Designing a runnability index using simulated routes based on running behaviour in the form of loops and goal-oriented running

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images/uulogo.png

Abstract

The growing amount of recreational running has led to research into estimating how well-suited areas are for the activity. This estimation can be done by the creation of a runnability index, a score attributed to each area representing the quality of the area in supporting running. Previous research has often relied on aggregating data over an area to create this index, without taking potential routes into account that a runner could take. We use the design science methodology to evaluate existing factors and runnability indices in order to create a method that uses simulated routes as a factor for estimating runnability. Our findings indicate that this incorporation is beneficial for the index, but will need further development to be properly adapted as an important factor in runnability index development.

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1 Introduction

1.1 Research Background

Recreational running is one of the most easily accessible methods of exercise, requiring nothing more than a suitable environment and legs, while providing both physical and mental benefits (Markotić et al., 2020). Additionally, it is also the second most practised form of exercise with 11% of the general population running at least once every week (CBS, 2022). Due to these benefits, there has been put a lot of effort in promoting and supporting running as a recreational activity by both governmental and private instances (Ettema, 2016).

To support these initiatives, a multitude of studies have been conducted in recent years to examine the relation between environment and running activity. These studies use the examined relation to create a walkability or runnability index, which measures the rate of which an area can be calculated as suitable for one of those activities. For example: Shashank et al. (2022) describes a generic runnability index as a composite measure of: slope, density of trees and other supporting infrastructure in combination with distance to parks and intersections to calculate a normalized measurement score of runnability. The resulting indices can then be used in potential city planning or running programs to promote a healthier lifestyle for the target population.

1.2 Problem statement

However, currently existing indices generally work by aggregating a set of environmental measurements and scoring a region based on the presence of these measurements. This method works well for a general overview, but does not include actual running behaviour that affects how well an actual person would run in an area. An example of this would be the inclusion of average running time in combination with the spatial features to take into account all possible routes that can be taken by the runner, rather than simply labeling certain areas as runnable.

Another issue is that the concept of runnability is quite vague across studies, as it can be seen as an aggregation of environmental factors, the probability that someone will start a run in an area or something else entirely. The ambiguity of the concept makes it harder to compare the rate of runnability across studies.

These problems are detrimental to the applicability of runnability indices in real world scenarios and thus reduces the effectiveness of any strategies or plans based on information from a runnability index. This study aims to test different approaches in forming an index that is able to properly account for human behaviour and define runnability in an effort to increase accuracy and validity.

1.3 Research questions

The solution to the problem statement will need to come in the form of a runnability index, capable of handling the aforementioned problems. Therefore, the main research question will be formulated as:

How beneficial is the incorporation of running behaviour into a runnability index?

This question helps setting the primary goal for creating a runnability index with solid real world application. For this study, we select the presence of loops and goal-oriented running towards parks as the main elements of running behaviour. Loops refer to the concept that recreational runners will generally finish their run close to their starting point and goal-oriented towards parks refers to the fact that recreational runners will specifically run towards a park, due to it being the best possible environment for running (Huang et al., 2022). To support this research question, the following subquestions are formulated:

- *How are currently existing runnability indices created?*
- *What is the effect of looping and goal-oriented running on route choice behaviour?*
- *How can we incorporate running behaviour into a runnability index?*
- *How can a runnability index with route choice behaviour be validated?*

These four questions follow the design science strategy formulated by Wieringa (2014) and focus on problem investigation, treatment design and treatment validation. This strategy will be further elaborated on in the methodology section.

2 Methodology

The following section discusses the implementations of the research questions and design science strategy that are necessary to design the runnability index as a functional product. The design science strategy consists out of three main phases, which are handled by the formulated research questions. An overview of these phases with accommodating deliverables and outcomes is shown in figure 1, with additional explanation in the following subsections.

