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Evaluation Tool for Proposed Multi-Use Trails

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The tool's objective is to measure the relative potential user demand for each MUT segment in the internal sample, on the logic that the agency has a charge to install transportation facilities where demand for them is greatest. With respect to MUTs, potential demand encompasses both utilitarian and recreational uses. The tool incorporates both sources of demand for MUTs through factors described by data capable of geolocation and GIS processing. In the tool, factor metrics by trail segment are normalized, and users can adjust weights on factor metrics so that priorities can be explored.

Additional consideration is given to two requests expressed by the project champion at the outset of the research, which are consideration of equity and a regional perspective. Equity dimensions of MUTs are carefully examined in the literature review, and two factors in the tool are selected to address the regional perspective. These efforts notwithstanding, two important factors bearing on equity and affecting potential trail demand lie outside the reach of the tool described here, which are community interest in a proposed MUT and the quality of connectivity provided to a MUT network by a specific segment.

It is recommended that VDOT use the tool results as a preliminary model for ranking the relative demand for specific MUTs. However, because the tool is only one of several inputs into the planning process, site-specific factors not encompassed by the tool, such as a proposed trail's acceptance by the community and the role the trail plays in network connectivity, may be used to supplement these rankings.

Supplemental materials can be found at https://library.vdot.virginia.gov/vtrc/supplements

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FINAL REPORT

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ABSTRACT

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INTRODUCTION

The topic of this report originated in the Transportation Planning Research Advisory Committee (2023) to answer a need associated with establishing a multi-use trail (MUT) inventory by the new State Trails Office (STO) within the Virginia Department of Transportation (VDOT). The MUT facilities created under STO will serve nonmotorized users. These trails will be physically separated from motor vehicle traffic, accessible and safe pursuant to current design standards, and regionally significant (VDOT, 2023). STO MUTs will feature hard surfaces, a maximum 5% grade, and a width sufficient to safely convey two-way traffic in differing modes. The trails will also potentially provide separated travel lanes as needed for safety or comfort.

An Excel-based tool answers the research need expressed by the Research Advisory Committee for a method to compare the proposed MUTs. However, the tool is considered preliminary in its design around a sample of trails provided to the researchers (Cook, 2024), rather than the trail inventory whose outsourced development was not connected to this project. That final trail inventory is expected to be finalized after the completion of this report.

This tool provides decisionmakers with scores to evaluate MUTs on a variety of factors selected in the process of reviewing trail literature. The exception is the estimated economic impact. Quantifying direct benefits before a trail project has been constructed, and before its function in a trail network is fully known, is a dubious undertaking. Rather, quantification of benefits and costs is better estimated after a trail has been in existence for some time and a provable baseline of use has developed. Examples of credible ex-post economic analyses include studies of the Washington and Old Dominion Trail (Bowker et al., 2004), the Virginia Creeper Trail (Bowker et al., 2007), the Tammany Trace Rail-Trail (Hammons, 2016), and more recently, four shared use paths in North Carolina (ITRE, 2018). In these studies, trail use is estimated from primary observational data such as intercept surveys, and only the benefits are modeled, as opposed to both use levels and benefits being modeled or assumed. Moreover, estimating economic benefits is more plausible when considering a lengthy regional trail system, such as the first three trails with economic analyses listed previously at 45, 34, and 31 miles long, respectively, rather than the short segments itemized in the trail database provided for this analysis, many of which are less than a mile in length.

Proposed MUTs in this tool are evaluated on their relative potential user numbers, in other words, by the relative latent demand for them because economic impacts—that is, benefits and costs—will ultimately reflect the volume of trail use. In summary, if VDOT wishes to fund routes that are *more* likely rather than *less* likely to be used for any ordinary purpose, this tool can assist in comparing MUT alignments.

Because MUTs have a wide range of users, scholars in many disciplines—including land conservation, landscape architecture, civil engineering, geography, sociology, economics, public health, psychology, and wildlife conservation—have conducted trail studies, all seeking insights into specific user groups and trails that most benefit the groups of interest. Methodologies and tools for comparing proposed trail projects are available, but as a rule, they pertain to a unique community, require copious amounts of data that are not easily obtained for a large sample of trails, or deliver assumption-based results, such as in a cost-benefit analysis of a not-yet-built trail. None of these methods or tools were judged to be directly applicable to the present need, but they helped to shape the methodology of the tool developed here.

PURPOSE AND SCOPE

The purpose of this project is to develop a tool to measure relative latent demand for various proposed MUT alignments. Six requirements govern the scope of this tool:

- The tool should use data that are feasible to attain at present and that can be refreshed in future years should STO desire to continue to use the tool.
- The tool should use comparatively simple indicators of potential trail use to provide transparency in the explanatory role of each demand factor selected.
- The tool is intended to complement, rather than replace, input from local or state planning staff.
- The tool should include factors that, based on a review of the literature, can represent equity considerations and regional dimensions.
- The tool should minimize the use of assumptions and instead should use data wherever possible.
- The tool should be feasible to apply to thousands of MUTs.

METHODS

The researcher performed six iterative tasks to develop the tool:

- Conducted a preliminary literature review.
- Incorporated trail attractiveness factors.
- Incorporated trail equity factors.
- Incorporated trail recreation factors.
- Incorporated trail transportation factors.
- Combined factors into an overall project score.

Conduct a Preliminary Literature Review

The purpose of the literature review was to identify the factors that could mark distinctions of value among MUT alignments and that could be applied to a large sample of trails. That said, the literature review firmly established that factors influencing trail use are specific to each trail and its context. For example, the physical attractiveness of a trail to users has drawn attention in recent years as a probable driver of trail use and resulting benefits (Johansen et al., 2020). For decades, researchers have examined the physical health benefits of trails as opportunities for outdoor activity (Smiley et al., 2020; Starnes et al., 2011), advancing more recently to the benefits of physical activity specifically in natural outdoor environments of "greenness" (Fong et al., 2018), with direct implications for the details of MUT design and alignment. In addition, societal benefits are claimed from using the trails as a transportation alternative to motorized travel, as a community-enriching resource, for economic stimulation of a community, and for ecological preservation, among other benefits. Still, precisely how healthful and economically stimulating a MUT can be and how much it can reduce carbon dioxide emissions are outside the scope of this research, which attempts to anticipate the level of use through the choice of factors but not quantitatively predict use levels.

Through a process of elimination facilitated by the literature search, the focus turned to two categories: (1) factors measuring incentives for MUT use and (2) factors having quantifiable estimates of potential user populations. Both factor categories required data for each MUT alignment in the working sample.

A subsequent detailed literature review was continued for the duration of the project but was combined with additional information to develop factors pertaining to trail attractiveness, equity, transportation performance, and recreational uses. This additional information included a survey of stakeholders conducted by STO, a sample of candidate trail projects for initial testing and refinement of evaluation factors, and feedback from the project's Technical Review Panel regarding these factors and possible weights. This information was incorporated into the remaining four tasks.

Incorporate Trail Attractiveness Factors

A distinct subset of the literature, including Duever and Teisenger (2001) and Gernhard and Hicks (2023), describes prioritization processes for an existing set of trails that precursor studies have already identified, a scenario like the present research. In these specific studies, the prioritization of MUTs is based partly on giving the user a high-quality experience by favoring alignments that feature points of scenic, historic, cultural, and natural interest. Similarly, numerous local and regional trails' master plans with defined prioritization criteria designed to capture local preferences are in place (City of Austin, 2014; City of Bowie Maryland, 2019; New Garden Township, Chester County, PA, 2019; Oregon Metro, 2022). These community planning reports universally employ surveys to gauge the level of local public interest in community trails in general and in specific trail alignments passing or terminating at destinations of interest. These reports frequently have the explicit goal of building trails that will connect trail users with popular scenic, historic, cultural, natural, civic, and commercial destinations.

On this logic, this tool utilizes a factor of "points of interest" (POI) grouped into categories of commerce (e.g., convenience stores, laundry facilities, or malls), civic (e.g., libraries, post offices, or schools), health (e.g., clinics, dental offices, or pharmacies), recreation (e.g., parks, dog parks, or playgrounds), and personal (e.g., public toilets, drinking fountains, or shelters), all for which geolocated data were readily collected from OpenStreetMap (Geofabrik GmbH and OpenStreetMap Contributors, 2024). The tool also contains bus and rail transit stops provided by the Virginia Department of Rail and Public Transportation as additional attractions on some MUT alignments (Stankus, 2024). Although introduced as an attractiveness factor, accessibility to transit is also acknowledged as a transportation factor in the tool.

However, a significant share of the trail literature finds that enticement measures, ranging from community activities to special trail features, could be necessary to prompt a local population to use a trail at all, that is, to engage in physical activity instead of sedentary habits (HHS, 2021; Johansen et al., 2020). In a direct comparison by intercept survey on two major trails in Georgia and Texas, Keith et al. (2018) found that different users described different motivations: "social interaction and community activity" predominated on the urban trail, and "physically active recreation" and experience of a natural setting predominated on the suburban trail. Keith et al. (2018), like other researchers, found that a top concern, especially for women and nonwhite trail users, was personal safety and security along the trail. Literature addressing trail features is highly beneficial to local trail planners designing to stimulate trail use, especially if the planners are designing for specific user populations (De Valck et al., 2017; Johansen et al., 2020; Keith et al., 2018). Overall, it appears to be a consensus that local community enthusiasm for a trail, the presence of natural vegetation, and the presence of safety features of proven worth are highly positive (Jain et al., 2020), if not key, influences in generating local trail use. However, no information about these extra features was available on MUTs in the internal database.

In sum, three raw factors pertaining to trail attractiveness were incorporated into the tool. The first two factors pertain to POI and public transportation stops, respectively, where these factors are assumed to be positively correlated with trail use because they measure incentives for MUT use. A third factor bearing on safety, that is, bicycle and pedestrian crashes near a MUT alignment, is used in the tool to capture the presumed design benefit of a MUT separated from traffic (VDOT, 2024). The tool assumes that higher crash rates will induce higher use of a MUT alignment in the same vicinity because it is physically separated from traffic.

Incorporate Trail Equity Factors

The literature regarding equity is fairly broad but may be categorized into three types of considerations: diversity of users, potential for gentrification, and presence of rent-burdened populations.

Diversity of Users

VDOT's STO conducted a survey in the fall of 2023 about the Virginia Statewide Trails Plan to determine public interest in Virginia MUTs (Cook, 2023). STO distributed the survey through social media and members of the newly convened advisory committee to the Statewide

Trails Plan. The survey results were available to researchers about 90 days before a working trail sample became available, providing time during the interim to consider the survey results alongside the findings in the literature.

About one-half of the survey respondents provided a home city in Virginia. By self-reporting, 89% were White and currently bicycled, walked, or jogged on trails at about respective equal rates of 68 and 66%. Respondents ranked connections to existing MUTs, recreational amenities, places of work or school, and between communities about equally as the most important factors when "considering new MUT projects." STO survey respondents clearly supported the POI trail factor selected for the tool. However, the question arose as to whether POI are a Caucasian preference because of the Caucasian-dominant profile of survey respondents.

The imbalance in respondent ethnicity was not surprising. Popular media has long assumed that most users of trails and other active outdoor facilities are Caucasian and predominantly male and young (Kearney, 2013), and the same is found incidentally in some public health research (Price et al., 2011; Smiley et al., 2020). Other synthesis research specifically on trails and physical activity does not find this feature (Starnes et al., 2011). Studies on specific trails of the influence of demographic characteristics on motivations for use and non-use have found race and ethnicity to be an insignificant or marginally significant predictor, even though actual users were mostly Caucasian (Hughey et al., 2015; Lee et al., 2002). Hughey et al. (2015) determined, by means of random residential phone calls, that gender, age, and income were statistically significant determinants of use of a well-known paved trail in South Carolina, whereas race and education were not.

