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Predictive policing in hospitality and tourism venues — The case of Orlando

Jalayer Khalilzadeh

School of Hospitality Leadership, College of Business, East Carolina University, 311 West - Rivers Building Greenville, NC, 27858-4353, USA

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ABSTRACT

The association between crime and tourism has been studied for more than 40 years. Most of the studies, however, have focused on differentiating crimes against tourists from crimes against locals despite the high correlation between the two. To date, there are only a few studies that have pointed out to the role of location and time in tourism-crime analysis despite the existence of theoretical frameworks such as routine activity, hot spot, and rational choice that validate the role of temporospatial analysis in tourism/hospitality crimes. Furthermore, prior literature has only used the predictive policing model in relation to police-criminal activities. This study, however, claims that by using the principles of the predictive policing model in conjunction with the community policing model, benefit can be derived from active public participation in preventing/disrupting crimes that have temporospatial patterns. In order to address the gap and achieve the purpose of the study, 160,947 structured observations of Orlando police public records from 2009 to 2015, types and locations of crimes, decision tree models of classification and regression (CART or CRT), and chi-square automatic interaction detection (CHAID) were employed. The results confirm that crimes at recreation/tourism and hospitality venues have a clear temporospatial pattern and, as such, they could potentially be intervened in and reduced with active participation of the public.

> "Ignorance, when voluntary, is criminal, and a man may be properly charged with that evil which he neglected or refused to learn how to prevent."

- Samuel Johnson, The History of Rasselas, Prince of Abissinia (P. 109)

1. Overview

On June 12, 2016, Orlando became the top news headline in all national news agencies. This time, it was not because of the opening of a new theme park or some noteworthy tourism events—it was because of a hate crime. The terror began when the 29-year-old Omar Mateen walked into a LGBT (Lesbian, Gays, Bisexual, and Transgender) club at 2:00 a.m. with a semi-automatic rifle and a handgun and began shooting everyone. By the time Mateen was killed by Orlando police officers at 5:00 a.m., 49 people were dead and at least 53 were injured (Lotan et al., 2017). Omar Mateen was described as a 'lone wolf' who had been inspired by the radical Islamist ideology of Daesh (also known as Islamic State, ISIL or ISIS), and had planned this terrorist attack for his deep hatred towards homosexuality and homosexuals of the LGBT community (Pizam, 2016b). Apart from its ideological roots and terrorism nature, the attack was in the first place a crime that occurred in a hospitality setting. It is worth mentioning that some tourism scholars discriminate between terrorism and crime by signifying some differences between the two such as predictability (Tarlow, 2006b), goal, type of victims, defense in use, political ideology, publicity, accuracy of reports, and length and/or strength of the negative impact (Tarlow, 2009). Although some such differences exist between the two concepts of crime and terrorism, the nature of the act of terrorism is considered criminal. In fact, since 1994, the United Nations General Assembly has adopted the following definition of terrorism that was first offered by League of Nations in 1937: "*All **criminal acts** directed against a state and intended or calculated to provoke a state of terror in the general public, a group of persons or particular persons for political purposes are in any circumstance unjustifiable, whatever the considerations of a political, philosophical, ideological, racial, ethnic, religious or any other nature that may be invoked to justify them* […]" (Salifu, 2017, p. 2, emphasis added). Furthermore, among the above-mentioned factors that differentiate between terrorism and crime, predictability is the one that Tarlow (2006b) insists on as the distinctive point. This claim, however, was repudiated with empirical studies such

E-mail address: Khalilzadehj19@ecu.edu.

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as Toure and Gangopadhyay (2016), who showed that stochastic risk models can accurately identify terrorist attacks patterns with a prediction precision of above 95%. Accordingly, the claim that terrorism is not a crime because it is impossible to predict is not accurate.

No place in a free community is fully defensible (Burton & Crotts, 2014) because in attempts of crime control, the frequency of crime does not necessarily decrease but rather leads to the crime displacement effect by shifting the criminal activities to other areas (Harper et al., 2013). Considering the positive impact of police visibility on crime reduction (Tarlow, 2006a), the notion of defensible space suffers the most in the context of recreation/tourism and hospitality (RTH) venues as these places usually fail to communicate any physical cues concerning the presence of law enforcement. As a result, targeting RTH venues seems to carry the least risk with regard to criminal activity but offer criminals the highest rewards (Burton & Crotts, 2014).

On this note, criminal activities have a devastating impact on tourism destinations and their image, especially when the market is heavily exposed to prolonged negative media coverage (Dimanche & Lepetic, 1999; Giusti & Raya, 2019; Hua et al., 2020). For example, the case of Natalee Holloway's disappearance in Aruba in 2005 was covered more than 950 times during the first six months, which resulted in 15% drop of the American market for Aruba as a destination after 2006 (Brown, 2015). Knowledge of crime rates, coupled with a perception of location and personal experience of victimization, might result in fear of crime, which reduces destination attractiveness (Lisowska, 2017) and the likelihood of an individual participating in activities such as visiting the destination (Deka et al., 2018). This is especially true for international tourism as it is a common practice for embassies and consulates to issue advisories and warnings regarding traveling to specific destinations, if any risks, whether actual or perceptual, exists (Schiebler et al., 1996). Accordingly, safety and security of destinations ensured by reliable police services is integral to tourism competitiveness (Wilks, 2011). In recent years, the reliability of the US police services has been on a rapid decline. In 2009 competitiveness report, the US was ranked 122 out of 133 in safety and security, with the reliability of police services ranked 18/133 (Blanke & Chiesa, 2009). In a more recent report (from 2019), while safety and security seems to have improved to 55/140, the reliability of police service dropped to 20/133 (Calderwood & Soshkin, 2019). The improvement of general safety and security can, to a great or lesser extent, be attributed to the improvement of economic conditions (considering the 2008 economic recession), but the decline in reliability of police task force has deeper implications that are rooted in the past 60 years of policing in the US. The recent racial tensions and social unrest due to the brutal police encounters is arguably the climax of the US′ broken policing culture (Brooks, 2020), which negatively impacts its competitive advantage as an international destination. Perhaps, therefore, the negative impact of crimes on destinations can be best explained by Boakye (2012, p. 327): "Providing security for tourists has become an imperative and any destination which ignores this responsibility stands to lose out on the keen competition for the tourist dollar."

The literature on crime and tourism/hospitality is relatively limited both empirically and theoretically (Mehmood et al., 2016). Crime in hospitality is even more under-researched compared to crime in tourism (Leung et al., 2018). Despite the long history of research on crime in tourism, it has been investigated from only a few perspectives. To be more clear, most of the published literature of crime in hospitality and tourism is from suppliers' standpoint, which is closely followed by research from consumers' viewpoint (Hua et al., 2020). Fewer studies, however, have investigated the subject of crime in RTH from the broader perspective of public service, and among those who have examined this area, none has adopted the outlook of predictive policing. Considering the effectiveness and importance of government organizations in general and police forces in particular in respect to crime prevention, lack of crime-focused research from the outlooks of public service and predictive policing has generated an opportunity to further explore the subject of crime and policing in RTH.

Most of the studies on tourism and crime have focused on differentiating 'crimes against tourists' from 'crimes against locals' because of the unique characteristics of tourists (Brunt et al., 2000). For example, compared to locals, tourists usually carry more cash, have portable wealth (camera, jewelry, etc.), and drive rental cars with lots of belongings inside. Furthermore, visitors typically exhibit higher risk-taking behaviors by traveling to remote and unknown (unfamiliar) areas where they are usually not aware of potential dangers. They also create demand for other types of risky behaviors such as prostitution, drugs, and narcotics, and to top it all off, tourists as strangers to the indigenous community demonstrate conflicting behaviors in terms of clothing, talking, and acting (Chesney-Lind & Lind, 1986). Even though most studies have separated crimes against tourists from crimes against locals and have concluded that crimes against tourists seems to be significantly higher than the ones against locals, a few studies such as Barker et al. (2002) who proposed a statistical model for America's Cup Yacht Race sporting event, which was hosted between October 1999 and March 2000 in New Zealand, identified no significant differences in the victimization rate of domestic and international tourists. Rather they reported significant differences among different ethnicities and forms of accommodation. It is also stated that location and the structural attractiveness of the RTH facilities (e.g., crowded venues, late night working hours, lack of proper security prevention initiatives, and emergency training as cited in Chesney-Lind & Lind, 1986; Pizam, 2002, 2016a) are the key in tourism-crime analysis. Therefore, with only a few studies highlighting the salient role of location in tourism-crime analysis, this study contributes to the literature by systematically linking the evolution of 'policing models' to crimes at RTH venues from a spatio-temporal perspective. Furthermore, in the existing literature, the predictive policing model has only been discussed and used in relation to police-criminal activities. The study, however, suggests that predictive policing models can be used in conjunction with community policing models by providing information to the public, so they also actively participate in preventing crimes that have temporospatial patterns.

Broadly speaking, crime theories can be categorized into two groups: (1) theories focused on explaining offenders' behaviors, and (2) theories focused on criminal events (Baker & Stockton, 2014). There are quite a few crime theories that can be employed in RTH-related crimes analyses (e.g. rational choice, deterrence, routine activity, hot spot, social disorganization, anomie/strain, subcultural, symbolic interaction, etc.) (Burton & Crotts, 2014). Based upon the relevancy of crime theories to the purpose of this research, however, routine activity, hot spot, crime pattern, journey to crime, and rational choice theories were deemed appropriate to be used in this study.