`images/DeliverableDiagram.drawio.png`

Figure 1: Process deliverable diagram

2.1 Problem investigation phase

The first phase is problem investigation in which the current situation is evaluated and research is done to find the roots of a problem. This is done by answering the research question: *How are currently existing runnability indices created?* Answering this question by performing a literature review and creating a benchmark runnability index will give more insight in the current situation and helps in laying a foundation for our final product.

2.1.1 Literature review method

To accommodate the problem investigation phase in answering the research question, it is necessary to conduct a literature review where three main elements are evaluated: the definition of runnability, the factors used in estimating runnability and a created benchmark model. To achieve this, a smaller scale version of the mixed literature review (MLR) is selected. A mixed literature review is a method in which literature is gathered and selected with a large amount of freedom with the goal of providing the most support for research questions consisting out of a qualitative and quantitative part (Harden, 2010). This is necessary due to runnability research being done in the form of a revealed preference study, but also as stated preference study. Furthermore, a MLR also helps with answering multiple subquestions, rather than one singular effect (Santos et al., 2018). Therefore, the MLR is a good fit for answering the qualitative part of runnability definitions in combination with the quantitative question of spatial feature frequency.

Digital libraries

The following digital libraries were used to collect literature:

- Google
- Google Scholar
- WorldCat

The Worldcat catalogue and Google Scholar both provide access to academically published articles, while searching Google allows us for the inclusion of 'grey' literature, which is not published in an academic journal.

Search strings

The following list of strings was used to find the initial set of sources for the literature review:

- Runnability AND (Index OR Factors OR Behaviour)
- Runnability Index AND Environmental Factors
- Recreational Walking AND (Index OR Factors OR Behaviour)

Inclusion Criteria

The following criteria determined if a source was relevant and fitting for this study:

- Publication date between 01/01/2000 - 01/07/2022
- Written in English
- Mentions recreational walking or running
- Mentions environmental factors
- Scientific foundation

The mention of specifically recreational walking or running is important, due to the differences between recreational movement and purposeful movement for transportation.

Snowballing method

To further gather more relevant literature after the initial set, a snowballing approach is used. This approach gathers more literature, by using the reference lists found in the initial set (Wohlin, 2014). Specifically, backwards snowballing is used where the reference list is examined, rather than forward snowballing that examines new literature which references the old literature. This is because it is more important to examine the original reasoning for the usage of certain factors or definitions, rather than the newest applications.

2.1.2 Creation of a benchmark index

The second part of the problem investigation phase is to create a benchmark index in order to create a baseline that the designed treatment can compare against. To accomplish this, a method similar to the generic index creation by Shashank et al. (2022) is used. This method aggregates a set of spatial features that are found in the literature review and sums the normalized values of these features, which results in a score that is normalized to a 0-1 value. This method works well for creating a baseline index, due to the fact that the spatial features are easily interchangeable and are all given the same weight. This means that it is not necessary to do a specific analysis beforehand to calculate a weight for every spatial feature in every area. The selection of spatial features is based on a spatial feature frequency analysis created from the examined literature. The selected spatial features are then added for each area by the use of the 'Extract by location' algorithm. [1] This algorithm allows for the count or summing of an area to be added to another vector based on location. Using this we can count the amount of objects for point-based features like trees and streetlights, calculate percentage of area that is a park or count unique polygons to measure the amount of residential housing. We use this method, as it can be adjusted for any type of data that needs to be aggregated over an area. It is important to note that all spatial features relating do density in an aggregated area will need to account for the difference in area between the different region to not introduce a size bias. Lastly, the spatial unit on which the data is aggregated, are the neighbourhoods of a city. The area of these regions is in between postcode-6 and postcode-4 areas in terms of size and is chosen because neighbourhoods have an advisory council that can push towards certain policies regarding tree placement or surface areas that are potential factors relating to runnability. As a result, this will allow us to evaluate a degree of neighbourhood policy regarding runnability.