To explore whether remediable barriers may cause ethnic imbalance in active transportation in general, Sadeghvaziri et al. (2024) performed a scoping review of 60 studies screened for a focus on "the use of active transportation among underrepresented populations in the United States." A primary objective was to identify gaps, or unanswered questions, in the collected findings. However, the scoping review yielded inconstant findings.

Among other findings, Sadeghvaziri et al. (2024) recounted that (1) Braun et al. (2019) found no "particular" proof that sociodemographic indicators explained race-specific trends in access to active transportation infrastructure across the United States; (2) Franckle et al. (2020) found that "safety issues, lack of helmets, lack of nearby stations ... and weather" deterred bikeshare use, and convenience, location, and economic, entertainment and health benefits facilitated it, all arguably rational calculations by any potential users; (3) Caspi and Noland (2019) showed that "bikeshare journeys from docking stations in low-income neighborhoods were for work commutes" in Philadelphia and that fewer trips were generated from low-income areas, plausibly implying that employment trims the leisure hours available for bike sharing by any user; and (4) Auchincloss et al. (2020) found, based on survey intake, that those "insufficiently active in bikeshare programs" in Philadelphia "were disproportionately older, woman, non-Hispanic black, and disadvantaged"—but without eliminating the role of simple preferences as the cause for the difference.

On the other hand, Sadeghvaziri et al. (2024) cite Quinn et al. (2016), who showed with 2009 National Household Transportation Survey data that "[i]ncreasing odds of active commuting and transportation were associated with younger age, lower income, urban dwelling, and [both] the highest and lowest education categories." Furthermore, Wang and Lindsey (2019) found that "people who live in areas with high concentrations of minorities and low socio-economic status use bikeshare *more* frequently, travel at different times of the day and ... days of the week, and have more frequently used origin-destinations stations pairs"—again plausibly implying a role for employment hours in their use of bikeshare. Moreover, Gehrke et al. (2021) found that "neighborhoods with a larger proportion of renter-occupied dwellings and historically disadvantaged populations have less access to dockless bikes while simultaneously having higher bike utilization rates" (Sadeghvaziri et al., 2024).

Sadeghvaziri et al. (2024) conclude that their literature review, on balance, might suggest ethnic underrepresentation in active transportation participation, but their main finding is that the need remains to determine the *reasons* for differential use of active transportation.

In contrast to academic studies, research by nongovernmental organizations reflects public sentiment relatively fluidly because of direct, informal access to target populations. In 2021, the Rails to Trails Conservancy conducted a study to understand trail use among Hispanic and African-American communities for the stated purpose of enhancing the appeal of trails to non-White populations (Rails to Trails Conservancy, 2021). Their survey sample was approximately balanced between African-American, Hispanic, and Caucasian respondents and between male and female respondents. Approximately 36% of African-American, 41% of Hispanic, and 40% of Caucasian respondents self-reported as regular users of trails. Similarly, 45% of male and 33% of female respondents self-reported as regular users of trails. Regarding the *ideal* frequency of trail use as "A lot more," 1 in 4 African-American respondents agreed, and about 1 in 3 Hispanic and Caucasian respondents both agreed. Regarding the ideal frequency of trail use being "No use at all," about 1 in 7 African-Americans, 1 in 20 Hispanics, and 1 in 14 Caucasians agreed. Furthermore, percentages of Black, Hispanic, and White participants agreeing with the statement "I never considered trails and open spaces as important" were 12, 6, and 7%, respectively. Unfortunately, the causes of the lower appeal of trail use to African-American respondents relative to Hispanic and Caucasian respondents were not identified in this survey.

In the Outdoor Foundation's (2023) Outdoor Participation Trends Report covering a broad array of outdoor activities, African-American and Hispanic participation rates were approximately 10 and 13%, respectively, whereas Caucasian participation soared by comparison at nearly 70%. In context, self-reported Caucasian participation was about 10 percentage points higher than representation in the U.S. population, whereas African-American and Hispanic outdoor recreation participation rates were about 2 and 6 percentage points *less*, respectively, than their population representation.

The imbalance in African-American participation rates in outdoor activity, including trails, relative to U.S. population representation has been observed across time and investigations, and it has generally been studied without a resulting consensus in findings. Some popular media sources respect a role for personal preferences (Williams, 2024), and other academic research has proposed deeper roots, such as the intentional preservation of an ethnic minority cultural identity against a dominant culture that urges outdoor activity (Washburne and Wall, 1980). A different perspective, rather than an "answer," may be the key. Assuming personal preferences may be credibly aggregated to "community desire" for a proposed MUT, studies do support that acceptance by local communities is key to the eventual local popularity of a new MUT among residents (Hughey et al., 2015; Kuzmyak et al., 2015; Noll, 2021).

As noted previously, many local communities acknowledge in practice the necessity for surveys of their residents to determine recommended trail alignments and features. Lacking this information for the trails in the sample database provided for development of this tool, the researchers explored measures of equity outside of ethnicity out of respect for the strong possibility that use of active transportation in general is a complex matter of need and desire, more than sociodemographic factors such as race. In any case, external forces that undermine community character and, therefore, cohesiveness, such as the imposition of an unwanted MUT alignment, would be expected to counter MUT popularity and use.

Potential for Gentrification

MUTs, especially if layered on historic footprints (e.g., abandoned rails, former main streets, or decommissioned streetcar routes), have been commended for the stimulating role they might play in local historic preservation, business vitality, and community health. The trails make a self-evident contribution to an aspiring "walkable community" (Brown, 2020) and can be the main attraction to pull tourist revenue into a willing and picturesque rural community (Chakraborty, 2019). For decades, trail advocates have relied on the existence of a "universal positive connection between well-designed open spaces and trails and important economic development indicators" (Rails to Trails Conservancy, 2007). Indeed, trail-oriented development, or "TrOD," was celebrated in the mid-2000s as a specialized strategy of community planning to facilitate the vaunted positive interaction between economic growth and MUTs (Rails to Trails Conservancy, 2007). Although TrOD surely offers an attractive paradigm suitable in some communities, it is nonetheless true that in some significant projects in which a consortium of entities was required for project planning and delivery, a sharp increase in property values around the projects delivered a marked "downside," that is, housing cost shock to local low-income renters in a process known as gentrification.

Homeowners may benefit in gentrifying neighborhoods by selling to capture capital gains, unlike renters who may be confronted with higher rental housing costs. Gentrification can harm low-income renters in two general ways: by rising renter costs (i.e., rent) absorbing more household income and causing "reinvestment dislocation," or by rising owner costs (e.g., property taxes) causing deteriorating housing quality and "disinvestment dislocation" (Kim and Wu, 2022). Observation and modeling indicate that renters are far more likely to be dislocated in neighborhoods undergoing gentrification than in neighborhoods that are not (Chapple et al., 2017).

Testing for gentrification due specifically to publicly funded outdoor amenities like MUTs became a relatively frequent social science research topic after 2000, when the statistical tool of hedonic analysis was combined with geographic information system (GIS) technology, apace with a noticeable uptick in zeal for economic “revivals” (i.e., blight elimination) of downtown neighborhoods and central cities. The documentation was abundant, as in Hwang and Lin (2016) and many other studies. Crompton and Nicholls (2019) note that after 1975, new railbanking legislation, the advent of federal funding for trails, and the movement to consider trails as urban amenities began to align into a force in community planning, spawning in subsequent years numerous opinion surveys of owners of property near trails. According to Crompton (2001), projects in those years were regularly obstructed by the relatively small share of property owners who feared property value *declines* from retrofitted trails traversing their neighborhoods. Soon after, Lindsey et al. (2004) found, through GIS technology and hedonic modeling of market prices for homes proximate to various Indiana greenways, that some but not all greenways raised home prices. Years later, Crompton and Nicholls (2019) concluded, from their review of 20 dissimilar hedonic analyses using various buffer distances from trails, that proximity to a trail caused a rise in single-family home prices of 3 to 5% compared with similar homes in a given location. However, the researchers also stressed that the scales of studies enabled by GIS technology, together with the wide variety of trails, only weakened general conclusions about trail effects on home prices.

Gentrification, defined here as the increase of previously stable rents, has been carefully documented on several highly publicized trail megaprojects meant to bring new vitality to cities (i.e., meant to reinvigorate a local economy). In May 2016, one year after the opening celebration for Chicago’s 2.7-mile Bloomingdale 606 Trail, hundreds of marchers protested the facility over sharp rent increases and other unwelcome changes in neighborhood character that allegedly resulted from the rails-to-trails project (Rigolon and Nemeth, 2018). In the interval between the 2013 ground-breaking and 2016, prices in the predominantly lower income rental property 606 West section of the trail alignment had increased by 48.2% compared with increases of only 13.8% in the wealthier condominium 606 East section (Crompton and Nicholls, 2019). Crompton and Nicholls (2019) also cite studies finding gentrification along New York City’s High Line completed in 2009 and the ongoing Atlanta Beltline initiated in 2005. Crompton and Nicholls (2019) and Rigolon and Nemeth (2018) note the critical roles of the prime entities that delivered these megaprojects because proactive impact-mitigation measures for low-income housing could have been, but were not, incorporated as part of the trail project contracts.

Gentrification illustrates that public provision of amenities to enhance communities can be ironically bedeviled by the popularity of such public works, for example, as transit-oriented development has been determined to have caused gentrification in California (Chapple et al., 2017). The revitalization of city centers is arguably an appropriate interest for elected officials, but the role of public funding in revitalization efforts is problematic if gentrification follows and low-income housing is lost. Hwang and Lin (2016) noted, with the decades-long trend of gentrification in the United States, a rise in “blame” for loss of low-income housing laid on a national policy shift away from “welfare-state” solutions (direct provision and preservation of designated low-income housing by the federal or state government) to “free market” solutions (attentiveness to “affordable housing” developments by a municipal government). In any case, the wrenching issue of “one’s right to their neighborhood” has been investigated sympathetically by scholars (Anguelovski, 2016). Furthermore, an extensive nonprofit housing-assistance industry exists today for the mitigation of factors that correlate with vulnerability to gentrification (Kriesberg, 2018), seemingly in agreement that public amenities should not cost a community its low-income housing or residents.

Evidence of reliable or universal causes of gentrification is lacking (Chapple and Zuk, 2016; Hwang and Lin, 2016). Rigolon and Nemeth (2019) found that the variables that were strong predictors of gentrification in the five most populous Combined Statistical Areas (CSA) in the United States were inconstant among those CSAs. The researchers argued that identifying the determinants of gentrification exonerates the "market" while implicating "local institutions, place quality, and housing programs." Specific to the Bloomingdale 606 trail, Rigolon and Nemeth (2018) analyzed and ultimately attributed gentrification to the planning *process*—particularly calling out the myopic collusion between so-called "green growth machine actors" and trail-advocating nonprofits—because neither the developers nor the nonprofits encompassed consideration of harmful rental housing impacts in their specific project development or delivery roles. In the view of Rigolon and Nemeth (2018), ineffective or insufficient public outreach in the planning phase lies at the very core of gentrification vulnerability.

Public engagement to learn community preferences and goals before a transportation facility is constructed has long been practiced pro forma, but the successor to public engagement—that is, "procedural justice"—has transformed public engagement into a matter of equity (City of Richmond, VA, 2022; Krings and Schusler, 2020; Lee et al., 2017; Oregon Metro, 2022; Rigolon and Nemeth, 2018). Today, scholars urge that affected communities be pursued early in the planning phase for the purpose of determining "*appropriate* and *meaningful* solutions" (emphasis added) to address historic transportation inequities (Krapp et al., 2021; Rigolon and Christensen, 2019; Rigolon and Nemeth, 2018). Today, meaningful community involvement in planning trails is regarded as a precondition to prevent harms of "top-down planning without community buy-in or leadership" (Rails to Trails Conservancy, 2024). The City of Richmond, Virginia (2022), recently published a transportation policy guide that states "[Transportation] equity surveys *should* (emphasis added) be used as a means to identify priority areas and may help provide weight to scoring criteria." The immense benefit of such surveys is to learn whether the local population favors local access to a MUT or not, as the previous discussion illuminates.

