Walking in an Urban Environment and a Virtual Reality Replica: Comparisons of Physical Activity Duration and Intensity

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Abstract

Increasing walking behavior is desirable from public health, environmental, and urban planning perspectives. Virtual reality (VR) has the potential to improve the design of walkable environments. However, the current research is necessary to determine whether walking decisions in VR mirror those in the real world (RW). Participants completed two study sessions: walking in a VR simulation of a historic district (VR session) and walking in the real-life district (RW session). During each session, participants were asked to complete three tasks (e.g., find a restaurant) and stop walking following task completion. Heart rate (HR) data contained a high degree of missingness, so no HR analyses are reported. Nevertheless, walking intensity is addressed through exploratory negative binomial and Poisson regression models predicting duration in light and moderate-to-vigorous physical activity using accelerometry. These models indicated no relationship between physical activity intensity in VR and the RW. Additionally, a paired *t*-test and mixed effects model indicated that walking duration was significantly longer in VR than the RW. However, exploratory analyses suggested order effects: those who walked first in the RW walked similar durations in both settings, but those that walked first in VR walked for about five minutes longer in VR (17.8) than in the RW (13.0). In conclusion, walking intensity in VR may not mimic walking intensity in the RW, but depending on order of conditions, walking decisions in VR may resemble RW decisions. Possible explanations for the observed order effects include history effects, VR navigation and skill transfer, and participant motivation.

Introduction

The built environment is a modifiable factor that boosts community-level walking [1–3]. Increasing community-level walking behavior in urban environments is beneficial from health, environmental, communal, and economic perspectives. Firstly, increased walking activity is associated with decreased risk for cardiovascular disease [4], cancer recurrence [5], and cognitive decline in elderly adults [6]. Concerning wellbeing, walking can increase social connection to people in the neighborhood [7] and lift mood among people struggling with mental health. Though some research has found that mood differentially improves when individuals walk in nature compared to urban environments (e.g., [8,9]), other research has found that both urban and outdoor nature walks equally succeed in improving mood (e.g., [10,11]). Secondly, walking for transport is also a protective factor in climate change as it reduces fossil fuel use and demand for building motor vehicles [12,13]. Thirdly, there are various community-level benefits to walking as advocated by urban designers. Walking is positively associated with the mutually-beneficial social connections that contribute to social capital [14,15]. Nonmotorized transport is linked to greater community engagement [15], and walking correlates with larger community networks and greater trust in neighbors [14]. Walking for transport is also discussed in urban design as an issue of equity [16] as walking can provide inexpensive access to necessary resources as well as recreation. Lastly, city planners design mindful of the economic benefits of walking. Having numerous pedestrians in an area is linked to greater retail sales [17]. In this way, increased walking behavior boosts the local economy and may relate to higher employment rates [18]. In summary, walking can provide numerous improvements to physical health, mood, environmental health, social capital, and local economies.

Alongside these numerous benefits, modifying the environment to boost walkability also has costs – changing environments can be expensive and time-consuming. Planners face challenges in identifying which of many possible environmental modifications will do the most to increase walking. Correlations between self-reported physical activity (PA) and the built environment in neighborhoods suggest a complex interplay between factors such as open space, traffic intensity, parking, water, infrastructure for walking and cycling, and intangibles like perceived ‘activity friendliness’ [19]. This interplay complicates the process of isolating any single intervention priority. Beyond the physical landscape, legal and social barriers may further restrict the effectiveness of any attempted intervention [20]. Additional complexities arise when considering responses in a given community. To focus on urban vegetation as one well-supported predictor for PA, even granular choices like spacing of trees may influence walkability [21]. Ideal land cover types to promote walking may vary across racial or ethnic groups [22]. These site-specific variations suggest that careful attention to local communities and conditions should be paid when seeking to apply previous research to a new context. Together, this complexity and context-dependence make it important to understand how a given intervention (e.g., a new park or trail, improved sidewalks) would fit into the fabric of a proposed community and setting.

The relatively permanent and cost-intensive nature of urban infrastructure makes observational studies and natural experiments the de facto modes for investigations into built environmental interventions to boost walking. These approaches explore associations rather than establish causality because they retroactively examine changes in behavior. In order to gain insights similar to those in an experimental setting [23], observational approaches require development of causal inference frameworks. These frameworks demand fairly detailed situational context to approximate randomized ‘treatment’ and ‘control’ groups (e.g., using otherwise similar populations differing in a feature of interest with associated statistical adjustments). Even with these approximations, there remains the possibility of systematic biases via unobserved or uncontrollable variables [23]. While observational and causal inference-based designs serve an important role in the research, true experimental study designs examining built environmental factors affecting pedestrian behavior remain an important gap. Experimental designs would enable researchers to prospectively compare alternate proposals for a constant study population. Unfortunately, the cost, time investment, and influence on behavior associated with construction makes this a daunting proposition.

Virtual reality (VR) has been promoted and employed as a method of addressing these issues of cost, time, and causality [24–26]. This application is afforded by the immersive nature of VR. This immersivity allows users to experience presence; a state of being where their cognitive processing is so engrossed with the virtual environment that they feel as if they are in that environment [27]. Presence is achieved through multiple different aspects of immersion, however, a key element to consider for physical studies such as walking is that of embodiment. Embodiment is the notion that thoughts, feelings, and behaviors are grounded in physical interactions through the corporeal form [28]. In VR, the body is used to interact with the digital world without layers of abstraction presented by human input devices (i.e., mouse and keyboard), enabling VR training and exploration of physical activities such as jumping [29] or climbing [30]. Thus, VR can produce a convincing illusion that allows for transferability of results from the virtual environment to the physical world.

There are several benefits to using VR environments as experimental tools to examine built environmental factors of behavior. First is the ability to easily modify and adapt the environment for testing different interventions, allowing for a superb level of control. The tools used for building VR environments (e.g., [31,32]) allow experimental designers to test differing environments and adjust them mid-experiment [33]. This process was utilized by Chung and Sparks [34] where participants experienced different virtual rooms to determine how simulation configuration affects memory. In sum, the digital control afforded by VR development tools enables deeper exploration of perceptive and cognitive concepts [35].

With this technology, researchers can immerse participants in virtual environments, leading to realistic behaviors that they perform in the real world (RW) [36]. In other words, by manipulating elements of interest within a virtual environment, VR can be used to experimentally test environmental factors affecting walking. This approach can aid municipal governments in their goal to make cost-effective and timely changes to the RW built environment that successfully promote walking behavior.

Still, if VR is to be used in this manner, researchers must understand how walking behavior in VR compares with RW walking. In the absence of this knowledge, the value of using VR in walkability research is unclear. As of yet, research has not definitively shown that walking decisions in VR are similar to RW decisions. Previous research comparing walking in VR with RW walking has provided mixed results with some studies supporting comparability [37–39] and others noting discrepancies [40–45]. While there is a wide base of literature concerning walking in VR employing various hardware, software, VR navigation methods, and RW locomotion techniques, most are outside the scope of the present study. Therefore, we have focused on those studies that use an immersive head-mounted display (HMD) and overground (i.e., room-scale) walking. These criteria were selected because HMD-delivered VR is currently regarded as the most immersive for walking [46]; additionally, gait-related mechanics and adaptions in VR using overground walking more similarly match those made in the RW than alternative VR locomotion techniques. Specifically, overground walking in VR results in larger adjustments in gait kinematics compared to treadmill walking, illustrating a greater kinematic response to the demands of the environment [47]. Further, previous research has shown overground walking in VR to be a feasible method of assessing environmental impacts on walkability [26]. In accordance, the set-up of the current study employs both methods.

