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Enhancing Neighborhood-Specific Mobility Self-Efficacy in Older Adults: A Wearable-Based Urban Crowdsensing Approach

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ABSTRACT: The interaction between urban infrastructure design and older adults' mobility remains a critical challenge. Frequent encounters with stressors in built environments, such as steep stairs, uneven sidewalks, or complex traffic signage, reduce older adults' mobility self-efficacy (MSE), ultimately impairing their ability to navigate urban spaces independently. While substantial research has focused on enhancing physical accessibility, limited attention has been given to psychological accessibility, particularly neighborhood-specific MSE, which directly correlates with older adults' likelihood of engaging in outdoor activities. This study explores the potential of wearable-based urban crowdsensing to enhance older adults' neighborhood-specific MSE by leveraging physiological and geolocation data to identify neighborhood stressors. An age-friendly mobile application, SafeCommute, was developed to provide older adults with visual previews of stressors and practical navigation tips, empowering them to anticipate and address challenges in their neighborhoods. A nine-week randomized controlled trial was conducted with 16 older adults, divided into an intervention group using the app and a control group receiving standard mobility support. Changes in Neighborhood-specific MSE and Mobility Intention levels were assessed pre- and post-intervention using mixed-model ANOVA. The results demonstrated significant improvements in the intervention group, with Neighborhood-specific MSE increasing by 21% compared to minimal changes in the control group. The significant group-by-time interaction for neighborhood-specific MSE [$F_{(1,14)}$ = 13.264, $p < 0.01$, $\eta^2 = 0.487$] highlights the intervention's targeted impact. These findings highlight the potential of wearable-based urban crowdsensing to address neighborhood-specific stressors and improve older adults' confidence in navigating their environments.

1. INTRODUCTION

The global population is aging at an unprecedented rate, with the proportion of individuals aged 65 years or older (referred to as older adults in this study) projected to rise from 9.3% in 2020 to 16% by 2050 (Nations, 2019). Concurrently, about 61 countries, representing 21% of the worldwide population, are expected to experience negative population growth from 2020 to 2050 (Bloom, 2020). This demographic shift underscores the importance of addressing challenges associated with aging, particularly mobility, which is critical for maintaining independence and overall well-being among older adults (Walker, 2002). Mobility, defined as the ability to move freely, engage in social activities, and perform daily tasks, is essential for a high quality of life (Rantanen et al., 2012). However, many older adults face significant mobility limitations due to a combination of physical, psychological, and environmental barriers (Maresova et al., 2023). These limitations can lead to adverse health outcomes, including sarcopenia, osteoporosis, and obesity (Rosso et al., 2011). Moreover, restricted mobility often results in social isolation, depression, and limited access to essential resources, exacerbating health disparities (Maresova et al., 2023; Rosso et al.,

2011). Over time, these factors contribute to increased frailty, disability, and even premature mortality (Webber et al., 2010).

One of the major obstacles to mobility among older adults is the frequent encounter with stressors in the built environment (Lee et al., 2020). The built environment refers to human-made spaces and structures, including buildings, roads, sidewalks, parks, and public transportation systems, which shape the physical settings of daily life (Hassan et al., 2023). For older adults, these environments often present physical barriers such as uneven sidewalks, inadequate pedestrian infrastructure, and poorly maintained public spaces. Stress arises when environmental demands exceed an individual's capabilities, with older adults, who often experience declines in functional capacity, are particularly vulnerable to such stressors (Yang & Matthews, 2010). These barriers not only induce stress but also hinder participation in outdoor activities, further limiting mobility and independence (Torku et al., 2022).

