanz, further visualisation options were developed and constantly adapted. The visualisation tool created, SKALA | MAP, offers an easy and intuitive access to geographical visualisation of predictions on an interactive map and is adapted to the needs of local police authorities. It also provides every police officer with the possibility to easily combine the predictions as well as other crime data or basically any geodata set with basic analyses such as frequency analysis and heat map visualisation for classic hot spot mapping (Stoffel, Post, Stewen & Keim, 2018). The visualisation of predictions is done by the local police authorities themselves with the help of SKALA | MAP. A web-based visualisation has also been realised so that police officers can work with predictions on tablets in their patrol cars.

Forecast utilisation

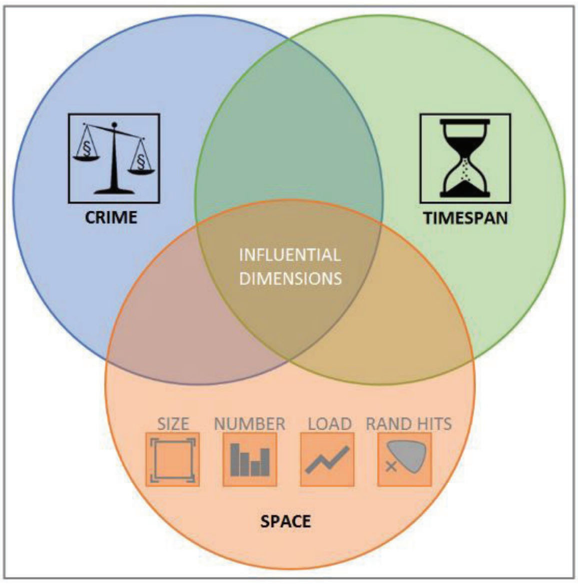
Depending on the concrete implementation of the PP solution, the utilisation of the outcomes may vary. For example, it may be the case that local analysts monitor what is distributed to operational units, as they should be able to enrich the predictions with their expertise and knowledge that is only available at the level of a local police department. In general, a variety of activities are conceivable, depending on the objectives of the police.

In NRW, there is no central decision on the specific activities to be initiated by the police authorities according to the predictions; the local police forces can make their own plans and measures on the basis of their own conclusions. The measures include preventive and repressive activities, such as increasing the visibility of the police forces through increased patrols, traffic checks and prevention counselling in areas where the likelihood of offenses is high (cf. LKA NRW, 2018b, p.80). After the local crime analysis units have enriched the prediction with local knowledge, they usually hold weekly meetings at management level to decide on the concrete police measures to be taken. The results are communicated to the local operational units by e-mail, made accessible as web-based visualisations or displayed on screens in the staff rooms. Ultimately, the outcome of SKALA is a building block in a comprehensive strategy of the police authorities in dealing with crime.

Formal evaluation, rating, feedback

A general problem of PP using automatic data analysis methods also concerns the basic assumption that the offense can be adequately described with the available data, e.g. space, time and local conditions. However, an objective and comprehensive description of a crime phenomenon is not entirely possible, since unobservable or non-quantifiable effects, e.g. the non-public environment of a potential offender, are of importance. There are three main dimensions that influence the quality of measurement: first, the offense (crime), second, the spatial dimension (space) and third, the temporal dimension (time span), see Figure 4. Results of quality metrics of PP models that incorporate these dimensions can be calculated in very different ways, so that variability in these metrics is inherently manifested. This variability, in turn, affects the validity of the applied metrics when trying to compare different models. Based on this finding, no valid statement can be made that one model is better than the other or which model provides a "better" prediction (Bode, Stoffel & Keim, 2017).

Figure 4: Fundamental influence dimensions (Stoffel et al., 2017).



The Effectiveness of Predictive Policing

Newspapers report quite positively about PP, published articles imply that PP is successful in combating crime. In contrast, there is no scientific literature that provides convincing, peer-reviewed, long-term studies with scientific background that analyse and prove or disprove the effectivity of PP implementations. To date, SKALA does not bring any outstanding new findings in this area either, as these are quite new tools used by police forces. This is due to the relatively new techniques used in the context of PP, but also the inherent problem of PP as an instrument of police forces. Primarily, PP is a tool for resource allocation.