Assessing distance has been found to be both equivalent [38,39] and divergent [42,44] in VR when compared to the RW depending on the method of assessment (e.g., verbal estimation, perceptual matching, and visually directed actions). A review summarizing the divergent results in VR distance estimation can be found in Feldstein [39]. Differences in gait characteristics have also been observed. Canessa and colleagues [48] reported that participants walked the same distance while navigating a defined walkway in VR as they did in the RW, yet they walked with a greater cadence in VR. Another study found that participants walked across crosswalks in VR at the average RW pedestrian crossing speed [37]. Still, other studies have observed reduced walking speed [40,41,43,45] and slower cadence in VR than in the RW [45].

Importantly, walkability research not only relies on distance and walking speed, but also on pedestrian judgements of safety and experience. Individuals evaluate the safety of a street similarly in VR as they do in real life, and their intention to cross is equivalent given similar conditions (e.g., speed of cars) [38]. Concerning experiential judgments, participants in Bhagavathula et al. [38] perceived traffic as moving faster in VR than in the RW. VR simulations of RW city locations are judged to be comparable to the corresponding RW locations on some experience dimensions that may influence walking behavior, such as pleasantness and unity, but not on others, such as brightness, and spaciousness [49]. A separate study found similar results with participants rating environments differently in VR on some dimensions (cohesive and clean) but identically on other dimensions (beauty, quietness, and familiarity) [50]. Of note is that this study employed landscape scenes, so these findings may not hold for streetscapes.

Whereas previous research has focused on assessing walking related perceptions, rather than behaviors (e.g., [38,49,50]) or on walking behaviors in indoor environments (e.g., [40,51]), the novel contributions of the present study are to empirically compare VR and RW urban-scale walking-related decisions (such as when to continue vs. stop walking while engaging in representative daily tasks) and behaviors using overground walking.

Specifically, the present study investigates how walking in a VR model of a RW street compares to walking in the corresponding RW street. This research can help clarify whether experiments utilizing VR to examine built environmental modifications are likely to provide meaningful findings concerning RW behavior. The aim is to understand whether walking duration and intensity differed in the two settings to inform the interpretation of walking behavior data gathered from VR models of RW environments while controlling for individual differences. To do so, we implemented a within-subjects design so that each participant would complete the same tasks in both VR and the RW. We hypothesized that participants would walk for the same duration at the same intensity in VR as in the RW.

Materials and Methods

Participants

An a priori sample of 60 participants was selected. We attempted to recruit and schedule as many participants as possible within the constraints of our 3-week data collection plan (see Procedure section). During the summer of 2022, 56 participants were recruited using a staff email list associated with a large public university in the western U.S. to complete two in-person study sessions: a VR session, in which participants walked in a VR simulation, and a RW session, in which participants walked in the real-life counterpart to the simulated environment. Eligibility criteria included being at least 18 years old, possessing the capability of walking for up to 30 minutes on two separate days, and not being prone to dizziness, or other problems that would preclude participants from using VR technology. Several participants did not attend either their first (6) or second session (4), so they were excluded from analyses. This resulted in 47 participants completing both sessions. See Figure 1 for participant attrition information. The participants who attended at least one session were primarily university employees (80.4%), but some were local residents unaffiliated with the university (13.7%); two were retired university employees, and one was a university student. The mean age was 41.7 years (SD = 14.3) Most of the participants were assigned female at birth (62.7%), and 37.3% were assigned male. The mean height was 5ft 7in (SD=3.89in). Most participants were right-handed (40) though 11 were left-handed, and 1 indicated that they used both hands equally. Participants were compensated with $30 cash. After completion of the first session, they received $10, and the remaining $20 was given to them after completion of the second session.

Figure 1

Exclusion flow diagram

Apparatus/Measures

Virtual Reality Simulation

This study employed a virtual environment simulation depicting a 0.5-mile portion of the main downtown corridor in a mid-sized Western city. An image capture of the simulation is depicted in Figure 2 Panel A, and the RW environment is visible in Figure 2 Panel B. The research team had previously developed the environment using SketchUp for 3D modeling, Blender for rendering, and Unity Game Engine for translation into a VR environment. The VR environment was structured with high fidelity to the real environment in terms of the building facades and shapes (i.e., the buildings were the same dimensions in the VR environment as in the real one, and the businesses included in the model were those that existed in the real environment at the time it was constructed, some of which no longer exist). Buildings were textured using photographs of the RW environment, making their appearances identifiable (See Figure 3). The simulation featured greenery, moving cars, and directional sound effects when passing cars and restaurants. Some elements in the VR environment did not have the same high level of fidelity to the real environment, and these included the traffic (there are fewer and less varied vehicles in the VR environment, there are no cyclists or pedestrians in the VR environment) and the range of sounds in the VR environment which was restricted to generic background auto traffic, bird sounds, and a din of conversation when passing by businesses where people congregate (e.g., restaurants, bars) in the VR environment. The standard Unity skybox was applied to simulate weather in VR. This skybox simulates a clear sunny day. The region in which the data was collected has overwhelmingly sunny days [52]. In fact, we recorded only four RW sessions in which it rained. (Research assistants carried umbrellas for this possibility). Therefore, the weather in VR sessions mostly mirrored that in the RW. Rotation in the VR environment was enabled through a snap turn function where a user can rotate left or right using the controller joystick. This method of viewport snapping or snap turns is recommended to reduce simulation sickness [53]. For further details about the simulation and its development process, see Oselinsky et al. [26].

Figure 2

VR and RW *environment comparison*

Note. RW image from CSU-AVL [54]

Figure 3

Detailed photographs of VR simulation

VR Apparatus

The research team loaded the VR simulation onto an Oculus Meta Quest 2 HMD (Model KW49CM). The Meta Quest 2 provides for an untethered VR experience (i.e. does not require a separate high-end PC to run the VR simulation) allowing for greater freedom for user mobility. The HMD head straps, interpupillary distance, and glasses spacer were fit to the participant for clarity and comfort. While in the VR environment, participants held both hand controllers.

Walking Duration

Walking duration was measured by stopwatch. The stopwatch began when the participant started walking and stopped when they ended the walking session. We did not record how many times the participants stopped walking. When RW constraints prohibited walking, the research assistant paused the stopwatch until the participant was free to walk. In other words, whenever participants stopped walking, the research assistant stopped the time on the stopwatch and resumed the stopwatch once participants resumed walking. Participants stopped primarily in response to stoplights in the RW and in response to rotating the simulation when approaching a room boundary in the VR condition. Participants were asked to walk in order to complete three tasks, which are described within the Procedure section. Although two of the three tasks were completed as soon as a participant found a particular location, the remaining task (finding a restaurant to take a friend visiting the area) could involve finding several locations or stopping as soon as the first restaurant was reached. Therefore, walking duration reflects not only the required tasks but also the decision to continue walking.

Empatica e4 wristband

The Empatica e4 wristband was used to measure HR and activity intensity via accelerometry. While it is possible to collect similar accelerometry data from the Meta Quest 2 HMD the frame the computational cost to collect that data each frame may have introduced stutter or frame drops which, in turn, would increase the risk of adverse VR symptoms (i.e., cybersickness). The e4 is a lightweight (25g) research-grade device worn on the nondominant wrist like a watch and is equipped with four sensors measuring movement and physiological responses. It records HR data at a frequency of 1 Hz [55], and its reliability concerning HR measurement has been established among adults in various common research paradigms [56]. It measures accelerometry data in three dimensions on a -2*g* to 2*g* scale with a frequency of 32 Hz [57]. This wrist-worn device was chosen over a dual-system of a HR chest-strap and hip-worn accelerometer because the Empatica e4 is a single device and less invasive. Participants were asked to don the HR and accelerometry device in a public space for the RW condition. For participants' privacy, the Empatica e4 wristband was selected as it does not require placement on the torso under clothes.

