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Evaluating the Impact the Weekday Has on Near-Repeat Victimization: A Spatio-Temporal Analysis of Street Robberies in the City of Vienna, Austria

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Abstract: The near-repeat phenomenon refers to the increased risk of repeat victimization not only at the same location but at nearby locations up to a certain distance and for a certain time period. In recent research, near-repeat victimization has been repeatedly confirmed for different crime types such as burglaries or shootings. In this article the near-repeat phenomenon is analyzed for each day of the week separately. That is, the near-repeat pattern is evaluated for all consecutive Mondays, Tuesdays, Wednesdays, etc. included in the dataset. These consecutive weekdays represent the fictive set of consecutive dates to allow for spatial and temporal analysis of crime patterns. Using these principles, it is hypothesized that street robberies cluster in space and time and by the same day of the week. This research analyzes street robberies from 2009 to 2013 in Vienna, Austria. The overall research goal investigates whether near-repeat patterns of robberies exist by weekdays and in an additional step by time of day, and whether these near-repeat patterns differ from each other and from purely spatial patterns. The results of this research confirm the existence of near-repeat patterns by weekday and especially by time of day. Distinctive locations have been identified that differ greatly per weekday and time of day. Based on this information, law enforcement agencies in Austria can optimize strategic planning of police resources in combating robberies.

Keywords: near-repeat; crime prevention; street robbery; Vienna

1. Introduction

Early empirical studies show that crime events are spatially concentrated [1,2]. More recently, such spatial patterns have been observed for various crime types, for instance, for residential burglaries [3], car thefts [4], or robberies [5]. In recent years few studies have been conducted considering both the spatial and the temporal component of crime events (e.g., [6,7]). Knowing where crime patterns cluster in both space and time has significant effects on strategic action towards crime prevention. Additionally, spatio-temporal clusters support the predictive work so that crime reduction actions can be planned in a more focused way [8]. This paper aims to progress research in the periodicity of spatio-temporal clustering of street robbery events. To begin with, the literature is reviewed, focusing on spatio-temporal clusters of crime, followed by a spatio-temporal analysis of a modified dataset of only consecutive Mondays, Tuesdays, Wednesdays, etc. in the city of Vienna, Austria. Those patterns will then be compared to purely spatial and spatio-temporal patterns of the total dataset of street robberies occurring in the actual sequence of Mondays, Tuesdays, Wednesdays, etc. This analysis should give new insights into the spatio-temporal patterns of street robbery events that only occur on particular weekdays, or only occur at a certain time on weekdays, and how this information could be useful for crime prevention purposes of law enforcement agencies.

2. Theoretical Background

In human ecology, Hawley [9] discusses daily activity patterns and routines in which he differentiates three types of temporal organization: tempo, rhythm, and timing. The number of events per time unit, such as an annual crime rate, is referred to as a tempo. A rhythm is the seasonality or periodicity of a temporal pattern. Monthly or seasonal cycles of crime are well known among criminologists [10]. Generally, the periodicity of crime events by day of the week has not been a focus in research on crime occurring in both space and time. The last term, timing, refers to the intersection of rhythms. Timing is best comprehended when considering theories of how crime relates to daily life. Cohen and Felson's [11] routine activity theory emphasizes that a crime would not occur if a motivated offender and an appropriate target (in the absence of a guardian) did not come into contact (at a certain place). Sherman et al. [12] highlight that routine activity theory is not only affected by the convergence of protagonists in space but also in time. Furthermore, the theory submits that a person's activities are rhythmic and daily routines are constantly repeated [11]. Using routine activity theory, it can be concluded that certain crime types are more likely to occur at certain times of the day, the week, or the year. One of the first studies of crime patterns by time of day was done by Sagovsky and Johnson [7], who concluded that repeat burglary victimization tends to occur during the hours of the working day, from 8:00 a.m. to 4:00 p.m. Tompson and Bowers [13] divided datasets of street robbery crime into four 6-h time intervals that have different levels of darkness and temperature throughout the year. In their study, they confirmed their expectations that darkness leads to a higher volume of robbery than in daylight [13]. In analyzing crime patterns by weekday and weekend, LeBeau [14] found that violent crimes are more frequent on weekends.

2.1. Repeat Victimization

While several crime prevention actions are effective, many of them are implemented by the persons, households, or institutions that experience the least risk of being victimized. However, those crime prevention strategies show promising results when focused directly on those who are most at risk of victimization [15]. Pease [16] found that once a crime has occurred it is very likely that the offender will repeat that crime, rather than moving on to a new location. This, however, does not always mean that the exact same property or the exact same location is revictimized, but, in general, numerous studies have confirmed that offenders are very likely to return to the initial target to repeat an offense (e.g., [15,17]).

Repeat victimization, or revictimization, is defined as a person or place victimized multiple times within a specific period of time. The amount of repeat victimization is usually expressed as the percentage of persons or addresses (in general: victims) multiply victimized during a time period for a particular crime type, compared to the total number of victims during the same time period. This term is referred to as repeat victims. Additionally, repeat victimization is often also represented as the proportion of offenses experienced by victims who were victimized more than once during a time period. This second measure refers to the term repeat offenses. In a study in Indianapolis, IN, USA, 65% of commercial robberies were experienced by 32% of victims, who were victimized twice or more during the study period [15,18]. Those numbers can be interpreted as many repeat victims suffering two victimizations, but several repeat offenses are linked to victims who were victimized more than twice during a specific time period. For a more comprehensive summary of repeat victimization numbers, see, for example, Weisel [15] or Grove et al. [19], who compare numerous crime types from various study areas.

Two approaches exist that explain why properties are repeatedly victimized, including an event-dependent and a risk-heterogeneity approach. These are often referred to as boost (event-dependent) and flag (risk-heterogeneity) accounts [16]. The boost account is associated with repeat offenders, insofar as the risk of future victimization is boosted by an initial event. Offenders gain specific knowledge about the target from their initial experience and use this information for future victimizations. For example, in a burglary case, offenders know how to get inside the property, know the property's layout, and know what they have left behind. With respect to the risk-heterogeneity approach, there are some general characteristics about the property that are independent of a property's victimization history. Properties that attract any passing opportunistic offender can be flagged by little security, good escape routes, or minimal natural surveillance. Thus, the property may be victimized occasionally, perhaps by unrelated offenders. In practice, both boost and flag accounts exist but their exact balance is not well understood, and may be dependent on the crime type. In addition, it is very likely that both explanations are at play [7,20].

2.2. Near-Repeat Victimization

Prior victimization is an outstanding predictor of future risk. Numerous studies have confirmed that repeat victimization, when it occurs, tends to happen shortly after an initial event (e.g., [6]), but the risk of repeat victimization diminishes in the months after the initial incident [21]. Further research on repeat victimization highlights that there is not only a temporal component of heightened risk. Risk is also related to a spatial component. Morgan [22] terms these spatio-temporal clusters as near-repeats. In other words, these are repeat victimizations that occur closely in both space and time after an initial victimization but not necessarily at the same location.

The boost account also extends to neighboring properties of a previously victimized property. The chances of nearby properties being victimized are boosted because the offender is already familiar with the surroundings, and the layout of the property is likely to be similar [23]. As a supporting theoretical concept, Johnson, Bowers, and Pease [24] refer to an approach borrowed from behavioral ecology, namely the optimal foraging theory, to potentially explain the behavioral pattern of near-repeat offenses. In this concept the offender is compared to a foraging animal. A foraging animal decides between the food that is instantly available and the effort that would be needed to reach a better food source. If there is a better food source within a tolerable distance, the animal travels and attains it.