When computing crime predictions, the question arises whether the expected (predicted) event has occurred, regardless of the criminological and mathematical models used. Some of the international evaluation studies on PP focus on this issue, using many different measures to reflect some kind of 'effectiveness', e.g. the predictive accuracy of a particular model. Of course, a historically accurate prediction is the basis of PP. The majority of PP implementations target the strategic and tactical benefits, i.e. the responses at the operational level to change the environment. This article does not intend to compare the different solutions based on quality metrics such as hit rates (HR), predictive accuracy indices (PAI), standardised accuracy efficiency indices (SAEI) or confusion matrices, as such comparison is not meaningful and invalid. This becomes particularly clear when considering the three essential dimensions 'crime', 'space' and 'timespan' (Figure 4) and their characteristics in the respective model (Bode et al. 2017). For example, the hit rate is likely to be higher if the spatial reference covers a larger area.

Looking at the evaluation study of SKALA, the hypothesis can be formulated that the use of Predictive Policing should reduce the number of observed burglaries. Since PP is a tool that aims to prevent crime by allocating typically limited resources in places associated with a potential higher risk of crime, it seems a logical conclusion that this will reduce crime. In NRW there was no statistical evidence to support the hypothesis that crime is reduced as a result of the use of PP. Nevertheless, a decrease in the number of burglaries was observed, but in the areas where PP was applied there was no significantly higher decrease compared to areas where PP was not applied.

In addition to a reduction in the number of burglaries, other hypotheses have also been formulated to measure the effectiveness of PP, such as the hypotheses that the time taken by police forces to get to the scene of an emergency call will decrease in areas where PP is applied. The motivation for this hypothesis was that, due to the presence of police officers in high-risk areas, the time police forces would take to get to the scene would be shorter than usual, as they are more likely to be scattered in space. Again, there is no statistical evidence to support this hypothesis.

Conclusion

Predictive Policing is an instrument for managing police forces with a primarily preventive orientation. SKALA is able to enrich authority specific knowledge and to improve the basis for decision-making with regard to force control and operational planning. In NRW, prediction models are trained for a number of offences and the predictions are submitted to the police authorities for their own assessment. Obviously, there must be enough data on the selected crime to make predictions. However, it is crucial to select an adequate set of variables on which the prediction is carefully based. If incorrect prognostic variables are used in the modelling, spurious findings can emerge. Furthermore, the accuracy of the prediction is likely to decrease.

In particular, various steps in the compilation and modelling of crime predictions can be traced back to decisions made and parameters applied. It can be observed that SKALA does not only include police data. Instead, an added value is seen in the use of socio-structural data. The available budget and different legislations must also be considered, since, for example, external data have to be purchased and data protection laws may restrict the use of personal data. This includes the places of residence of known perpetrators, which in consequence cannot be used for predictions. In contrast, the Netherlands for example uses such variables and is able to increase the computed risk of burglary from 4.7% to 6.1% (Willems, 2015; for a short comparison of the German and Dutch implementation of PP see van der Ende & Seidensticker 2020).

Especially considering the ever-increasing availability of georeferenced data sets, the potential of PP does not yet seem to have been fully exploited. However, this is also the limit of the method: The results of the analysis and the quality of the model are always heavily dependent on the quality and temporal availability of the incoming data sets. Here, different recording modalities can have an impact on the creation of the models. It should be noted that the data quality of the police data limits the predictions, since much information on current acts is not yet available in the system at the time of the prediction and therefore cannot be used. Police organisations must be aware that even high data quality does not always create a true representation of reality, which means that forecasts are always subject to uncertainties. The aspect of legal limitations must also be kept in mind and always be subject to a strict evaluation. This is one of the reasons why NRW completely dispenses with the use of personal data in the calculation of crime forecasts.

It can be discussed in which cases PP can be considered effective. On the one hand, there are a number of factors that can cause and also reduce crime. Furthermore, the implementation of PP must be correct and effective on so many different levels, e.g. the statistical level, the interpretation level and the operational level. In such complex systems with an interaction of different components, unintended side effects can occur. It is therefore difficult to evaluate a Predictive Policing implementation as a whole.

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