In environmental criminology, routine activity theory focuses on opportunistic factors in an area (Suh et al., 2018). To be specific, routine activity theory suggests that the existence of the three elements of '*potential offenders*,' '*suitable targets*,' and '*absence of capable guardians*' (Burton & Crotts, 2014; Suh et al., 2018) are directly related to predatory crimes. Routine activity theory gave rise to another theoretical approach to environmental criminology known as the hot spot theory. According to hot spot theory, some places such as bars and shopping centers are more prone to crimes since large groups of potential victims are more attractive to criminals for their higher reward probability (Yu et al., 2016). Five factors of *being in a high-crime area*, *being out late at night*, *engaging in risky behaviors* such as drinking alcohol, *carrying valuables*, and *being without companions* are identified by hot spot theory as the predictors of victimization (Burton & Crotts, 2014). As will be discussed in the following sections, RTH related venues satisfy all three criteria of routine activity theory as well as most of the five factors of hot spot theory. Crime pattern theory combines the two aforementioned theories to explain the distributions of offenders, targets, handlers, guardians, and managers over time and place. In fact, crime pattern theory relates the routine activity theory to spatial patterns in crime (Haberman et al., 2018). This theory recognizes that certain criminal activities have spatial patterns that are repetitive. On this note, repetitive victimization and serial crimes with spatial qualities justify the use of predictive policing in RTH related settings which will be discussed in further detail in the next section. Journey to crime theory is based on the distance of the crime location from offender's habitat as well as the perceived time required to travel the distance. Finally, based on rational choice theory, place is critical in offender's selection of target and choice of means to achieve his/her goals (Baker & Stockton, 2014). Broadly speaking, offender's choice of location is determined by perceived differences in reward, effort, and risk (Boivin & D'Elia, 2017). The journey-to-crime and rational choice theories are employed to justify the temporospatial approach adopted by the current study to investigate the use of predictive policing in crimes that take place in RTH related settings.

2. Policing models

Random patrolling, rapid response, and reactive investigation have become the main operations of police departments from 1960s by the start of the professional era of policing. Later, in the 1990s, the community-policing model was introduced to focus on problem-solving through active public participation, partnership, and prevention (Beck & McCue, 2009). With the community-policing model gaining popularity, police departments started using geospatial data to map crimes (Hvistendahl, 2016). Next, intelligence-led policing (ILP), a research-based approach which focuses on the importance of information and communication technologies, was added to the previous models in the 2000s as a new pillar of police department operations. With the development of computational power and data storage capacity (Hvistendahl, 2016), the predictive policing model was suggested by the Los Angeles Police Department (LAPD) which took the ILP model one step further, and the practice of proactive actions substituted reactive actions for the very first time (Beck & McCue, 2009). "*Predictive policing refers to any policing strategy or tactic that develops and uses information and advanced analysis to inform forward-thinking crime prevention*" (Ferguson, 2012, p. 265). Two algorithms are actively used in big data predictive policing: (1) predicting potential offenders/victims with whom police contacts to deter, and (2) predicting crime hot spots based on the intelligent information police receives known as 'risk-based deployment', which increases police presence and surveillance to deter offenders (Hvistendahl, 2016). Based upon the second algorithm, the predictive policing model predicts potential future criminal incidents by using the time and location of present and past criminal activities (Friend, 2013). To be specific, the predictive policing model (i.e. proactive actions) allows police departments to pinpoint crime locations in real-time (Friend, 2013) by using big data analytics and cloud computation (Pearsall, 2010). The popularity and development of predictive policing has, however, not been without criticism. Some critics believe that the predictive policing model's efficiency and accuracy is incremental at best (Hvistendahl, 2016). Other critics state that although the decrease of crime rate is notable, predictive policing model instigates the emergence of racial prejudice among police officers towards citizens (Hvistendahl, 2016). More broadly, the issues that predictive policing model might cause with respect to the fourth amendment (Ferguson, 2012) are among the major concerns stand in the way of its development and use. It should be noted, however, that the concerns over the use of predictive policing in relation to the fourth amendment is not an issue in RTH related places because they are mostly considered as public spaces.

The suggestion for using the principles of community policing to solve tourism related crimes is not new and has been previously proposed in various occasions (for more information, see Sönmez et al., 1999; Tarlow, 2018). In fact, the adoption of community policing gave birth to the idea of tourism policing or to be more specific, tourism-oriented policing and protection services (TOPPs). In spite of all these efforts, however, there are usually no or minimal collaborations between police and tourism officials (Tarlow, 2014b), which has led to either the halt of the establishment process of TOPPs or a slowing of its growth. One of the reasons could be that principals and policy makers have mostly focused on police force as the only entity involved in action upon potential offenses and have neglected the important role of community-policing's *active public participation* in decreasing crime rates. Moreover, TOPP takes on different structures from being an entirely separate police force in some destinations such as Thailand to being part of the police departments in the US (Tarlow, 2000a, 2000b, 2011, 2014a). On this note, in case of the US, the police department structure can also be considered as a major issue in implementing TOPP efforts since there is no central system and less than 10% of public police force are national agencies with many local parallel state and county level entities (Mawby et al., 2015). More effective implementation of community policing in tourism is possible through predictive policing as emphasis is shifting from law enforcement, criminals, and industry stakeholders to criminal events/incidents and locations. In view of this, the present study, claims that it is possible to resurrect active public participation by regressing to community-policing doctrines and employing predictive policing's principles so the target population can actively participate in preventing crimes as well. Successful applications of these principles can reduce the crime rate significantly in tourism destinations as well as local communities.

3. Setting

The main source of US crime statistics is the criminal justice information services division of the Federal Bureau of Investigation (FBI). Most of the crime reports use the FBI's uniform crime reporting (UCR) program as the source of data which collects and provides statistics on two major types of crimes: (1) violent crime, which includes the offenses of murder and non-negligent manslaughter, rape, robbery, and aggravated assault, and (2) property crime, which includes the offenses of burglary, larceny-theft, motor vehicle theft, and arson (FBI, 2015).

Orlando, a world class destination located in Central Florida, also known as the world's theme park capital (Braun et al., 1992), is ranked the 89th the most dangerous city in the US with respect to violent crimes (Neighborhoodscout, 2017a). Although a ranking of 89 does not seem high, it certainly is a more dangerous tourist destination compared to the lower section of the list. With a crime rate of 70 per thousand residents, indicating that there is a 1 in 14 chance for an individual to become a crime victim, Orlando has one of the highest crime rates in Florida as well as America (Neighborhoodscout, 2017b). In fact, with its crime index of 2, Orlando is only safer than 2% of US cities (Neighborhoodscout, 2017b). In terms of violent crimes, Orlando has one of the highest murder rates of the nation. Similarly, the property crime rate (e.g., motor vehicle theft) in Orlando is as high as 61 per thousand population which is a higher rate compared to Florida (28 per thousand) and the US national median (26 per thousand). This information underlines that in such a crime-prone environment, predictive policing is a necessity and needs to be paired with community-policing models for a synergic outcome. Tourists and locals should be informed about the probability, types, time, and location of offenses so that they make wiser decisions during their trip.

4. Data

In this study, the times, locations, and types of offenses were profiled by using 160,947 structured observations of Orlando police public records from 2009 to 2015 (https://data.cityoforlando.net/). There were 73 locations in the database which, for the purpose of the current study, were grouped into nine categories (Table 1). The group 'Resident' with 58,252 (36.2%) crime records was the biggest category followed by 'Transportation' (22.3%) and 'Retail' (22%). The 'Industrial' category, on the other hand, was the smallest category with only 1320 (0.8%) crimes recorded.

The dataset also included 24 types of offenses that are grouped into 12 categories (Table 2). 'Theft' with 78,145 (48.6%) records was the

Table 1
Frequencies of crime locations and location categories in Orlando from 2009 to 2015.