[1] `https://docs.qgis.org/3.22/en/docs/user_manual/processing_algs/qgis/vectorselection.html`

2.2 Treatment Design

The second phase is the treatment design phase with the goal of creating a first version of the solution. The design that is used for the solution is determined by answering the research questions: *What is the effect of looping and goal-oriented running on route choice behaviour?* and *How can we incorporate running behaviour into a runnability index?* The answer to the first question gives validity for the usage of looping and goal-oriented running in a runnability index, while answering the second question allows for these patterns to be added to the previously created benchmark index in an effort to improve the effectiveness of the index.

2.2.1 Pattern analysis

The validity of the usage of patterns can be determined by analyzing the running track dataset, which is described in the data section. The dataset contains a large amount of recreational running tracks that will be examined for two main patterns. The first pattern is the rate in which runners will loop back to their original starting point. A key difference between commute-running and recreational running is that commute-runners have a certain goal that they are travelling to, while recreational runners are mainly focused on the physical activity after which they return to home or their starting point. The existence of these looping runs can be determined by calculating the length between the end point and the starting point. If this distance is less than 500 meters, we can conclude that the runner has looped back to the starting point, assuming that the total run distance is more than 500 meters. 500 meters is selected as the range, due to runners typically following a running program that allows them for cool-down time, a period where the runner walks back home to slowly relax muscles. Other distances are also examined to determine if this distance is not too large.

After determining the rate of looping, we can investigate running goals for recreational runners. Looping runners do not have a place that they want to arrive at, however, they will have preferences for the location that they are running at. The most important running preference being a park or similar green space (Huang et al., 2022). To examine if this is the case in our running data, we check for the number of routes that intersect with a park area. If a significant number of routes come in contact with parks, we can take these two patterns into account to use for integration of human running behaviour into the created runnability index.

2.2.2 Incorporating the running patterns

The patterns are added to the baseline index by calculating the distance from the centroid of each administrative area to the edge of the nearest park area via existing roads and a distance-matrix. The shortest and second shortest route are calculated using the SQL statements and Python script present in Appendix A. Centroids are used to mitigate the difference in potential starting area that exists between the administrative area due to the difference in area size. Once the shortest route is calculated, a small buffer of 10 meters is created around this route that calculates the density of the relevant spatial features discovered in the problem investigation phase. 10 meters is selected, due to a standard residential road being 7 meters (Civilsir, 2022) with additional meters to account for residential housing. After this, the second shortest route is calculated between the park and the starting centroid with another buffer to calculate the density of relevant features. A second route is calculated, instead of using the same path two times, due to the fact that runners often avoid running back on the exact same path.

This strategy gives the index three important elements to work with, which are the distance to the park, quality of the paths to the park and overall quality of the administrative area that is determined by the baseline index. All these element have an equal weight for the runnability score that is determined by normalizing these scores and taking the average. All scores have an equal weight, due to the fact that precise weights cannot be determined without the use of the running track dataset that is validated against.

2.3 Treatment validation

Lastly, the treatment validation phase in which the designed solution is validated against existing running track data. To properly accomplish this, a validation method is constructed by answering the research question: *How can a runnability index with route choice behaviour be validated* Answering this research question will help us validate our index, as well as helping with the validation of future indices.

2.3.1 Creation of a validation method

Our runnability index can be validated by comparing the outcome against the generic baseline index. This can be done by examining both results against the true outcome and calculating the accuracy loss. The first task for this method is to define a goal function that the accuracy can be compared for. For this, we choose to define runnability as the probability that a runner will start their track in a specific area. The higher the probability, the higher the runnability. Using starting points helps with evaluating tracks instead of specific buffered general environment scores. These starting points are gathered by extracting the first vertex of each running track in the dataset. It is important that due to the lack of data for all potential tracks that have not been run, an adjustment is made to account for the difference in residents per area. Unadjusted, an area with more residents will have more tracks ran and will therefore have a higher probability of having a track starting point in the area. We adjust for this issue, by dividing the number of tracks by the density of residential housing. After this, the starting track point density is normalized using min-max normalization to a 0-1 range in order for it to be compared against the estimated data.

