



What's the safest way home? Mapping safe transport routes in South Africa with (and without) crime data

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Abstract

Safety is arguably the single biggest daily concern for commuters. Popular navigation software systems such as Google Maps, TomTom and Waze do not however currently give the same weight of consideration to crime risk when directing road users to the safest and shortest routes as they do existing traffic knowledge. In this study we propose three simple methods to delineate the safest and shortest route between any two locations in South Africa considering crime risk. The first method uses historical crime data to delineate the safest and shortest route; the second method, uses only the location of so-called 'risky facilities' to determine the safest and shortest route; while the third method uses a combination of both historical crime data and facility data to delineate the optimal route. We contrast the resultant routes delineating by these three methods and speculate on the policy implications of integrating this knowledge into future navigation software systems.

Keywords Crime analysis · Street segment · Network · Routing · South Africa

Introduction

South Africa is synonymous with crime. The most recent crime statistics indicate that while crime is slightly decreasing overall, certain categories of crime such as homicide, attempted homicide, and assault continue to rise unabated, with the country's per capita homicide rate for 2022/23 being the highest in 20 years at 45 per 100,000 population (a 50% increase compared to 2012/13) (South African Police Services

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(SAPS), 2023). Crime in South Africa is not ubiquitous however but is rather heavily concentrated in certain police precincts of the country, notably in precincts located in the so-called townships (see Breetzke 2018). In South Africa, a ‘township’ refers to a built-up residential area on the periphery of former Whites-only urban neighborhoods. Under the spatial planning policies of the former apartheid government, these areas were reserved for non-White people only (i.e., Black African, Coloured and Indian population groups) although townships are still predominantly (>95,0%) inhabited by non-Whites more than thirty years into democracy. Recent evidence has, however, shown that even in high-crime police precincts in South Africa, crime is heavily concentrated in certain neighborhoods (Breetzke and Edelstein 2019), and even along certain street segments (Theron et al. 2023). Identifying high crime concentrations at the finer street segment level of aggregation is vitally important in resource-poor countries such as South Africa as it enables geographically-targeted policing intervention strategies to be implemented at these locations. The identification of ‘high-crime’ streets also has important implications for public safety in general as transport routes can potentially be delineated which can reduce an individual’s risk of victimization at this spatial level.

Using environmental criminology as a theoretical backcloth, in this study we outline three simple methods to determine the safest and shortest route between any two locations in South Africa considering crime risk. The first method uses historical crime data to delineate the safest and shortest route; the second method, uses only the location of existing facilities that have previously been shown to be spatially associated with crime to determine the safest and shortest route; while the third method uses a combination of historical crime data and facility data to delineate the optimal route. Importantly, no crime data is employed in the second method. Point level crime data is extremely difficult to obtain in South Africa (see Breetzke 2006 for an outline) and we were motivated in this study to demonstrate how a safest and shortest route between two locations could still possibly be delineated between locations in instances where no crime data is available.

The geographical focus area for the study is the township of Khayelitsha located approximately 30 km to the south east of central Cape Town in the Western Cape province of South Africa. Khayelitsha is the largest township in the province with a population of roughly 400,000 inhabitants, of which almost 99% are black African (Statistics South Africa (SSA), 2011). The township is socially and economically marginalized from Cape Town however with roughly 40% of residents unemployed, and youth unemployment (aged 15–23) at over 50% (SSA, 2011).¹ Notably, crime is rampant in Khayelitsha with the main policing precinct in the township consistently among the most violent precincts in the country with contact crime² almost double the national average (Crime Hub 2023).

¹ This was the most recent census undertaken for which data is available. The 2021 census was postponed due to the Covid-19 pandemic and is in the process of being conducted (July 2022).

² ‘Contact crimes’ refer to when a person or people are injured/harmed or threatened with injury/harm during the commission of a crime. A further sub-category of ‘contact-related crime’ is used for violent crimes committed against property with the intention of causing damage to a person, for example arson or malicious damage to property.