Post-experience Survey

At the conclusion of each study session, participants completed a short survey. The survey following the RW session included 17 items. It inquired about number of previous visits to the historic district, physical discomfort, judgements and emotions about the experience, distractions, recommendations, and demographic information. The survey did not inquire about participant's prior knowledge of the buildings in the RW. For most items about physical discomfort, participants rated the degree to which they experienced various dimensions of discomfort, such as eyestrain, nausea, and dizziness, on a 5-point Likert scale (1=none at all, 5=a great deal). Other questions relating to emotions and judgements presented statements like "The environment felt safe" or "The environment was attractive" and were answered on a 5-point Likert scale from strongly disagree (1) to strongly agree (5). Lastly, two free-response questions asked, "Was anything in the environment distracting?" and "What would make you want to spend more time walking around this environment?"

The survey presented at the end of the VR session included all items from the RW survey and eight additional items specific to the VR experience for a total of 25 items. These additional items inquired about familiarity with VR and the adjustment to, navigation of, immersion in, and realism of this particular VR experience. For items concerning navigation, immersion, and realism, participants rated their agreement with statements such as "The environment seemed realistic and believable" and "I felt immersed in the VR environment" on a 5-point Likert scale (1=strongly disagree, 5=strongly agree). One VR-specific free-response question was added: "What changes to the environment would you recommend to make it feel more real / immersive?" The survey, walking duration, accelerometry, and heart interbeat interval data (HR raw data) will be made available on OSF.

Procedure

Before recruitment, the host university's institutional review board approved the study (#3526). After expressing their interest in participation by responding to the recruitment email, possible participants were assigned a participant ID and randomized to complete either the RW session first order (RW->VR group) or the VR session first order (VR->RW group) to counterbalance for order effects. Each participant was subjected to both VR and RW conditions. Following this randomization, participants were prompted to sign up for two study sessions that corresponded to their randomized order. Most manufacturers discourage the use of their HMD devices outdoors due to potential lens damage from the sun [58,59]. Further, HMDs rely on sensors for tracking movement. The researchers tested the HMD in outdoor environments and observed bright outdoor lighting (i.e., sunlight) can interfere with these sensors, leading to inaccurate tracking and a disruptive experience. Therefore, we needed to rent a large (60'x80') indoor space to complete VR sessions. Due to financial constraints, this space was only rented for a single week. Consequently, data collection lasted three weeks. The RW->VR group completed their RW session during the first week of data collection. The indoor space was rented during the second week, during which all participants completed their VR session. The VR->RW group performed the RW session in the third and final week of data collection. At the onset of both study sessions and before completing any research tasks, participants gave informed consent.

RW *Session*

For the RW session, participants arrived at a landmark in the historic district. After obtaining informed consent, a research assistant placed the Empatica e4 wristband on the participant's nondominant wrist. The research assistant instructed the participant to walk around and attempt to find and use a crosswalk, to find a restaurant where they would want to bring a friend who is visiting the city, and to find a specific shipping courier store. These tasks were chosen because they illustrate behaviors that are performed in the RW setting (the historic district). Specifically, the use of crosswalks is necessary to navigate the historic district. Finding a restaurant to bring a visiting friend requires choice on behalf of the participant (i.e. they could choose the first restaurant they saw, or they could choose to walk until they were satisfied with their decision). Lastly, finding the specific shipping courier store represents the task of finding a specific location; an endeavor that can occur frequently in the RW. This specific shipping courier store was selected because it is a well-known store (FedEx) but difficult to locate. The participant was unable to use their phone, or any other type of device that utilized a Global Positioning System to complete any of the tasks. This was done to ensure that the attempted tasks in the RW and VR session were the same. The participant was reminded that they could choose to stop walking and take a break if they felt uncomfortable at any point, and if they did not wish to continue, they could quit the study. The temperature and humidity were measured using a digital hygrometer at the starting location. After marking the temperature, humidity, and time, the research assistant informed the participant that they could begin their tasks.

As the participant completed their tasks, the research assistant walked behind them so that they did not influence the participant's chosen pace and direction of walking. When participants completed each task, they notified the research assistant. Participants were not required to walk for the 25-minute duration. Participants could choose to stop walking at any point in the session. If the participant completed all three tasks, the walking segment of the session was concluded. When the stopwatch showed 20 minutes, the research assistant asked the participant how they felt and if they desired to continue walking. If they chose to stop walking, the walking session ended. If the participant chose to continue walking, they were given five additional minutes before the research assistant ended the walking segment.

Following the session's walking segment, the research assistant removed the Empatica e4 wristband from the participant's wrist and directed them to a street bench or chair where they could rest and complete the post-experience survey. Following the survey, the research assistant thanked the participant, provided compensation, and debriefed them.

VR Session

VR study sessions were held in an indoor room measuring roughly 60'x80' (18.3m x 24.4m). Upon arrival, the participant gave informed consent. Next, a research assistant placed the Empatica e4 wristband on the participant's nondominant wrist and walked the research assistant to the center of the room. The participant was then trained on the use of hand controllers. The research assistant showed the participant the two buttons (the trigger button and thumbstick) and clarified that these were the only buttons that the participants would touch. The participant was also educated on the proper fit of the HMD. If the participant wore glasses, a glasses spacer was utilized in the headset. The research assistant fit the HMD to the participant using the head straps and verified the clarity of the image with them. The starting position of the VR simulation was the same landmark where the RW session began. Then, the researcher gave both hand controllers to the participant and explained how to use the trigger button to jump to a new location. The research assistant emphasized that walking should be the primary method for navigating the environment, and that this button was only to be used if they became stuck in the virtual environment (i.e., inside a building). Next, the research assistant explained how to use the thumbstick to rotate the environment. This was to be used when the participant reached a boundary in the RW but wanted to continue walking in the same direction in the VR environment. The participant was reminded that these were the only buttons the participants would touch. The participant practiced rotating the VR environment around them until they were comfortable. The participant was then reminded that they were able to remove the headset if they felt uncomfortable at any point and were told twice that if they did not wish to continue, they could quit the VR experience. Additionally, after twenty minutes they were asked if they would like to continue and were eventually stopped at 25 minutes.

The research assistant instructed the participant to walk around the VR environment and attempt to complete the same three tasks as in the RW session (1. find and use a crosswalk; 2. find a restaurant where they would want to dine with a friend from out of town; 3. find the shipping courier store). The VR environment was designed with identifiable details from the RW environment; see Figure 3 for an image capture of various businesses (i.e., a restaurant) in the virtual environment compared to those same businesses in the RW. The research assistant explained that they would walk beside the participant throughout the entire experience, and when the participant approached a RW boundary (i.e., a wall), the research assistant would tell them to stop, rotate their body so that no obstacle is in their path, and then use the hand controllers to rotate the VR environment around them so that in VR, they can walk in the direction they desire. The temperature and humidity were measured using a digital hygrometer. After marking the temperature, humidity, and time, the research assistant informed the participant that they could begin their tasks.

When participants completed each task, they notified the research assistant. Participants were not required to walk for the 25-minute duration. Participants could choose to stop walking at any point in the session. If the participant completed all three tasks, the walking segment of the session was concluded. When the stopwatch showed 20 minutes, the research assistant asked the participant how they felt and if they would like to continue walking. If they chose to stop walking, the walking session ended. If the participant chose to continue walking, they were given five additional minutes before the research assistant ended the walking segment.