To address these challenges, three primary types of interventions have been developed and deployed in literature: (1) reducing environmental demands through improved design and maintenance standards (WHO, 2007; Lawton, 1999), (2) enhancing physical and cognitive capabilities through targeted programs (Patel et al., 2012), and (3) minimizing stressful interactions with the environment through alternative transportation solutions, such as ADA Paratransit and ride-hailing services (Smith et al., 2018; Lee et al., 2020). However, research indicates that raising self-efficacy should complement these interventions. Even when environmental modifications are made to address physical barriers, older adults with low self-efficacy, often due to previous negative experiences, may remain hesitant to venture outdoors (Clarke et al., 2009; Rosso et al., 2011). Therefore, alongside these interventions, increasing mobility self-efficacy (MSE)—an individual's belief in their ability to move independently—have garnered significant attention (Feltz & Payment, 2005). This emphasis stems from MSE's role as a key determinant of willingness to engage in mobility activities (Bandura, 1997). While much of the existing literature emphasizes general MSE, emerging evidence suggests that a more specific approach; neighborhood-specific MSE (i.e., an individual's confidence in their ability to navigate their local environment) may have a stronger association with outdoor mobility intentions (Clarke et al., 2009). This is due to the principle of specificity in self-efficacy, which suggests that self-efficacy exists on a continuum from generalized to context-specific constructs. Generalized self-efficacy refers to broad, context-independent confidence in one's ability to cope with a variety of challenging situations, whereas specific self-efficacy pertains to perceived competence in well-defined, situational contexts (Schwarzer, 1995). The significance of specificity lies in its predictive power: the more closely self-efficacy aligns with a specific task or context, the more accurately it predicts an individual's willingness to engage in that task (Bandura, 1997).

Given that neighborhoods represent the immediate environments older adults encounter after leaving their homes, enhancing neighborhood-specific MSE is likely to have a greater impact on encouraging outdoor mobility (Clarke et al., 2009). However, designing effective interventions to enhance neighborhood-specific MSE is challenging due to the diverse and complex nature of neighborhoods, which vary widely in size, layout, and environmental characteristics. Traditional approaches often rely on labor-intensive and time-consuming methods, such as surveys and manual observations, to identify specific stressors (Torku et al., 2022). A significant limitation of these approaches is their reliance on manual planning and lack of real-time data collection, which often results in suboptimal outcomes (Patel et al., 2012).

Recent advancements in wearable technology present a promising avenue through urban crowdsensing (Lane et al., 2010). Urban crowdsensing utilizes sensors to collect real-time physiological and location-based data, enabling researchers to identify specific areas where older adults experience mobility-related stress (Lane et al., 2010). Wearable biosensors, such as photoplethysmography (PPG) devices, facilitate continuous monitoring of physiological indicators of stress (Sano et al., 2014). When combined with geolocation data, these tools allow researchers to efficiently narrow down stress hotspots, allowing researchers to collect detailed, neighborhood-specific data on stressors without the laborious effort traditionally required (Lee et al., 2020). Despite its potential, the application of wearable-based urban crowdsensing in improving neighborhood-specific MSE and outdoor mobility among older adults remains underexplored. To fill this gap, this study investigates the potential of wearable-based urban crowdsensing to enhance neighborhood-specific MSE and improve outdoor mobility among older adults. By leveraging

physiological and geolocation data, the study aims to identify environmental hotspots, develop targeted interventions, and ultimately support healthier aging.

2. NEIGHBORHOOD-SPECIFIC MOBILITY SELF-EFFICACY

Albert Bandura, a Canadian-American psychologist, first defined self-efficacy in 1977 as an individual's belief in their capability to perform actions necessary to achieve specific goals. According to his social-cognitive theory, human behavior is influenced by the dynamic interplay of personal, environmental, and behavioral factors (Bandura, 1977). Bandura's theory provides a foundational framework for understanding how perceptions of ability influence individual actions. Importantly, Bandura emphasized that self-efficacy is not a global trait but rather a context-specific construct that varies across different domains and tasks. This perspective positions self-efficacy on a continuum, ranging from general self-efficacy, which reflects an individual's overall confidence across a wide range of situations, to task-specific self-efficacy, which pertains to confidence in performing particular activities or overcoming specific challenges (Schwarzer, 1995). Research has consistently shown that task-specific self-efficacy is a stronger predictor of behavior in defined contexts, as it aligns more closely with the demands of the task at hand (Bandura, 1997).