For the tool, takeaways from the gentrification literature include three major points. First, gentrification may be a real risk only in limited parts of Virginia. The effects of green infrastructure on low-income housing have been more pronounced in the downtown areas of big cities than in those of smaller cities (Hwang and Lin, 2016; Rigolon and Nemeth, 2019), although the presence of historic housing in a downtown area, such as in Richmond, may be a strong correlate with gentrification potential (Chapple and Zuk, 2016; Rigolon and Nemeth, 2019). Second, gentrification is not universally or inevitably racially delineated. Rigolon and Nemeth (2019) found, like other researchers, that gentrification was more likely to happen in neighborhoods with larger shares of racial or ethnic groups other than Black and Latino. Third, should Virginia trail alignments fall in zones considered to potentially carry gentrification risk, local authorities should be proactively intent on involving the local community in the MUT project scoping phase and, if necessary, planners should expect to apply housing mitigations suited to the jurisdiction (Kriesberg, 2018).

Although it is encouraging that Kim and Wu (2022) found that trails, specifically designated in their study as “active” green spaces, have a statistically insignificant effect on gentrification indicators, whereas passive green spaces have a significant positive effect, the most fundamental takeaway from trail literature is that no perfectly predictable rules about MUTs and gentrification seem to exist. Consequently, much depends on the local population’s receptivity to a proposed MUT alignment.

Presence of Rent-Burdened Populations

The literature on gentrification steered the researchers to investigate measurable factors that could indicate gentrification-vulnerable populations near proposed MUT alignments. Because the tool factors require quantitative measures, a review of census files supporting the Screening Tool for Equity Analysis of Projects (U.S. DOT, 2022) suggested using census data on rent-burdened populations in the tool developed here.

Housing can scarcely be overestimated as a “social determinant” of health. Graetz et al. (2024) constructed a novel dataset linking U.S. census data with eviction records spanning the period from 2000 to 2019 and found that higher rent burden, increases in rent burden in middle-age, and eviction judgments were all significantly associated with increased mortality. Indeed, associations were higher if eviction had been perceived a lower risk—that is, if it surprised the renters. The Graetz et al. (2024) study covered 2 decades, but it proves that even slowly rising rents in originally low-rent neighborhoods can be disruptive if low-rent housing options are not adequate locally.

The U.S. Department of Housing and Urban Development (2014a) defines “rent burden” and “severe rent burden” as rent-to-income ratios exceeding 30 and 50%, respectively. Renters in the lowest income quintile are self-evidently the most vulnerable to rent burden. According to Larrimore and Schuetz (2017), the median percentage of income spent on rent by the U.S. population in the lowest income quintile rose 11 percentage points between 2000 and 2015, from about 45% to about 56%. By contrast, the median rent paid by the population in the next higher quintile did not meet the “rent burden” threshold in 2000 or 2015, let alone the severe rent burden standard. Interestingly, in 2015, rural areas of the country were not low-rent havens because rural renters in the lowest income quintile paid a median rent of 41% of income versus 58% in metropolitan areas.

Although Larrimore and Schuetz (2017) found that higher income quintiles also paid higher shares of income in rent in 2015, among the lowest income quintile, the researchers found that the decline in “residual” income after paying rent was approximately 67% because of falling median incomes during 2000 through 2015, with the remainder caused by rising rents. From either of the causes, however, these dual pressures on low-income renting households suggested increasing vulnerability to the effects on rental housing stock—that is, housing supply—in the runup to COVID-related telework shifts that drove up national home-ownership demand *and* a sharp fall in multifamily housing starts, including rental housing (Bauer et al., 2024).

In Virginia, rents respond differently in different regional markets. Although rents fell in Northern Virginia from 2020 to 2021, probably because of the loosened federal workforce telecommute policy, rents rose in the Richmond and Hampton Roads regions by up to 9 and 6%, respectively, just for the lowest quality housing (Sturtevant, 2021). Furthermore, from 2020 to 2021, rents for the *poorest* quality housing declined the *least* in Northern Virginia and rose the *most* in Richmond, followed by Hampton Roads, according to Sturtevant (2021). Price (2022) asserts that ongoing homebuying demand and rising mortgage rates likely caused the increase in statewide average rents of 11.3% from the first quarters of 2021 to 2022 because of spillover demand from thwarted homebuyers-turned-renters At the same time, during the 3-year period from 2019 to 2022, the annual rental vacancy rate in Virginia fell from 7 to 5% and most rapidly in 2020 (U.S. Census Bureau, n.d.e.). When considered collectively, recent conditions created by the pandemic may be fairly judged to have differentially affected low-income renters in Virginia. Care should be taken to avoid exacerbating the negative effects on this population.

Market forces may yet nudge multifamily rental vacancy rates toward the 6% “norm” (MRI Software, 2024) through new construction because the declines in vacancy rates from 2020 to 2021 were followed by higher multifamily construction permit issuance in 2022 (U.S. Census Bureau, n.d.d.), and multifamily buildings are the dominant type of rental housing stock, holding more than 47% of all renting households in 2022 (Chandan Economics, 2024). However, higher vacancy rates are not an unqualified positive harbinger for low-income renters because the rates may be a sign of an undesirable housing location (e.g., far from transit or shopping) or poor property management, both being unattractive features directly or indirectly suppressing MUT demand.

For this reason, the tool compounds two census data sources into a single composite factor of “vulnerability” that is assumed to bear negatively on a MUT score. These two sources are (1) median gross rent as a percentage of household income in the past 12 months, under the logic that low-income housing for residents with relatively higher rent burdens might be destabilized by the construction of a MUT that becomes popular, and (2) the percentage of all occupied and unoccupied housing units that are vacant “simple” rentals—that is, not special-purpose rental housing such as vacation homes and so on—on the logic that areas with higher rental vacancy rates may be less able to generate greater MUT demand because of possible safety and aesthetic perceptions by potential users (HUD, 2014b).

It may be simplistically argued that low-income households especially benefit from having an active-transportation option in their neighborhood. However, planners should be alert to relatively high concentrations of vulnerable renter households near a proposed MUT alignment and to relatively high vacancy rates proximate to a proposed MUT. Both conditions *may* be economic indicators of a problematic environment for public investment where level of use is the measure of success.

Summary of Equity Factors

In sum, two raw factors that relate to equity were incorporated into the tool: median gross rent as a percentage of income and the “simple” vacancy rate of housing units. It should be noted here that a relatively high vacancy rate in census data may indicate new housing rather than persistently vacant rental housing. Nonetheless, if one agreed purpose of a MUT is for it to be *used sooner rather than later*, placing the trail near properties with higher vacancy rates for any reason will probably be less effective than placing it near housing with lower existing vacancy rates. Finally, it is stressed that the important equity issue of local support for a planned MUT cannot be captured in the tool alone.

Incorporate Recreation Factors

The Virginia Statewide Trails Plan Survey, distributed in the fall of 2023, captured responses from individuals around the world, although the largest set of respondents seems to have been in Central to Northern Virginia. Predictably, 89% of respondents reported Caucasian ethnicity, and 84% had a bachelor's degree or higher. Unexpectedly, 71% of respondents reported being 46 years or older, and females edged males at 49 to 48%.

The survey asked various questions about the frequency and mode of MUT use, reasons for infrequent or non-use, how information about MUTs is obtained, the most important factors for deciding to use MUTs, opinions on trail development priorities, desired destinations to access via MUTs, frequency of access for recreation or for transportation purposes, and whether MUTs are beneficial to human health.

A composite "profile" of a respondent may be created from answers that attracted 50% or more of respondents. This "person" uses MUTs at least once each week; uses online resources or personal contacts to acquire information about MUTs; drives to MUTs to either bike or walk, would like to do a little more biking than walking in the future but expects to be on foot if using MUTs more often; uses it mainly because it creates a feeling of safety from vehicles; prefers longer MUTs "that connect localities and destinations" over local MUTs that connect only residential areas to POI or business, or to local MUTs within the respondent's community; has no predominant opinion on the top priority for MUT development (e.g., connections to other trails and locality connectivity, closing gaps, access to MUTs near home, building new MUTs, and so on), and seems not to value amenity upgrades to existing MUTs (e.g., benches or lighting) or expedient routes that save travel time; sees MUTs as the destination but would appreciate MUTs leading to other recreation facilities like parks, playgrounds, and pools and, slightly less avidly, restaurants and cafes; prefers asphalt or concrete surfaces for MUTs; believes MUTs are important predominantly because the trails facilitate physical health benefits and because they provide safe space for physical activity; uses a MUT at least once per week for recreational biking but a few times per year or less for utilitarian transportation purposes; emphatically appreciates the separation from traffic that a MUT provides but wants MUTs to be accessible and connected to destinations; and strongly agrees that new MUTs should connect to other MUTs, connect residential and work and school locations, connect to recreational amenities, and connect communities.

Overall, this composite mid- to upper-income, prime- to older-working-age MUT user drives to MUTs to enjoy long, safe, recreational bicycle rides on a weekly basis. This person highly enjoys MUT connectivity to other MUTs, POI, food, and other recreational opportunities. However, this cyclist is happy to use MUTs for physical exercise alone because it is considered exceedingly beneficial to mental and physical health. Thus, this composite respondent is motivated to seek out and use a MUT as a health-generating recreational opportunity.

The aggregate profile derived from the survey certainly endorses the recreational value of a MUT in Virginia, but the sample trails evaluated in the tool developed for VDOT are heterogeneous, as seems appropriate given VDOT's fiduciary charge to provide Virginians with transportation options. Therefore, it is presumed that a given trail may have both recreational and utilitarian functions or may have one predominant function. At the same time, the tool should contain factors capable of reflecting both functions. Given this user "profile," researchers identified two ready-made resources for a GIS-based tool to use in the present tool.

First, from a 2021 GIS database compiled by the Virginia Department of Conservation and Recreation (VDCR), the Land-Based Recreation Need (LBRN) Composite Score (Hazler and Bucklin, 2021) provided a factor reflecting demand for recreational opportunities via a raster with 30-meter pixel resolution. The LBRN score reflects access to "green, open space recreation requiring only minimal facilities, like trails" and excludes conserved lands that the public may not access. This score illuminates the comparative regional *recreation* value of a given MUT.

The LBRN Composite Score is calculated from four factors (VDCR, 2021b):

- Driving travel time to the nearest protected land with public access (PPA) offering at least 5 acres of available greenspace (Proximity Score).
- The number of PPAs offering at least 100 acres of available greenspace that can be reached within a 30-minute drive (Local Options Score).
- The number of PPAs offering at least 600 acres of available greenspace that can be reached within a 60-minute drive (Regional Options Score).
- Land-based recreation pressure based on population size and the amount of available greenspace within service catchments and gaps delineated for PPAs with at least 25 acres of available greenspace (Pressure Score).

LBRN sub-scores are combined into a composite need score for nature-based recreation with five gradations from very low (1) to very high (5). This score is based on the locations of all protected lands *with public access* in Virginia, including parks, forests, historic sites, and preserves (Hazler and Bucklin, 2021), and the GIS layers are posted for public use (VDCR, 2021a). This score indicates where MUTs drawing recreational users could relieve greater regional need for outdoor recreation on public lands. Consequently, a positive relationship between the composite need score and the MUT score was assumed in the tool.

Second, the University of Wisconsin Population Health Institute produces annual County Health Rankings (CHR) in 34 "dimensions," two of which seemed to be of high regional value in comparing Virginia MUTs: average daily air particulate matter less than 2.5 micrometers ($PM_{2.5}$) in mcg per cubic meter and the percentage of the population with access to places for physical activity. Both scores were presented at the county level (County Health Rankings and Roadmaps, 2024a). The Institute's 2024 release was employed in the tool, although the metrics on access to exercise opportunities date from 2023, 2022, and 2020, and the levels of fine particulate air pollutants date from 2019. Exercise opportunity scores were compiled from ArcGIS Business Analyst, ArcGIS Online, YMCA, and U.S. Census Bureau TIGER/Line Shapefiles. $PM_{2.5}$ levels were derived from monitoring supplemented modeling performed by the Centers for Disease Control and Prevention's Environmental Public Health Tracking Network (County Health

Rankings and Roadmaps, 2024b). CHR GIS layers for Virginia were provided on request (Hoffelder, 2024). The purpose of the CHR metrics is to distinguish MUTs that are needed for exercise and that are located where the air quality is better for outdoor exercise. They are compounded into a single metric as a factor in the tool score.