Literature review

A large number of studies over the past twenty years support the spatial concentration of crime at the street segment level of analysis, across varying contexts (see Chainey et al. 2019; de Melo et al. 2015; Umar et al. 2021; Weisburd et al. 2012; Wuschke et al. 2021). While researchers have historically examined spatial crime concentrations at coarser levels of spatial aggregation (see Bursik and Grasmick 1993; Kubrin and Weitzer 2003; Sampson et al. 1997), there is a growing realization that these larger places are spatially heterogenous (see Braga et al. 2017). This increased acknowledgement has led to a plethora of studies examining crime at the street segment level (see Braga et al. 2010; Groff et al. 2010; Kim and Hipp 2018; Weisburd et al. 2009) as well as studies delineating the safest and shortest routes between locations based on the underlying crime risk of the street network (see Galbrun et al. 2016; Garvey et al. 2016; Goel et al. 2017; Mata et al. 2016; among others). In terms of graph theory, street networks are a collection of nodes (intersections) and edges (street segments linking intersections) which can either be topological (nonspatial) graphs (with topological distance in terms of number of street segments along a path (Goddard and Oellermann 2011) or spatial graphs (with spatial/metric distances in meters or kilometers (Crucitti et al. 2006). Edges between nodes in street networks can be assigned 'weights' which act as external factors that can impede the movement through the street network. The kinds of weights are myriad and can include the cost of travel in terms of distance (Martínez Mori and Samaranayake 2019), time (Jenelius and Koutsopoulos 2013), volume of traffic (Zhong et al. 2014), and, importantly crime (de Souza et al. 2019; Hossain et al. 2022; Sarraf and McGuire 2020; Zoad et al. 2023).

In spatial criminology, the cost of movement through a network can be determined by the level of crime risk per edge (i.e. a street segment in the case of street networks). This is most often represented by some form of 'index' which assigns a numerical level of 'danger' to a particular edge. Concomitantly, the safest and shortest routes are those that minimize traversing on streets with the highest risk index values whilst still getting to the desired destination in the shortest distance possible. In past literature, these indices are most often created using historical open crime datasets (see Galbrun et al. 2016; Goel et al. 2017; Mata et al. 2016; Puthige et al. 2021), although crowdsourced crime data has also been increasingly used (see Mata et al. 2016; Shah et al. 2011). Regardless, in both instances a street is assigned a measure of risk based on the number of historical crime events (real or perceived) that have occurred there. Researchers have also combined open crime datasets with other more dynamic information in order to identify the safest and shortest path for users. For example, Kim et al. (2014) used sentiments inferred from real-time, geotagged messages from X (formerly Twitter) to delineate safer transport routes for users in Chicago while Pang et al. (2019) proposed a safety application that used street camera video data to identify the safety status of streets across the United States. Researchers have also increasingly integrated other non-crime datasets, notably traffic-related information, to assign a level of 'danger' per street segment. For example, Alfonso (2017) developed a safe routing application in California using historical crime data as well as various road barriers that may act as impediments to travel such as intersections, walkways,

freeways, and areas that has previously experienced pedestrian collisions. Likewise, Eckdale-Dudley et al. (2018) designed a safe routing application in Wisconsin that took infrastructural features such as crosswalks and sidewalks, and adequate traffic signage into account while Sarraf and McGuire (2020) developed a safe route navigation system which provides users with the safest route based on past motor vehicle crash data. Finally, Oh et al. (2017) took historical crime events and various types of facilities into account when determining the safest and shortest route between locations. The researchers calculated a crime risk rate for a route based on the crime risk rate of the facilities included in the user's route.