Following the walking portion of the session, the participant removed the equipment with the help of the research assistant and subsequently, completed the post-experience survey while seated. After the survey, the research assistant thanked the participant, provided compensation, and debriefed them.

Analyses

Transformations and analyses were performed using RStudio Statistical Software version 2022.07.2+576 and 2023.12.1+402 (RStudio Team, Boston, MA, USA) and R Statistical Software version 4.1.1 and 4.3.3 (R Core Team, Vienna, Austria). To determine the similarity of VR and RW walking, paired t-tests and mixed effects models controlling for weather, completion of all tasks, and order of conditions were performed. Alpha was set at 0.05 for all analyses.

Data Cleaning

Concerning walking duration, some participants completed all tasks or walked for the maximum of 25 minutes, and then asked if they could continue walking. They were permitted to do so, but the time at which they originally completed the tasks or the maximum of 25 minutes was used in relevant analyses, respectively. This was done in order to treat them identically to those participants who did not ask to continue walking. Lastly, two of the eight researchers who ran VR sessions did not pause the stopwatch when participants paused walking. However, all other researchers did. To amend this discrepancy, the VR sessions run by those two researchers (total of 7) were removed from walking duration analyses. Figure 1 depicts all exclusions through the stages of the study.

Calculation of Activity Index

We conservatively identified accelerometry data between the start and conclusion of the walking session within each participant's larger accelerometry dataset using the R package "adept" [60] created by Karas et al. This package identifies periods of walking from accelerometry data by comparing the vector magnitude of the data to a template of the vector magnitude from an accelerometer worn in the same location while walking. Select templates are included in the package "adeptdata" [61] while researchers are able to create additional templates. Both approaches were used in the current study together with an additional approach intended to identify resting and nonresting periods using the "adept" package described by Karas et al. [62]. Converging data from these three approaches identified the walking session start and end points within participants' accelerometry datasets.

Following this identification, activity index (AI) was calculated. Activity index (AI) was proposed by Bai and colleagues [63] and is more sensitive to sedentary behavior and low-intensity PA than activity counts, a common accelerometry metric. AI has been shown to differentiate PA intensities with higher accuracy than activity counts [63]. Unlike ActiGraph and Actical activity counts, which use proprietary algorithms, AI can be calculated by the researcher from raw accelerometry data, using an open-source algorithm; consequently, it can be easily computed from any accelerometry device that reports raw data, like the Empatica e4 wristband. The AI metric reflects a ratio of the magnitude of the accelerometry data from the study period to the magnitude of the data when the accelerometer is still and not worn. To obtain data from the still accelerometer (i.e., the comparison data), each of the three Empatica e4 devices used in the current study was left on a still desk (as suggested in Bai et al. [63]) for approximately 15 minutes. During each study session, the researcher noted which Empatica e4 wristband was used so that the comparison data for that same device could be used in the calculation of AI.

Using only the data between the determined walking session start and end points, we calculated AI over a one-second epoch as presented by Bai et al. [63] using the "ActivityIndex" R package.

To do so, all accelerometry data were first transformed into units of *g* as required by the package. Next, we calculated the mean AI for each session in order to address the varying session durations. To our knowledge, there are not established thresholds to differentiate intensities of PA for AI; however, mean AI has been previously employed to analyze wrist-mounted accelerometry data [64]. Mean AI can be interpreted relatively with higher mean AIs indicating higher intensity PA [63].

Treatment of Missing Data

For all participants, the e4 wristband reported tri-axial accelerometer data. When identifying accelerometry data between the start and conclusion of each walking session, there was no clear threshold for one session. This session has been omitted from the AI analyses. Additionally, two participants in the RW condition showed an abnormally long measurement session (52.7 and 118.4 minutes) with a large (~17 and ~47 minutes) period of inactivity near the middle/end of the measurement session, which suggests a measurement error. The timestamp of the measurement onset aligned with the scheduled time of the participant session, indicating that the device was most likely not turned off correctly at the end of the session. Since participants donned the device within seconds or minutes of beginning the walking session, and the researchers constrained the walking session to be at most 25 minutes of active walking, device measurement sessions should not be longer than 35 minutes even when including time spent stopped at stoplights and other barriers. For these two abnormal sessions, we chose to remove any data occurring after 35 minutes following the onset of measurement. For both sessions, this point was within the long period of inactivity indicating that it was appropriately separating the participant's walking session from data occurring afterward. Following removal of this data, the accelerometry data between the start and end of the walking session were determined using the identical method as with other sessions.

The HR data provided by the Empatica e4 wristbands were characterized by a high degree of missingness. This led the researchers to examine the validity of Empatica e4 devices under light physical activity conditions (e.g., walking). Empatica notes that these devices can produce missing values when the wrist is in motion [65], thereby producing biased data under our study's conditions. For this reason, we do not report analyses on HR data.

Results

Fifty-one participants completed their first session. Four participants did not return after their first session (three completed VR, one completed RW), resulting in data for both sessions from 47 participants. The exclusions detailed above produced a final sample size of 46 participants for mean AI analyses and 40 participants for walking duration analyses.

Post-Experience Survey

Just under half of the 47 participants had experienced VR previously (22), primarily via video games (16) or educational/entertainment outlets (12). See Table 1. Roughly 80% of the 47 participants had visited the historic district in real life over 20 times, and 60% had done so over 50 times, indicating most participants had familiarity with the RW location. Descriptively, participants with experience in VR seemed to walk for longer in VR than those without experience. Additionally, walking duration in VR and the RW may diverge with increasing age. Due to limited sample size, inferential statistics are not reported.

Table 1

Participant characteristics and LPA, MVPA, and walking duration across conditions

	n	LPA duration (min)	MVPA duration (min)	Walking duration (sec)
		VR (RW)	VR (RW)	VR (RW)
Experience with VR				
No	24	4.92 (.83)	1.79 (12.21)	975.91 (751.68)
Yes	22	5.73 (1.24)	3.86 (13.57)	1208.94 (760.22)
# previous visits to Old Town				
0	0	-	-	-
1-5	3	7.67 (0.00)	4.00 (14.00)	1130.33 (816.33)
6-20	6	7.00 (1.50)	0.67 (19.83)	1319.00 (1121.40)
21-50	9	5.56 (0.67)	4.89 (16.44)	987.71 (858.00)
≥ 51	29	5.00 (1.11)	2.66 (10.29)	1053.24 (646.36)
Age				
≤ 30	13	6.08 (1.00)	2.85 (16.46)	1183.00 (905.5)
31-45	21	4.90 (1.10)	2.86 (11.5)	942.22 (724.39)
46-60	4	0.50 (0.75)	0.25 (15.75)	1113.00 (698.00)
≥ 61	9	8.44 (0.89)	4.33 (10.00)	1270.50 (587.33)

Note. Values for *n* may not sum to number of participants as participants were permitted to skip questions. LPA and MVPA duration were calculated using MIMS (described below).

Figure 4 visualizes post-experience survey responses concerning perceptions of both environments (Panel A), experience of adverse symptoms (Panel B), and experiences of the VR environment (Panel C). The majority of these participants felt little to no discomfort although this percentage was lower in VR (76% in VR vs. 96% in the RW). For a comparison of symptomology, see Figure 4 Panel B. Participants felt less comfortable wearing the VR equipment when compared to only the Empatica e4 wristband in the RW, but 76% still at least agreed that the VR equipment was comfortable (Figure 4 Panel A). This trend continues for judgements of safety (VR: 92%, RW: 95%), relaxation (VR: 70%, RW: 100%), and attractiveness (VR: 60%, RW: 98%). Nearly all participants in the RW agreed that the tasks were easy (92%), but only 68% did so in VR. Still, more participants completed the RW in their second session (28) than did so in their first (19), so these judgements may be influenced by learning effects.