Like the LBRN Composite Score, the two CHR metrics supply regional insights into conditions near planned MUTs. However, whereas the LBRN factor measure is higher in proportion to greater regional need for land-based recreational access and, therefore, positively affects MUT scores in the tool, the CHR compounded factor negatively affects MUT scores in the tool because greater access to exercise opportunities renders a MUT less needed. If $PM_{2.5}$ is also relatively high, a MUT could be unintentionally a source of *poor* health for users, contrary to the trail's purpose. Combined, then, a higher composite CHR score conveys a trail that is both less needed and less healthy to use. Therefore, a negative relationship between the CHR composite score and the MUT score was assumed in the tool.

In sum, three raw factors related to recreation were incorporated into the tool: access to exercise opportunities, $PM_{2.5}$, and LBRN scores. It was assumed that these factors have opposite effects on MUT scores.

Incorporate Trail Transportation Factors

In addition to recreational users, the tool aimed to identify metrics to capture a MUT's relative utility as a facility for work commutes. Potential numbers of commuters using MUTs are not likely to exceed potential recreational users on the average MUT, judging by census data on commute modes and responses to the Virginia Statewide Trails Plan Survey described previously, but with sufficient density and connectedness, new MUTs could induce demand for active commute facilities, much as roads have done for such reasons as "growth in demand attributable to population, employment, or new activities in the market area … [or] new trip generation … as trip distribution patterns change" (Polzin, 2023). In other words, the more efficient the MUT network becomes, the higher the utility of MUTs to the active-mode commuter. Given this transferable logic, several factors were developed for the tool to reflect the relative values of MUTs for commuter use.

First, the U.S. Census Bureau's (n.d.c.) OnTheMap tool demonstrates an application of Longitudinal Employer-Household data that the researchers adapted in the current tool to obtain a direct measure of the relative active-commute potential of MUTs. OnTheMap Inflow-Outflow analysis shows, among other analyses for a buffered selection area, counts of jobs in a selected area for which job holders' home census blocks lie within the same selected area. To measure the "labor force efficiency" of a proposed MUT, this metric provides a census estimate of the total number of jobs whose holders could actively travel between home and work by using the MUT of interest for part or all of the journey. For the "labor-force efficiency" factor in the MUT tool, the researchers employed 2021 (the latest available at that time) Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES) pertaining to all jobs, except civilian or military employment in the U.S. Department of Defense (U.S. Census Bureau, n.d.b.). LODES data have been recently updated to 2022 in OnTheMap and are available for download. Trimming the complete file of LODES data to yield a factor measure for each MUT in the internal sample was a complex, multistep process for which details are provided in the Appendix.

American Community Survey (ACS) data provide population characteristic estimates by census block groups and census tracts that can be narrowed to the environs of a proposed MUT alignment by geoprocessing with TIGER/Line Shapefiles for Virginia and the year corresponding to the census data (U.S. Census Bureau, n.d.f., n.d.g.). The ACS population characteristics selected to reflect relative latent demand for a MUT—or simple population availability near it—consist of total population (transformed to population density), housing occupancy (transformed to housing occupancy rate), means of transportation to work (transformed to numbers of workers using any counted nonmotorized commute mode), housing tenure by vehicles available (transformed to the percentage of owned or rented occupied housing with no vehicles available), and means of transportation to work by tenure (transformed to numbers of workers taking public transportation or walking to work, or telecommuting) (U.S. Census Bureau, n.d.a.). The extent of vacant rental housing (i.e., nonspecial purpose rental housing, for rent but unrented) serves in this tool as a relative indicator of neighborhood desirability, related to both the perceived safety and the aesthetic of a proposed MUT, but not as an indicator of blight because simple rental vacancy occurs for many other reasons than blight, which has other more direct correlates than vacancy (Schilling and Pinzon, 2016).

In sum, six raw factors related to transportation demand were incorporated into the tool. These factors include the total number of jobs occurring in work-home census block pairs when each of the two census blocks in the work-home pair is intersected by a one-half-mile buffer around a specific MUT segment, or "in-area labor force efficiency"; and total population, housing occupancy, means of transportation to work at the census tract level, means of transportation to work by housing tenure at the block group level, and housing occupancy categorized by vehicles available.

Combine Factors into an Overall Project Score

Measures for the 19 raw factors identified were produced for each MUT through geoprocessing the raw data sources with the trail sample. They were then exported to an Excel spreadsheet in array form, each row representing all 19 raw factor measures for a unique feature identifier (FID)—that is, the unique identifier for a MUT in the geodatabase developed for the tool. In some cases, additional geoprocessing was performed to derive a raw factor measure. For example, for four of the census datasets—population density, housing occupancy rates, number of workers not taking motorized vehicles (transit excepted) to work, and occupied housing units with no vehicles available—and for "in-area labor force efficiency," raw values were derived by summing values in all census units intersected by a one-half-mile buffer around the MUT alignment. This process allowed a larger relevant "catchment" area for the population attribute of interest. For the other three census datasets (median gross rent as a percentage of household income, means of transportation to work by tenure, and rental vacancies), original raw factor values were derived by weighting values in census units traversed by the MUT by the percentage of MUT length therein. Weighting raw data by percentage of MUT length lying within census units is an effort to conserve variability in the MUT environment for more sensitive scoring.

For the LBRN scores, raw measures were calculated by length-weighting the level-of-need grids through which a given MUT passes. The two CHR factors were weighted nearly identically by percentage of mileage in each county when MUT alignments passed through more than one. In the Excel sheet, the five raw factors related to POI and two raw factors related to public transportation were summed separately for each MUT and divided by MUT segment length, as was in-area labor force efficiency. Overall, the additional manipulations of raw data reduced the 19 original (raw) factors to 14 intermediate factors.

The 14 intermediate factors are broad indicators of the size of potential demand for each MUT, and a final score can be similarly understood as a broad and multifaceted indicator of higher or lower relative potential demand for one MUT over another. The final score is an ordinal ranking in which numerical scores have no intrinsic meaning. As such, it would seem to allow factor simplification to calculate final scores more easily. To this end, raw CHR factors and raw census data were consolidated into composite final factors in the Excel spreadsheet, allowing a reduction from 14 intermediate raw factors to 9 final factors. The consolidation methodology of raw census data into composite factors is provided in this section. Consolidation of the two CHR factors is analogous and, therefore, omitted.

ACS products, except time series, do not simply replicate survey questions. The population attributes sought in each survey are differentiated across products, if subtly, as are the census unit levels (tract versus block group or block). Given the high margins of error frequently reported in ACS products, survey data are used in the tool with acknowledgment of low precision. Consequently, pooling the seven census surveys into fewer multifaceted factors of potential MUT demand seemed feasible and advantageous.

Initially, each raw census factor value for each FID was first normalized by the maximum raw value for that specific census factor across all FIDs, thus eliminating units of measurement. Then, normalized raw census factor values for the FID were summed to form each desired composite factor. Last, the composite factor value for each FID was normalized by the maximum composite factor value across all FIDs. As noted previously, the same double-normalization process was used to create a composite factor from the two original CHR factors.

On examining the raw data, however, it was noted that housing occupancy rates jumped from values of 0 to 57%, leading to an alternate calculation for the composite factor of population density and housing occupancy rate, specifically minimum-maximum normalization.

Seven individual census surveys were consolidated as described into three final composite factors. First, calculated population density (based on Total Population, B01003) and Occupancy Status (B25002) were consolidated into a factor providing a quantitative measure of simple population *availability* near a MUT.

Second, "Means of Transportation to Work by Tenure" (ACS B08137) was consolidated with "Means of Transportation to Work" (ACS B08301), and a third population was captured in "Tenure by Vehicles Available" (ACS B25044). This composite factor pooled the percentage of workers aged 16 and older who reported taking public transportation, excluding taxis, *or* walking to work *or* working from home with the number of workers aged 16 and older who reported *not* taking any type of motorized vehicle to work *and* the percentage of occupied housing that has no vehicles available. Consolidating these three surveys into one final factor provides a measure of relative *need* for a MUT as a transportation facility for work or other purposes.

Third, two ACS products (B25003 and B25004) were used to calculate the percentage of rental vacancy in a census tract, and ACS B25071 provided the median rent as a percentage of household income during the previous 12 months. The composite factor formed from these three surveys summarizes the environments of MUTs in two dimensions by indicating neighborhoods with higher existing rent burden and/or rental vacancies, neither of which qualities is judged, based on the literature review, to point to a preferred location for a MUT.

In the tool workbook, factor weights entered in the Interface page are automatically linked to the Tool page, where factor measure data are held and final scores are calculated. Factors may be disregarded in final scores by setting a weight equal to zero in the Interface page. As the final step, preliminary FID scores are normalized to limit the scoring range to a maximum of 1, although weights are unrestricted and elective.

Testing the tool revealed 25 segments of less than 10 feet in length that regularly scored very highly under the influence of heavily weighted factor measures provided per unit of MUT length, which causes shorter lengths to have higher factor measure scores. Each of these 25 segments was examined in ArcGIS Pro, judged to have been created as the result of a geoprocessing error, and eliminated from the trail sample in the tool. These segments are listed by FID for review in the tool workbook on a sheet titled “Short Segmi.” Other short segments were also examined individually under various weight scenarios, as addressed in the Results and Discussion section.

Once the final spreadsheet tool with the nine final factors was constructed and tested, two weighting schemes were evaluated. The first weighting scheme generally favors the use of trails for utilitarian travel purposes. In this scenario, the highest weights are given to two factors that indicate the relative propensity to use a MUT for utilitarian travel purposes: in-area labor force efficiency (number of jobs for which employees could likely use MUTs to commute from home) and the composite census factor indicating potential use of a MUT for any utilitarian travel purpose. The second weighting scheme gives higher weights to factors that indicate a propensity to use the trail for recreational purposes. In this scenario, the two factors with the highest weights are the LBRN score and the number of POI. It should be emphasized that the selection of weights could be more or less aggressive than those selected here. The scores of the 2,553 MUTs under these two weighting schemes were then compared.

RESULTS AND DISCUSSION

Results

Raw Data for Factor Measures

Table 1 shows a summary of the selected raw data, their sources, and the final factors for scoring in the tool. The five POI types and the two public transportation types are consolidated by source in the first column, producing 14 measures in the second column and nine final factors. Acknowledging that categories are not mutually exclusive, three final factors fall primarily in the attractiveness-utility category (POI, transit stops, and bicycle and pedestrian crash scores), one factor falls in the equity category (the composite factor of vulnerability), three final factors fall in the recreation category (the composite CHR factor, the LBRN factor, and POI), and the remaining three factors fall in the transportation-utility category (in-area labor force efficiency, availability of any-purpose users, and potential need for travel facility). Signs indicate a factor's impact on a MUT score.