This is similar to offenders who victimize properties for satisfying reasons (e.g., valuable items). Once an area does not offer any fulfilling goods, the offender moves on to a new location [23,24]. This foraging behavior is also consistent with the results of interviews done with offenders [25].

3. Approach

3.1. Research Objectives

Street robbery is defined as "the use or threat of force to steal property from a person in public space" [26,27]. Street robbery is distinct from theft due to its appertaining violent nature. Street robbery is believed to be the main source of fear among people in urban areas [27]. Thus, it can involve life-threatening violence, a loss of control, and an assault to personal space and privacy. Street robbery tends to concentrate at specific times and at particular places. In the interpretation of why these patterns of street robberies occur, routine activities of both offenders and victims, and the time of contact between these, can be useful [27]. While the theoretical concept of an optimal forager was mainly associated with an offender's behavior committing burglaries (e.g., [28]), the same theory can also be related to other types of crime, namely robbery. As a forager, a robber needs to weigh between the opportunities that are immediately available and the effort that needs to be expended to reach more "profitable" victims or places. More "profitable" victims or places could be described as not overly crowded places, places that are not well illuminated, places with good opportunities to escape such as public transport stops, or victims who are more vulnerable than others (tourists, people under the influence). Additionally, boost and flag accounts play an important role in explaining why robberies occur. Some environments are more at risk so that these areas are flagged by robbers. Examples of flagged places are identical to those identified in the optimal forager theory: places that stay open late and make cash transactions (e.g., bars, fast food restaurants), places that are not well illuminated, places with good opportunities to escape, and places with tourists and (young) people under the influence of alcohol or drugs [27]. These flagged places and people have enduring attributes and are therefore attractive to robbers [29]. Once a robber has identified an appropriate place and offended successfully, the area is boosted by the initial event, and it is very likely that the robber will return and commit repeat crimes. Due to the experience gained from the first offense, the offender uses this knowledge to optimize robberies and to re-victimize. The first hypothesis in this analysis refers to the existence of a statistically significant near-repeat pattern in street robberies in Vienna. Based on existing near-repeat patterns in street robberies (e.g., armed street robberies in Philadelphia, PA, USA, as discussed by Haberman and Ratcliffe [30]), it is hypothesized that street robberies also tend to cluster in space and time. Since the environmental requirements and daily routines differ by weekday, it is assumed that offenders choose the place to rob accordingly. For instance, there are numerous places to go out at night spread over a city such as Vienna. However, not all of these are known to be equally attractive on each day of the week. Reasons for these differences on particular weekdays may be seen in student discounts, preferred music style, specific events, popularity for tourists, etc. Based on the daily routines and movements of both residents and visitors, specific places are well frequented and offer greater value to robbers. Thus, it is further hypothesized that near-repeat robberies occur rhythmically, only on specific weekdays, such as only on Mondays, only on Tuesdays, only on Wednesdays, and so on. Additionally, due to various locations such as people's place of residence, workplace, shopping, recreation areas, etc., people are moving frequently during the day. These movements result in different patterns of daily routines. These statements are compliant with the routine activity theory, which emphasizes that a person's activities are rhythmic and daily routines are constantly repeated [11]. Thus, it is hypothesized that near-repeat patterns differ by time of day. Hence, the periodicity of crime events by weekday has not been analyzed in previous research. The aim of this paper is to analyze whether there are distinct spatio-temporal patterns by weekday for street robberies, and whether there are differences by time of day on weekdays. Additionally, the study will determine differences between weekday-specific near-repeat locations and near-repeats for the total dataset. A well-known concept in spatio-temporal pattern analysis will be used, the Near-Repeat Calculator developed by Jerry Ratcliffe [21]. These near-repeat patterns will finally be compared to hotspots of the total dataset of street robberies. While stable hotspots are more likely to need complex crime prevention actions, such as a greater allocation of police resources or a redesign of the physical environment, temporally unstable hot spots indicate short-term crime outbreaks that have an impact on the temporal length for the allocation of police resources [31]. In our discussion, we will focus on how this information can be useful for law enforcement agencies to predict future victimizations and optimize crime prevention strategies of police resources.

3.2. Data Preparation

The study area for this research is the city of Vienna, Austria, where research on near-repeat victimization has never been done before. Crime data were collected from the so-called Security Monitor ("Sicherheitsmonitor" in German, or SIMO for short), which has stored all reported crimes in Austria since 2004. SIMO is administered by the Criminal Intelligence Service Austria (Federal Criminal Police Office). The collected crime incidents are stored in the SIMO database and are available for queries to about 25,000 police officers. Each reported crime contains the positional information of its occurrence (if known) in the form of X and Y coordinates in a local Austrian projection ("Bundesmeldenetz"), together with the quality of the geocoding process. This is the process of assigning positional coordinates to a street address. In the SIMO, three different quality levels can be distinguished. If the exact address of the crime incident is known, then the positional accuracy after the geocoding process is very high. If an exact address for the crime incident cannot be determined, the exact position cannot be geocoded. In such instances, the entire street where the crime happened is included in the SIMO. In case not even a street can be identified, then the crime location is geocoded to the district or to the entire city. Temporal information is collected in the form of the start and end date and time of the crime incident, and the date and time of reporting to the police officer. Townsley et al. [3] state that research on repeat victimization is only reliable if addresses are recorded and geocoded accurately, and if the time window of the start and end date (and time) is not too large. A large time window may arise if a victim does not know the exact time of victimization. For example, daytime burglaries may occur when residents are at work. Thus, the police officer can only record a time window of several hours, or, in a case when residents are on vacation, a time frame of up to several days or weeks. In this case, Ratcliffe and McCullagh [32] applied an aoristic method to improve the analysis of the temporal component of crime data. The need to apply a temporal interpolation method, such as the aoristic method, is usually not an issue with robbery incidents, as the victim is directly involved in the victimization process. Further attributes of each crime incident included in the SIMO, which are important for this study, are the crime type and any crime subtypes.

In this study street robbery incidents for five years (2009–2013) from the city of Vienna, Austria are analyzed. Vienna, as the capital city of Austria, is home to about 1.7 million people, which is about one-fifth of all inhabitants of Austria [33]. In recent times, approximately 550,000 crime events have been reported in Austria per year. Approximately 210,000 of those 550,000 incidents (38%) occur in Vienna. Vienna experienced about 3800 robberies—ca. 2% of all reported crimes in that city—per year. The total number of robberies can be subdivided into ca. 1800 street robberies and ca. 2000 commercial robberies per year [34]. In this study, only street robberies in Vienna over the five-year time period are investigated. The street robberies dataset consists of a total of 8972 incidents from 2009 to 2013. Of this total number of incidents, ca. 92% (8217 events) were geocoded to a specific address, and only 8% (755 events) were referenced to the street segment. None of the incidents have been geocoded to the entire city—the lowest level of positional accuracy.

As far as the temporal component is concerned, the robbery dataset includes all but one robbery event that occurred within a time span of 24 h. In addition, 99.6% (8934 events) of all robberies have a start and end time on the same day. The single event with a time span longer than 24 h was excluded from the analysis. In sum, 8971 street robbery events were used in the analysis.