Building on this theoretical foundation, neighborhood-specific MSE emerges as a specialized form of task-specific self-efficacy that reflects an individual's confidence in navigating their local environment. Unlike general MSE, which encompasses overall confidence in mobility, neighborhood-specific MSE is context-dependent and directly tied to the unique challenges of the immediate environment (Rosso et al., 2011). This distinction is critical for understanding older adults' outdoor mobility intentions, as they are particularly vulnerable to the influence of their residential surroundings. Older adults tend to spend more time in their neighborhoods compared to younger individuals, who often travel outside their local areas for work or school (Rosso et al., 2011). Furthermore, age-related declines in physical and mental health, shrinking social networks, and increased fragility can diminish older adults' capacity to cope with environmental demands (Webber et al., 2010). Consequently, the neighborhood environment has a more pronounced impact on older adults than on other age groups. Research indicates that supportive environments can significantly enhance older adults' quality of life by boosting their confidence and mobility (Clarke & Gallagher, 2013; Crane et al., 2023).

The significance of neighborhood-specific MSE lies in its strong correlation with outdoor mobility intentions and behaviors. Older adults with higher confidence in navigating the local environment are more likely to engage in outdoor activities, such as walking or visiting local amenities, which promote physical and mental well-being (Hirsch et al., 2014). In contrast, low confidence in navigating the local environment can discourage older adults from venturing outdoors, leading to reduced physical activity, social isolation, and a decline in overall quality of life (Rosso et al., 2011). Further emphasizing the importance of this context-specific self-efficacy, Clarke and Gallagher (2013) found that older adults with higher confidence in their neighborhood environments reported greater participation in outdoor activities and lower levels of mobility-related anxiety. This suggests that confidence in navigating the local environment is a more accurate predictor of outdoor mobility behaviors than general self-efficacy because it directly reflects an individual's ability to address the unique challenges of their immediate surroundings (Rosso et al., 2011). Given these insights, neighborhood-specific MSE emerges as a critical factor in designing targeted interventions that promote healthy aging and encourage outdoor mobility among older adults.

Despite the critical role of neighborhood-specific MSE, designing and implementing effective interventions at the neighborhood scale presents significant challenges. One major obstacle is the need for precise, neighborhood-specific data on environmental stressors, which is essential for designing effective interventions. Neighborhoods exhibit considerable heterogeneity in size, spatial configuration, and environmental attributes, rendering the development of universally applicable solutions difficult (Clarke et al., 2009). Traditional methods for identifying environmental stressors, such as surveys and manual observations, are labor-intensive and time-consuming, often resulting in datasets that are incomplete, lack real-time relevance, or quickly become outdated due to the dynamic nature of environmental conditions (Torku et al., 2022). These limitations hinder the ability to obtain the detailed, neighborhood-specific information needed to effectively tailor interventions to the unique challenges faced by older adults in

different neighborhoods. This highlights the need for data-driven approaches that can efficiently collect and analyze neighborhood-specific data, thus enabling the development of impactful and precisely targeted interventions.

3. URBAN CROWDSENSING AND HOTSPOT ANALYSIS TO MEASURE STRESSFUL INTERACTIONS WITH THE BUILT ENVIRONMENT

Recent advancements in wearable sensing technologies have expanded the potential for understanding human interactions with the built environment, particularly through urban crowdsensing. This approach typically leverages wearable devices and mobile technologies to systematically capture how individuals interact with and respond to their surroundings (Lane et al., 2010). By providing continuous, objective measurements, it overcomes key limitations of traditional approaches that rely on self-reports or intermittent observations, which often miss subtle yet critical stress responses (Lee et al., 2020). This technological paradigm proves particularly valuable when studying vulnerable populations like older adults, whose physiological stress responses to environmental stimuli often exhibit distinct temporal patterns and magnitudes compared to younger individuals (Rosso et al., 2011). Studies like those conducted by Lee et al. (2021), Patel et al. (2012), and Sano et al. (2014) have demonstrated the efficacy of wearable biosensors in natural environments. These studies demonstrate the efficacy of wearable biosensors in capturing physiological signals and highlight their comfort and user-friendliness, making them suitable for prolonged usage among older adults (Patel et al., 2012).