The inclusion of other infrastructural features and/or facilities in delineating safer routes is largely informed by crime pattern theory (Brantingham and Brantingham 1991). Housed within the school of environmental criminology, crime pattern theory focuses on the criminal incident itself - specifically when and where a crime occurs - rather than on the criminal per se. According to crime pattern theory offences are most likely to occur where opportunity spaces—places perceived by the offender to contain attractive targets—intersect with awareness spaces—places about which an offender has specific environmental knowledge, for example the surroundings of his or her home. Of course, street segments and their components (nodes, paths, and edges) greatly influence an individuals' routine patterns and awareness spaces. Paths in particular shape individuals' activities and in turn, determine where individuals go, which also influences their awareness space (Brantingham and Brantingham 1995). According to crime pattern theory, common urban infrastructure facilities that lie on streets such as shopping malls and schools can increase the risk of crime occurring on these segments. Collectively, these facilities are known as either crime generators or crime attractors. Both types of facilities increase the risk of crime occurring due mainly to the fact that they attract a large number of motivated offenders and suitable targets to a particular location. The former places attract a considerable amount of people who do not intend to commit a crime at that place necessarily but increase the risk of crime in these locations due to the increased number of potential targets, while the latter places attract motivated offenders for more nefarious reasons. Research indicates that the presence of certain types of facilities on street segments can increase the risk of crime (see Kim and Hipp 2018; Xie et al. 2022) which can, concomitantly, make certain street segments riskier to traverse than others. Our study aims to delineate the safest and shortest route between two locations using historical crime data as well as the presence of crime generators (or so-called 'risky' facilities (see Eck et al. 2007) along street segments.

Data and methods

Crime data

Historical crime data for the study was obtained from the South African Police Service (SAPS). A total of 26,109 point-level crime incidents were captured for the Khayelitsha policing precinct from 2012 to 2016 (five calendar years). A number of attributes were recorded per crime incident including a unique identifier, an x and y

coordinate, and the type of crime. All crime types were included in ascribing historical crime risk to a street segment. This was done to improve the statistical power of the routing analysis as well as it is assumed that most crime, regardless of the offence type, poses a threat to public safety although we do readily acknowledge that certain types of crime may be more visible and therefore 'relevant' to ascribing crime risk to road users than others.

Street centreline data

Street centreline data for Khayelitsha was obtained from the City of Cape Town Open Data Portal (<https://odp-cctegis.opendata.arcgis.com/>). The data consisted of line features which were segmented at every road intersection. Only the formal street network in Khayelitsha was used in the study (i.e., informal streets and footpaths were excluded). A total of 6,089 street segments were obtained for the township.

Facilities data

Data were obtained for the location of five different types of facilities in Khayelitsha including shopping malls, parks, transport interchanges, alcohol outlets, and schools. The selection of these specific five facilities were informed by both local (Breetzke and Edelstein 2022; Breetzke et al. 2021; Lancaster and Kamman 2016) and international studies (Day et al. 2012; Groff & McCord, 2012; Newton et al. 2015; Pride-more and Grubestic 2013) which have previously found these specific five types of facilities to be spatially associated with an increase in crime in their surrounding areas. The location of *shopping malls*, and *parks* were obtained from the City of Cape Town Open Data Portal. A total of four shopping malls and 62 district and community parks were located within Khayelitsha. The location of *transportation interchanges* including bus stops ($n=38$) and railway stations ($n=5$) were sourced from OpenStreetMap (OSM). A list of officially licensed *alcohol outlets* was acquired from the Western Cape Government Liquor License Authority. The location of 138 alcohol outlets in Khayelitsha were obtained and subsequently geocoded. We are aware of previous research that has mapped an alarmingly higher number of illegal alcohol outlets in Khayelitsha (see Matzopoulos et al., 2017), however, these data were not available to us and only the official licensed data was used. Finally, the location of 98 *schools* in Khayelitsha was obtained from the Western Cape Department of Education and were also geocoded.