	Location	Frequency			Location	Frequency			Location	Frequency	
I	**Education**	**2911**	**(1.81%)**	23	*Park/Woodlands/Field*	1717	(1.07%)	49	*Flower Shop*	16	(0.01%)
1	*School/University*	2911	(1.81%)	24	*Recreation Facility*	1080	(0.67%)	50	*Furniture Store*	87	(0.05%)
II	**Financial Institution**	**1781**	**(1.11%)**	25	*Restaurant (Fast Food)*	1250	(0.78%)	51	*Gas Station*	1420	(0.88%)
2	*ATM/Night Depository*	109	(0.07%)	26	*Restaurant (Other)*	2472	(1.54%)	52	*Hardware Store*	242	(0.15%)
3	*Bank/Financial Inst.*	1672	(1.04%)	27	*Restaurant (Pizza)*	234	(0.15%)	53	*Jewelry Store*	101	(0.06%)
III	**Industrial**	**1320**	**(0.82%)**	28	*Theater*	124	(0.08%)	54	*Laundromat*	152	(0.09%)
4	*Construction Site*	803	(0.50%)	29	*Theme Park*	2753	(1.71%)	55	*Lawn/Garden Shop*	17	(0.01%)
5	*Industrial/Mfg*	517	(0.32%)	**VII**	**Resident**	**58252**	**(36.19%)**	56	*Liquor Sales*	339	(0.21%)
IV	**Medical**	**2561**	**(1.59%)**	30	*Apartment/Condo*	32810	(20.39%)	57	*Mall*	3362	(2.09%)
6	*Doctor's Office/Dental Office*	516	(0.32%)	31	*Residence/Other*	1602	(1.00%)	58	*Other Repair Facility*	29	(0.02%)
7	*Drug Store/Hospital*	1900	(1.18%)	32	*Residence/Single*	22901	(14.23%)	59	*Pawn Shop*	102	(0.06%)
8	*Pharmacy/Rest Home*	145	(0.09%)	33	*Vacant Apartment or Condo*	231	(0.14%)	60	*Shoe Store*	186	(0.12%)
V	**Other**	**2805**	**(1.74%)**	34	*Vacant; House*	708	(0.44%)	61	*Speciality Store*	2289	(1.42%)
9	*Cemetery/Graveyard*	3	(0.00%)	**VIII**	**Retail**	**35451**	**(22.03%)**	62	*Sporting Goods*	99	(0.06%)
10	*Government/Public Bldg*	979	(0.61%)	35	*Antique Store*	13	(0.01%)	63	*Storage (Commercial Only)*	370	(0.23%)
11	*Jail/Prison*	254	(0.16%)	36	*Auto Dealer/Car Lot*	674	(0.42%)	64	*Supermarket*	2473	(1.54%)
12	*Laundry Room; Apt. or Condo.*	36	(0.02%)	37	*Auto Parts Store*	157	(0.10%)	65	*Vacant; Commercial*	163	(0.10%)
13	*Other*	405	(0.25%)	38	*Auto Repair Shop*	426	(0.26%)	66	*Video Store*	26	(0.02%)
14	*Other Mobile*	57	(0.04%)	39	*Barber/Beauty Shop*	205	(0.13%)	**IX**	**Transportation**	**35925**	**(22.32%)**
15	*Other Structure*	234	(0.15%)	40	*Camera Store/Photomaton*	4	(0.00%)	67	*Airport*	5215	(3.24%)
16	*Religious Bldg*	686	(0.43%)	41	*Clothing Store*	1112	(0.69%)	68	*Bus/Rail Terminal*	1272	(0.79%)
17	*Unknown*	151	(0.09%)	42	*Commercial/Office Bldg*	7276	(4.52%)	69	*Highway/Roadway/ Sidewalk*	21117	(13.12%)
VI	**Recreation/Tourism & Hospitality**	**19941**	**(12.39%)**	43	*Computer Store*	28	(0.02%)	70	*Motor Vehicle*	1888	(1.17%)
18	*Arcade/Game Room*	6	(0.00%)	44	*Convenience Store*	3808	(2.37%)	71	*Parking Garage*	1164	(0.72%)
19	*Arena/Stadium*	289	(0.18%)	45	*Delivery Vehicle (beer; pizza; etc.)*	17	(0.01%)	72	*Parking Lot*	5154	(3.20%)
20	*Bar/Nightclub*	5268	(3.27%)	46	*Dept/Discount Store*	9699	(6.03%)	73	*Taxicab*	115	(0.07%)
21	*Hotel/Motel*	4730	(2.94%)	47	*Dry Cleaners*	60	(0.04%)				
22	*Lake/Waterway*	18	(0.01%)	48	*Electronics/Stereo Store*	499	(0.31%)				

Table 2
Frequencies of offense categories in Orlando from 2009 to 2015.

Offense Category	Frequency	
Theft	78145	(48.55%)
Burglary	24263	(15.08%)
Narcotics	18393	(11.43%)
Assault	17026	(10.58%)
Fraud	10372	(6.44%)
Vehicle Theft	7637	(4.75%)
Robbery	4624	(2.87%)
Arson	244	(0.15%)
Homicide	109	(0.07%)
Kidnapping	83	(0.05%)
Embezzlement	48	(0.03%)
Bribery	3	(0.00%)

biggest offense category, followed by 'Burglary' (15.1%) and 'Narcotics' (11.4%). The 'Bribery' category, on the other hand, was the smallest category with only three records. All of the records in the dataset also included the times, dates, and locations' longitude and latitude of offenses. Since there were some similarities among the technical terms used to explain crime categories, a glossary is included in Appendix A (Glossary), which explains all the offense terminologies that have been used in this study.

Before moving to the data analysis, there are two critical issues that need to be addressed. The first is related to the type of data and whether it is big data. The characteristics of big data were initially introduced as volume, velocity, and variety but later on were expanded to include the three more qualities of veracity, variability, and value (Gandomi & Haider, 2015). It may be argued that the data used in this study do not include all of the above-mentioned qualities and therefore are not big data. However, in terms of volume, it is possible to discount the issue due to the sample size (number of rows) of the study. To be specific, although the file size of the current study does not meet the volume characteristic of big data (i.e., terabyte, petabyte), from the sample size perspective, 161,000 records is not a small sample size as, statistically speaking, anything larger than 300 or 500 observations is considered to be a large sample size (Khalilzadeh & Tasci, 2017). Regarding the variety characteristic of big data, the database in hand focuses on structured data, which constitutes 5% of big data (Gandomi & Haider, 2015). The other forms of available data on police records of crimes were unstructured textual descriptions which were not included in this study solely because their nature does not match the study focus. Regarding the velocity characteristic of big data which is about the rate of data generation and analysis, the data of this study does not satisfy this specific characteristic; to be specific, as the data of the current study is limited to the timeline of 2009–2015, it is not real-time data. That being said, it is not a major issue, since the primary purpose of this study is to demonstrate that it is possible to apply the principles of predictive policing and doctrines of community policing to reduce the crime rate of RTH locations. In fact, it is possible to conduct and repeat the entire analyses of this study with the real-time data. Concerning the veracity characteristic of big data, since the data of this study are structured and from police records, it is possible to claim that the dataset is reliable and meets this specific criterion. In addition, variability is controlled in this study due to the limited time frame and the fact that the models were re-validated through repetition of different years. Finally, the value of big data can be discussed based on the results and findings of the current study to see if it offers any added value to be adopted and practiced. Despite the arguments above and regardless of the terminology used (whether big data or open data), the results and reality will not change much since the changes in volume, velocity, etc. is a matter of technicality rather than conceptuality. The second issue that needs to be addressed is that in big data, there is a high likelihood of making a Type I error and rejecting the non-false null hypothesis. In other words, there is a high probability of finding a statistical significance when in reality, it is not practically significant. Therefore, as a measure of effect size, the raw number of cases along with their proportions and statistical results are considered while conducting the analysis (Khalilzadeh & Tasci, 2017).

5. Analysis

In big data literature, the advantages of decision tree predictive models over other modeling techniques have been highlighted (see Pokryshevskaya & Antipov, 2017; Varian, 2014). On the subject of this study, decision trees can act as early warning systems for visitors by profiling the offense and location categories. In this study, the two families of classification and regression (CART or CRT) and chi-square automatic interaction detection (CHAID) growing algorithms are used (For more information on CHAID and CRT decision trees refere to Chen, 2003; Díaz-Pérez & Bethencourt-Cejas, 2016; Legohérel et al., 2015). The variables of time of day, year, offense location, and offense type are employed to classify and build the crime predictive models for RTH locations. There were four main trees used in this study. Two of them were grown by using the CRT algorithm: once with location as the dependent variable and once with offense as the dependent variable. The other two trees were then grown by using the CHAID algorithm with the same variables to provide more insights (details) into the predictive models. To train the algorithm, first, the models were built by using half of the data, and then the test model was examined using the other half. Finally, to cross validate the models, the final CHAID and CRT models of the entire dataset were run with the data of different years to spot any discrepancies.

6. Findings

Table 3 shows the frequency of crime categories for each location. Similar to Table 2, in most locations, theft, burglary, assault, narcotics, and fraud are among the most common offenses. Concerning the average number of records per year in RTH locations, theft (59.2%) and assault (17.1%) are the two major offenses followed by fraud (7.4%), burglary (6%), narcotics (5%), robbery (2.9%), and vehicle theft (2.2%). As Table 3 shows, the effect size of the share of homicide, arson, kidnapping, embezzlement, and bribery constituted less than 0.1%. It should be noted, however, that these offense categories are among the rare records in all locations.

The initial tree, built with the **CRT** growing algorithm and with the *offense categories* as the dependent variable, resulted in a tree with maximum depth of 5 and 41 nodes of which 21 are terminal. The test model risk ratio is 0.511 with a standard error of 0.002. As shown in Fig. 1, the results suggested the two location categories of transportation and all other locations that are different with regards to crime frequency. The other location category was then further divided into resident and financial institutions versus remaining locations (improvement = 0.026). Next, the remaining locations were divided by time. According to the CRT model, assault (36.7%) and theft (33.6%) mostly occured before 7:56 a.m. in RTH locations (improvement = 0.002). After 7:56 a.m., assault and theft were also the most frequent crimes in RTH locations (improvement = 0.001); the main difference being that the frequency of theft (64.1%) was much higher than assault (12.5%). Additional investigations on time of day further showed that, on the one hand, theft (45.4%), burglary (17.1%), and assault (16.5%) were the most-frequent three offenses in RTH settings between 3:10 a.m. and 7:56 a.m., on the other hand, assault (47.4%) and theft (27.4%) were the two major offenses in RTH locations before 3:10 a.m. On a similar note, between 7:56 a.m. and 9:30 p.m., theft (66.3%) and assault (11.2%) were the most-frequent crimes in RTH venues. After 9:30 p.m., the pattern was similar to before 9:30 p.m., with the difference that the rate of assault substantially increased (from 11.2% to 22.2%) while the rate of theft substantially decreased (from 66.3% to 47%) (see Fig. 1 for more information).