Urban crowdsensing offers substantial improvements over conventional data collection techniques. Modern biosensors achieve sufficient temporal resolution to precisely document stress onset and recovery patterns, revealing how individuals physiologically adapt to specific urban challenges. When synchronized with geolocation data, these physiological measurements create detailed spatiotemporal mappings that establish causal relationships between discrete environmental features and stress responses (Lee et al., 2021). Moreover, the passive nature of this data collection method helps eliminate recall bias and reduces the burden on participants (Patel et al., 2012).

When implemented at scale, urban crowdsensing transcends individual monitoring to establish a collective intelligence framework (Lee et al., 2020). The aggregation of wearable-derived stress data across multiple participants facilitates the identification of consistent spatial patterns through hotspot analysis techniques (Lane et al., 2010). This analytical approach yields insights at multiple levels of spatial resolution. At the micro-scale, this analysis can pinpoint discrete environmental elements such as poorly designed crosswalks, areas of excessive noise pollution, or locations lacking adequate seating that trigger stress responses. At the macro-scale, it helps identify larger zones of persistent stress accumulation, signaling the need for broad urban design interventions to alleviate these stressors (Torku et al., 2022). Identifying these stress hotspots is essential for addressing the mobility challenges faced by older adults, as these locations often represent systemic failures in environmental design that disproportionately affect this vulnerable group (Michael et al., 2006). By establishing clear spatial correlations between specific environmental features and physiological stress markers, urban crowdsensing provides critical, neighborhood-wide information necessary for designing targeted interventions aimed at enhancing mobility and reducing stress among aging populations.

Despite the growing potential of wearable biosensors and urban crowdsensing, a significant knowledge gap persists in their application to enhance neighborhood-specific MSE among older adults. This study seeks to bridge this gap by investigating the potential of wearable-based urban crowdsensing to enhance neighborhood-specific MSE, and ultimately improve outdoor mobility among older adults. In doing so, the study aims to deliver actionable insights for designing targeted interventions that empower older adults to navigate their neighborhoods with greater confidence.

4. RESEARCH METHODS

The feasibility of using wearable biosensors and urban crowdsensing to enhance neighborhood-specific MSE among older adults was evaluated through a structured comparative analysis of self-efficacy and mobility metrics between control and intervention groups. Ethical approval for this study was obtained from the University of Alberta's Institutional Review Board (Pro00137747). The research process is structured into four key subsections: Sample, Equipment and Procedures, Measures, and Data Analysis.

4.1. Sample

Participants were recruited in collaboration with a local senior center in Edmonton, Alberta. Flyers and informational sessions were used to invite older adults aged 65 and above. Inclusion criteria required participants to be able to walk independently or with minimal assistance (e.g., cane or walker) and to have no severe cognitive impairments that would hinder their ability to use the intervention app. The final sample comprised 16 older adults (9 males and 7 females) with a mean age of 70.5 years (SD = 4.95). Demographic characteristics revealed that the largest marital status group was divorced individuals (48%), the majority of participants (13 out of 16) lived alone, and most (12 out of 16) did not use any assistive devices for mobility. Prior to participation, all individuals were provided with detailed information about the study's purpose, procedures, and potential risks. Written informed consent was obtained from each participant before their involvement in the study.