Analysis

Three methods were proposed to delineate the safest and shortest route between any two locations in Khayelitsha. The first method involved determining the safest and shortest route based on historical crime incidents only. For the first method a street segment analysis of crime was initially undertaken whereby all crimes within the five-year study period were snapped to their nearest street segment and each street segment was then assigned a weighting based on the number of crimes per meter per

street segment. The safest and shortest route was simply the path that minimized the historical crime risk from the origin to the destination locations.

The second method involved determining the safest and shortest route considering only the location of various crime generators (i.e., the five facility types). This method demonstrated an approach to finding the safest and shortest route between points when no crime data is available. For this method, the five types of facilities were geocoded and a 50-metre buffer was generated around each of these facilities. Street segments that intersected these buffered areas were considered ‘barriers’ as they can increase the risk of criminal victimization along these segments. It is challenging to empirically identify the distance at which the ‘criminogenic’ effect of these facilities dissipates. Previous research has shown how the risk of crime will dissipate at various distances away from a crime generator (Boessen and Hipp 2018; Groff and Lockwood 2014). Ultimately, it was decided on a 50-metre buffer was appropriate since this distance broadly approximates a cadastral block in Khayelitsha. These ‘buffer zones’ were used as route polygon barriers for the routing analysis. Importantly, these barriers were ascribed as either being a restriction or a scaled cost. A barrier is a restriction if it has to be avoided completely when choosing a route to travel. On the other hand, a barrier is a scaled cost if it merely altered the cost of travel when being traversed. To illustrate this, if a road user wished to strictly avoid any crime generator on their route, for example, then the buffer zones would be regarded as restriction barriers so that any street segments that passed through these zones would have to be avoided completely. This means that the route could be any distance, as long as it avoided the crime generators entirely. Conversely, if a road user merely regarded street segments that intersected crime generators as being perhaps less safe but was not willing to travel greater lengths to avoid it completely, then these crime generators would be scaled cost barriers. This means that these barriers only further impeded the cost of travel (by a positive scaled value) on the street segments that it intersected. In this study, barriers were set as *scaled costs* meaning that the cost of travel increased by a certain scaled value if a street segment intersected these danger zones. For the second method, all scale costs were set to the same value ($n=2$) for all facilities. In other words, no type of facility was considered ‘more criminogenic’ than another type of facility. Finally, it may be possible for barriers to overlap, for example, when crime generators are located close to each other. In such instances, their individual scaled costs were multiplied to form a new combined weight. For example, if an alcohol outlet polygon barrier overlapped with a transport interchange polygon barrier their weights were multiplied, and this multiplied value was applied to the portion of the street segment that passed through the overlapping polygon barriers.

The third method combined both historical crime data as well as the location of crime generators to create the safest and shortest route. This was done by first examining the extent to which crime was spatially associated with each type of facility. Similar to Oh et al. (2017), the density of crime that occurred within a 50-metre buffer from each facility was calculated and aggregated per facility type. This provided a measure of spatial clustering of crime or ‘crime risk’ around each facility type. These density values per facility type were normalized and the resultant value (scaled cost) was ascribed to each street segment depending on its intersection with a facility. The

resultant risk rates of the facilities along a particular route were combined in order to acquire the risk rate of the entire route. In our analysis, the most criminogenic facility based on the underlying crime density were shopping malls, followed by bus stops and parks.

Results

Figure 1 shows the results of the first method and shows the shortest and safest route (in green) between a random origin and destination location compared to the shortest route (in brown). The shortest route between the two locations was 8.4 km long and traversed street segments that encountered a total of 735 historical crime incidents. There were approximately seven crimes per meter along this route. On the other hand, the safest and shortest route was approximately 12 km and traversed street segments with 278 historical crime incidents, resulting in roughly 0.7 crimes per metre. It is clear that the road user would have to travel a further distance to reach their destination if they wished to follow a path that minimized the overall number of historical crime incidents per meter. Despite the longer distance, the safest and shortest route avoided just over 450 historical crime incidents in total, when compared to the shortest route.