2.3.2 Validation of the index

For the calculating of accuracy loss, mean squared error (MSE) is used. This method squares the mean error between the actual data and generated estimates. MSE has the advantage of harshly punishing outliers and is thus effective in eliminating bad performing parameters. This is useful for seeing if any of the individual elements perform significantly worse than the combined runnability index. The elements that are the closest to 0 have the least amount of error and thus perform the best in estimating runnability.

Lastly, validation can also be done by visually comparing the estimates and actual maps, however, this approach is very subjective and therefore holds less weight than the MSE comparison.

2.4 Data

To construct the runnability index, it is necessary to use a variety of datasets containing spatial features. However, one dataset consisting out of running track data will serve as the main source for investigating human running behaviour and validating the runnability indices. This dataset is the 2015 Endomondo running track dataset put together by Ren et al. (2019), containing exercise data from 350.000 unique workout ids.

2.4.1 Subset selection

To gather more accurate and usable information, a subset is created from the dataset. This subset, visible in figure 2 contains all routes that are completely within the boundaries of Amsterdam to focus solely on urban running tracks.

images/Extent.png

Figure 2: Spatial extent of the data

2.4.2 Features

The cut dataset consists out of 6062 unique tracks, with a selection of additional information. The information columns that will be the most important are: *average speed*, *distance* and *duration*. The full set is shown in table 1.

Name	**Explanation**
workout_id	The unique id of the track
uid	The id of the user that entered the track
speed_max	The maximum speed that has been ran
speed_avg	The average speed that has been ran
distance	The length of the track
osmids	Geometric information about the tracks as linestrings

Table 1: Features of the running track dataset

2.4.3 Other datasets

A selection of other datasets are used for the aggregation of data and route generation, this selection is shown in table 2.

Dataset	**Source**
Amsterdam administrative areas	`https://maps.amsterdam.nl/open_geodata/?k=198`
Parks	`https://maps.amsterdam.nl/open_geodata/?k=99`
Residential housing	`https://data.overheid.nl/dataset/cxsrcn9ahipipq`
Streets	`https://maps.amsterdam.nl/open_geodata/?k=303`
Trees (part 1-4)	`https://maps.amsterdam.nl/open_geodata/?k=254`
Lighting	`https://data.overheid.nl/dataset/ovl-amsterdam`

Table 2: Other datasets

2.4.4 Tools & CRS

All transformations of the data and creation of the maps and runnability indices are done within QGIS, due to it being open-source software and having an easy way to integrate the postGIS database that contains the running track data. The data itself is projected to *EPSG:28992 - Amersfoort / RD New – Netherlands*, as this projection is optimal for The Netherlands and has it's units set to meters. It is necessary to have meters as the unit to correctly calculate distance between start and end points and calculating generated route distance.

3 Problem investigation

In this section, we examine existing literature and runnability indices in order to answer the research question: *How are currently existing runnability indices created?* In order to accomplish this, we follow the literature review method as described in the methodology section and answer the question in three parts. Firstly, examining the definitions that are given in existing literature. Secondly, the spatial features that are used to determine runnability of a certain area and finally the creation of a benchmark index based on the information gathered by the previous two questions.

3.1 Definitions

A total of 7 articles have been examined for their definition of runnability, leading to the total table of results visible in table ref 3.