Table 3
Frequency of crime categories in each location category.

	Education		Financial institution		Industrial		Medical		Recreation/Tourism & Hospitality		Resident		Retail		Transportation		Other	
Overall	**2911**	**(1.81%)**	**1781**	**(1.11%)**	**1320**	**(0.82%)**	**2561**	**(1.60%)**	**19941**	**(12.43%)**	**58252**	**(36.31%)**	**34952**	**(21.78%)**	**35925**	**(22.39%)**	**2805**	**(1.75%)**
Arson	9	(0.31%)	0	(0.00%)	3	(0.23%)	5	(0.20%)	12	(0.06%)	94	(0.16%)	20	(0.06%)	92	(0.26%)	9	(0.32%)
Assault	753	(25.87%)	28	(1.57%)	36	(2.73%)	334	(13.04%)	3414	(17.12%)	5503	(9.45%)	1268	(3.63%)	5416	(15.08%)	267	(9.52%)
Bribery	0	(0.00%)	0	(0.00%)	1	(0.08%)	0	(0.00%)	1	(0.01%)	0	(0.00%)	0	(0.00%)	0	(0.00%)	1	(0.04%)
Burglary	192	(6.60%)	29	(1.63%)	388	(29.39%)	162	(6.33%)	1192	(5.98%)	19093	(32.78%)	2674	(7.65%)	72	(0.20%)	385	(13.73%)
Embezzlement	0	(0.00%)	4	(0.22%)	1	(0.08%)	6	(0.23%)	3	(0.02%)	3	(0.01%)	27	(0.08%)	0	(0.00%)	4	(0.14%)
Fraud	26	(0.89%)	1295	(72.71%)	21	(1.59%)	265	(10.35%)	1466	(7.35%)	2498	(4.29%)	3750	(10.73%)	737	(2.05%)	235	(8.38%)
Homicide	1	(0.06%)	0	(0.00%)	0	(0.00%)	1	(0.04%)	13	(0.07%)	47	(0.08%)	8	(0.02%)	39	(0.11%)	0	(0.00%)
Kidnapping	1	(0.03%)	1	(0.06%)	1	(0.08%)	1	(0.04%)	10	(0.05%)	20	(0.03%)	7	(0.02%)	39	(0.11%)	3	(0.11%)
Narcotics	188	(6.46%)	16	(0.90%)	5	(0.38%)	76	(2.97%)	1024	(5.14%)	2855	(4.90%)	887	(2.54%)	13036	(36.29%)	303	(10.80%)
Robbery	37	(1.27%)	117	(6.57%)	5	(0.38%)	44	(1.72%)	581	(2.91%)	1069	(1.84%)	605	(1.73%)	2131	(5.93%)	25	(0.89%)
Theft	1673	(57.47%)	286	(16.06%)	808	(61.21%)	1635	(63.84%)	11797	(59.16%)	22705	(38.98%)	24848	(71.09%)	12558	(34.96%)	1512	(53.90%)
Vehicle Theft	32	(1.10%)	4	(0.22%)	51	(3.86%)	32	(1.25%)	428	(2.15%)	4365	(7.49%)	858	(2.45%)	1805	(5.02%)	61	(2.17%)

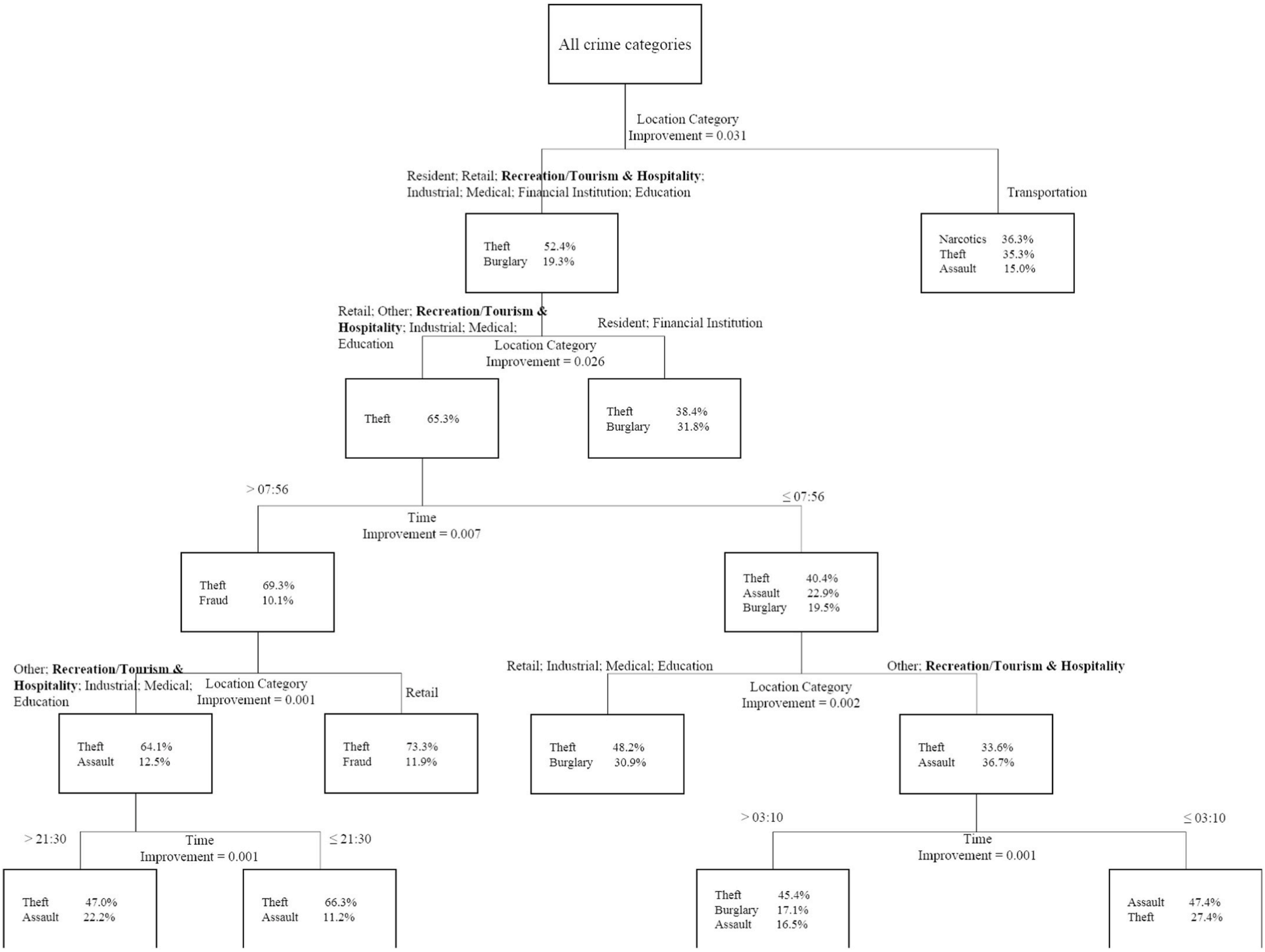

Fig. 1. *The CRT model with crime categories as the dependent variable (only relevant nodes are included).*

In order to test the results of the initial model, a second model was developed using the **CRT** growing algorithm and *location categories* as the dependent variable, which resulted in a tree with maximum depth of 5 and 45 nodes of which 23 are terminal. The test model risk ratio is 0.457 with a standard error of 0.002. In the initial step, assault, narcotics, fraud, theft, robbery, homicide, arson, kidnapping, embezzlement, and bribery were separated from burglary and vehicle theft categories (improvement = 0.045). In the second step, assault, fraud, theft, embezzlement, and bribery were separated from the other categories (improvement = 0.036). Finally, in the third step, assault and bribery were separated from fraud, theft, and embezzlement (improvement = 0.008).

Time of day, again, was the next significant divisor of the CRT model, splitting assault and bribery into two classification of before and after 3:47 a.m. Before 3:47 a.m., transportation (39%), RTH (35.7%), and resident (19.6%) were the most common places for assault and bribery offenses. After 3:47 a.m., however, resident (36.8%) followed by transportation (30.1%) and RTH (13.8%) were the three most-frequent locations. Next, time of day was used again to further divide the before and after 3:47 a.m. categories. Before 3:47 a.m. was divided to before 2:11 a.m. and after 2:11 a.m. Before 2:11 a.m., RTH (42%) was the location with the highest rates of assault and bribery. After 2:11 a.m., however, the rate of assault and bribery in RTH dropped to make it the second location (28.7%) following transportation (47.6%). After 3:47 a.m. was also divided to before 5:11 p.m. and after 5:11 p.m. In both of these time intervals, RTH had the lowest rate of assault and bribery compared to residents and transportation locations. Time of day as the further divisor of the CRT model into two categories of before and after 11:27 a.m. for fraud, theft, and embezzlement offenses showed that in these two time intervals, RTH was the fourth (14.9%) and third (15.1%) most-frequent location for these offenses respectively (see Fig. 2 for more information).