Figure 4

Quantitative survey responses by condition

Regarding experience in VR environments (Figure 4 Panel C), 87% of participants adjusted to the VR environment in less than 5 minutes, while 2 participants never adjusted. Only about a quarter of participants disagreed with a statement that the environment was realistic and believable (26%), with about a third responding neutrally (34%) and 40% agreeing. Lastly, the majority of participants felt immersed in the VR environment (79%).

To better understand influential street elements for walking behavior, two raters independently open-coded participants' post survey responses. After coding, the raters discussed and resolved disagreements. When a resolution was unable to be reached, a third rater was consulted. Codes mentioned by at least 3 different participants are visualized within Figure 5. Participants commonly identified car movement/traffic (21%) and adjustment to walking with street curbs (23%) as distractions in VR. Three participants found a mismatch between their actual height and their height in VR to be distracting. Participants also frequently found car movement/traffic to be distracting in the RW (26%), as well as the presence of other people (34%). They cited better weather (32%), more interactions (9%), and having more time (11%) as elements that would encourage them to walk more in the RW. In VR, participants discussed wanting more interaction in the virtual environment (34%), including with other people (13%), better graphics and animation (19%), and having a larger walking space in the RW (17%) in response to this question. Lastly, they recommended adding humans and pets (38%), increasing the resolution and improving the animation of the simulation (32%), and adding more realistic details (30%) in order to make the VR environment more realistic.

Figure 5

Survey free responses by condition

Activity Index

The AI difference data did not conform to a normal distribution according to a Shapiro Test for normality (p=0.001). Mean AI data for the RW condition was bimodal while the VR mean AI data was unimodal (See Figure 6). The mean of mean AIs in the VR condition was 27.1 (SD = 7.33), and the mean in the RW condition was 32.5 (SD = 26.6). However, further exploration of the mean AI distributions uncovered a concentration of mean AI values in the RW clustered near zero and a second concentration clustered near 50 (See Figure 7). In contrast, mean AI values in VR presented much less spread and centered around 30. This pattern prompted the researchers to investigate the role of arm-swinging in mean AI values derived from wrist-mounted e4 devices. The e4 wristband is designed to be wrist-worn with a built-in wrist strap [66] and is validated for wrist use [56]. However, participants were free to swing their arms in the RW condition but were constrained to holding the VR controllers in front of them while in the VR condition. Pilot data from one of the researchers (A.N.S.) walking at a standardized speed on a treadmill for 50 seconds while swinging arms or holding VR controllers demonstrated a discrepancy in mean AI based on arm movement (Arm swinging=30.30; Holding controllers=20.89). Therefore, using AI created by wrist-mounted e4 devices does not seem to be a useful measure of activity intensity in conditions where arm-swinging may vary systematically. For this reason, no inferential statistics are reported on the AI data.

Figure 6

Mean AI distribution by condition

Figure 7

Mean AI by condition per participant

Note. Each graphed line represents one participant.

MIMS

After learning that AI was not a viable accelerometry analytic method for our purposes, we conducted exploratory data analysis of the accelerometry data using MIMS [67]. MIMS is an open source raw accelerometry processing approach that is “device-independent” [67]. Although it does seem to be susceptible to arm swinging like AI, MIMS appears to be a less biased approach. (The same researcher, A.N.S., walking on a treadmill at a standardized speed while swinging arms and while holding controllers resulted in a MIMS value of 23.1 and 17.4, respectively).

Karas et al. [68] provides MIMS equivalents to Activity Count light physical activity (LPA) and moderate to vigorous physical activity (MVPA) adult cut-points presented in Montoye et al. [69] for accelerometry data processed over a 1 min. epoch. We employ these MIMS equivalent cut-points: LPA-15.047-19.614 MIMs units, MVPA >19.614 MIMs units. First, we used the “MIMSunit” R package (version 0.11.2) [67] to calculate MIMS over a 1 min epoch from the raw accelerometry data between the determined walking session start and end points. Next, we applied Karas et al.’s thresholds to calculate the number of minutes spent in LPA and MVPA for each session [68].

Because the number of minutes spent in LPA and number of minutes spent in MVPA are positive integers (i.e., counts) and their mean was not sufficiently large enough for the distribution to approximate normality, multiple linear regression is not appropriate. To determine if number of minutes spent in LPA during the VR session predicted number of minutes spent in LPA during the RW session, a negative binomial model using a logistic link function was fit. Negative binomial regression was chosen over Poisson regression because the dispersion parameter was greater than 1 (DP=1.81), indicating overdispersion and violation of the mean-variance relationship assumption of the Poisson distribution. To account for differences in walking duration, an offset of RW walking duration was included in the model. Including an offset alters the interpretation of exponentiated coefficients from multiplicative differences in average count of the outcome variable to multiplicative differences in rate of the outcome variable, meaning that with this offset, our model predicts number of minutes spent in LPA in the RW divided by walking duration in the RW. Lastly, control variables included weather in the RW, whether the participant completed all tasks in the RW (Y=1, N=0), and session number of the RW condition (Session 1=0, Session 2=1). Since temperature and humidity were moderately correlated (r = -0.68), they were transformed into a single heat index variable (°F), using the formulas available from the NOAA [70] to reflect weather. Evidence for an effect of number of minutes spent in LPA during the VR session was determined by a likelihood ratio test with alpha set at 0.05. The Pearson residual plot indicated a residual outlier. To check for robustness, this model was run with and without this outlier. Removing the outlier did not alter results of likelihood ratio tests; thus, model results are presented only for the model including the outlier.

There was no evidence that the number of minutes spent in LPA during the VR session predicted the rate of time spent in LPA during the RW session (b= -0.04, chi-square=0.91, p=0.34, Table 2, Figure 8). Each additional 1 min in LPA during the VR session was associated with 4% decrease in rate of LPA in the RW (95% CI 12% lower, 4% higher) when controlling for heat index, completion of all tasks, and session number though this relationship was not significant.

Table 2

Negative binomial model results regressing minutes spent in LPA in the RW *on minutes spent in LPA in VR, heat index, completion of tasks, and session number with an offset for* RW *walking duration*

Predictor	b [95% CI LL, UL]	b^2 [95% CI LL, UL]	df	LR statistic	*p* value
(Intercept)	-5.50 [-12.48, 0.80]	0.004 [0.000004, 2.23]			
LPA min in VR	-0.04 [-0.13, 0.04]	0.96 [0.88, 1.04]	1	0.91	0.34
Heat index	0.04 [-0.03, 0.11]	1.04 [0.97, 1.12]	1	1.01	0.32
All tasks	0.57 [-0.39, 1.55]	1.77 [0.68, 4.72]	1	1.34	0.25

completed					
Session number	-0.53 [-1.51, 0.43]	0.59 [0.22, 1.54]	1	1.16	0.28
McFadden’s Pseudo R^2 [71]	0.05				

Note. LL (UL) represents the lower (upper) boundary of the confidence interval. * indicates *p* < .05. ** indicates *p* < .01. Dummy codes are as follows: All tasks completed: Y=1, N=0; Session number: Session 1=0, Session 2=1. Pseudo R^2 was calculated using R package “DescTools” [72].