4.2. Equipment and Procedures

The study followed a structured, multi-phase procedure to develop and evaluate a dedicated age-friendly mobile application designed to enhance Neighborhood-specific MSE among older adults. First, physiological data were collected using an armband-based photoplethysmography (PPG) sensor, combined with continuous location tracking, over a four-week period. These data were analyzed using an urban crowdsensing approach to identify approximate locations where participants frequently experienced mobility-related stressors (Lee et al., 2020). Selective site inspections were then conducted at these locations to validate the specific environmental stressors present. Based on the findings from the urban crowdsensing data and site inspections, an age-friendly mobile application, SafeCommute, was developed (see Figure 1 for an overview). The application was designed to enable users to preview upcoming trips and navigate their local environment with greater confidence. It provided visual aids (e.g., maps, pictures) and practical tips on how to reach destinations with reduced stress. Previewing upcoming tasks is a well-established approach for enhancing task-specific self-efficacy, making the app a targeted intervention for improving Neighborhood-specific MSE (Carolina, 1989). To ensure accessibility, smartphones preloaded with the dedicated application were distributed to participants, along with internet access, to facilitate seamless use throughout the study period.

The study utilized a randomized controlled trial (RCT) design to evaluate the effectiveness of the intervention. Participants were randomly assigned to either the experimental (n = 8) or control group (n = 8). Prior to the intervention, all participants completed pre-intervention surveys within 24 hours of the experimental group beginning the intervention. The experimental group engaged with the mobile application over the subsequent four-week period, while the control group received no intervention. Post-intervention surveys were administered to all participants one week after the experimental group's final intervention session. The design not only facilitated the evaluation of temporal changes in key outcomes but also the determination of the intervention's overall effectiveness.
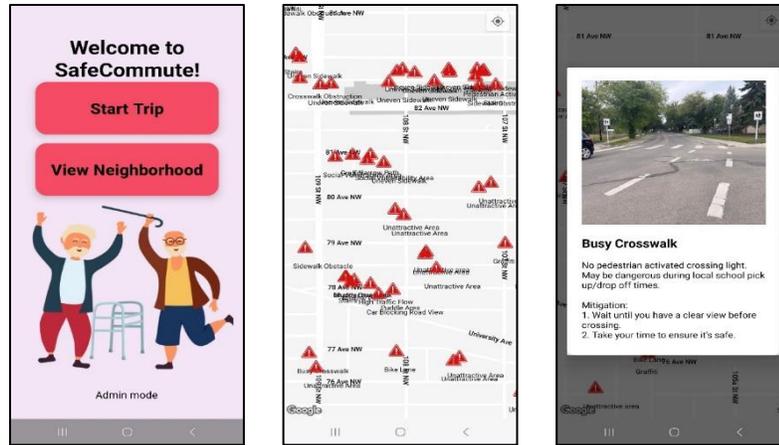
Figure 1: User Interface of the SafeCommute Application. The first screen (left) displays the home screen. The second screen (middle) presents a map highlighting identified environmental stressors. The third screen (right) provides details on a specific stressor.

4.3. Measures

Data were collected on two primary constructs: Neighborhood-specific MSE and Mobility Intention. Mobility Intention was selected as the primary outcome measure because intention is a well-established predictor of actual behavior, particularly for planned activities such as outdoor mobility (Ajzen, 1991). Neighborhood-specific MSE was evaluated using a newly developed five-item scale designed to measure participants' confidence in navigating their local environment. Informed by Bandura's (1997) work on self-efficacy, which underscores the importance of context-specific measures, the scale was structured to reflect the multidimensional nature of mobility challenges faced by older adults. These dimensions included navigation confidence, physical ability, built infrastructure, and emotional regulation. Mobility Intention was measured using a scale adapted from Cheng et al. (2019), which assesses participants' plans to engage in outdoor mobility activities. Both Neighborhood-specific MSE and Mobility Intention were rated on a 10-point scale, allowing for a nuanced evaluation of participants' confidence and intentions. All scales used in this study were validated in advance through expert review and a pilot study to ensure their reliability and validity for the target population.