In this study, near-repeat patterns of robbery events are analyzed for each day of the week, separately. This implies that near-repeat analysis is done for all consecutive Mondays, Tuesdays, Wednesdays, etc. included in the street robberies dataset. These consecutive weekdays characterize the fictitious set of consecutive dates to allow for spatial and temporal analysis of crime patterns. For example, all robberies occurring on Mondays are collected in a single dataset. The first (oldest) event, occurring on 5 January 2009, is then given a fictitious and initial date such as 1 January 1900. For each incident the weekly difference between the dates of the actual event and the initial event is calculated, and added to the fictitious date of the initial event. Thus, an incident occurring on 19 January 2009, or two weeks after the initial event, is assigned the fictitious date of 3 January 1900. Based on these reassignment principles, datasets of consecutive weekdays are derived. To account for street robberies that start before and end after midnight of a weekday and to test for patterns by time of day for each weekday, the dataset was further divided into three 8-h time intervals. These time intervals are 6:00 a.m.–1:59 p.m., 2:00 p.m.–9:59 p.m., and 10:00 p.m.–5:59 a.m. These time intervals are logically defined based on the number of occurrences of street robberies (see Figure 1), with 6:00 a.m. as the beginning of the day and 10:00 p.m. when it is definitively dark outside, with people still being present in the streets. Each event is assigned to the appropriate time interval using the end date and time of the street robbery incident (compliant with analyses done by crime analysts of the Criminal Intelligence Service Austria).

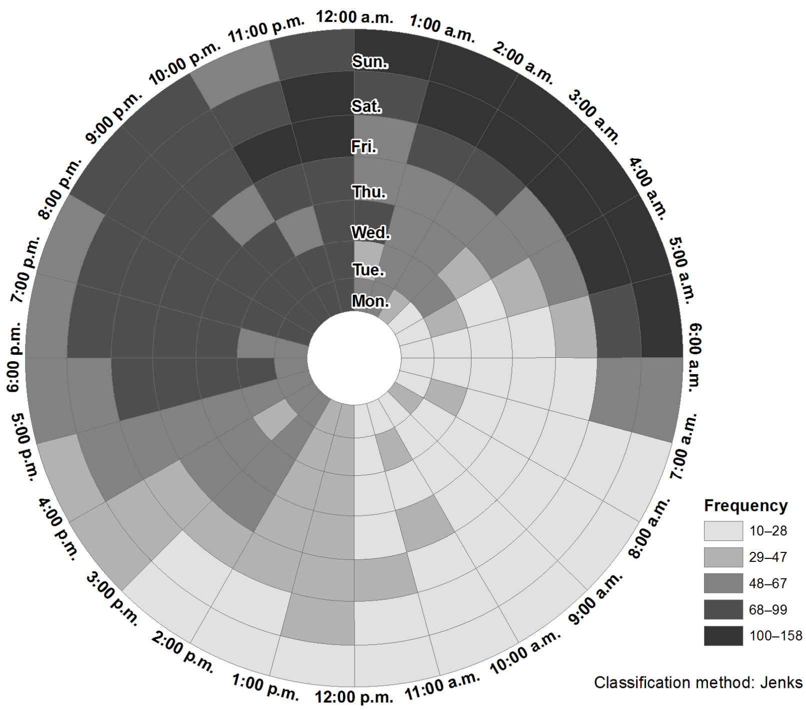

Figure 1. Street robberies from 2009 to 2013 by time of day and by weekday.

3.3. Exploratory Temporal Data Analysis

As can be seen in Figure 1, most street robberies occur in the evening and during the night. The share of robberies occurring between the morning hours (from 6:00 a.m.) and early afternoon (2:00 p.m.) is comparatively low. This was the main reason for grouping all occurrences within these eight hours together. One possible explanation for the relatively low number of robberies during the morning hours was proposed by Van Koppen and Jansen [35]. The authors argued that since most robbers are unemployed, the robbers do not get up early and thus will not commit robberies in the early morning. Other possible explanations are that people are at work in the morning hours, and that during daylight hours robbers do not feel comfortable and safe to rob.

Considering the robbery frequency by day of the week, there are no clearly visible patterns except for the weekend. A relatively high robbery frequency starts on Friday night at about 10:00 p.m. and lasts until Saturday morning at about 5:00 a.m. A similarly high frequency can also be observed on Saturday, where the number of street robberies is elevated from 11:00 p.m. until about 6:00 a.m. Such observations are consistent with findings from other studies, such as LeBeau [14], where more violent crimes are found on weekends. Possible reasons for the increased street robbery crimes on weekends may be related to more motivated offenders who need money for their weekend activities [35], streets that are well-frequented because people are off the job, tourists that usually come to visit the city on weekends, and people who tend to be under the influence of alcohol and drugs more often during weekends.

The aggregated numbers of street robberies by time of day and weekday can be seen in Table 1. In the morning hours, from 6:00 a.m. to 1:59 p.m., about 15% of all events occurred. In general, there is no variation in the numbers of street robberies occurring in the morning by weekday. About 40% of all street robberies from 2009 to 2013 occurred in the afternoon, from 2:00 p.m. to 9:59 p.m. During the week, there is slightly more street robbery crime observable with peaks on Mondays, Wednesdays, and Thursdays. The number of street robberies in the afternoon hours is at the lowest level on Saturdays and Sundays. A possible reason could be that professional robbers are inactive after previous Friday and Saturday nights, which are the absolute peaks in the weekday patterns. Generally, night hours accounted for 45% of all events occurring between 2009 and 2013. While the number of robberies at night is significantly lower from Monday to Thursday than robberies in the afternoon, the number of robberies on Friday and Saturday night are twice as high as the nights before. This confirms and combines the conclusions of Van Koppen and Jansen [35], and Tompson and Bowers [13], who found that violent crime, especially street robberies, tends to occur on the weekend and in darkness.

Table 1. Absolute numbers of street robberies in Vienna, Austria from 2009 to 2013 by time of day and by weekday.

	Total	Mon.	Tue.	Wed.	Thu.	Fri.	Sat.	Sun.
Entire day	8971	1118	1139	1131	1188	1315	1606	1474
6:00 a.m.–1:59 p.m.	1385	209	206	187	196	204	201	182
2:00 p.m.–9:59 p.m.	3528	533	504	535	531	512	486	427
10:00 p.m.–5:59 a.m.	4058	416	435	460	514	948	934	351

3.4. Methodology

To test for the presence of near-repeat patterns, the Near-Repeat Calculator (NRC) is used. The NRC is a stand-alone software program developed by Jerry Ratcliffe [21]. It is public-domain software and can be downloaded for free from the following URL: http://www.cla.temple.edu/cj/center-for-security-and-crime-science/projects/nearrepeatcalculator/. The program identifies whether there is a statistically significant near-repeat pattern in a (crime) dataset. The algorithm of the NRC is based on the revised Knox close-pair test. In the 1960s, the first tests such as the Knox and the Mantel test were developed in the field of epidemiology to test for space–time interaction [36,37]. Space–time interaction emerges when spatially close events occur at about the same time [38]. The Knox test determines whether there are more incident pairs observed in both space and time than would be expected on the basis of a random distribution. Statistical significance is assessed using Monte Carlo simulations [39]. Additionally, the software creates a tabular file including events that are the originators of near-repeats. An originator event is an initial event after which subsequent (near-repeat) events may occur that are close in both space and time. The file also includes events that are near-repeats of those originating events. Using a Geographic Information System (GIS), the file containing the originating and its subsequent near-repeat events can be easily mapped to identify locations of these incidents. The structure of the input dataset consists of a unique ID, the geographic location, and a date field. The user is required to specify spatial and temporal bandwidths in the NRC. The spatial bandwidth refers to a threshold distance of events being close to an originating event. The temporal distance is the time span in which events occur after an initial event. Using the combination of these bandwidths, the program analyzes whether there is a significant near-repeat pattern. Most research in environmental criminology suggests that near-repeat patterns occur for a few hundred meters at most. Johnson et al. [8] analyzed residential burglaries in five different countries with spatial bandwidths ranging from 200 to 1200 m. Ratcliffe and Rengert [39] and Haberman and Ratcliffe [30] selected the approximate length of a city block as the spatial unit, which is about 120 m (400 feet) in Philadelphia, to analyze near-repeat patterns of shootings or armed street robberies, respectively.