Fig. 3 shows the results of the third tree, built by the **CHAID** growing algorithm and employment of *location categories* as the dependent variable (χ^2 (56) = 37,702.5, $\rho < 0.001$). This tree has a maximum depth of 3 with 100 nodes of which 74 are terminal. The analysis shows that the test model risk ratio is 0.511 with standard error of 0.002. Among the four crime types of narcotics, theft, fraud/embezzlement/bribery, and assault/homicide, RTH locations were the major target of the last three with records of 15.4%, 14.7%, and 20% respectively.

The theft category can be further divided to three groups by time: before 3:43 a.m., 1:53 p.m. to 5:08 p.m., and after 9:15 p.m. (χ^2 (64) = 2732.8, $\rho < 0.001$). According to Fig. 3, the results show that the highest rate of theft offenses in RTH venues belongs to the time interval of 9:15 p.m. to 3:43 a.m. Nevertheless, when looking at the absolute value of the theft records, it is evident that most of thefts in RTH venues occurred between 1:53 p.m. to 5:08 p.m.; however, because the growth of theft in other locations (e.g., retail and residents) are much higher than RTH locations, the percentage rate of theft in RTH locations between 1:53 p.m. to 5:08 p.m. was perceived lower compared to the other two time

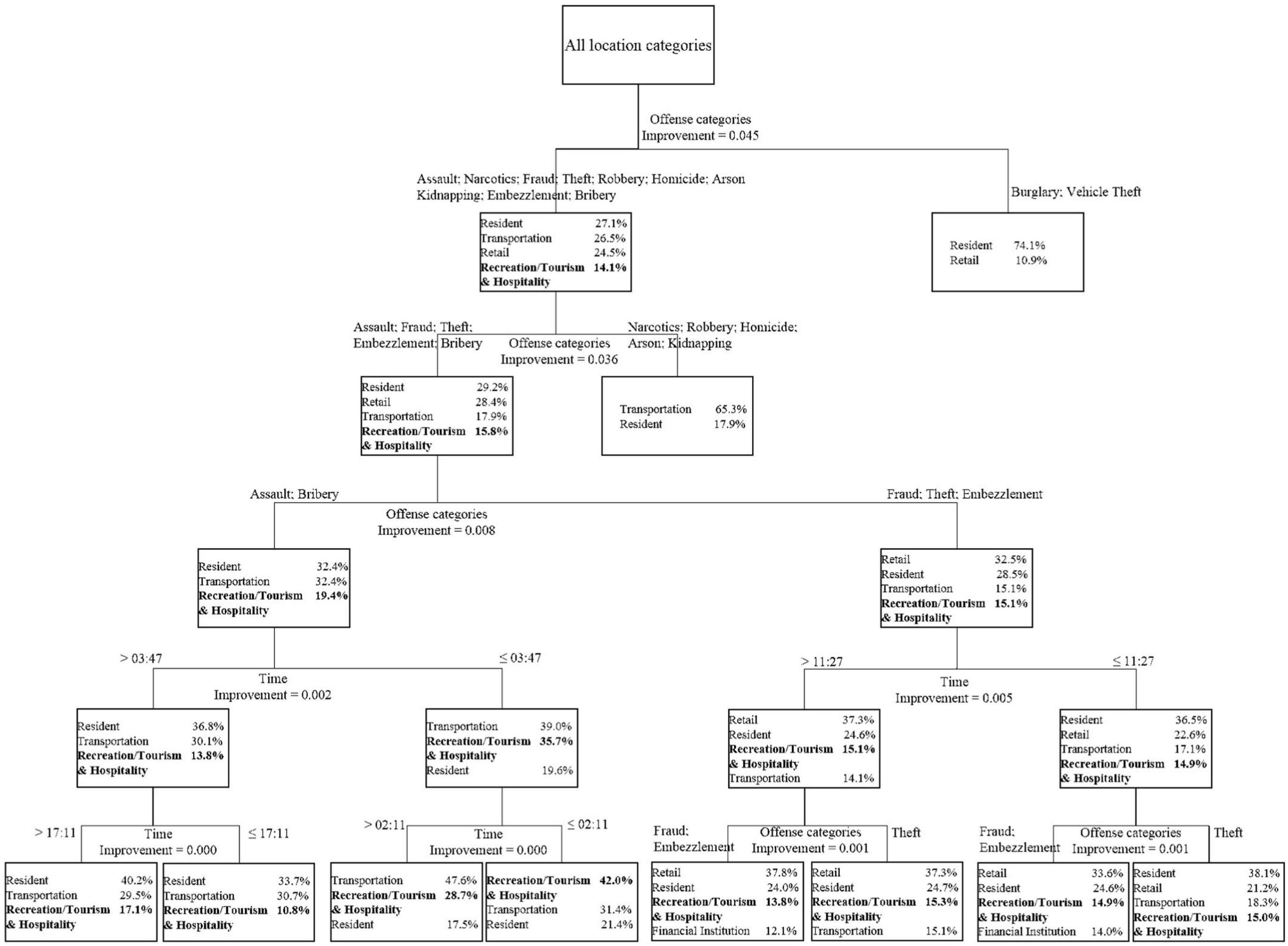

Fig. 2. *The CRT model with location categories as dependent variable (only relevant nodes are included).*

intervals.

The category of fraud/embezzlement/bribery can be further divided to four time-intervals: before 3:43 a.m., between 12:25 p.m. to 5:08 p. m., between 7:02 p.m. and 9:15 p.m., and after 9:15 p.m. (χ^2 (48) = 635.8, $\rho < 0.001$). Before 3:43 a.m., between 7:02 p.m. to 9:15 p.m., and after 9:15 p.m., RTH locations with 60.6%, 31.2%, and 49.7%, respectively, were the most unsafe places to be in concerning the fraud/embezzlement/bribery offenses. With regards to the time interval of 12:15 p.m. to 5:08 p.m., the analysis shows that the patterns of fraud/embezzlement/bribery related offenses can be further split based upon date (i.e., month and year): before October 2011, between October 2011 and June 2012, between June 2012 and November 2013, and after November 2013 χ^2 (24) = 150.3, $\rho < 0.001$). The findings indicate that the number of fraud/embezzlement/bribery records in RTH venues before October 2011 (12.1%) was higher than the records of the years after. On this note, it is worth mentioning that the same pattern applies to locations of financial institutions, retail, resident, transportation, medical, and others, indicating that the police department and/or social institutions are successful in controlling these offenses.

The category of assault/homicide can be divided to three classifications based upon time: before 3:43 a.m., between 8:41 a.m. to 1:53 p.m., and after 9:15 p.m. (χ^2 (40) = 1388.7, $\rho < 0.001$). Before 3:43 a.m., RTH (37.7%) was the most unsafe location in terms of assault/homicide offenses. During daytime (i.e., 8:41 a.m. to 1:53 p.m.), the rate of assault/homicide offenses in RTH locations significantly decreased but picks up again after 9:15 p.m. Regarding the time interval of 8:42 a.m. to 1:53 p. m., the analysis shows that the patterns of assault/homicide offenses can be further split by date (month and year): before November 2013 and after November 2013 (χ^2 (8) = 30.6, ρ = 0.001). Although after November 2013, the number of assault/homicide records in RTH locations were less than those of before November 2013, the share of assault/homicide records in RTH locations had increased from 8.4% to 12.7%. It should be noted that the reason for fewer records of assault/homicide after November 2013 is only due to the shorter time period of observations used in this study, from 2009 to 2015 (see Fig. 3 for more information).