Figure 8

RW *LPA by VR LPA*

Note. Trend line represents the modeled relationship between minutes spent in LPA in the RW and minutes spent in LPA in the RW at the median heat index, median RW walking duration, completion of all tasks, and first session number

To determine if number of minutes spent in MVPA during the VR session predicted number of minutes spent in MVPA during the RW session, a Poisson regression model using a logistic link function was fit. The dispersion parameter was less than 1 (DP=0.66), indicating that the mean-variance relationship assumption was met. Identical to the LPA analysis, an offset of RW walking duration was included in the model to account for differences in walking duration. This inclusion in Poisson regression results in the same alterations to interpretation as in negative binomial models. Control variables were identical to the LPA analysis, and evidence of an effect was determined by a likelihood ratio test with alpha set at 0.05.

There was no evidence that the number of minutes spent in MVPA during the VR session predicted the rate of time spent in MVPA during the RW session (b= -0.001, chi-square=0.01, p=0.91, Table 3, Figure 9). Each additional 1 min in MVPA during the VR session was associated with 0% change in rate of MVPA in the RW (95% CI 2% lower, 2% higher) when controlling for heat index, completion of all tasks, and session number.

Table 3

Poisson model results regressing minutes spent in MVPA in the RW *on minutes spent in MVPA in VR, heat index, completion of tasks, and session number with an offset for* RW *walking duration*

Predictor	b [95% CI LL, UL]	b^2 [95% CI LL, UL]	df	LR statistic	*p* value
(Intercept)	-0.76 [-2.09, 0.53]	0.47 [0.12, 1.70]			

MVPA min in VR	-0.001 [-0.02, 0.02]	1.00 [0.98, 1.02]	1	0.01	0.91
Heat index	0.01 [-0.01, 0.02]	1.01 [0.99, 1.02]	1	1.36	0.24
All tasks completed	0.10 [-0.11, 0.31]	1.10 [0.89, 1.36]	1	0.81	0.37
Session number	-0.04 [-0.25, 0.17]	0.96 [0.78, 1.19]	1	0.14	0.71
McFadden's Pseudo R^2 [71]	0.01				

Note. LL (UL) represents the lower (upper) boundary of the confidence interval. * indicates $p < .05$. ** indicates $p < .01$. Dummy codes are as follows: All tasks completed: Y=1, N=0; Session number: Session 1=0, Session 2=1. Pseudo R^2 was calculated using R package "DescTools" [72].

Figure 9

RW *MVPA by VR MVPA*

Note. Trend line represent the modeled relationship between minutes spent in MVPA in the RW and minutes spent in MVPA in RW at the median heat index, median RW walking duration, completion of all tasks, and first session number.

Walking Duration

The walking duration difference data conformed to a normal distribution according to a Shapiro Test for normality (p=0.20). Participants walked for about 13 minutes in the RW condition (M = 777 sec., SD = 424) and for about 18 minutes in VR (M = 1085, SD = 350). The results of a paired t-test confirmed that this difference was statistically significant (t = -4.14, p < 0.001). This difference of 325.25 seconds (95% CI [166.21, 484.29]) or about 5.5 minutes was a moderate effect (d = -0.65).

To control for the completion of all tasks, session number, and heat index, mixed effects models were performed. Table 4 presents the output of the mixed effects model using the R packages "lme4" [73], "lmerTest" [74] and "sjPlot" [75]. Condition was dummy-coded as 1 for VR and 0 for RW; session number (Session 1=0, Session 2=1), completion of all tasks (Y=1, N=0), and heat index (°F) were included as fixed effects. Participant number was included as a random effect. The QQ plot for this model indicated that the distribution of residuals was approximately normal (Figure 10).

Controlling for heat index, if the participant completed all tasks, and if it was their first or second session, there was evidence of an effect of condition (t = 2.35, p = 0.02) as calculated using Satterthwaite's method. Based on the model estimate, participants walked 223 seconds (95% CI [39.29, 408.71]) or roughly 2 minutes more in VR as compared to the RW, accounting for heat index, task completion, and session number.

Figure 10

QQ plot for mixed effect model results regressing walking duration on main effects of condition, task completion, session number, and heat index

Table 4

Mixed effect model results regressing walking duration on main effects of condition, task completion, session number, and heat index

Fixed effects					
Predictor	Estimate	95% CI [LL, UL]	df	*t* value	*p* value
(Intercept)	1138.88	[132.66, 2149.10]	69.09	2.20	0.03*
Condition	223.43	[39.29, 408.71]	60.04	2.35	0.02*
Heat index	0.69	[-11.04, 12.34]	70.50	0.12	0.91
All tasks completed	-551.36	[-678.33, -423.70]	74.31	-8.33	<0.001**
Session number	-95.53	[-202.52, 12.42]	49.29	-1.71	0.09
Marginal R^2	0.61				
Conditional R^2	0.75				

Note. LL (UL) represents the lower (upper) boundary of the confidence interval. * indicates *p* < .05. ** indicates *p* < .01. Participant ID was included as a random effect. Dummy codes are as follows: Condition: VR=1, RW=0; All tasks completed: Y=1, N=0; Session number: Session 1=0, Session 2=1.

We visualized these effects in Figure 11. Visual analysis of this figure suggested order effects: the distributions of VR walking duration for the RW->VR group and VR->RW group as well as the RW walking duration for the RW->VR group seem similar, but the RW walking duration data from the VR->RW group seems to deviate from this distribution as it shows less spread and a concentration of relatively short durations around 500 seconds (~8 minutes). We performed an exploratory analysis of these order effects using a mixed-effects model with an interaction term. Condition (VR=1, RW=0), session number (Session 1=0, Session 2=1), interaction between condition and session number, completion of all tasks (Y=1, N=0), and heat index (°F) were included as fixed effects. Participant number was included as a random effect. The QQ plot for this model indicated that the distribution of residuals was approximately normal (Figure 12). The results of this model are presented in Table 5. Importantly, we chose to dummy-code binary variables, meaning that condition and session number effects are simple effects and must be interpreted with reference levels [76]. In this model, we do not find evidence of a condition simple effect (t = 0.40, p = 0.69) at the session 1 reference level, meaning that there is no evidence of a difference between VR and RW conditions among session 1 observations. There is evidence of a session number simple effect (t = -2.48, p = 0.02) at the RW reference level: Participants completing their second session in the RW walked about 4 minutes less than participants completing their first session in the RW. This study was not powered to detect interaction as none was expected; still, the interaction term suggests there may be order effects (t = 1.82, p = 0.08). These results are best visualized in the bar graph in Figure 13.

Figure 11

Walking duration distribution by condition and session number

Figure 12

QQ plot for mixed effect model results with added condition-by-session number interaction

Table 5

Mixed effect model results with added condition-by-session number interaction

Fixed effects					
Predictor	Estimate	95% CI [LL, UL]	df	*t* value	*p* value
(Intercept)	1466.98	[421.32, 2505.37]	66.96	2.70	<0.01**
Condition	53.73	[-200.80, 307.98]	73.81	0.40	0.69
Heat index	-2.36	[-14.15, 9.50]	67.77	-0.38	0.70
All tasks completed	-537.18	[-662.74, -411.53]	73.71	-8.17	<0.001**
Session number	-239.17	[-424.40, -55.28]	68.81	-2.48	0.02*
Condition x Session	260.41	[-13.89, 537.88]	41.14	1.82	0.08

Marginal R^2	0.63
Conditional R^2	0.75

Note. LL (UL) represents the lower (upper) boundary of the confidence interval. * indicates *p* < .05. ** indicates *p* < .01. Participant ID was included as a random effect. Dummy codes are as follows: Condition: VR=1, RW=0; All tasks completed: Y=1, N=0; Session number: Session 1=0, Session 2=1.