The NRC requires the user to choose a spatial and a temporal bandwidth. This can be seen as a limitation because the researcher can set the parameters arbitrarily. Previous research proposes using seven days as the temporal bandwidth (e.g., [28]). Haberman and Ratcliffe [30] also use seven days in their analysis of armed street robberies. They argue that a seven-day bandwidth supplies a short timeframe as well as a simple measure to interpret and understand the results. In this study, a seven-day temporal bandwidth will be adopted to analyze near-repeats in the total dataset of robberies. In the analysis of consecutive weekdays, a bandwidth of four consecutive weekdays is used. This means that, for example, four days represent four consecutive Mondays over a four-week period. This choice is consistent with Perry et al. [40], who advise using about five weeks' worth of data when analyzing effects by weekday. Considering the spatial bandwidth, different spatial bandwidths between 100 to 500 m are used in numerous previous studies (e.g., [8,39]). In this study, a spatial bandwidth of 300 m is applied. Additional analyses were performed using a spatial bandwidth of 500 m and a temporal bandwidth of seven consecutive weekdays. In sum, the results were not significantly different. The bandwidth combination of 300 m and four consecutive weekdays offers slightly more significant results; these are considered by the police to be more practicable and useful for preventative action.

The first analysis discusses whether a distinct near-repeat pattern exists in the total dataset of street robberies. Then, this research comparatively analyzes street robberies, first by weekday and second by time of day and weekday to confirm (or reject) the hypothesis that specific patterns by weekday and time of day (and weekday) exist. In addition to the analysis of whether patterns exist, this research analyzes the commonalities and differences within spatial patterns of near-repeat pairs (of originating and near-repeat events) by weekday and time of day. Furthermore, this research discusses whether near-repeats tend to occur in areas where street robberies cluster purely spatially.

4. Results

4.1. Near-Repeat Pattern of Street Robberies

In this section, we first investigate whether a near-repeat pattern of street robberies exists in Vienna from 2009 to 2013 using the NRC. It is expected that street robberies cluster in space and in time. The results of this analysis are presented in Table 2, which shows the risk and the significance levels across the selected bandwidths. The risk level indicates the ratio of observed pairs with defined spatio-temporal bandwidths (numerator) over the average number of expected pairs with the same bandwidths (denominator). The larger the frequency, the larger is the difference between the observed risk and the risk, if there were no space-time interaction. The significance level in each cell is based on Monte Carlo simulations and indicates whether the associated risk level is statistically significant or not.

Table 2. Near-repeat risk values (observed over mean expected frequencies) and significance levels of street robbery for the total dataset.

Spatial Distance	Temporal Distance in Days			
	0 to 7	**8 to 14**	**15 to 21**	**22 to 28**
Same location	4.77 **	1.85 **	1.82 **	1.45 **
1–300 m	1.20 **	1.08 **	1.06 *	1.04
301–600 m	1.07 **	1.04 *	1.01	1.01
601–900 m	1.04 **	1.05 **	1.01	1.00

* $p < 0.05$, ** $p < 0.01$.

The upper-left cell of Table 2 contains a value of 4.77. This value can be interpreted such that, after an initial robbery event, it is very likely that another event will happen at the same location within the next seven days. The chance of another incident happening, the risk level, is 377% greater than if no near-repeat victimization pattern existed. A clear decay in the risk level is observable in the spatial band from 1 to 300 m around the initial robbery event, as indicated in the cell below the upper-left cell. The chance of a second robbery event happening is “only” 20% greater than if there were no expected near-repeat pattern. As can be seen in Table 2, risk levels for repeat victimization further decrease with greater distance from the originating event: 4.77 at the same location, 1.20 within 1 to 300 m, 1.07 within 301 to 600 m, and 1.04 within 601 to 900 m. A similar decay is observable considering the temporal bandwidth: At the same location risk levels decrease from 4.77 within 0 to 7 days, to 1.85 within 8 to 14 days, to 1.82 within 15 to 21 days, and finally to 1.45 within 22 to 28 days. This means that after 28 days the risk level of another street robbery event occurring at the same location is still 45% greater than if there were no expected near-repeat pattern. It thus can be concluded that there is a significant near-repeat pattern for street robberies.

4.2. Near-Repeat Patterns of Street Robberies by the Day of the Week

The second research question in this study is whether a significant rhythmic pattern of street robberies exists by the day of the week. Therefore, the entire dataset was separated into seven sub-datasets, each representing a single day of the week. In addition, the date information for each weekday was rearranged in order to have consecutive dates in the seven datasets with only Mondays, Tuesdays, Wednesdays, and so on. For each of these seven datasets a near-repeat analysis was now conducted. In this analysis, spatial (300 m) and temporal (four consecutive weekdays) bandwidths were used in order to make the results comparable with each other. The results of the near-repeat analyses by weekdays are shown in Table 3. Generally speaking, the results show mostly statistically significant near-repeat patterns at the same location and in the bandwidth from 1 to 300 m, up to four consecutive weekdays from the originating street robbery. This answers the research question of whether a significant pattern by the day of the week exists. The near-repeat analysis was conducted using additional spatial (301 to 600, and 601 to 900 m) and temporal (5 to 8, 9 to 12, 13 to 16 consecutive weekdays) bandwidths, but none of these risk values were statistically significant. Thus, these numbers are not included in Table 3.

Table 3. Near-repeat risk values (observed over mean expected frequencies) and significance levels of street robbery by weekday.

Spatial Distance	Temporal Distance: 0 to 4 Consecutive Weekdays						
	Mon.	**Tue.**	**Wed.**	**Thu.**	**Fri.**	**Sat.**	**Sun.**
Same location	4.37 **	5.12 **	6.42 **	5.57 **	8.37 **	3.95 **	3.81 **
1–300 m	0.98	1.26 *	1.21 *	1.20 *	1.19 *	1.26 **	1.09

* $p < 0.05$, ** $p < 0.01$.

On each of the weekdays, the risk level of another street robbery event happening increases by at least 281% at the same location within the next four consecutive weekdays. Among all weekdays, Wednesdays and Fridays experience the highest risk levels for a repeat street robbery at the same location as the initial street robbery event. The risk level of being re-victimized within 1 to 300 m of the initial robbery event is about 20% higher and statistically significant on all weekdays except for consecutive Mondays and consecutive Sundays. These results confirm that there is predominantly an elevated risk of near-repeat victimization at consecutive weekdays. However, risk levels of each weekday pattern vary slightly. While this information may have a minor impact on the crime prevention strategies of law enforcement agencies, it is more useful to identify locations of near-repeat clusters. Based on this information, law enforcement agencies can optimize tactical planning of police patrols, or protect potential victims at certain places and weekdays through awareness campaigns [27].