Finally, the fourth tree model was built by using the **CHAID** growing algorithm with *offense categories* as the dependent variable (χ^2 (99) = 37,735.7, $\rho < 0.001$). The result is a tree with a maximum depth of 3 and 109 nodes of which 81 were terminal. The test model risk ratio is 0.456 with a standard error of 0.002. Fig. 4 shows the results of CHAID for RTH venues which can further be developed by including time of day (χ^2 (60) = 2329.3, $\rho < 0.001$). While assault (48.2%) was the major crime before 3:38 a.m., it was one of the fewest occurred offenses between 8:41 a.m. to 10:34 a.m. (3.8%). On the contrary, theft, which was one of the least frequent offenses before 3:38 a.m. (28.9%) became the main offense in all other time intervals. The findings further show that after 9:14 p.m. (9.9%), before 3:38 a.m. (8.1%), and between 5:07 p.m. to 9:14 p.m. (6%), narcotics was at its highest rate in RTH locations. Fraud was also in its highest rate in RTH venues, with an average proportion of 8.2%, between the time interval of 10:34 a.m. to 9:14 p.m. Further analysis shows that date (month and year) was also a significant divisor of offenses for some of the time intervals. For instance, for the time period of before 3:38 a.m., the date divided the offenses into two groups of before

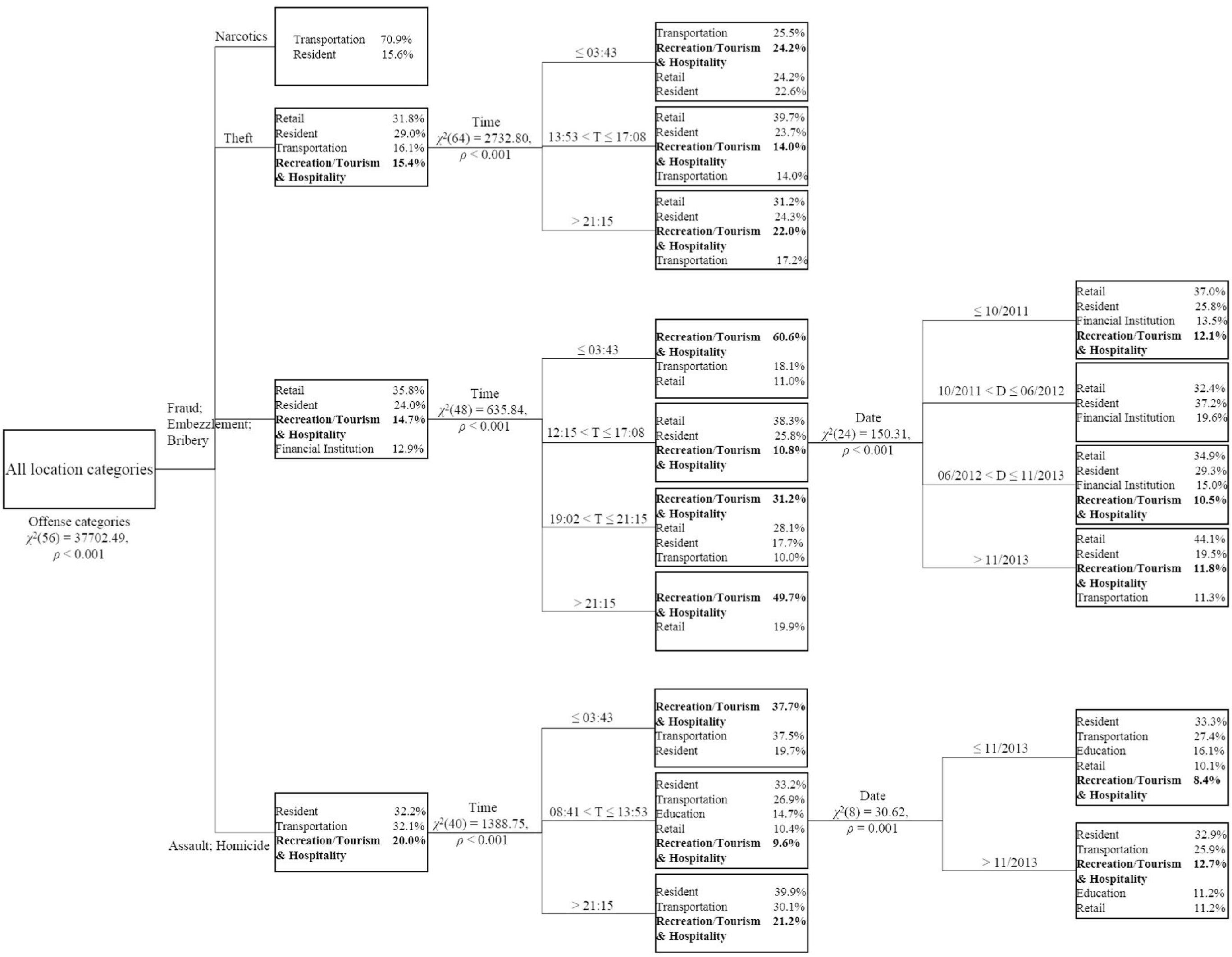

Fig. 3. The CHAID model with location categories as dependent variable (only relevant nodes are included).

April 2015 and after April 2015 (χ^2 (7) = 26, $\rho = 0.005$). The findings show that whereas assault held a more or less similar share of crime before and after April 2015, theft held a higher share after April 2015 (37.2%) compared to before April 2015 (28.1%) (see Fig. 4 for more information).

6.1. Further comments

1 Crimes can take place at any locations and at any time. However, the nature of crimes in various locations could be different which calls for a careful investigation. For instance, with regards to fraud, automated teller machine (ATM) fraud is prevalent in retail and financial institutions, while credit card fraud is high in RTH locations. On a similar note, shoplifting is the major theft in retail, purse snatching and robbery are more likely to occur in transportation, robbery and burglary are more prevalent in the resident category, and pickpocketing and theft from coin-operated machines are the main types of thefts in RTH. The assault category can also be broken down into aggravated assault and simple assault. With regards to aggravated assault, the resident and transportation locations, compared to all other locations including RTH, are more prone to be subjected to such offenses between 4 a.m. and 9 p.m. and before 4 a. m., respectively. Simple assault, however, can occur in any of these two locations (i.e. resident and transportation) as well as RTH venues regardless of time of day. It is important to note that there is no separate categorization for sexual assault in the database and so, as most of the assaults in RTH settings fall into the category of simple assault, it is possible to claim that sexual assault is relatively lower than what is expected in a tourist destination. That being said, it should be noted that in the current study, airport, taxi and parking lots are considered as transportation. This means that had we added these records to RTH instead, the crime rate would have increased in the assault category as well as homicide and narcotics.

2 As previous studies have mentioned, drugs/narcotics and prostitution are part of a tourism destination (Yan et al., 2017). While there were no available records for prostitution in the database we used, about 5% of all offenses in Orlando's crimes in RTH fit into the drug/narcotics category. Five percent in drug/narcotics crime is a low statistic considering that Orlando is one of the major tourist destinations. It should be noted, however, that although Orlando is a significant tourist destination, it has a family-oriented nature which explains the lower number of drug/narcotics records (Kim et al., 2013).

3 Looking into the similarities of offense types in RTH settings can provide further insights on police interventions' effectiveness. For example, in terms of burglary, the year 2011 was not different from 2014 in the time interval that burglary reaches its highest point. In a similar vein, when theft was divided to before and after May 2010, it became evident that the share of theft is more or less the same for both time stamps, which means that throughout different years, the

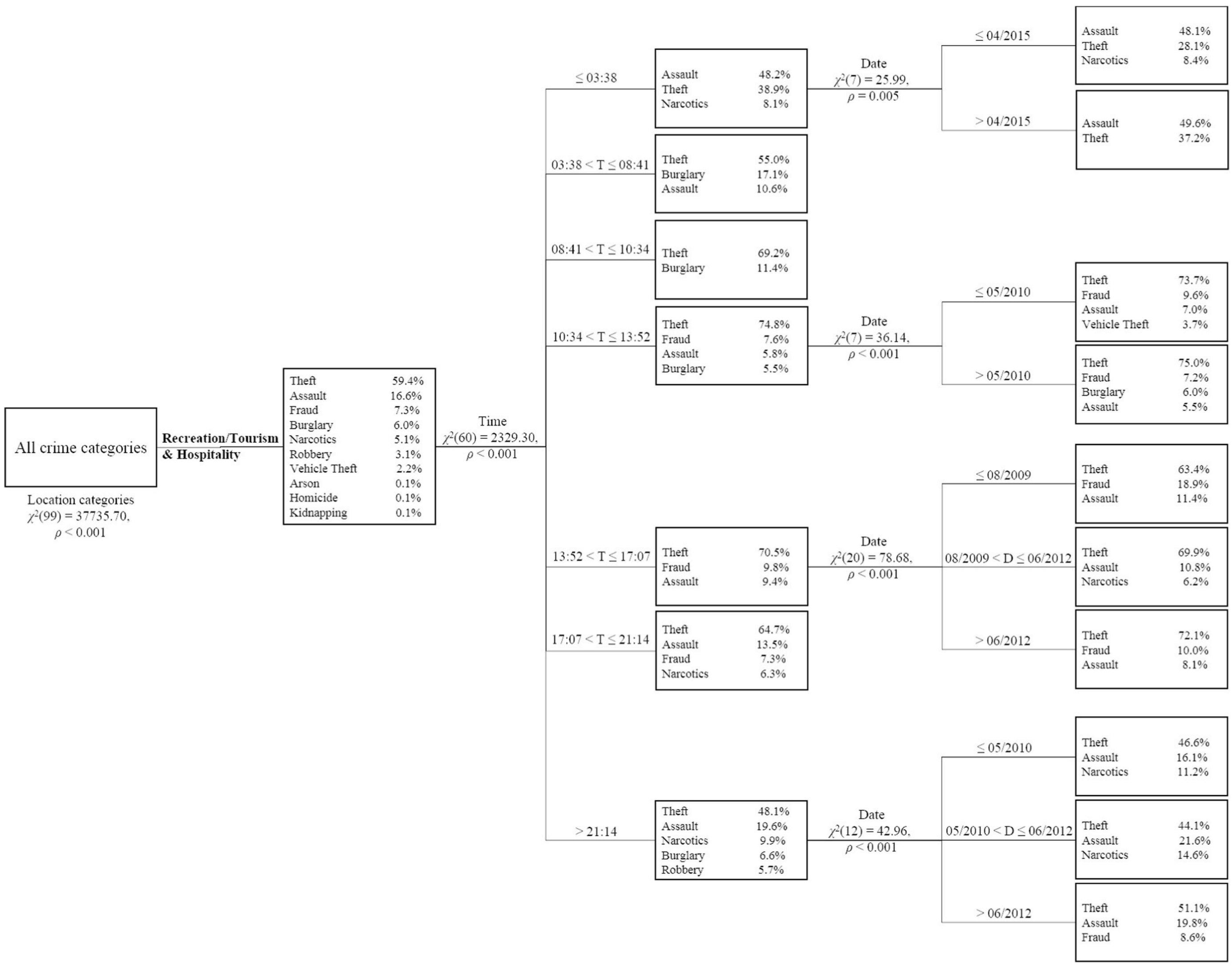

Fig. 4. The CHAID model with crime categories as dependent variable (only relevant nodes are included).

pattern of theft records has remained the same. These similarities in temporospatial patterns of crimes can be attributed to lack of successful interventions by law enforcement which calls for their further attention.