Figure 2 shows the safest and shortest route (in pink) between the same origin and destination points but in this analysis only the location of the crime generators (at equal scaled cost) was considered. Although this route was the shortest and saf-

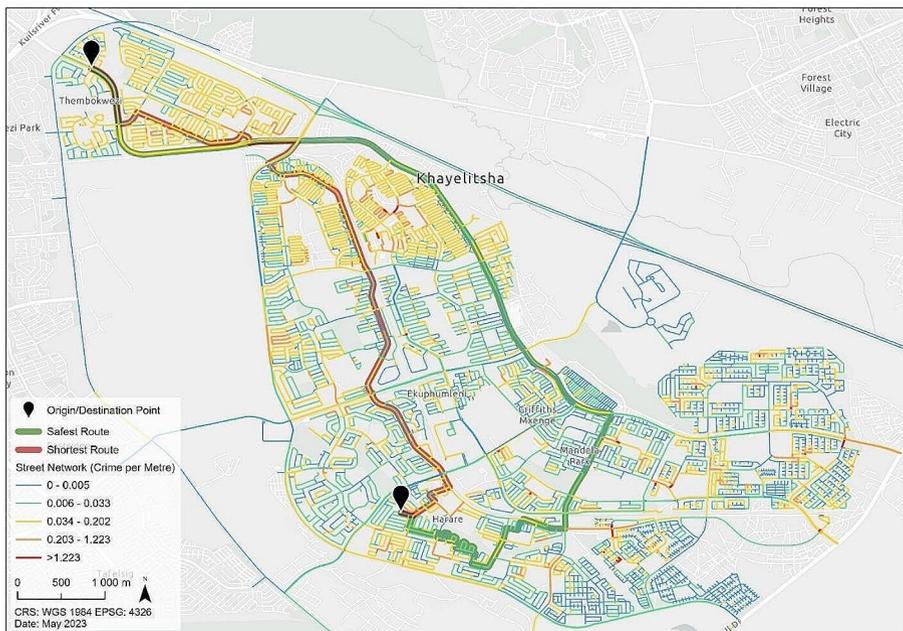


Fig. 1 The shortest and safest routes between an origin and destination point in Khayelitsha (based on historical crime data)

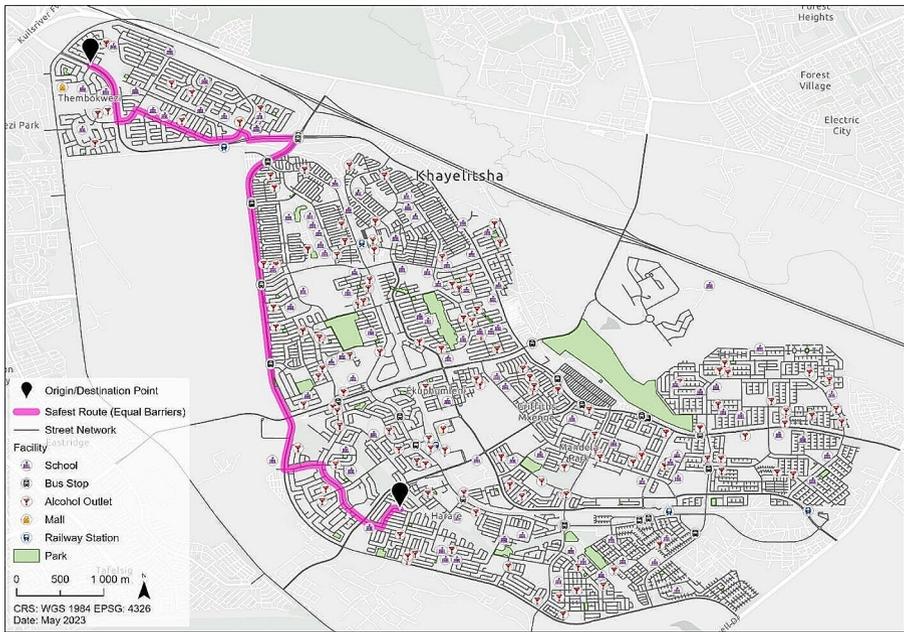


Fig. 2 The safest and shortest route between two points in Khayelitsha based on equal polygon barriers