The output of the near-repeat analysis of the NRC includes locations of all originators (initial events of near-repeat clusters) and near-repeat events that occurred within the specified bandwidths of 0 to 300 m and seven days for the total dataset of street robberies, and 0 to 300 m and four consecutive weekdays for the weekday analysis. From the 8971 robbery events in the entire dataset, the NRC found 1961 originators that experienced at least one other event within 0 to 300 m and up to seven days of the originating event. The highest number of near-repeat events after an initial event was six. This means that after an initial robbery, six additional robberies occurred within 0 to 300 m and during the next seven days.

For the following visualizations of street robbery patterns, kernel density estimations (KDE) are used to create hotspots. KDE is a popular interpolation technique used to generalize event locations over an entire area. Many interpolation techniques such as Kriging, trend surfaces, or local regressions are available but those require an intensity variable to be estimated as a function of location. Instead, KDE does not require an intensity variable and is therefore appropriate for individual event locations [41,42].

In the calculation of a KDE three steps are necessary: First, a grid is generated over the point pattern. Second, a three-dimensional mathematical function is placed over each event and calculates intensity values for each cell within the kernel's radius. Grid cells that are closer to the event will receive a higher intensity value. Third, grid cell values are calculated by summing all estimates for each event location [41,43]. In this research, the widely accepted quartic kernel function is used [41,43–46]. Limitations of KDE are possible misinterpretations due to smoothing density values into areas where no crime occurred and the choice of the bandwidth [42,43]. For the calculation of KDE a spatial bandwidth of 600 m is used. This is twice the distance used for the near-repeat analysis. Two additional bandwidths of 300 and 900 m have been tested. Generally speaking, the wider the bandwidth, the smoother the resulting density estimation and vice versa.

In the comparison of multiple hotspots, we need to consider how to map overlapping density surfaces. Therefore, we classify any intensity value above a determined threshold as a hotspot. Chainey et al. [47] suggest using quantiles to group values into five thematic classes. The top thematic class is then considered a hotspot. Eck et al. [41] propose using standard deviations to classify thematic ranges and to identify clusters of very high or low values. In this research, hotspots are generated using KDE values of three standard deviations above the mean. In the following section describing the analysis and findings, a hotspot always refers to the "hottest" area of KDE intensity values with three standard deviations above the mean.

Figure 2 contains three relevant analyses: First, street robbery hotspots of the total dataset. The term total dataset refers to the original dataset of a Monday, followed by a Tuesday and so on. These purely spatial hotspots are shown with dashed black lines. Second, the map shows street robbery hotspots of near-repeats. These include originating and near-repeat events of the near-repeat analysis using a spatial distance of 0 to 300 m and a temporal distance of up to four days. The dataset consists of the original dataset of a Monday followed by a Tuesday and so on. These hotspots are represented with solid black lines. Third, street robbery hotspots of near-repeats by weekday are mapped. Again, these analyses include originating and near-repeat events of the near-repeat analysis using a spatial distance of 0 to 300 m and a temporal distance of up to four days. In these analyses, each of the seven fictive datasets consists of either consecutive Mondays, or consecutive Tuesdays, and so on. These hotspots by weekday overlap to some extent. Therefore, we map the number of overlapping hotspots by weekday using an increasingly darker grayscale. This means, e.g., that a number of "3" represents three hotspots by weekday overlapping in a specific area. The number of overlapping hotspots does not reflect which weekdays are affected. In fact, labels of the weekday hotspots are mapped accordingly to give insights into the variation in weekday patterns.

One research question discusses whether near-repeats tend to occur at the same places as purely spatial hotspots. Figure 2 shows that this research question can be affirmed. All of the near-repeat hotspots of the total dataset (solid line) lie within purely spatial hotspots of the total dataset (dashed line). This has significant influence on crime prevention actions, as these near-repeats should be used for tactical short-term responses. However, since these near-repeats are located within or close to persisting hotspots, these areas should also be in the focus of strategic long-term responses [30]. Note that there are areas of purely spatial hotspots that do not reflect near-repeat hotspots. From a visual perspective, street robberies are more common in areas of major public transportation hubs, in shopping areas, and in areas with prominent nightlife.

Another research question deals with the existence of near-repeat patterns by weekday. It is hypothesized and confirmed in Table 3 that these near-repeat patterns of street robberies by weekday exist. In addition, the question arises whether there are differences in the spatial distribution of these hotspots by weekday. In Figure 2, street robbery hotspots of near-repeats by weekday are mapped as unique to stable hotspots. That means that in stable locations multiple hotspots by weekday are present, while at unique locations single hotspots by weekday are found. Several stable hotspots are identified. These areas are street robbery hotspots on each weekday (representing seven overlapping hotspot areas by weekday). Besides these stable hotspots, there are three notable hotspots: First, in an area of a major transportation hub, street robberies mainly occur during the week from Monday to Friday. The second and third street robbery hotspots occur mainly on the weekends (Thursday to Sunday or Saturday and Sunday).

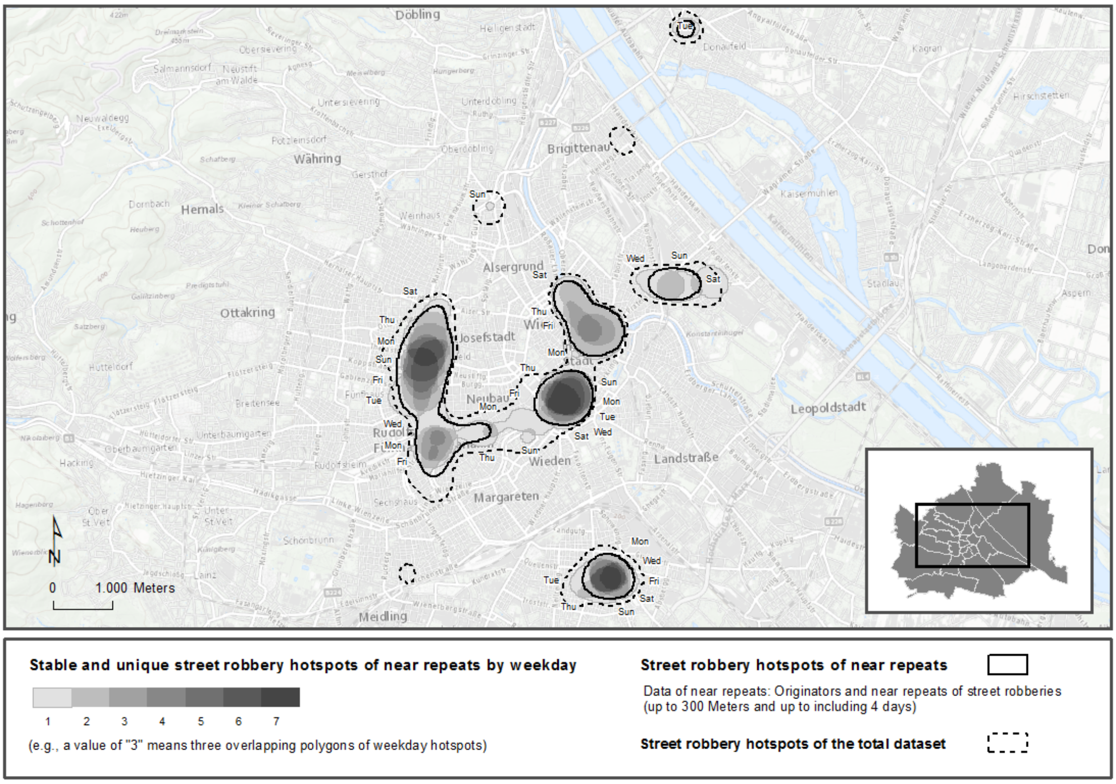

Figure 2. Street robbery hotspots of near-repeats by weekday.