Table 1. Selected Data for Tool Factors

Data Source	Raw Factor Measure	Factor Logic	Final Factor Impact on Score (+ or -)
Population Health Institute County Health Rankings (Hoffelder, 2024)	Access to Exercise Opportunities	Regional need for MUT for exercise opportunity	**[-]** Level of existing access to exercise opportunities and level of $PM_{2.5}$
	Air Particulate Matter Level ($PM_{2.5}$)	Regional use of MUT for exercise opportunity	
Land-based Recreation Need Composite Score (VDCR, 2021a)	Land-Based Recreation Need Composite Scores	Regional need for MUT for recreation and exercise	**[+]** Greater need for "green" recreation on public lands
Longitudinal Employer-Household Dynamics (U.S. Census Bureau, n.d.b.)	In-area labor force efficiency: # of jobs linked to homes where both census blocks fall in vicinity of given MUT	Local use of MUT for work commute	**[+]** # potential commute users of MUT
VDOT Pedestrian and Bicycle Safety Action Plan (VDOT, 2024)	Bicycle and Pedestrian Crash Scores by Severity	Local need for MUT for safer active travel option	**[+]** # potential any-purpose users of MUTs
OpenStreetMap (Geofabrik GmbH and OpenStreetMap Contributors, 2024)	Recreation, Personal, Health, Commerce, Civic Points of Interest	Local use of MUT for attractions	**[+]** # potential any-purpose users of MUTs
Virginia DRPT (Stankus, 2024)	VRE, Metro Stops BRT, Bus, TIDE Stops	Local use of MUT to access public transit	**[+]** # potential travel users of MUTs
U.S. Census Bureau American Community Survey 5-Year 2022 (U.S. Census Bureau, n.d.a.)	Population (B01003 by CBG)	Population density in vicinity of MUT	**[+]** Availability of any-purpose users in vicinity of MUT
	Housing Occupancy (B25002 by CBG)	Housing occupancy rate in vicinity of MUT	
	Means of Transportation to Work (B08137 by CT)	# Workers who take transit or walk to work, or telework in vicinity of MUT	**[+]** # potential active-travel users or teleworkers in vicinity of MUT

Data Source	Raw Factor Measure	Factor Logic	Final Factor Impact on Score (+ or -)
	Occupied Housing Units by Vehicles Available (B25044 by CBG)	Occupied housing units with no vehicle available in vicinity of MUT	
	Means of Transportation to Work by Tenure (B08301 by CBG)	# of workers who commute to work by public transit and three active modes or telework in vicinity of MUT	
	Median Gross Rent as % of Household Income past 12 Months (B25071 by CT)	Median rent burden in vicinity of MUT	**[-]** Vulnerability of neighborhood to MUT or MUT to neighborhood
	Occupied and Vacant Housing Units (B25003 and B25004 by CT)	Simple rental housing vacancy rate in vicinity of MUT	

BRT = Bus Rapid Transit; CBG = census block group; CT = census tract; DRPT = Virginia Department of Rail and Public Transportation; MUT = multi-use trail; $PM_{2.5}$ = particulate matter less than 2.5 microns; TIDE = Hampton Roads Transit Light Rail network; VDCR = Virginia Department of Conservation and Recreation; VRE = Virginia Railway Express.

Interface Page Use

The Interface page is where weights are selected for final factors. Figure 1 shows the tool Interface page with an arbitrary set of weights assigned to the final factors in the leftmost column. Details of the Interface page are discussed in the Read Me page of the tool, whereas only weights are manipulated here. The selected weights show that four factors are considered of more interest than the others, being assigned the maximum (although arbitrary) weight of 5. The Interface page also shows, for any chosen weight scenario, raw mean weighted factor scores for all 2,553 MUTs and shared-use paths (hereafter, included in the term MUT) in the sample and the mean normalized score for all MUTs resulting from the selected weights, as generated in the adjacent Tool page. These mean scores do not change unless the weight scenario is altered.

On the right of the Interface page, a specific MUT may be examined by entering its unique FID in cell J8 (as were FIDs 2579 and 720 in Figure 1). An FID can be obtained by looking in the Tool page at the reference table in columns BA–BC. Specific data on MUT location, name (if any), length, raw component scores, and normalized final score are autopopulated from the Tool page. In this way, an individual MUT, or a factor measure of a selected MUT, can be compared with the mean of the MUT sample for a given weight scenario.

Multi-Use Trails and Shared-Use Paths only		RAW MEAN WEIGHTED FACTOR SCORES	FID	2579	Arlington County
n = 2553	WEIGHTS		LENGTH (MI)	0.035	565
COUNTY HEALTH RANKING	-3	-2.685		-2.822	BELOW AVERAGE NEED/USE
LAND-BASED RECREATION NEED	2	1.143		1.088	BELOW AVERAGE NEED
IN-AREA LABOR FORCE EFFICIENCY (ALL JOBS)/SEGMENT MI	5	0.082		3.680	ABOVE AVERAGE
BIKE/PED CRASHES	5	0.097		0.970	ABOVE AVERAGE
POI/SEGMENT MI	3	0.015		0.283	ABOVE AVERAGE
BUS_BRT_RAIL STOPS/SEGMENT MI	3	0.019		0.431	ABOVE AVERAGE
POPULATION DENSITY + % OCCUPIED HOUSING UNITS	5	3.411		5.000	ABOVE AVERAGE
NO VEHICLE / ACTIVE COMMUTE	5	0.924		4.319	ABOVE AVERAGE
VULNERABILITY	-1	-0.188		-0.311	ABOVE AVERAGE
MEAN NORMALIZED SCORE		0.173	NORMALIZED FID SCORE	0.776	ABOVE AVERAGE

Multi-Use Trails and Shared-Use Paths only n = 2553	WEIGHTS	RAW MEAN WEIGHTED FACTOR SCORES	FID LENGTH (MI)	720 1.178	Arlington County 110 Trail /Cemetery Wall Trail 737
COUNTY HEALTH RANKING	-3	-2.685		-2.822	BELOW AVERAGE NEED/USE
LAND-BASED RECREATION NEED	2	1.143		0.501	BELOW AVERAGE NEED
IN-AREA LABOR FORCE EFFICIENCY (ALL JOBS)/SEGMENT MI	5	0.082		0.000	BELOW AVERAGE
BIKE/PED CRASHES	5	0.097		0.162	ABOVE AVERAGE
POI/SEGMENT MI	3	0.015		0.030	ABOVE AVERAGE
BUS_BRT_RAIL STOPS/SEGMENT MI	3	0.019		0.006	BELOW AVERAGE
POPULATION DENSITY + % OCCUPIED HOUSING UNITS	5	3.411		3.566	ABOVE AVERAGE
NO VEHICLE / ACTIVE COMMUTE	5	0.924		3.495	ABOVE AVERAGE
VULNERABILITY	-1	-0.188		0.000	BELOW AVERAGE
MEAN NORMALIZED SCORE		0.173	NORMALIZED FID SCORE	0.303	ABOVE AVERAGE

Figure 1. Tool Interface: Comparison of Two Multi-Use Trails in Arlington County

Interpreting Tool Scores

Because of its location, FID 2579 has the same or higher scores in absolute value in all nine factors as compared with FID 720. Moreover, the negative sign on Vulnerability causes a greater score deduction for FID 2579 than for FID 720, where Vulnerability is not as high a measured risk, judging by its composite factor value. The final scores suggest that FID 2579 would offer more gains in bike and pedestrian safety than FID 720, and FID 2579 would offer a transportation option to a local population that both lives and works in the area around FID 2579, unlike FID 720 (as shown by their individual scores for "in-area labor force efficiency (All Jobs)/segment mi"). The trail segments are available in a GIS layer that supplements tool scores with visual information about location and potential connectivity to other segments in the database (Figure 2).

Figure 2. Map of Physical Environments of FIDs 2579 and 720. Red lines are other proposed MUT alignments. FID = feature identifier.

Tables 2a and 2b show the top 10 planned MUTs statewide as generated under the weight schemes shown and after screening the results for MUTs of at least 15 feet in length, a bound that eliminated the same MUT from each table. The weight schemes were selected to stress the active-commuter potential in Table 2a and recreational use of MUTs in Table 2b.

Results in Table 2 show that very short segment lengths are present among the highest final scores under these relatively aggressive weights. Because not all segments are very short, however, the effect of short length on factor values computed on a per-mile basis cannot be said to achieve high final scores unilaterally. The selected weights in the two tables and commonalities between the weight scenarios, such as keeping higher weights on POI per segment mile and the composite factor for population availability, resulted in four FIDs in common between the tables, ranging in length from 11 to 62 yards.

The influence of short segment length on scores and the question of the roles of short segments in trail network planning are explored further in the Discussion and Implementation sections.

Table 2a. Top 10 Tool Scores for "Active Commuter" Weight Scheme

		FID	**1438**	**2579**	**1342**	**2574**	**2140**	**2139**	**2279**	**2772**	**3039**	**808**
		Jurisdiction	Charlottesville	Arlington	Multiple	Arlington	Fairfax	Fairfax	Fairfax	Loudoun	Staunton	Fairfax
		Length (mile)	0.007	0.035	33.516	0.011	0.013	0.012	0.012	0.004	0.003	21.078
FACTORS	**WT.**	**MEAN WEIGHTED FACTOR SCORES**	**FID FACTOR SCORES**									
County Health Rankings	– 1	– 0.895	– 0.902	– 0.941	– 0.834	– 0.941	– 1.000	– 1.000	– 1.000	– 0.859	– 0.874	– 0.987
Land Based Recreation Need	1	0.572	0.800	0.544	0.713	0.800	0.800	0.400	0.800	0.800	0.200	0.594
In-Area Labor Force Efficiency per Segment Mile	5	0.082	5.000	3.680	0.002	4.149	5.000	4.353	3.816	5.000	5.000	0.004
Bike and Pedestrian Crash	5	0.097	0.803	0.970	5.000	0.226	0.226	0.231	0.132	0.051	0.026	1.808
POI per Segment Mile	5	0.025	1.681	0.472	0.002	0.556	0.495	1.401	1.717	0.330	0.836	0.004
Bus_BRT_Rail Stops per Segment Mile	5	0.032	1.681	0.718	0.003	1.077	0.835	0.829	0.398	0.546	1.026	0.005
Population Density + Occupancy Rate	5	3.411	3.588	5.000	3.271	3.771	3.355	3.607	3.421	3.676	3.292	3.490
No Vehicle and Active Commute	5	0.924	2.337	4.319	3.798	1.355	1.160	0.958	1.399	0.938	0.732	4.404
Vulnerability	– 1	– 0.188	– 0.317	– 0.311	– 0.235	– 0.051	– 0.210	– 0.306	– 0.312	– 0.352	– 0.234	– 0.147
Mean Normalized Score		**0.191**										
		Normalized FID Scores	**0.689**	**0.679**	**0.550**	**0.514**	**0.501**	**0.492**	**0.487**	**0.476**	**0.470**	**0.431**

BRT = Bus Rapid Transit; FID = feature identifier; POI = points of interest; WT. = weight.

Table 2b. Top 10 Tool Scores for "Recreation" Weight Scheme

		FID	1438	722	1377	1384	63	2279	2574	1375	2772	2579
		Jurisdiction	Charlottesville	Arlington	Multiple	Multiple	Greensville	Fairfax	Arlington	Multiple	Loudoun	Arlington
		Length (mile)	0.007	0.119	1.731	16.654	4.300	0.012	0.011	0.939	0.004	0.035
FACTORS	**WT.**	**MEAN WEIGHTED FACTOR SCORES**	**FID FACTOR SCORES**									
County Health Rankings	– 5	– 4.475	– 4.511	0.000	– 2.705	– 2.664	– 2.505	– 5.000	– 4.704	– 2.705	– 4.295	– 4.704
Land Based Recreation Need	5	2.858	4.000	1.907	5.000	5.000	4.760	4.000	4.000	5.000	4.000	2.719
In-Area Labor Force Efficiency per Segment Mile	1	0.016	1.000	0.000	0.000	0.000	0.000	0.763	0.830	0.000	1.000	0.736
Bike and Pedestrian Crashes	1	0.019	0.161	0.000	0.003	0.000	0.000	0.026	0.045	0.000	0.010	0.194
POI per Segment Mile	5	0.025	1.681	0.141	0.001	0.000	0.000	1.717	0.556	0.000	0.330	0.472
Bus_BRT_Rail Stops per Segment Mile	1	0.006	0.336	0.009	0.001	0.000	0.000	0.080	0.215	0.000	0.109	0.144
Population Density + Occupancy Rate	3	2.047	2.153	2.139	1.821	1.611	1.559	2.052	2.263	1.229	2.206	3.000
No Vehicle and Active Commute	1	0.185	0.467	0.350	0.274	0.157	0.230	0.280	0.271	0.053	0.188	0.864
Vulnerability	– 1	– 0.18	– 0.317	0.000	– 0.183	– 0.180	– 0.352	– 0.312	– 0.051	– 0.257	– 0.352	– 0.311
Mean Normalized Score		**0.054**										
		Normalized FID Scores	**0.555**	**0.508**	**0.470**	**0.438**	**0.413**	**0.403**	**0.383**	**0.371**	**0.357**	**0.348**

BRT = Bus Rapid Transit; FID = feature identifier; POI = points of interest; WT. = weight.