7. Discussion

From a demand perspective, the world population is ageing, and senior citizens are the future of tourism markets (Tarlow, 2019). Seniors demand higher security level (Tarlow, 2019), making safety and security a critical element of destination competitive advantage (Wilks, 2011). Some destinations (e.g. the US) have failed to show adequate measures of safety and security and, trust in reliability of police services is on a declining path (Blanke & Chiesa, 2009; Calderwood & Soshkin, 2019). Furthermore, efforts to develop TOPPs are in most cases either abandoned or growing slowly, which has led to considerable security issues for destinations. As a result of this mismatch between demand and supply, crime control and tourism policing have become major challenges for most destinations in the US.

Proactive and prevention policing, compared to reactive policing, have always been a preferred approach for destinations (Tarlow, 2014b). The benefit of educating visitors and locals (i.e., increasing their awareness) in assisting the parties who are responsible for prevention implementation is emphasized by Pizam (1999) as one of the strategies to deal with tourism destination crimes. Stated differently, public education of both tourists and the local community is considered as the most effective measure in ensuring safety and security. Distributing brochures with safety tips at destinations' port of entry and accommodations, and utilizing media, billboards, and school programs are mentioned as available tools for public safety education (Albuquerque & McElroy, 1999). Despite all these suggestions, however, public education and locals'/visitors' active participation in community policing have been completely ignored in practice.

As stated in the overview section, recent racial tensions and social unrest due to brutal police encounters revealed what has been described as the broken culture of the US policing system (Brooks, 2020). Apart from 'a few bad apples' and 'systematic racism' theories that are used to explain police racial injustice (Brooks, 2020), paramilitary tactics as a common practice in law enforcement agencies (Clayton et al., 2014) have caused escalation of minor confrontations to use of lethal force in many cases (Clayton et al., 2014). Needless to say, preventive acts can deescalate fatal situations to a great extent through confrontation avoidance. Amidst concerns over the use of predictive policing (for more information see section: policing models), it should be noted that predictive policing is only a method or an approach at best, and the way it is used determines the outcome. If predictive policing is used with the current toolbox of police force and without any changes in procedures and policies, it can potentially result in visitor/guest harassment (for examples of tourist harassment by police, see McElroy et al., 2007). Predictive policing, however, can enhance the long-term resilience of destinations by fostering the formation of TOPP either in form of tourism specific operations or in form of separate tourism police units (Mawby et al., 2015) if law enforcement agencies, tourism stakeholders, and locals collaborate together for the common purpose of crime prevention and reduction (Pizam et al., 1997; Tarlow & Santana, 2002). The findings of the current study, similarly, signify that predictive policing in conjunction with community policing can further prevent and reduce the occurrence of crimes in RTH venues with crimes in these settings having temporal patterns (weekly and hourly according to this study). Although the current practice of deploying the police to certain areas with high likelihood of crime occurrence during a specific time reduces crime instances, providing similar information to the crime target population (herein, tourists and visitors) can therefore further reduce the crime rate as they would be more cautious or even avoid certain areas at specific times. In view of this, destination management organizations (DMOs) can use the methods and results of the current study to not only increase the success rate of predictive policing but also to significantly reduce the number of offenses in RTH locations by engaging visitors and local communities. When providing information, however, it must be instructed that locals/visitors should never interrupt and/or interfere with police tasks.

The findings of this study can further be utilized to reduce crimes in a rather unconventional way. It has been previously discussed that increase in number of visitors results in higher crime rate (Boivin & Felson, 2018). Nevertheless, there are empirical studies showing that increase in inflow of visitors might result in increase of guardianship in crime-prone areas (Boivin, 2018), which in turn results in the reduction of crime rate (Traunmueller et al., 2014). Stated differently, increase in the inflow of visitors, to some extent, can contribute to the notion of *defensible* space in RTH venues (as discussed in overview) by enhancing the sense of guardianship. Accordingly, for the findings of this study on crimes that take place between 9 p.m. and 3 a.m., it can be argued that improvement of quality of night life would attract more individuals which in turn increases the sense of guardianship and reduces crime incidence probability. It should be noted, however, that type of crime, type of location, and time of day should be carefully taken into consideration as they influence the strategies of crime reduction.

7.1. Limitations

The choice of accommodation type is shown to have a significant impact on the type of crime a visitor may experience. For example, tourists who prefer homestays over hotels are more likely to experience criminal acts such as phone snatching and verbal assault (Boakye, 2010). With the development of the sharing economy accommodations (e.g. Airbnb) and their increasing popularity, differentiating the crime statistics of residential locations from RTH locations have become more difficult. In other words, due to the nature of the available data for the current study, it was not possible to achieve an estimate of the number of crimes in residential locations where visitors (e.g. Airbnb guests) were the victims and not the locals. As a result, it was not appropriate to combine the residential locations with other RTH locations as it would have made the predictive model less accurate. Using a database with information on victims and a clear indication as to whether the victim was a visitor or a local can significantly improve the quality of a decision tree model.

For simplification purposes and to save on analysis time, wording, and space concerns, I condensed the crime locations from 72 categories to nine and used offense categories instead of offense types. The findings, nevertheless, confirmed the existence of distinct patterns of location, type, and time of RTH-related crimes in comparison to other locations. Similarly, to make the results manageable, the maximum depth of trees was limited to three and five for CHAID and CRT growing algorithms respectively, which makes the results partial in terms of tree growth. Therefore, future studies should use bigger categories with more iterations and larger maximum depths to obtain more accurate data and profiles. Moreover, 12 different locations were bundled together which made up the category of RTH. Not all these locations, however, were homogenous with regards to crime type. As shown in Table 1, different types of restaurants were combined with theater, theme parks, hotels, arenas and lakes. As a result, finding homogenous subsets in growing trees became more difficult to achieve. For example, whereas in the time interval of 9:00 p.m. to 3:00 a.m., the rate of simple assault is about 30% in bar/nightclubs, the rate of assault in theme parks is about 4%. This variance in rates is because fewer people in theme parks are as intoxicated as individuals in bar/nightclubs. Also, the operation hours of theme parks are the other reason for the low rate of crime during the above-mentioned timeline. Future studies, therefore, should adopt more homogenous subsets of RTH industry to deliver more accurate results, considering that there are more detailed public datasets available. For example, future studies can include day of the week, and locations' longitudes and latitudes.

Previous studies have suggested that tourism shapes cities over time such that touristic cities become significantly different from other urban areas in respect to frequency of crimes. The reason for this difference is the increase in the number of arterial roads, amount of public spaces, and other environmental/structural factors, as well as tolerance of the host community (Jackson et al., 2011). On this note, the approach of this study to focus on locations only might have mitigated the impact of the above-mentioned factors on crime frequency to some extent. Therefore, it would be more realistic if some of these environmental variables are added to the model in future studies. Moreover, crime type, itself, creates a major issue in generalizability of findings; Predictive policing is not a one-size-fits-all solution for all types of crimes, meaning that when applying predictive policing techniques, the type of crime in which the destination is interested should be predetermined and critical factors related to that specific type of crime should be included in the model. Doing so increases the accuracy of the model, which in turn decreases the potentials for prejudice and/or visitor harassment. For example, as indicated previously, due to several differences between terrorism and other types of crime, variables such as potential for mass casualties, media coverage, potential economic damage, potential for creating fear, anger and depression should be included in terrorism modeling (Tarlow, 2006b), while most of these criteria are unnecessary for modeling crimes such as larceny or theft. Future studies should thus incorporate context-specific criteria to capture context-related data in their models.

It should be noted that open data with public police records was used in this study. Police datasets have high propensity to bias especially when it comes to RTH. For instance, there are offense cases that police authorities have failed to register because the crime has taken place against a tourist/visitor rather than a local (Lisowska, 2017). Another example is numerous underreported RTH crimes due to plenty of reasons including the duration it takes the tourist to realize victimization, lack of awareness among visitors with regards to procedures and processes, wrong assumption that the damage cannot be overturned, low propensity of visitors to become involved in prosecution of criminals, and visitors being part of the criminal acts as seen in prostitution and drug related cases (Tarlow, 2006a). Avoidance of the effects of these missing data is the reason that the present paper focused on temporospatial patterns and locations instead of visitors/tourists To solve this issue, however, future studies can resort to triangulations of findings by using supplementary data/method as suggested by Leung et al. (2018).