4.3. Near-Repeat Patterns of Street Robberies by Weekday and by Time of Day

Until this point, these findings have confirmed the authors' assumption of the existence of stable and weekday-specific street robbery hotspots. To further confirm these assumptions, and to analyze daily near-repeat patterns, the entire dataset was separated into three 8-h intervals of morning/early afternoon hours (6:00 a.m.–1:59 p.m.), middle to late afternoon/evening (2:00 p.m.–9:59 p.m.), and night/early morning hours (10:00 p.m.–5:59 a.m.). These three sub-datasets were then separated by each weekday to account for differences by weekday and time of day.

The first analysis was to identify whether near-repeat patterns by time of day and, additionally, by weekday, show significant results. This global analysis was conducted using the NRC. Table 4 shows results by time of day and by weekday. In general, the classification of the total dataset into three 8-h intervals resulted in more statistically significant results and higher risk levels. While the 24 h (entire day and night) risk level for the total dataset (Table 3) was 377%, the near-repeat analyses of the three 8-h intervals resulted in even higher risk levels. For the same location it is 1302% more likely to witness another robbery event from 6:00 a.m. to 1:59 p.m. when compared to the same time period of the next seven days. Elevated risk values compared to the 24-h risk levels are also found from 2:00 p.m. to 9:59 p.m. and from 10:00 p.m. to 5:59 a.m. Additionally, risk levels from 1 to 300 m for all three 8-h intervals are greater or similar, when compared to 24 h risk levels, but only the risk values for the 2:00 p.m. to 9:59 p.m. and 10:00 p.m. to 5:59 a.m. time periods are statistically significant.

Table 4. Near-repeat risk values (observed over mean expected frequencies) and significance levels of street robbery for the total dataset and weekday and by time of day.

D&NT	Spatial Distance	Temporal Distance							
		0 to 7 d	0 to 4 Consecutive Weekdays						
		Total	Mon.	Tue.	Wed.	Thu.	Fri.	Sat.	Sun.
M	Same location	14.02 **	0.00	66.00 **	9.90	23.29 **	33.00 *	6.60	10.61 **
	1–300 m	1.23	0.96	1.75	0.70	2.65 **	1.20	1.52	0.91
A	Same location	9.94 **	7.84 **	3.14	13.50 **	8.25 **	14.49 **	8.68 **	13.50 **
	1–300 m	1.38 **	1.81 **	1.12	1.40	1.28	1.28	1.83 **	1.22
N	Same location	5.78 **	3.81	8.25 **	5.58 *	9.58 **	3.32 **	5.26 **	8.74 **
	1–300 m	1.18 **	1.21	1.37	0.77	0.86	1.38 **	0.99	0.83

* $p < 0.05$, ** $p < 0.01$; D&NT . . . Day & Night-time (0:00 a.m.–11:59 p.m.), M . . . Morning (6:00 a.m.–1:59 p.m.), A . . . Afternoon (2:00 p.m.–9:59 p.m.), N . . . Night (10:00 p.m.–5:59 a.m.).

Compared to the near-repeat patterns from the total dataset, the morning to early afternoon hours by weekday show quite different near-repeat patterns. First, only four near-repeat patterns are statistically significant. While the risk level of another incident occurring at the same location for Sunday mornings to early afternoons is lower than the risk level for the same time period of the total dataset, the risk level of Tuesday mornings to early afternoons, with a maximum risk level of 6500%, and the risk level of Thursday and Friday mornings to early afternoons are greater than the risk level for all mornings to early afternoons. Within the spatial bandwidth of 1 to 300 m, only one risk level is statistically significant. The risk level of near-repeats on Thursday morning is 165% higher than the expected risk. This is the highest risk value measured within the distance band of 1 to 300 m for the next four consecutive weekdays.

Although four out of seven results of the NRC are statistically insignificant, hotspots of near-repeats in the morning to early afternoon hours by weekday are mapped in Figure 3. The research question whether near-repeat pairs of originators and near-repeat events tend to cluster in purely spatial hotspots of events in the morning to early afternoon hours can be confirmed. However, the pattern of street robbery hotspots of near-repeats by weekday that occur only from 6:00 a.m. to 1:59 p.m. is quite different from the pattern seen in Figure 2. Hotspots for weekdays of events that occurred in this 8-h interval are more dispersed and rarely overlap. Many small and unique street robbery hotspots are visible and few of them lie within areas of street robbery hotspots by weekday. In comparison with the same analysis for the total dataset in Figure 2, we conclude that few places are not as vulnerable as other areas to street robberies in the morning to early afternoon hours. Possible explanations are the absence of people in these areas as these are mainly attractive in the afternoon to nighttime hours (amusement park, restaurant, bars, and night clubs).

In the afternoon and evening hours, from 2:00 p.m. to 9:59 p.m., the risk level of the NRC results in a significantly higher value (Table 4) compared to the all-day (24 h) dataset. The risk level of near-repeats in this 8-h interval shows a value of 894%, which is more than twice the risk value of the all-day (24 h) risk level of 377% (see Table 3). At the same location, risk values in the afternoon and evening hours by weekday show more values that are significant as compared to risk values in the morning and early afternoon hours. Statistically significant values range from 684% to 1349%. Risk values for consecutive Wednesdays (1250%), Fridays (1349%), and Sundays (1250%) are higher than the risk level of the afternoon and evening hours from the total dataset (894%). Only two risk levels of the near-repeats from 1 to 300 m and consecutive weekdays from up to four weeks are statistically significant with values of 81% and 83%, respectively.

Street robbery hotspots for near-repeats emerging in the afternoon to evening hours (2:00 p.m. to 9:59 p.m.) are mapped in Figure 4. Generally, hotspots of near-repeats match in areas of hotspots of the total dataset of street robberies (solid and dashed lines). The pattern of street robbery hotspots in the afternoon and evening hours by weekday is dispersed, but not as much as hotspots in the morning to early afternoon hours. A stable hotspot is identified in the city center. Small, local hotspots are found throughout the city. This pattern is, in fact, quite different to the observed pattern of hotspots of street robberies in the morning to early afternoon hours (see Figure 3).