Discussion

The developed tool may be used as is and without further modification. Alternatively, VDOT may wish to modify the tool for additional factors or update and add new data. Both options are discussed here.

Use of the Tool in Its Present Form

Several strengths and shortcomings in this prototype tool are self-evident but are selected here for discussion because of their importance. First, the factor scores reveal strengths and potential weaknesses in specific MUT alignments. For example, interpretation of the scores in Figure 1 highlights an ambiguity about publicly funded amenities: a MUT that would seem to have relatively more latent demand for it (e.g., FID 2579) might also, over time, harm resident renters in its vicinity, as indicated by higher prevalence of rent burden among residents near FID 2579, at least in 2022 or be in a less appealing neighborhood despite its other qualities for MUT use, as indicated by a higher rental vacancy rate in its environs in 2022, than another proposed MUT (e.g., FID 720). The ambiguity of the score highlights the criticality of input from local planners to establish "ground truth" around proposed MUT alignments and, as importantly, to gauge receptivity of the MUT by residents of the area.

Second, the tool is based on a VDOT sample with significant asymmetry in trail segment lengths (Figure 3).

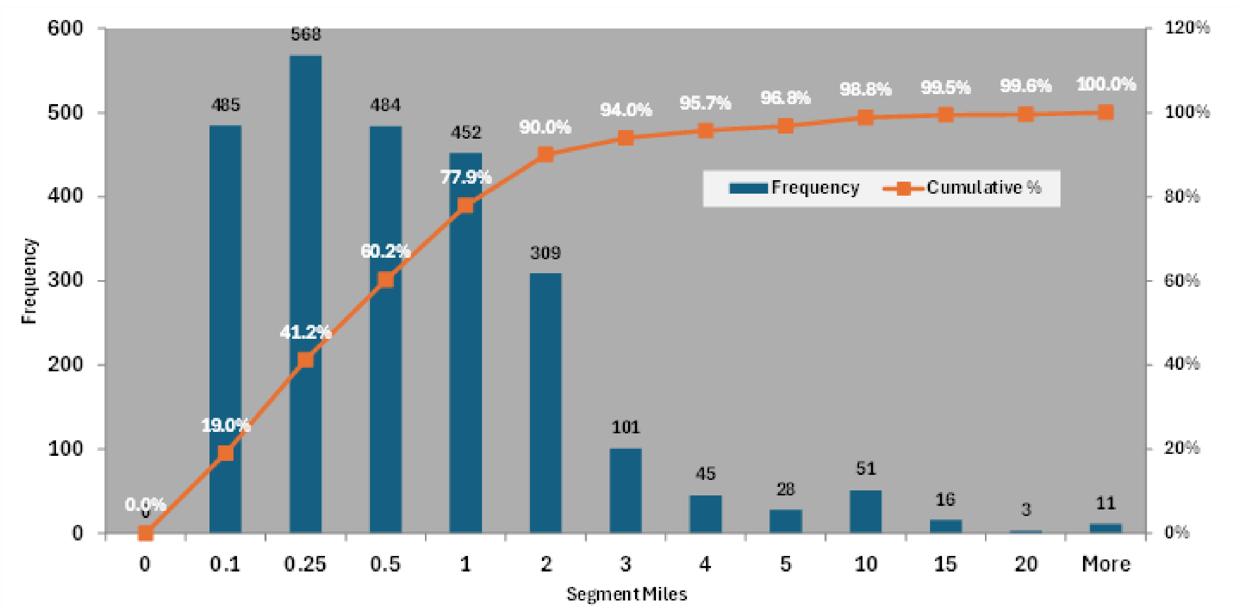
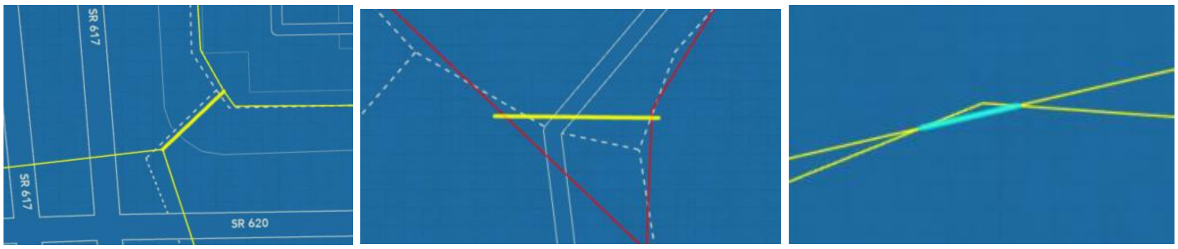


Figure 3. Distribution of Proposed Multi-Use Trail Lengths in the Sample

The MUT sample included 25 trail segments that appeared in ArcGIS Pro as distinctive anomalies. These 25 segments—all less than 12 feet in length—have been removed from the tool (i.e., are not included in the current 2,553 MUTs in the tool) but are recorded in the adjacent Short Segmi page. The next 19 segments (11–36 feet) were also examined for anomalies and recorded in the Short Segmi page. Twelve of these 19 segments appear to be anomalous, and seven segments (15–36 feet in length) are connector segments between proposed segments or existing trails or are not unambiguously anomalous. Figure 4 shows 3 of these 19 segments. FID 1599 (Fig. 4c) was considered potentially but not definitively anomalous. In the next 20 trail segments, sorted by length from 36–61 feet, only one segment of about 59 feet was identified as an anomaly (FID 1424), suggesting that anomalies nearly vanish with increasing MUT segment length.



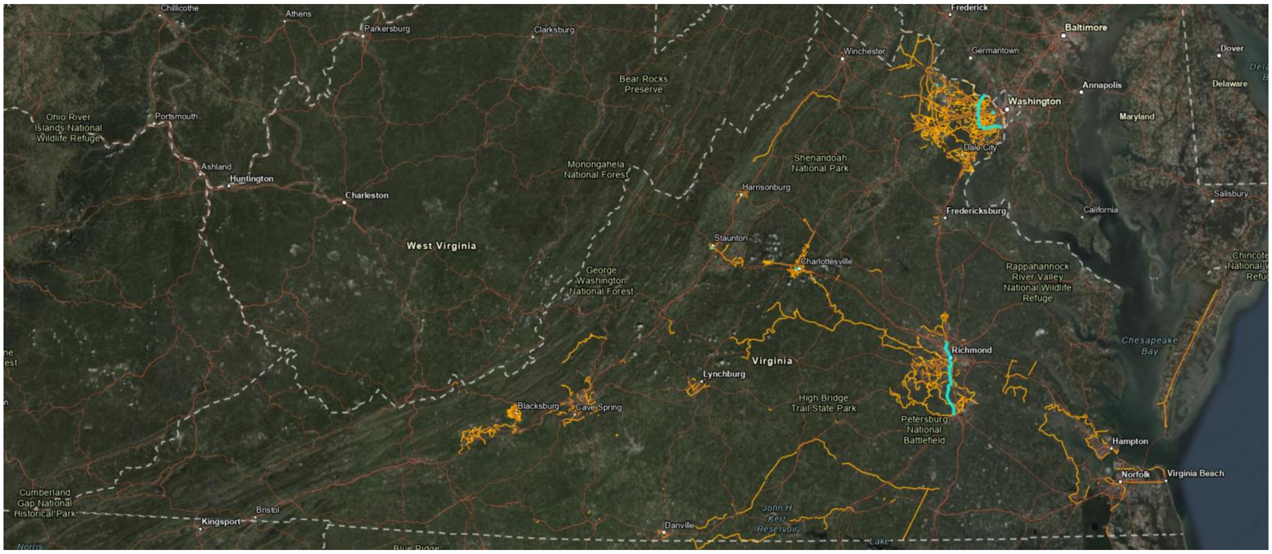
(a) (b) (c)

Figure 4. Examples of Very Short Trail Segments in the Current Tool Database: (a) Connector between Proposed Trail Segments; (b) Connector between Existing Trail Segments; (c) Feature Identifier 1599

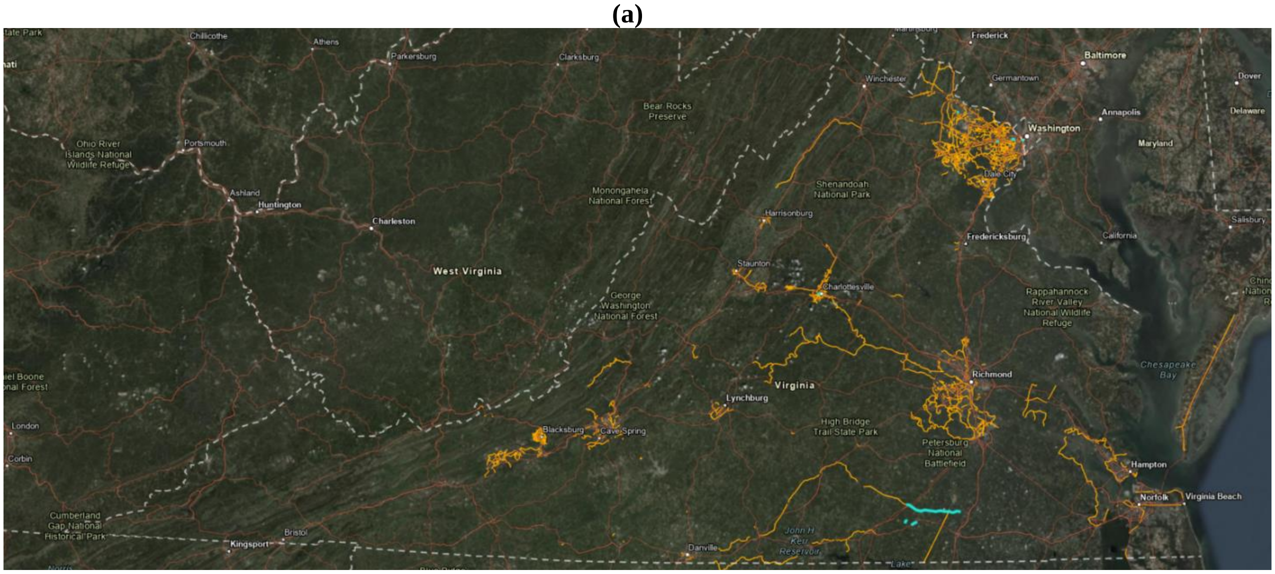
Deciding whether to remove *suspected* anomalous segments from the database requires some judgment. If these segments remain, they will skew normalized numerical scores because of their short lengths and high scores in the factors that are computed per mile of segment length. If the segments are removed, normalization must be refreshed on the revised database to derive final factor measures. The research team decided to remove only the initial 25 segments that seemed to be definitive anomalies, disregarding MUTs discovered subsequently, which *could* also be anomalies.

Because the final scores are ordinal, no substantive adverse effect of the presence of questionable FIDs is present in the database. Short segments can be effectively eliminated from results by sorting the final scores first from highest to lowest and then by segment length, choosing a relevant floor length for consideration as was previously chosen for Table 2. Visual inspection in ArcGIS should always be performed as well.

In Table 2a, two short MUTs (FIDs 1438 and 3039) in central Virginia score in the top 10, but Figure 5a shows that most of the trails, seven in northern Virginia and one trail in the Richmond area, are in relatively populated areas. Tables 2a and 2b share four MUTs in their top 10 scores, including FID 1438 in central Virginia. Figure 5b shows locations of MUTs with the highest scores from Table 2b; four are directly related to the Tobacco Heritage Trail system, and five are in northern Virginia. (Very short trails may not be visible.) Three relatively short segments in northern Virginia score in the top 10 in both Tables 2a and 2b. All three segments were examined in ArcGIS Pro and were determined not to be distinctively anomalous.