Figure 13

Estimated marginal means of walking duration by condition and randomized order

Note. Error bars represent 95% confidence intervals. * indicates *p* < .05. ** indicates *p* < .01.

We ran pairwise comparisons to follow up on these results using the package "emmeans" [77] (see Table 6). Participants in the VR->RW group walked on average 293 seconds more (95% CI [30.8, 555]) or roughly 5 minutes more in VR than they walked in the RW (VR=1070 sec, RW=777, t = 2.97, p = 0.02, see Figure 13). This discrepancy was not present among participants in the RW->VR group (RW=1016, VR=1091, t = -0.59, p = 0.93).

Table 6

Pairwise comparison results of condition and session number on walking duration

Contrast	Estimate	95% CI [LL, UL]	df	*t* value	*p* value
RW Session 1 – VR Session 2 (RW -> VR group)	-75.0	[-408.6, 259]	59.9	-0.59	0.93
VR Session 1 – RW Session 2 (VR -> RW group)	292.9	[30.8, 555]	49.1	2.97	0.02*

Note. LL (UL) represents the lower (upper) boundary of the confidence interval. * indicates *p* < .05. ** indicates *p* < .01.

To provide a useful effect size (i.e., the degree to which walking duration in VR can predict walking duration in the RW), we conducted exploratory analysis using multiple linear regression (MLR). A Shapiro-Wilks test indicated that the walking duration data in the RW did not conform to a normal distribution (W = 0.91, p-value = 0.004); still, MLR is robust against violations of normality. To verify our results using MLR, we employed bootstrapped confidence intervals. Model 1 used walking duration in VR (s), heat index in the RW (°F), task completion in the RW (Y=1, N=0) and session number (Session 1=0, Session 2=1) in the RW to predict walking duration in the RW (s). Model 2 added an interaction term between walking duration in VR and session number, thereby, accounting for order effects. The interaction model (model 2) did not fit the data significantly better than the model without the interaction (F=0.001, p=0.97). Model comparison indicated that the inclusion of an interaction term explained no variance above and beyond main effects for predictors (partial $R^2<0.001$). Concerning the best fitting model (model 1 without the interaction), we did not observe evidence that walking duration in VR predicted walking duration in the RW when controlling for session number, task completion, and heat index (b=0.14, F=1.33, p=0.26). A one second increase in walking duration in VR was associated with about a tenth of a second increase in walking duration in the RW though this relationship was not significant. Walking duration in VR accounted for 1% of variance in walking duration in the RW not accounted by session number, task completion, and heat index (partial $R^2=0.012$). Bootstrapped confidence intervals confirmed these results.

Discussion

The current study examined how walking decisions in the RW compared to a VR replica of the same environment. If environmental planning decisions are to be informed by data gathered in VR models, it is necessary to know how RW behavior compares to behavior in the VR setting. Poisson and negative binomial regression did not provide evidence of a relationship between intensity of walking in VR and intensity of walking in the RW when controlling for session number and heat index. The lack of an association between time spent in different PA zones in VR and in the RW may be partially due to placement of the accelerometry device on the wrist. When choosing this device, we prioritized participant comfort and privacy as they donned the device in public; however, wrist-worn accelerometers are generally less accurate than hip-worn devices [69]. In their establishment of the PA intensity cut-points used in the present study, Montoye and colleagues [69] discuss how wrist-worn accelerometers can be susceptible to local movement of the arm leading to higher rates of incorrect PA intensity classification (e.g., playing cards categorized as MVPA). In the current study, participants' local arm movement was constrained in the VR condition by holding hand controllers, which may explain why there was no association between PA intensity in VR and in the RW.

The results of a t-test, mixed effects model, and multiple linear regression indicate that people do not always choose to walk for the same duration in VR as they do in the RW. That is, walking duration was found to be shorter, on average, in the RW than in VR. This may be a factor of perceptive differences in VR versus the RW. As noted, the VR environment was created to match the RW environment complete with building shapes, façades, and legible signage; still, participants recommended that we increase the clarity of the simulation environment in the free response survey. Not only would the fidelity of the environmental design have a potential effect on walkability perceptions, but there are inherent perceptive differences in viewing VR environments over RW. For instance, Bach et al. reported individuals consistently underestimating distances in VR; a perception that became exacerbated as the spatial distances increased [78]. Also, Bogon et al. demonstrated that individuals expect the duration of events (e.g. How long it would take for a car to drive down the street) to be longer in VR compared to the RW even though individuals experience time similarly in both environments [79]. Further exploration of perceptive differences may help to explain the subtle variations in walking behavior between VR and RW. Additionally, there was a descriptive divide in VR walking duration between participants with and without previous VR experience. Familiarity with VR technology may have influenced behavior in VR, including participant motivation.

HR could not be incorporated due to error associated with the Empatica e4 devices. This study was important in understanding the need for clarification of the context in which repeated measures may contribute to fatigue and order effects, and the need for understanding HR through more reliable measures of physical activity when comparing behavior in a virtual and RW environment. Thus, further investigation is needed to understand the circumstances in which these differences exist before definitive conclusions can be drawn concerning the use of VR in decision-making for urban planning.

Analysis of free response items of the post-experience survey demonstrated that participants were similarly distracted by cars in RW and VR environments, but the primary distractor in the RW was other people, which were not present in VR, though participants commonly suggested that we add them in VR. Participants were also distracted by the presence of curbs in VR, possibly because they received no tactile feedback to match the visual curbs in VR (i.e., participants saw a curb in VR but physically were walking on a flat plane). When asked what would encourage them to spend more time walking in the VR environment, participants focused primarily on simulation limitations, such as lack of interaction, graphic features, and the size mismatch between the VR environment and the physical room where the VR session was conducted. These same priorities carried into their responses regarding suggested changes to the VR environment, including increasing resolution and the depth of the simulation. There was less consensus among participants in the RW concerning what would encourage them to walk longer with the most common answer being better weather. Future researchers may consider conducting qualitative work to gain more understanding of how the experiences of an urban environment in VR and in the RW compare.

Exploratory analyses suggested that the relationship between condition and walking duration may be more complex than a simple increase in duration when navigating a VR environment. Moreover, walking duration in VR may match walking duration in the RW under certain conditions. A mixed effects model revealed that there was no longer evidence of a condition simple effect when the interaction between condition and session number was included in the model. This implies order effects: the sequence by which one walks in VR and walks in the RW may matter. Pairwise comparisons of this interaction showed that the RW walking duration of the VR->RW group was significantly shorter than their VR walking duration. Conversely, VR walking duration and RW walking duration did not differ among participants in the RW->VR group. Still, these results must be replicated before strong conclusions can be drawn.

Possible explanations were investigated for these order effects. First, participants completed the RW condition in different weeks depending on their assigned order due to logistical limitations regarding renting a large enough space to conduct the VR condition. Randomization to order was completed before participants were provided an opportunity to sign up for a session. It is possible that this resulted in unknown but meaningful differences between groups. The participants who were available during the first week of data collection (RW->VR group) may have differed from the participants who were available during the last week of data collection (VR->RW group). Notably, the proportion of participants reporting previous experience with VR was equivalent across the RW->VR group (47%) and the VR->RW group (48%). Second, weather differed between the first week of data collection and the last week of data collection. This difference seems unlikely to explain our observed order differences, as the weather in week one was presumably less pleasant for walking outside (Mean heat index=87.3°F) than in week three

(Mean heat index=81.2°F) when participants walked less. Moreover, Martins et al.'s results [80] depict that heat is negatively correlated with engagement in PA during summer; thus, weather does not explain our order effects. Third, history effects may explain these results. We recruited primarily employees from a large university in the western U.S. (83%): the third week of our data collection coincided with the penultimate week of this institution's summer courses. Participants walking in week three (VR->RW group) may have been short on time due to this pending deadline and chose to end their walking session sooner.