Definition of runnability	Source
The perceived attractiveness and restorative quality of running environments and running behavior	(Ettema, 2016)
A quantification of the features of the built environment that facilitate movement of runners	(Shashank et al., 2022)
The environmental preferences and concerns of recreational runners	(Schuurman et al., 2021)
The perceived satisfaction of the running environment	(Huang et al., 2022)
The presence of built environment	(Troped et al., 2010)
50 meter-radius around presence of runnable environment	(Rodríguez et al., 2012)
How the different embodied rhythms of running interact with the rhythms of others, the material affordances and other temporalities	(Edensor et al., 2017)

Table 3: Identified definitions in literature

From this overview we can see that a lot of existing definitions are focused on the features that are present existing environment that the runner is in and how the runner perceives these features. This approach is well-suited for stated preference studies, as qualitative research in the form of surveys or similar studies can gather the opinions about the type of environment that runners like. However, the limitation of this approach is that the runners also have preferences about running tracks that are either subconscious or are not included in the study surveys. Furthermore, only one study explicitly mentions quantification as an important part in identifying runnability. This study by Shashank et al. (2022) quantifies this runnability by counting the amount of features in a grid of hexagons to assign a normalized score of 0 to 1. To be able to compare effectivity of runnability indices, it is important to also have a score that can be normalized. Otherwise, it enhances the previously discussed problem of not being able to compare runnability indices and their validation. The solution for our proposed design should have a form of quantifiable runnability score in order to be measured and validated.

3.2 Spatial features

The next step is to evaluate which spatial features are relevant for determining runnability in existing studies. The goal of this is to select a base set of relevant spatial features for a runnability index that can be used to create the benchmark index. To achieve this, the previous set of mentioned runnability studies have been used to extract a frequency set of certain spatial features that is presented in figure 3.

`images/Frequencyofspatialfeatures.png`

Figure 3: Frequency of spatial features

The presence of parks is the most frequent spatial feature, appearing in all 7 studies. This is expected as public green spaces, such as parks have the goal of promoting physical activity like recreational running (Wolf and Wohlfart, 2014). Following are residential density and the presence of trees, which are comparable to parks in the fact that a low residential density and a high presence of trees can indicate a public green space meant for promoting physical activity. The last set of common spatial features are safety (lack of human threats), running surface and the presence of street lights. The specific preference for running surface is sidewalk or asphalt routes, as these harder surfaces provide more stability and thus and easier running experience for runners Schuurman et al. (2021). However, due to the spatial extent solely focusing on urban environments, almost every area will be hardened ground with exception of the parks that promote running. Therefore, using the presence of sidewalks or asphalted roads is counter intuitive in urban environments. Lastly, Safety and presence of street lights are a set of features that also have a relation to the time of the run, as street lights will light up dark roads for runs in the evening or night when general safety can also be a concern. The issue of using safety by lack of threats as a spatial feature is the fact that it is difficult to quantify without using a proxy, such as crime rate in a neighbourhood. For this reason, we exclude safety and only use the previously 4 mentioned spatial features for the benchmark index.

3.3 Creation of a benchmark index

Using the quantification of a selection of 4 spatial features as the basis, we are now able to create our benchmark runnability index using the process described in the methodology section. The result of this process is visible in figure 4. 5 classes with equal count are created to show the most runnable areas of the city, any area with a score of 0 as a result of missing data is removed from the map.

images/benchrunnable.png

Figure 4: Benchmark runnability index results

Most of the lower scoring areas are scoring really low, while the highest scoring range are in a wide distribution. Furthermore, the areas close to the city center are scoring the highest, while the outskirts are scoring low. This is most likely a result of the current selection of spatial features; high residential density will often be paired with a higher number of street lights and road-placed trees. Furthermore, the equal weight scaling means that features with generally low impact, such as street lights will have the same amount of impact as the presence of a park that has promoting recreational running as one of it's aims. As a result, selecting too much features can have a negative impact in removing the predictive power of key factors, such as the presence of parks. This is visible in figure 5, where most of the high scoring runnability areas in the center do not have a large park nearby.

images/2nrunnability.png

Figure 5: Benchmark runnability with parks

4 Problem treatment

This section consists of two parts; the first part will analyze the presence of the aformentioned running patterns and lays the foundation for including these patterns in a runnability index by answering the research question *What is the effect of looping and goal-oriented running on route choice behaviour?* The second part incorporates these patterns into a runnability index according to the process described in the methodology section and answers the research question: *How can we incorporate running behaviour into a runnability index?*

4.1 Analyzing route choices

Two main types of behaviour are analyzed in this section; the tendency of runners to run in loops and the goal of runners to reach a park. The amount of looping is analyzed by comparing the absolute distance in meters between the start and end point of a track. The result of this analysis is shown in table 4.