(a)



(b)

Figure 5. (a) Locations of 10 Top-Scoring Planned Trails under the "Active-Commute" Weight Scenario of Table 2a; (b) Locations of 10 Top-Scoring Planned Trails under the "Recreation" Weight Scenario of Table 2b. All proposed multi-use trail alignments are orange, and the 10 top-scoring alignments are blue.

Last, in the Interface page, weights can assume any values within their sign limits, including zero, in all cases. Still, a plausible argument can be made that people will use MUTs for mixed purposes. Those who find a trail recreationally attractive may also begin to use it for active commutes or personal trips to various POI. Further, the final factors are not exclusively linked to a single category of MUT use. For this reason, giving any factors zero weights may be too restrictive, even when a single main trail purpose is of interest. Nevertheless, the option of zero weights can remove factors from influencing a final tool score.

Extensions of the Existing Tool

Ideally, the tool would have included a factor measure for "connectivity," which would allow a proposed MUT segment to (1) provide "infill," that is, be credited with the number of miles of existing contiguous trails it connects by linking them together or (2) be grouped with other contiguous proposed segments to become a “new” MUT. The distribution of proposed MUT lengths shown in Figure 3 indicates why this option may be important—78% of MUTs in the database are a mile or less in length. Note also, however, that a number of proposed but already-defined trail systems are identifiable through their NAMEWITHID identifier in the Tool page, columns BA–BC.

As an example of item (1), providing an “infill” segment, suppose that all trail sections shown are built except the highlighted (i.e., proposed) segment in Figure 6. Under that scenario, construction of the proposed segment would result in 19 miles of a contiguous trail system, assuming the inclusion of all existing connected trails within a 2-mile radius of the proposed segment as a necessary bounding condition. Alternatively, construction of the highlighted segment would result in 57 miles of contiguous trails if a 4-mile radius around the proposed segment were imposed as the bound. This calculation can be performed on a one-off basis, or the current tool can be modified, with some effort, for batch calculations. For the latter, a 10th factor of “Infill Connectivity” would be created in the tool, requiring the original shapefile of both proposed and existing trails and a new geoprocessing function to impose a radius and enclosed trail length calculation for each FID. If incorporated into the current tool, the “Infill Connectivity” factor in miles would be normalized and weighted like other factors.

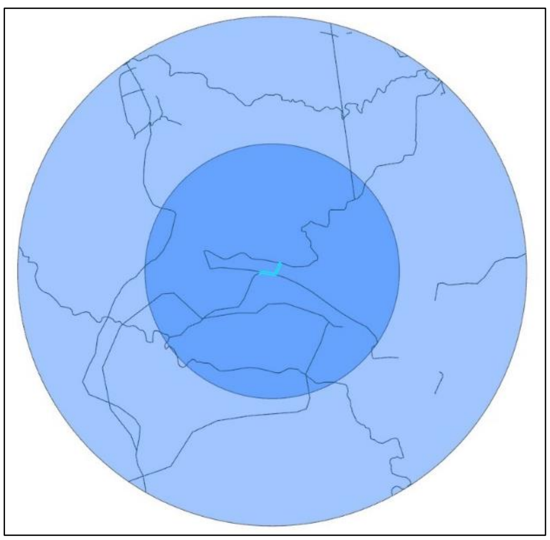


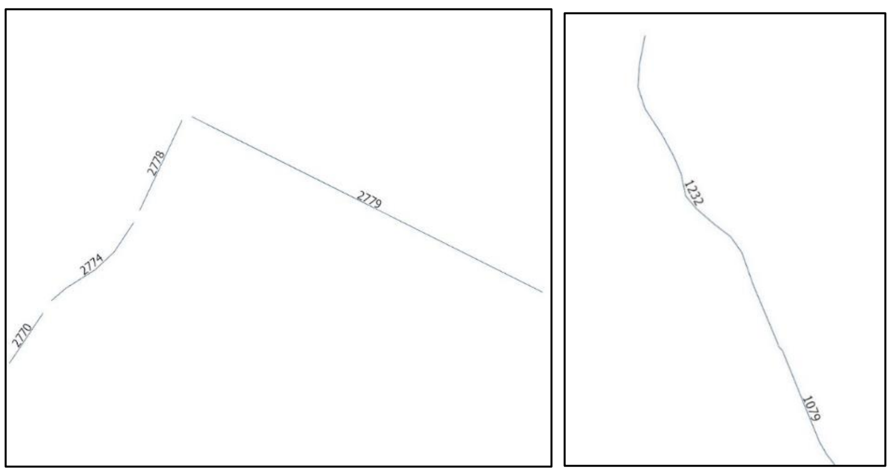
Figure 6. Trail Segment as “Infill” (Highlighted) to Create Contiguous Trail System. Two- and 4-mile bounds are shown.

As an example of item (2), contiguous new “systems” made of proposed trail segments already present in the Tool, proposed MUT segments could be linked by practical knowledge or inspection of the proposed trail layer in ArcGIS Pro. Such systems could be ordinally scored by simply summing their constituent FID scores and dividing by the total mileage of the contiguous segments. Equation 1 describes this ad hoc scoring method.

System score = ∑Normalized final scores by segment / ∑Segmi of selected segments   Eq. 1

Double-counting of data (e.g., at overlapping endpoints of segments) as a biasing influence on the numerator will occur for all constructed trail “systems” but could be visually inspected by imposing one-half-mile buffers on proposed MUT segments in ArcGIS to estimate the magnitude of bias. This scoring method extends the same bias of potential overcounting of factor measures to all FIDs and preserves the information inherent in individual segment scores. In some cases, this scoring method could facilitate alignment adjustments for “system” score improvements (i.e., substituting a segment with lower latent trail demand for a segment with higher latent trail demand).

For example, for one particular weighting scheme, proposed segments in the hypothetical system in Figure 7a summed to a score of 0.992, with a total length of 0.71 miles for a ratio of 1.40 per mile. The system shown in Figure 7b scored 0.663, with a total length of 0.78 miles for a ratio of 0.85 per mile. This provisional method extends the same bias of potential overcounting of factor measures to all FIDs and preserves the information inherent in individual segment scores. In some cases, this method could facilitate alignment adjustments for “system” score improvements (i.e., substituting a segment with lower latent trail demand for a segment with higher latent trail demand).



(a) **(b)**

Figure 7. Two Hypothetical Trail Systems

Updating the Tool Data

The datasets used by the tool could be updated for the current proposed trail sample as newer datasets become available. The simpler datasets consist of ready-made shapefiles (CHR, LBRN, transit stops, OpenStreetMap) and census survey data, whereas LODES is a more complex dataset. If the current trail layer is also out of date, the tool would provide a basic framework in which to update all elements, including a 10th factor of bounded “infill connectivity” (Figure 6), potentially provided by proposed MUTs, equipping the tool for batch calculations in all factors.

Although the National Accountability dataset, built on LODES data, was evaluated to support a factor measure to estimate latent commuter demand for a specific proposed MUT, the existing methodology of OnTheMap (U.S. Census Bureau, n.d.c.) was preferred because it allows a specific buffered MUT alignment to be analyzed for the presence of pairs of home and work census blocks within that buffered MUT alignment for a particular census year, thus representing actual residents who are also job holders in the vicinity of the proposed MUT. Therefore, LODES data were used directly in the tool developed here.

CONCLUSIONS

- *The Excel GIS-based tool developed in this project offers a compact ordinal scoring framework for understanding potential trail demand from various user populations near proposed MUT alignments that VDOT may fund.* This tool and a zipped shapefile of the trails currently evaluated by the tool are provided as a supplemental file to this report.

- *The tool's capability to handle thousands of trail segments in batch calculations comes with tradeoffs.* Specifically, tool scores exclude three important factors affecting trail use that require site-specific knowledge from local planners: aesthetic design, connectivity nodes, and project acceptance by local residents.

- *The tool is useful at a screening level but should be augmented by current knowledge of factor measures used in the tool. Knowledge of the current environment of a planned MUT alignment is necessary to use the tool scores satisfactorily.* Such knowledge supports forecasting how the construction of a proposed trail might affect rent burden, how the rental vacancy rate may affect the trail's use, and the benefit it would provide by connecting to existing trails. Furthermore, census data may have captured transiently high rental vacancy rates when new housing was constructed, vacancy that no longer exists.

RECOMMENDATIONS

1. *VDOT STO should use the tool provided with this report.*

2. *VDOT STO should examine the tool scores of the 2,553 proposed MUT segments under various weight scenarios representing differing priorities.*

IMPLEMENTATION AND BENEFITS

Researchers and the technical review panel (listed in the Acknowledgments) for the project collaborate to craft a plan to implement the study recommendations and to determine the benefits of doing so. This process is to ensure that the implementation plan is developed and approved with the participation and support of those involved with VDOT operations. The implementation plan and the accompanying benefits are provided here.

Implementation

1. With regard to *Recommendation 1*, by June 2026, STO will examine the ordinal rankings of trail segments by different weighting schemes in the Tool. If FIDs consistently score highest under most or all weight scenarios, STO will ascertain whether it is attributable to superior

planning or a computational bias in the Tool. The reason for performing this examination is to establish trust in batch calculation results under various weighting scenarios for all trail segments.

2. With regard to *Recommendation 2*, by June 2026, STO will decide whether the focus of the tool should remain on the existing 2,553 MUT segments or also consider "systems" of trails. If the focus will be on systems of trails, STO will consider at least two general types: "infill" segments and contiguous new "systems" of segments.

    - As an example of "infill" connectivity, consider the highlighted trail shown in Figure 8. One could consider a "system" of the four connected trail segments (FIDs 1617, 1619, 1622, and the "infill" segment 1621) and compare it with other "systems" connected similarly. If this option is pursued, STO will decide the radius that is a reasonable bounding condition across comparisons. The factor can be derived as a one-off calculation for a few comparisons or, with additional effort, could be integrated into the tool as a 10th factor for batch scoring.

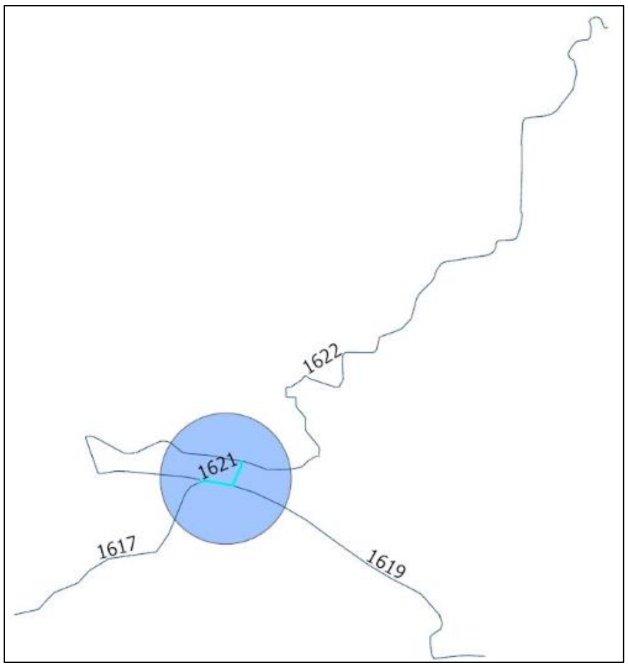
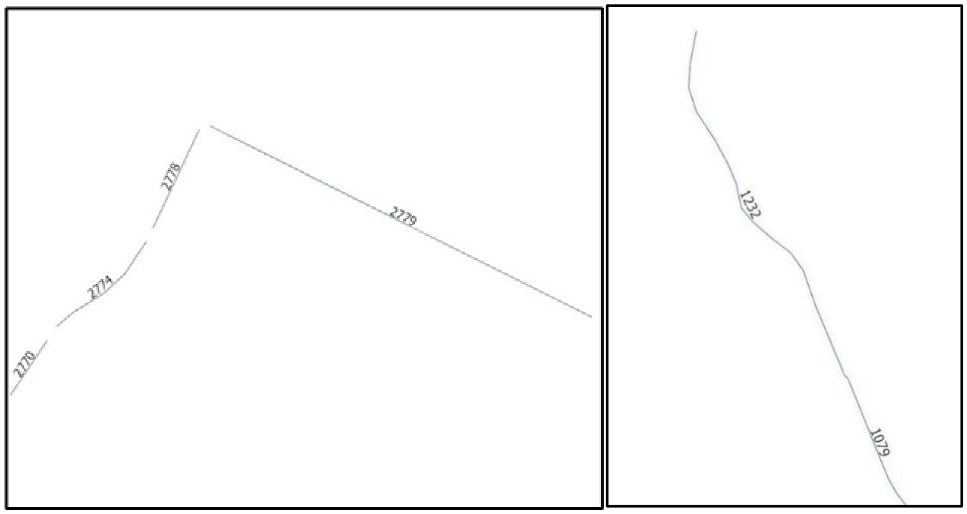


Figure 8. Four Segments that Comprise a Trail System. The buffer shown has a one-half-mile radius.