Lastly, there may be true order effects in the comparability of RW and VR walking. Order effects have been shown when measuring recall of distance perception in VR, and it is possible memory plays a role when estimating how long it takes to walk certain distances depending on the order of RW and VR walking scenarios [81]. However, other previous studies did not find differences in walking duration [82] or order effects of RW and VR walking [42]. Pastel and colleagues [42] randomized order of participating in RW and VR walking. They also mirrored the walking route in VR to minimize learning effects, which may have contributed to this lack of order effects [42,81]. In our study, we can identify two potential sources of true order effects. First, one of the study tasks asked participants to search for an obscure location (i.e., the shipping courier); the difficulty of navigating and therefore, finding, this location may have differed in VR than in the RW, leading to order effects. Descriptively, a larger proportion of participants found the tasks to be more challenging in VR. In contradiction, the proportion of participants who completed all tasks in their first session is descriptively comparable regardless of if that first session was in VR (43%) or the RW (41%). An alternative explanation is that the experience of finding this specific location transfers better from VR to the RW compared to the RW to VR. In other words, for the VR->RW group, the skill of finding a location may have transferred well to the RW, leading to a large decrease in walking duration for the RW condition. However, for the RW->VR group, this skill may not have transferred well, so their second session (VR) was a comparable length as their first (RW). Of those in the VR->RW group who did not complete all tasks in their first session (13), 92% completed all tasks in their second session in the RW (12). In contrast, of those in the RW->VR group who did not complete all tasks in their first session (10), only 40% completed all tasks in their second session (4).

There are some mixed results regarding differences in VR vs. RW navigation. Some have speculated that navigating in VR is more difficult than in the RW due to difficulty moving one's head to walk in the desired direction, which often requires more coordination than RW walking [83]. Similarly, participants in VR conditions have demonstrated weaker navigational skills in regard to pointing to start and finish lines as well as drawing a map of the route they walked compared to those in RW conditions [84]. To mitigate head movement effects while navigating, Drewes and colleagues [82] had participants hold a system controller close to their body to orient themselves while making walking decisions. Interestingly, they found that there were no significant navigational differences between VR and RW walking. These varied findings suggest that following directions and navigating in VR may pose more challenges but do not necessarily play a large role in order effect differences.

The second source of true order effects could be that participants may have volunteered for the study because they were excited to experience VR. By their second session, participants in the VR->RW group may have already performed the more attractive session of the study. Knowing the study session ends when they complete the walking session, they may have chosen, consciously or not, to end the walking session sooner. If future confirmatory studies indicate that there are true order effects either due to navigation differences or participant motivation, practitioners interested in using VR to examine potential built environmental interventions may consider strategies to minimize these effects, such as providing participants directions in VR, recruiting participants through diverse channels, or selecting repeated-measure study designs that account for carryover effects.

Strengths

This study successfully compared actual decisions regarding walking behaviors in VR with those in the RW using the VR locomotive technique (i.e., overground walking) which individuals use in the RW. Prior work has focused on walking-related perceptions such as judgements of pleasantness, safety, or intention to walk [38,49,50] instead of actual walking. Other researchers compared the kinematics between walking in a VR room to walking in a RW room identical to the VR room [40,51], this does not address the decision to continue or stop walking in an urban environment, which is central to walkability research. This study is unique in that empirically examines the similarity of actual walking decisions made in VR and the RW at an urban scale using overground walking. Also, the walking decisions made by participants in this study mirror the types of decisions made while walking in urban environments. We believe this study brings PA researchers one step closer to using VR to address the causal gap between built environmental factors and the decision to engage in walking.

Limitations

The findings of this study must be understood in the context of its limitations. The manufacturer of the HMD used in the present study discourages its use outdoors as sunlight can harm the device; consequently, the VR condition took place inside a climate-controlled room while the RW condition used an outdoor location where the heat index may vary throughout the walking area. That is to say, condition was confounded by weather. To reduce the effect of this confounding, heat index was included in multi-level and regression models; still, the results of statistical models with intercorrelated predictors can be unstable [85,86]. Weather variability presents a persistent challenge for individuals aiming to utilize VR technology to simulate RW behaviors, as the current limitations of VR technology (i.e., the sensitivity of VR equipment to both light and heat) restrict its application to indoor locations. Also, because the historic district and its simulation are larger than the room in which participants walked in VR, participants needed to pause their walking, turn their bodies, and reorient the VR environment. This added step in VR, which was not necessary in the RW, may have affected walking decisions. Additionally, due to the limited availability of the large indoor space, all VR sessions occurred within the second week of data collection while RW sessions either occurred in the first or third week. This necessity created the possibility of selective attrition bias, weather differences, and history effects discussed above. Additionally, using cut-points to categorize time epochs into PA intensity levels has inherent limitations [87], including compounding measurement error from the study that employs cut-points with that of the cut-point validation study. Separating LPA and MVPA into two separate analytic models may have masked a relationship between them due to range restriction.

Gait-based locomotion for VR has been shown to reduce the risk of motion sickness and is preferred by users over other locomotion techniques [88,89]. As this was the primary mode of locomotion for the user the effects of simulation sickness are minimal. The other two locomotion techniques integrated into the experience, snap turns and teleportation, would be used minimally by the user. Additionally, these techniques have also been shown to reduce discomfort for users [90]. However, despite these design considerations there is a chance that participants were acutely aware of the VR headset, which in turn can increase perceived levels of fatigue, resulting in a desire to remove the HMD as soon as possible [91]. This may be reflected in the slightly higher reported symptom questions in Figure 4B.

Future directions

Future researchers should avoid using the Empatica e4 wristband for measuring HR under movement conditions. Although the Empatica e4 wristband contains an accelerometer and is marketed as research-grade, its HR functionality is not validated for use when the wrist is moving. Additionally, researchers should abstain from using wrist-worn accelerometers to measure PA intensity for VR research as arm, and thereby, wrist, movement in VR (i.e., holding controllers) does not parallel that of RW walking (i.e., arm swinging).

Further research is needed to explore the order effects suggested by the exploratory analyses of this study. Future research using a similar procedure as the current study but completing both VR and RW sessions within the same timeframe could determine if the order effects observed here are meaningful to all researchers using VR to study walkability or an artifact of our research design. Additionally, research teams may consider highly-powered study designs to enable examination of individual factors affecting the similarity of VR and RW walking, such VR experience and age. Lastly, as VR hardware and software continue to develop, it is important to continue testing the comparability of VR walking decisions with RW walking decisions if VR is to be used as a highly-controlled and ecologically valid technique for studying walking behavior.

Conclusions

Walking decisions in VR may differ from those made in the RW. These differences may only be present under specific circumstances. We encourage researchers to investigate the conditions under which walking decisions in VR may equate to those made in the RW and the conditions under which they are not similar. Through understanding that there might be differences in how individuals interact with VR (vs. RW) environments, simulations can be adjusted or interpreted with these discrepancies in mind. This research is necessary for the emerging use of VR to evaluate the causal influence of specific built environmental factors on walking behaviors.

Additional Information

Data Availability Statement

The data that support the findings of this study will be openly available in OSF at https://osf.io/s395w/.

Conflict of Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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