Distance in Meters	**Percentage of runs**
10 meters	7.5%
50 meters	35%
100 meters	47%
200 meters	60%
500 meters	78%

Table 4: Percentage of runs with a short absolute distance between start and end

A large amount of runs have a very low distance between the start and end point and can therefore be seen as a looping run, a run that ends closely to where it starts. These distances are low in comparison to the average run length of 5252 meters, meaning that the high percentages are not a result of a low running distance.

The second element of running behaviour that we can examine, is the tendency of runners to run towards parks. Parks are often the main area where recreational runners would want to run and can therefore be seen as a main goal. Other factors, such as amount of street lights or trees can improve running quality, but do not function as a goal to specifically run towards, unlike parks. We test this hypothesis by calculating the percentage of runs that intersect with a park, which results in a count of 4428 unique routes out of the total 6062 tracks that cross a park at some point during the route, which is 73% of all tracks.

Confirming these hypotheses is necessary to support the decision to incorporate these running behaviour patterns into the runnability index, as no formal literature has been found on the subject. However, it is important to note that these calculations only support the theoretical foundation of the inclusion of running behaviour, as no true observed data can be used as factor in a runnability index.

4.2 Creation of the runnability index

The following section discusses the creation of the runnability index and the incorporation of running patterns. The first step is the calculation of distances and connect each adminstrative section with the closest park using a different path for going back and forth. A sample of the result of this process is shown in figure 6.

images/Shortestroute.png

Figure 6: The shortest routes from each neighbourhood to a park area

Interestingly, a large number of paths converge in similar routes, indicating that certain straight main roads are preferable over more specific unique roads for each point. The next step after creating the routes is adding 10 meter buffers around every route that encapsulate the tree, light and residential density. The visual result is visible in figure 7.

images/BufferedRoutes.png

Figure 7: The buffered routes from each neighbourhood

This figure is fairly similar, as it shows the same routes as figure 6, however it highlights the general extent that each route has in determining relevant environmentally variables, such as the residential density. Finally, combining the score for route, route length and the benchmark variables leads to the resulting runnability index shown in figure 8.

images/NewRunnabilityGood.png

Figure 8: Runnability Index Results

The most runnable areas are grouped together in the center, which is expected as most of the areas on the outside consist of industry zones with low amounts of residential buildings and running opportunities. The center also contains the most access to parks, as is visible in figure 9.

images/NewRunnableWithParks.png

Figure 9: Runnability Index Results with highlighted parks

This result also shows that the current index gives more weight to the number and spread of parks, rather than a few large parks, due to the top-left, bottom and bottom-left having large amount of park area in combination with a low runnability score. This is due to the generation of routes from the centroids to any park space, no matter the size.

5 Treatment Validation

The following section discusses the comparison of performance between the benchmark and running behaviour runnability indices by using the running track dataset in order to answer the research question: *How can a runnability index with route choice behaviour be validated?* Answering this question, helps us get a better insight in the effectiveness of including running behaviour, such as loops and goals in a runnability index.

5.1 Starting point density

The first step in evaluating effectiveness is to create a map containing the amount of running starting points, scaled using the population density and normalized to a 0-1 value. This map is visible in figure 10.

images/NormStart.png

Figure 10: Normalized Starting Point Density

The starting point density has rough similarities with the indices in having the center as the highest rated areas, however, higher scoring areas are not completely grouped together like is visible in the runnability indices. This is most likely the result of the starting points density not being directly dependent on environmental measures, such as ratio of parks that could cover multiple areas next to each other and thus increase the runnability score of these grouped areas.