est route, it still traversed 12 barriers (10 transport interchanges; one park, and one school). This resultant safest route was 8.4 km long and encountered a total of 601 historical crime incidents along the way ($n=4.62$ crimes per metre).

Finally, Fig. 3 shows the safest and shortest route (in blue) between the same origin and destination points but with street segments weighted on different scaled costs. The safest route and shortest route had a total length of 8.9 km, which was slightly longer than the route avoiding the equal scaled costs. This route encountered a total of 699 historical crime incidents along the way ($n=7.65$ crimes per metre). The delineated route still traversed a total of 13 barriers including five alcohol outlets, four transport interchanges, one park and three schools. This route encountered the least amount of scaled added costs while minimizing the total distance travelled.

Discussion

Two recent events in South Africa highlight the need for the integration of public safety related information into existing navigation software systems. First, an award-winning British doctor was shot and killed in August 2023 in Nyanga – a township located adjacent to Khayelitsha - after taking a ‘wrong turn’ from the Cape Town International airport on the way to his hotel in central Cape Town (Gregory 2023). Two months later, an American tourist was robbed and shot in the face (also in Nyanga) after the mapping application on his iPhone indicated a route that traversed through various high-crime areas that lie adjacent to the Cape Town International

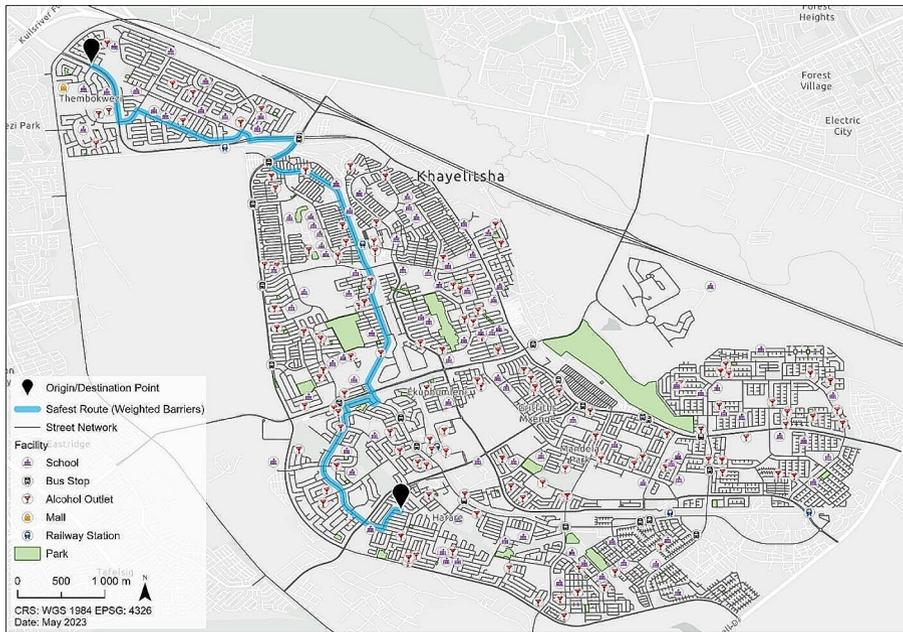


Fig. 3 The safest and shortest route between two points in Khayelitsha based on weighted polygon barriers