Declaration of competing interest

None.

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Appendix A: Glossary

The definition of the terms arson, assault, aggravated assault, battery, bribery, burglary, kidnapping, robbery, and theft are extracted from the 2017 Florida Statutes (Online Sunshine, 2017) and no modifications/changes have been applied to the definitions of these terminologies.

The terms, simple assault, embezzlement, fraud, homicide, and drugs/narcotics were extracted verbatim from Find Law (FindLaw, n.d.), and no modifications/changes have been applied to the definitions of these terminologies.

Arson

(1) Any person who willfully and unlawfully, or while in the commission of any felony, by fire or explosion, damages or causes to be damaged:
  (a) Any dwelling, whether occupied or not, or its contents;
  (b) Any structure, or contents thereof, where persons are normally present, such as: jails, prisons, or detention centers; hospitals, nursing homes, or other health care facilities; department stores, office buildings, business establishments, churches, or educational institutions during normal hours of occupancy; or other similar structures; or
  (c) Any other structure that he or she knew or had reasonable grounds to believe was occupied by a human being, is guilty of arson in the first degree, which constitutes a felony of the first degree, punishable as provided in s. 775.082, s. 775.083, or s. 775.084.

(2) Any person who willfully and unlawfully, or while in the commission of any felony, by fire or explosion, damages or causes to be damaged any structure, whether the property of himself or herself or another, under any circumstances not referred to in subsection (1), is guilty of arson in the second degree, which constitutes a felony of the second degree, punishable as provided in s. 775.082, s. 775.083, or s. 775.084.

Assault

(1) An "assault" is an intentional, unlawful threat by word or act to do violence to the person of another, coupled with an apparent ability to do so, and doing some act which creates a well-founded fear in such other person that such violence is imminent.

(2) Whoever commits an assault shall be guilty of a misdemeanor of the second degree, punishable as provided in s. 775.082 or s. 775.083.

Simple Assault

A criminal assault that is not accompanied by any aggravating factors (as infliction of serious injury or use of a dangerous weapon). NOTE: Simple assault is usually classified as a misdemeanor.

Aggravated Assault

(1) An "aggravated assault" is an assault:
  (a) With a deadly weapon without intent to kill; or
(b) With an intent to commit a felony.
(2) Whoever commits an aggravated assault shall be guilty of a felony of the third degree, punishable as provided in s. 775.082, s. 775.083, or s. 775.084.

Battery

(1)
  (a) The offense of battery occurs when a person:
    1. Actually and intentionally touches or strikes another person against the will of the other; or
    2. Intentionally causes bodily harm to another person.
  (b) Except as provided in subsection (2), a person who commits battery commits a misdemeanor of the first degree, punishable as provided in s. 775.082 or s. 775.083.

(2) A person who has one prior conviction for battery, aggravated battery, or felony battery and who commits any second or subsequent battery commits a felony of the third degree, punishable as provided in s. 775.082, s. 775.083, or s. 775.084. For purposes of this subsection, "conviction" means a determination of guilt that is the result of a plea or a trial, regardless of whether adjudication is withheld or a plea of nolo contendere is entered.

Bribery

(1) "Bribery" means to knowingly and intentionally give, offer, or promise to any public servant, or, if a public servant, to knowingly and intentionally request, solicit, accept, or agree to accept for himself or herself or another, any pecuniary or other benefit not authorized by law with an intent or purpose to influence the performance of any act or omission which the person believes to be, or the public servant represents as being, within the official discretion of a public servant, in violation of a public duty, or in performance of a public duty.

Burglary

(1)
  (a) For offenses committed on or before July 1, 2001, "burglary" means entering or remaining in a dwelling, a structure, or a conveyance with the intent to commit an offense therein, unless the premises are at the time open to the public or the defendant is licensed or invited to enter or remain.
  (b) For offenses committed after July 1, 2001, "burglary" means:
    1. Entering a dwelling, a structure, or a conveyance with the intent to commit an offense therein, unless the premises are at the time open to the public or the defendant is licensed or invited to enter; or
    2. Notwithstanding a licensed or invited entry, remaining in a dwelling, structure, or conveyance:
      a. Surreptitiously, with the intent to commit an offense therein;
      b. After permission to remain therein has been withdrawn, with the intent to commit an offense therein; or
      c. To commit or attempt to commit a forcible felony, as defined in s. 776.08.

Embezzlement

Embezzlement is defined in most states as theft/larceny of assets (money or property) by a person in a position of trust or responsibility over those assets. Embezzlement typically occurs in the employment and corporate settings.

Accounting embezzlement, a common form of the crime, is the manipulation of accounting records to hide theft of funds. Offenders are given lawful possession of the property, and then are accused of converting the property to their personal use.

A person is often given access to someone else's property or money for the purposes of managing, monitoring, and/or using the assets for the owner's best interests, but then covertly misappropriates the assets for his/her own personal gain and use, this is an example of embezzlement.

Common examples include bank tellers or store clerks who are given lawful possession of money, which is the property of the bank or business owner, during regular business transactions. Other examples include employees who are given lawful possession of company property such as laptop computers or company vehicles.

This type of crime is most common in the employment and corporate fields. Some embezzlers simply take a large amount of money at once, while others misappropriate small amounts over a long period of time. The methods used to embezzle can vary greatly and are often surprisingly creative. They can include fraudulent billing, payroll checks to fabricated employees, records falsification, "Ponzi" financial schemes and more.

In order for a charge of embezzlement to be supported, four factors must be present:

- There must be a fiduciary relationship between the two parties; that is, there must be a reliance by one party on the other
- The defendant must have acquired the property through the relationship (rather than in some other manner)
- The defendant must have taken ownership of the property or transferred the property to someone else
- The defendant's actions were intentional.

Fraud

Fraud is a broad term that refers to a variety of offenses involving dishonesty or "fraudulent acts". In essence, fraud is the intentional deception of a person or entity by another made for monetary or personal gain.

Fraud offenses always include some sort of false statement, misrepresentation, or deceitful conduct. The main purpose of fraud is to gain something of value (usually money or property) by misleading or deceiving someone into thinking something which the fraud perpetrator knows to be false. While not every instance of dishonesty is fraud, knowing the warning signs may help stop someone from gaining any unfair advantage over your personal, financial, or business affairs.

Types of Fraud:

There are many types of fraud offenses, several of which occur through the mail, internet, phone, or by wire. Common types include:

Bankruptcy fraud.
Tax fraud (a.k.a. tax evasion).
Identity theft.
Insurance fraud.
Mail fraud.
Credit/debit card fraud.
Securities fraud.
Telemarketing fraud.
Wire fraud.

Homicide

Homicides include all killings of humans. Many homicides, such as murder and manslaughter, violate criminal laws. Others, such as a killing committed in justified self-defense, are not criminal. Illegal killings range from manslaughter to murder, with multiple degrees of each representing the gravity of the crime.

Kidnapping

(1) (a)The term "kidnapping" means forcibly, secretly, or by threat confining, abducting, or imprisoning another person against her or his will and without lawful authority, with intent to:
   1. Hold for ransom or reward or as a shield or hostage.
   2. Commit or facilitate commission of any felony.
   3. Inflict bodily harm upon or to terrorize the victim or another person.
   4. Interfere with the performance of any governmental or political function.

(b) Confinement of a child under the age of 13 is against her or his will within the meaning of this subsection if such confinement is without the consent of her or his parent or legal guardian.

Drugs/Narcotics

Federal and state drug possession laws make it a crime to willfully possess illegal controlled substances such as marijuana, methamphetamine, cocaine, LSD, "club drugs," and heroin. These laws also criminalize the possession of "precursor" chemicals used in drug cultivation and manufacturing, as well as certain accessories related to drug use. However, what constitutes drug possession can vary according to the type of drug, the amount, and the geographic area where the offense took place.

Robbery

(1) "Robbery" means the taking of money or other property which may be the subject of larceny from the person or custody of another, with intent to either permanently or temporarily deprive the person or the owner of the money or other property, when in the course of the taking there is the use of force, violence, assault, or putting in fear.

(2)
   (a) If in the course of committing the robbery the offender carried a firearm or other deadly weapon, then the robbery is a felony of the first degree, punishable by imprisonment for a term of years not exceeding life imprisonment or as provided in s. 775.082, s. 775.083, or s. 775.084.
   (b) If in the course of committing the robbery the offender carried a weapon, then the robbery is a felony of the first degree, punishable as provided in s. 775.082, s. 775.083, or s. 775.084.
   (c) If in the course of committing the robbery the offender carried no firearm, deadly weapon, or other weapon, then the robbery is a felony of the second degree, punishable as provided in s. 775.082, s. 775.083, or s. 775.084.

Theft

(1) A person commits theft if he or she knowingly obtains or uses, or endeavors to obtain or to use, the property of another with intent to, either temporarily or permanently:

(a) Deprive the other person of a right to the property or a benefit from the property.

(b) Appropriate the property to his or her own use or to the use of any person not entitled to the use of the property.

Author's contribution

Dr. Jalayer Khalilzadeh has conducted the analysis and developed the manuscript. The data for this study is obtained from https://data.cityoforlando.net/as an open source data for Orlando city. The study had received no funding from any external sources.

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