5.2 Calculating MSE scores

Using the starting point map, we calculate the MSE scores based on the normalized running score values. The scores for the new runnability index also have a calculated MSE score for each of the three different elements that make up the total runnability score. The outcome of these calculations is visible in table 5

Benchmark	**Length**	**Route Score**	**Combined**
0.072	0.09	0.13	0.069

Table 5: MSE scores for the different elements

The MSE scores show that the combined runnability index is the closest to the observed data, however, the difference with the benchmark index is very small. Furthermore, the benchmark element also scores better compared to the other elements in length and generated route runnability score. This indicates that the benchmark method of aggregating environmental factors is the best basic method for estimating runnability and only slightly improves with the inclusion of other methods.

We can also compare the mse scores of the generated route length and runnability score against the individual scores of tree density, lighting density, residential density and park ratio. The MSE scores of these last four environmental measures are shown in table 6.

Lighting	**Trees**	**Park**	**Residential Density**
0.166	0.146	0.255	0.108

Table 6: MSE scores for the individual elements of the benchmark aggregations

Interestingly, generated route length is the best scoring individual predictor with route score in third place. This means that the estimators based on running behaviour perform well enough to be incorporated in a runnability index. However, creating these estimators based on running behaviour is more complex and costs more time than creating a simpler generic index that could easily add more simple environment measures to improve effectiveness.

6 Discussion

6.1 Conclusion

The purpose of this research was to find ways to improve existing methods for creating runnability indices with the use of human running behaviour in the form of running loops and running towards parks as a goal. Using existing methods to create a benchmark index and the design science methodology, a method has been developed that takes running distance and runnability score for the two shortest routes towards a park into account for the creation of a runnability index. This method aims to reduce the limitations of existing runnability methods, listed in the problem statement and problem investigation phase. These limitations being the lack of track simulation and ambiguity in the concept of runnability leading to difficulty in validating indices.

Current findings suggest that the implemented factors in the form of distance and route runnability score do indeed have a beneficial impact on the effectiveness of a runnability index. However, while positive, these effects are fairly minimal and require significantly more time and data than aggregating data over a general area. That being said, we set the foundation that the incorporation of running behaviour in runnability indices using even relatively basic methods is valuable for reducing estimation error. Furthermore, defining runnability as the probability of starting a run in a certain area with a score ranging from 0-1 has allowed us to create a method that allows for the validation of runnability indices.

6.2 Limitations

While creating the validation method, a lot of scores required adjustment by residential density. However, this dataset contained multiple areas without any data, meaning that no density could be calculated for this area. Therefore, not all scored areas could be validated. Additionally, return routes from parks to adminstrative areas centroids would have a large overlap with the initial route, due to small deviations already counting as a new original route. The effect of this is that the same route score or extremely similar route score is used for the calculations of runnability.

These limitations mean that there are some areas that may have gotten a biased estimate as a result of areas with a missing or low residential density being unable to be validated. Using the amount of residents instead of counting residential buildings would improve the quality of validation and estimates. Similarily, using the same or similar route score twice can also enforce specific trends that are only found in one route, potentially skewing the estimate of that area. Specifying a maximum allowed amount of overlap would help in this regard.

6.3 Future Research

Future research in improving the methods of incorporating running behaviour into runnability indices could be useful for reducing the time cost and improving overall effectiveness, thus increasing the value that this incorporation of running behaviour has. The potential improvement this would give to runnability indices and estimation of runnability is worth exploring.

6.4 Scientific Contribution

The main contribution of this study is the proof that it is effective to simulate routes to estimate running behaviour, as well as the proof that certain running behaviour exists, such as looping and running towards parks is. Another contribution is the process of validation, that could be used to validate other future runnability indices.

Appendix A

Listing 1: Selecting the shortest routes

Listing 2: Selecting the second shortest routes

images/pictureofcodes.png

Figure 11: Code for generating the routes

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