airport (Swart, 2023). Sadly, this situation is not unique to South Africa with similar incidents having been reported in Brazil (Phillips 2015) and the United States (Shellow-Lavine 2024), among others. Given these collective incidents it is increasingly clear that crime risk needs to be urgently considered when delineating the safest and shortest path for road users. In a country such as South Africa, which is one of the most violent countries in the world (World Population Review 2024), it is even more imperative for road users to know where the risk of crime is elevated and to allow the user of the navigation app to decide what consideration to give historical crime risk in proposing a route between two locations. Current navigation software systems such as Google Maps, TomTom and Waze do not currently give the same consideration to historical crime risk in determining safe routes between an origin and destination point. Although this does appear to be changing, at least in South Africa. Indeed, fearing the impact that these two criminal events would have on the summer tourist season in Cape Town, an agreement was quickly formalized between the country's Minister of Tourism and Google's Country Director for South Africa to "leverage Google's technological expertise in promoting South Africa as a tourist destination and providing digital training support to those operating in the sector." (Haripersad 2023) Among others, Google agreed to, in future, re-route individuals via its Google Maps application to avoid 58 crime hot spots in Cape Town although no information was provided regarding where these hot spot areas were located, nor how they were identified.

In this study we outline three simple methods to delineate the safest and shortest route between any two locations in the country, with (and without) crime data.

Similar to previous studies (see Kim et al. 2014; Lisowska-Kierepka 2022; Pang et al. 2019; Puthige et al. 2021), in our first method we assigned a level of safety per street segment based on historical crime data and determined the safest and shortest route based on this information alone. In our second method, we delineated the safest and shortest route based solely on the location of 345 crime generators located in the study area. In truth, the second method we propose in this study is probably the most feasible in a country such as South Africa if such a method were to be incorporated into future real-world applications. The main reason being that official and spatially replete point-level crime data is notoriously difficult to obtain in the country. Rather spatial crime researchers are continuously reliant on official crime data that are released quarterly and at the coarse police precinct level of spatial aggregation. There are 1144 police precincts in a country covering an area of roughly 1,217,290 square kilometers (mean=1064 square kilometers). Official crime data disseminated at this level of aggregation is simply not fine enough to ascribe neighborhood-level crime risk let alone street-level risk in the country. Point-level crime data also provides a much more nuanced, and accurate, indication of crime risk (see Braga et al. 2017 for details) and allows for more detailed analysis to be undertaken. In our study we were fortunate enough to obtain point-level crime data for Khayelitsha and use this to determine the safest and shortest path (in the first method). Notably, the safest and shortest routes indicated in the first and second method do differ considerably both in terms of route direction and length which highlight the fact that relying solely on the location of crime generators in the community may not necessarily be the best proxy for actual crime risk per se but there are few viable alternative data sources available to act as proxy crime data. Of course, other sources of crime data were considered for inclusion in the study such as crowd-sourced crime data as employed in other past studies (see Goel et al. 2017; Keler and Mazimpaka 2016; Mata et al. 2016). Again, however, these data were not available in South Africa at the level of spatial detail required for analysis and in instances where data did exist the coverage was incomplete for Khayelitsha. Notwithstanding the fact that crowd-sourced crime data has a number of other associated disadvantages such as self-selection bias (Chataway et al. 2017) and the overrepresentation of certain groups (Solymosi and Bowers 2018).

In terms of policy implications, the identification of certain ‘criminogenic’ streets and facilities could inform policing strategies aimed at reducing crime. Specifically, hot spot policing which is aimed at directing a variety of police-led crime control efforts towards locations abundant with crime (e.g., particularly a neighborhood or street segment) in order to have a disproportionate effect on reducing crime outcomes. From an urban planning perspective, local authorities could improve the physical environment on certain high-crime risk streets through targeted lighting, increased visibility, traffic calming measures, and effective signage and marking, among others. ‘Safer’ commuting paths through the township could also be delineated. This is particularly relevant for pedestrians in Khayelitsha given the fact that almost every individuals’ journey in Khayelitsha starts with walking (City of Cape Town 2021). A related strategy could be the development of ‘safe nodes’, or multi-purpose sub-centres which are intended to reduce the likelihood of violent behavior along certain hot spot routes. Finally, it is worth mentioning that the delineation of ‘safer routes’ in this particular local context raises a broader ethical dilemma. That is, delineating

safer commuting routes could lead to the further stigmatization and marginalization of certain areas deemed too risky to traverse. Given South Africa's history in this regard under the former apartheid regime, there is no easy solution.