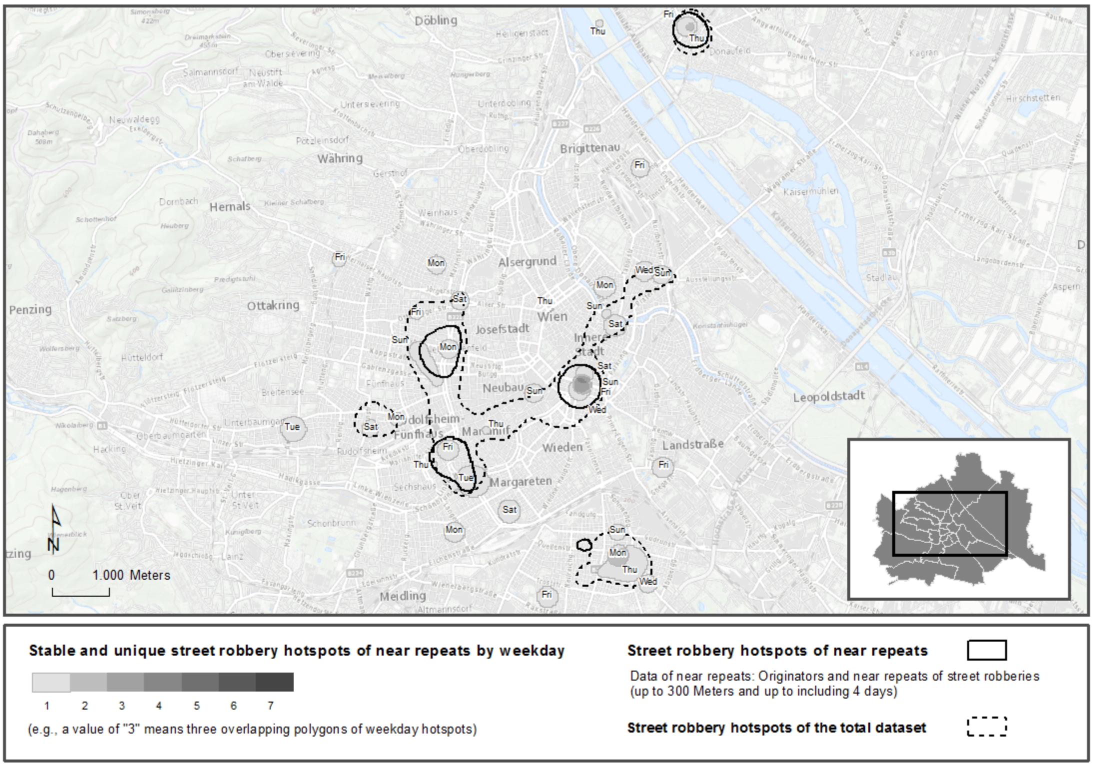

Figure 3. Street robbery hotspots of near-repeats from 6:00 a.m. to 1:59 p.m. by weekday.

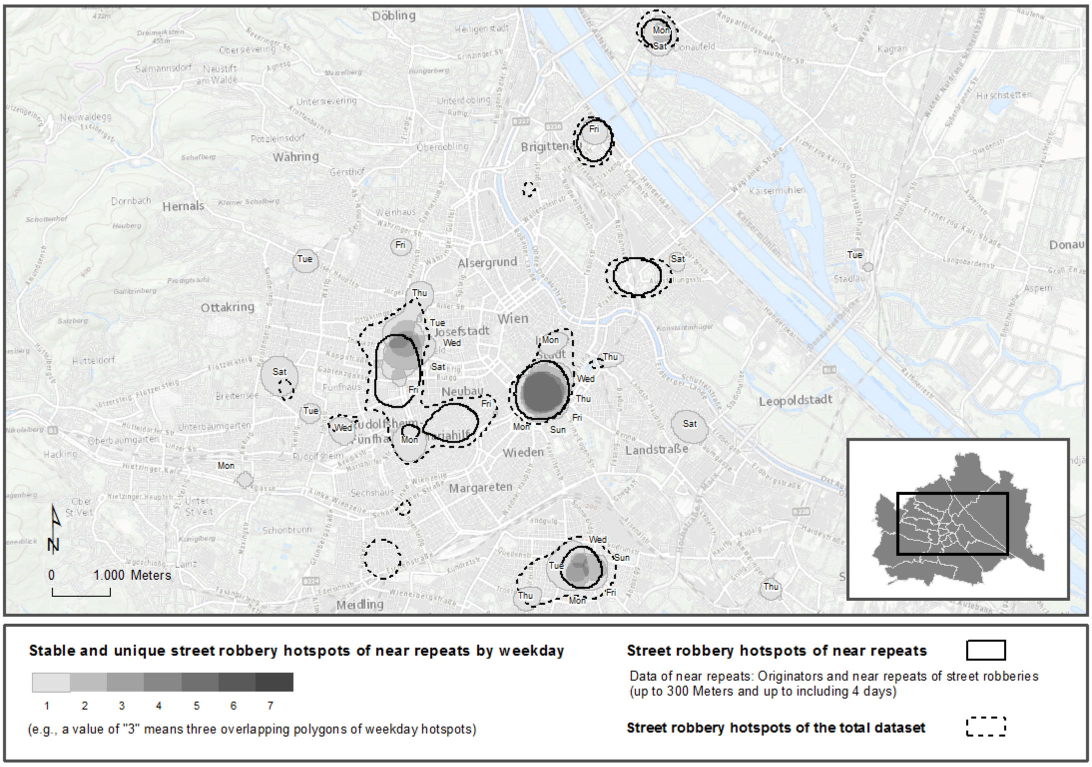

Figure 4. Street robbery hotspots of near-repeats from 2:00 p.m. to 9:59 p.m. by weekday.

The last time period to be discussed is the analysis of near-repeats during the night and early morning hours from 10:00 p.m. to 5:59 a.m. The risk level for this time period for the total dataset is statistically significant (478%; see Table 4) and again higher than the overall risk level for the all-day dataset of street robberies (377%; see Table 2). Risk levels at the same location for each weekday night are all, except for consecutive Mondays, statistically significant. Risk levels at the same location for consecutive Tuesday (725%), Thursday (858%), and Sunday nights and early mornings (774%) result in higher risk values than the risk level of night hours for the total dataset. Risk values from 1 to 300 m are only statistically significant twice: First, for the risk value of the total dataset of street robberies (18%), and second for the risk value of consecutive Friday nights and early mornings (38%).

The final map (Figure 5) shows street robbery hotspots for events occurring in the night and early morning hours. Hotspots of near-repeat events from 10:00 p.m. to 5:59 a.m. lie, again, completely within hotspot areas of the total dataset of events occurring in this 8-h interval.