    - As an example of a contiguous new "system," consider Figure 9. The system shown in Figure 9a has four short proposed segments, and the system in Figure 9b has two short proposed segments. Equation 1, using data in the existing Tool with no modifications, can provide a valid comparison of these two new MUT "systems."



(a) **(b)**

Figure 9. Two Constructed Trail "Systems"

Benefits

Compared with the absence of this tool, given the preliminary internal sample, the information the tool generates about relative user demand for planned MUTs replaces many person-hours of manual work researching trail alignments individually while attempting to include multi-perspective data sources. It is estimated that manually performing this analysis for each trail could require a minimum of 2 person-hours of work per trail if analysts were to collect the raw data shown in Table 2. With 2,553 trail segments, it amounts to roughly 5,000 person-hours of manual processing of all planned MUTs to assemble the database for a full-sample ranking, which is a minimum time threshold because alterations in factor weightings for scenario comparisons would require additional person-hours. In contrast, the tool accomplishes instant batch scoring with a unique trail ranking output for any selected weight scheme.

Suppose that after a couple of years, however, additional trails are added and newer versions of the current datasets in the tool are desired. The research team estimates that updating only the existing datasets in the current framework would require a maximum of 1,000 person-hours of work. Using a loaded rate of $100 per hour, the research team estimates the net savings attributable to updating the tool versus manually creating a new database to be (5,000 – 1,000 hours) at $100 per hour = $400,000 per year, assuming the data were updated annually.

When including the societal benefits of MUTs selected by using the tool compared with selecting MUTs by other criteria, a larger cost savings should result in the sense that the tool should direct investment to MUTs with higher potential demand. However, until a sample of MUTs is built, estimating this larger benefit would be highly speculative.

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APPENDIX

Preparation of LODES Data for Geographic Information System Processing

In the current tool, the labor-force efficiency factor scores for multi-use trail (MUT) segments are based on 2021 Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES). In the future, as the LODES data are updated, VDOT may wish to update these raw factor scores. Accordingly, this appendix describes the process for revising or refreshing the LODES data. For example, the “All Jobs” data used in the current factor can be replaced by the “Primary Jobs” LODES, or the “All Jobs” LODES can be updated from 2021 to 2022. Both changes require new data files from the U.S. Census Bureau (n.d.a.). The “All Jobs” update requires the file “va_od_main_JT00_2022.csv.gz” (Census Bureau, n.d.a.) whereas “Primary Jobs” differs only in the designator “JT01.”

The “Labor Force Efficiency” factor score for any given trail segment is based on a metric provided in the OnTheMap Text Only Tool (U.S. Census Bureau, n.d.c.). The factor in the current tool is technically defined as the total number of jobs occurring in work-home census block pairs when a one-half-mile buffer around a specific MUT segment intersects each of the two census blocks in the work-home pair. The census blocks may be adjacent or far apart along the buffer, as long as the given buffer intersects them both. For the red trail segment shown in Figure A1, the raw “labor market efficiency” score is the total number of jobs for which both work and home census blocks are in the full set of black-outlined census blocks intersected by the blue buffer. The factor logic is that the MUT could be used as a commute facility for these jobs.

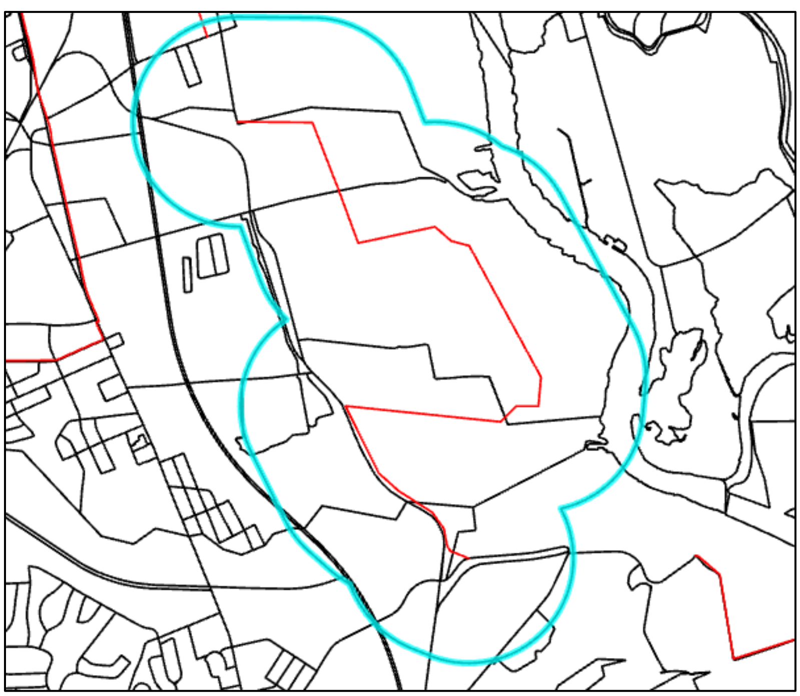

Figure A1. Labor-Force Efficiency Factor: Sum of Jobs in Work-Home Pairs of Census Blocks Intersected by One-Half Mile Buffer Around Trail

Note that the final file of relevant home-work (or origin-destination) pairs potentially consists of both “lines” (two different census blocks for home and work) and “points” (the same census block for both home and work), as illustrated in Figure A2.

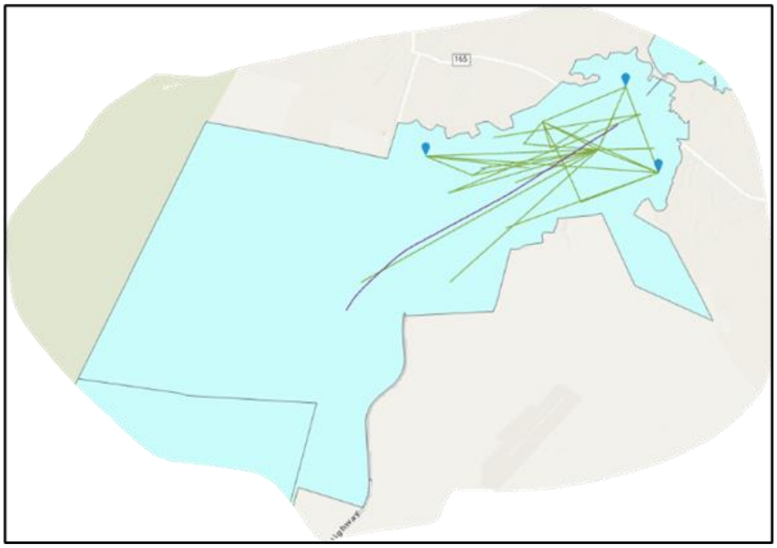

Figure A2. “Lines” (Two Different Census Blocks in Work-Home Pair) and “Points” (One Census Block Holding Both Work and Home) Corresponding to 0.5-Mile Buffer Around Multi-Use Trail (Miller, 2024)

LODES JT00 contains every work-home census block pair in Virginia, amounting to nearly 3 million pairs, with many pairs accounting for only one job. Of all these pairs, the tool uses only those work-home pairs intersected by the buffers around MUTs in the sample, allowing much of the LODES JT00 data to be eliminated before import to ArcGIS for final factor score computation.

To accomplish this reduction, LODES JT00 data were copied from Notepad into Excel, requiring diligent manual work by a student and three Excel worksheets at near-maximum capacity. Next, using the trail sample and Virginia census block shapefiles in ArcGIS Pro, a feature class consisting of census blocks intersected by one-half-mile buffers around each MUT in the sample was developed. This list was exported back to Excel for comparison with the LODES JT00 data—formatted as previously noted as origin (work) and destination (home) census block pairs. In the Excel JT00 data, all work-home pairs in which *both* census blocks were listed in the new ArcGIS feature class were retained for further analysis. In sum, for each work-home pair in JT00, if both census blocks were in the list of census blocks in the new ArcGIS feature class, that is, census blocks lying within a one-half mile of any MUT alignment, that JT00 work-home pair was retained for further analysis. All other work-home pairs from LODES JT00 were eliminated from further use.

Four steps, described in concept here, were then taken to create the appropriate JT00 output for each MUT (Figure A2). It bears note that the original trail sample used for this factor contained 3,079 segments and held a variety of facilities in addition to MUTs.

1. *Convert (reduced) JT00 work-home pairs to lines and points*.

Using the geographic information system (GIS) command XY to Line, a line feature class was created for each work-home pair where the work and home census blocks differed. For work-home pairs where work and home were in the same census block, the GIS command XY to Point was used to create a point feature class.

2. *Create temporary polygons based on census blocks intersected by the one-half-mile buffer around each trail segment in the sample*.

   For the first segment—Segment 0—all census blocks intersected by that segment's buffer were dissolved into a single polygon feature with a label of 0. This step was repeated for the remaining (3,078) segments. When completed, as many polygons as segments were within the new single feature class, where each polygon represents dissolved census blocks with any portion lying within a one-half mile of the given segment alignment. Note that physically, many of these polygons could overlay others (i.e., "share" census blocks). An example of the output for one sample segment is the single blue polygon completely contained within Figure A2.

3. *Identify all work-home census block pairs completely within each segment's temporary polygon*.

   Essential for factor scoring, the JT00 census block pairs contained within each polygon created in step 2 were then linked with the specific corresponding segment, forming the basis for the polygon. For instance, Figure A2 represents 32 work-home census block pairs comprising the polygon pertaining to the specific segment shown in purple. For 29 of these pairs, the work and home blocks were different, as shown by the green lines connecting them. For three of these work-home pairs, the blocks were the same, as shown by the blue points. Note, however, that some census blocks could lie within several different polygons and so contribute to labor-force efficiency factor scores for a number of trail segments.

4. *Link the sum of the jobs from the work-home pairs in step 3 to specific trail segments by unique identifier*.

   For example, for the purple segment shown in Figure A2, the 32 work-home pairs represent 50 jobs where both the home census block and the work census block are within a one-half mile of the specific trail segment alignment.

Although the four steps are conceptually simple, the large datasets (i.e., 3,079 sample trail segments and roughly 1 million work-home census block pairs relevant to the sample trail segments) necessitated the development of a script that required several hours to run. Furthermore, five techniques greatly facilitated script execution within the ArcGIS Pro environment: the "MakeFeatureLayer" command created a layer stored in memory that supported the iterative nature of the script; three successive geoprocessing tools (Feature to Line, Feature to Polygon, and Dissolve) eliminated irrelevant voids in census blocks (and therefore in the temporary polygons) by using spatial joins to associate data geographically; the "Select

Layer by Location" tool allowed choosing of blocks meeting various criteria; and "Add (and Calculate) Fields" facilitated calculation of factor scores by trail segment.