Last, a short note on some of the limitations of the study. First, crime is notoriously under-reported in Khayelitsha (see O'Regan et al. 2014) and this poses significant challenges to accurately identify safer routes based on historical crime risk. Several factors contribute to this broader issue including a lack of trust in law enforcement agencies (Prinsloo 2019), fear of retaliation (Seedat et al. 2009) and the social stigma and shame associated with certain types of crime (Jewkes et al. 2017). Given this data challenge, researchers in South Africa can either undertake research with the only official crime dataset available from the SAPS, whilst acknowledging the limitations, or seek alternative ways of getting 'proxy' crime data. We choose the former option, knowing that what we find may not be the exact magnitude and location of crime occurring during this study period in Khayelitsha but being relatively certain that the data we have broadly approximates its true magnitude and distribution. Second, we are aware that considering only distance and crime-related information to delineate safer routes for users does not achieve the desired requirements of proper transportation management. Indeed, a range of other factors could impact road user safety including road infrastructure, lighting conditions, crowdedness, public transport, and traffic congestion, among many others, and that these factors may be more important at certain places along a route, than others. From a purely criminological perspective, we also did not consider the broader environmental backcloth when considering crime risk. These include, among others, the underlying land use, and urban infrastructures which collectively can lead to an increase in crime opportunities along certain routes (see Umar et al. 2021). In our study, we did not 'control' for crime opportunities, per se, but rather in a way similar to Garvey et al. (2016) and others, in this study we delineate the safest and shortest route in a new and unique location. In fact, to our knowledge, this empirical study is the first of its kind in Africa in general, and South Africa specifically. Future research could examine whether these routes may differ based on these other factors, although it should be noted that identifying other crime risk factors in Khayelitsha is challenging. This is largely due to the informal nature of the township. The township is notoriously under-developed with relatively few formal built facilities. These combined factors make more comprehensive future micro-spatial routing analysis incorporating the underlying environmental backcloth harder to undertake, but is an avenue for future research. Finally, we not take into consideration the fact that the routes delineated would necessarily differ across the three methods depending on various temporal resolutions (daily, weekly, monthly). Crime varies temporally and facilities also open and close at various times of the day and night. These factors would impact street-level crime risk and this would impact the delineation of the shortest and safest route. We felt, however, as a first iteration of this process to rather delineate an optimal route regardless of the temporal resolution of the crime data. Future research could aim to tease out the differences that may occur when determining the safest routes by time.

These limitations notwithstanding this study represents the first empirical attempt to undertake a safest path analysis in any context in South Africa. Given the high rates of crime in the country, it is becoming increasingly important for individuals to

know their risk of being victimized. For residents in Khayelitsha in particular, any and all information that can reduce their risk of victimization is better than no information at all, regardless of the limitations. We believe that this study has addressed this in a small but meaningful way, and potentially introduce an application in the future which will give residents of Khayelitsha access to this vital information. In a high crime country like South Africa any and all information that could potentially make a trip safer is more relevant and important than ever.

Author contributions K.T undertook the spatial analysis for the paper. G.D. wrote the paper.

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Data availability The data for this study is a combination of open datasets and data compiled by the South African Police Services (SAPS). Due to the sensitive nature of some of the datasets, they are not publicly accessible. However, the data can be made available by the authors upon reasonable request and subject to the approval of the SAPS.

Declarations

Competing interests The authors declare no competing interests.

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