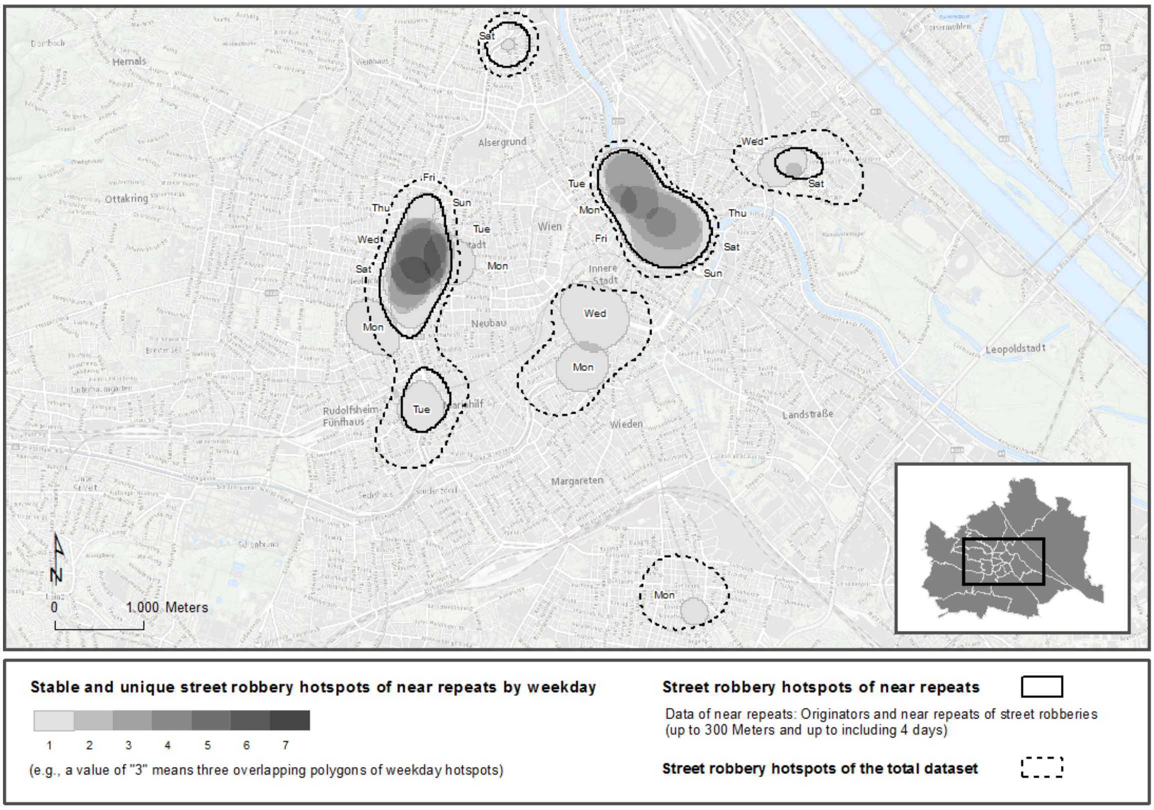

Figure 5. Street robbery hotspots of near-repeats from 10:00 p.m. to 5:59 p.m. by weekday.

In the analysis of the distribution of street robbery hotspots by weekday, it is clearly recognizable that hotspots show a more concentrated and less dispersed pattern in the morning to early afternoon (Figure 3) and in the afternoon to evening hours (Figure 4). Stable hotspots are identified in areas that are hotspots for tourists and night-time activities as there are many restaurants, bars, and night clubs. Thus, both areas are considered flagged places, where environments are appropriate for street robberies to occur, with many possible victims engaging in night-time activities in these locations. Obviously, no clusters are identified along shopping streets as no shops are open in the late night and early morning hours. Needless to say, street robberies in the night to early morning hours are predominantly found in areas with nightlife opportunities.

5. Discussion

Numerous studies have confirmed the existence of the near-repeat phenomenon for various crime types, such as burglaries or shootings [8,39]. Only a few studies have ever analyzed robberies, especially street robberies (e.g., [30]). The identification of near-repeat patterns holds practical implications for target-oriented crime prevention strategies. The current study contributes to the near-repeat victimization literature by analyzing street robberies in the city of Vienna, Austria. This has been the first contribution to the near-repeat phenomenon literature using crime data from Vienna. The research presented in this article describes how street robberies are clustered in both space and time, and how these near-repeat patterns differ by weekday. The analysis was further extended to determine whether there are differences in near-repeat patterns by weekday and time of day. Finally, it was discussed whether these patterns differ from purely spatial patterns of street robbery hotspots. Based on potential intersections of near-repeat hotspots and spatial hotspots, this may have implications for either short-term or long-term preventative responses.

The results of this research showed that there is an elevated risk of revictimization of street robberies after an initial event at the same location or in close proximity (1–300 m) in both space and time. More specifically, the risk of another street robbery occurring at the same location and during the next seven days is 377% greater than if there were no space–time interaction. Additionally, a drastically reduced risk to "only" 20% of another street robbery happening within a spatial bandwidth of 1 to 300 m is observed. Street robbery hotspots of the near-repeat analysis are identified at noticeable areas with major public transportation hubs, shopping areas, and in nightlife areas.

Crime prevention strategies work best when targeting problematic areas focusing on specific times and locations. For this reason, it was further examined whether there is a distinct near-repeat pattern by weekday and by time of day. The total dataset was divided into three 8-h time periods that include a morning and early afternoon dataset of events occurring from 6:00 a.m. to 1:59 p.m., an afternoon and evening dataset with events happening from 2:00 p.m. to 9:59 p.m., and finally, a night and early morning dataset for those events occurring from 10:00 p.m. to 5:59 a.m. The findings of this analysis are consistent with previous studies (e.g., [13,35]). Results of the near-repeat analyses by the three 8-h time intervals show significantly higher risk values than the near-repeat analysis of the complete 24-h dataset. To account for daily near-repeat patterns by consecutive weekdays, datasets were further separated into 21 datasets by consecutive weekdays and three 8-h intervals (for example, the first dataset included events of consecutive Mondays that occurred from 6:00 a.m. to 1:59 p.m.). Overall, near-repeat risk levels are mostly statistically significant at the same location and during the next consecutive weekdays for a total of four weeks. The hypothesis that there is a statistically significant near-repeat pattern by weekday, and, furthermore, by weekday and 8-h time intervals, can be confirmed. The second hypothesis about whether those near-repeat patterns differ by weekday and by 8-h time interval was again tested using hotspots of kernel density estimations of locations of near-repeat pairs (originators and near-repeats). In the morning and early afternoon hours, the hotspot pattern is highly dispersed. Many small local and unique hotspots are found for each weekday.

Finally, it is analyzed whether these hotspots of near-repeat locations are located within or close to purely spatial hotspots of the total dataset of street robberies occurring during the complete 24-h time period. Almost all near-repeat hotspots are either completely within or close to purely spatial hotspots. In fact, locations of the near-repeat clusters have important implications as to preventative action. This way, near-repeats occur at locations where street robberies generally tend to occur without especially considering the weekday. Johnson et al. [31] suggest that, due to the stability of hotspots, it is likely to require complex crime prevention action such as a greater allocation of police resources or a redesign of the physical environment.

6. Conclusions

Based on these results, it is important to understand why street robbery events are spatially and temporally clustered by weekday and by time of day. This is especially important to improve theoretical explanations of the near-repeat pattern and optimize crime prevention strategies. Referring to the routine activity approach, results of this research show the varying and repeating activity places of victims and offenders within the city for weekdays and for 8-h time intervals. Hotspots of near-repeats can be theoretically explained with the boost and the flag thesis. While environments of those areas attract robbers and are, therefore, likely to support the flag theory, the boost theory cannot be neglected as an offender tends to return to well-known places. Hence, the boost theory is also supporting the idea of a social network, where robbers communicate information about places to rob. Further research needs to be done to explain why those areas are more likely to attract robbers. Promising approaches for explanations could be the integration of Risk Terrain Modeling [48] to identify environments that attract offenders to prove the existence of the flag mechanism.

This research does not include information on serial offenders. We do not know the names of the offenders. The hypotheses and results are related to aggregated crime data and therefore we cannot and do not make any inferences about individuals from the aggregated crime data. Another option for future research would be the integration of offender information to determine the involvement of repeat offenders. Based on such an analysis, the boost theory could be explained and confirmed more thoroughly. Unfortunately, the available data did not allow for direct testing of whether the boost and flag explanations are in play.

Based on the information gathered from this study, crime prevention policies can be applied instantly. There is a distinct rhythm of street robberies by weekday and especially by 8-h time intervals, which should guide law enforcement agencies to deploy limited but targeted capacities. Police resources should therefore be positioned at critical places on specific weekdays and time intervals, as identified in this near-repeat analysis. An example of such a critical place would be if a street robbery occurs on a Monday night within an identified area where street robberies repeat on Monday nights. In this case, targeted resources should be deployed to that area not only days after the initial street robbery but also on subsequent Monday nights. In addition to these operational activities, focusing crime prevention actions on stable hotspots should be included in strategic, long-term responses to criminal activities.

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