4.4. Data Analysis

To evaluate the effectiveness of the intervention, the authors statistically compared changes in key outcomes (i.e., Neighborhood-specific MSE and Mobility Intentions) between the experimental and control groups. A mixed-model analysis of variance (ANOVA) was employed, incorporating a between-subjects factor for the group (experimental vs. control) and a within-subjects factor for time (pre-intervention vs. post-intervention). Additionally, a group-by-time interaction term was included to investigate the simultaneous influence of group and time on the outcomes. This approach allowed for the examination of changes in key outcomes, Neighborhood-specific MSE, General MSE, and Perceived Mobility levels over time, while also assessing differences between the experimental and control groups. To quantify the magnitude of these effects, classical eta-squared (η^2) effect sizes were calculated for each interaction. These η^2 values indicate the proportion of total variance in the outcome variables that is attributable to the group-by-time interaction, providing insight into the practical significance of the intervention's impact (Field, 2013).

The robustness of the analysis was ensured by rigorously assessing the statistical assumptions required for mixed-model ANOVA. This included evaluating the normality of data distributions using the Shapiro-Wilk test, assessing homogeneity of variances with Levene's test, and checking for sphericity using Mauchly's test to determine if correction factors for repeated measures were necessary (Field, 2013).

5. RESULTS

A visual inspection of the means in Figure 2 revealed significant improvements in the intervention group from pre- to post-intervention across all measured variables. Neighborhood-specific MSE increased from a mean of 7.1 to 8.6 and Mobility Intentions from 7.3 to 9.4, reflecting percentage gains of 21.10% and 28.76%, respectively. These results suggest that the intervention was effective in boosting both the confidence in and the intentions toward neighborhood mobility among participants. Conversely, the control group's results indicated minimal, and in some aspects, negative changes. Neighborhood-specific MSE saw a decline of 4.20% (from 7 to 6.7), and Mobility Intentions decreased by 2.81% (from 7.1 to 6.9).
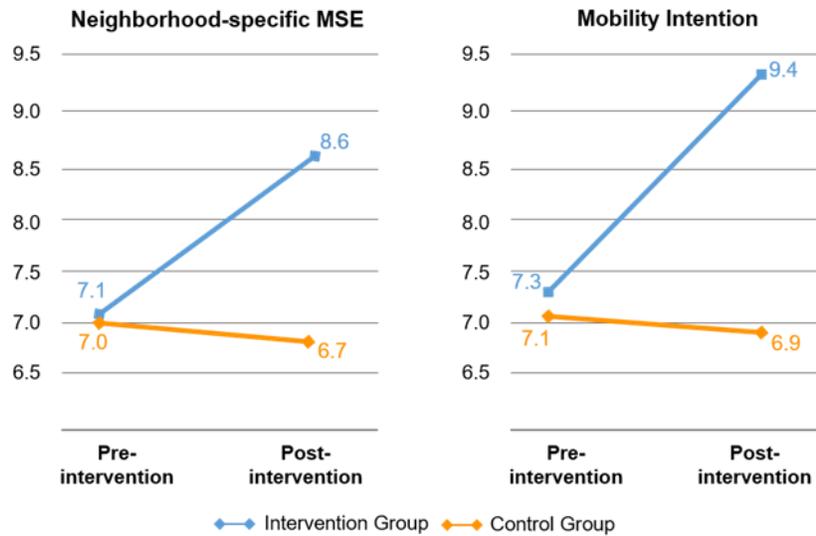

Figure 2: Pre- and post-intervention changes in Neighborhood-specific MSE and Mobility Intention for intervention and control groups.

Prior to conducting analyses, statistical assumptions for mixed-model ANOVA were thoroughly assessed. Shapiro-Wilk tests confirmed normality for Neighborhood-specific MSE and Mobility Intention at both pre- and post-intervention phases, as all p-values exceeded the 0.05 threshold. Levene's test confirmed the homogeneity of variances across groups (all $p > 0.05$). Additionally, sphericity tests for all variables showed assumptions were met (all p-values were non-significant, with an epsilon value of 1.0), indicating that correction factors for repeated measures are not needed. With these assumptions satisfied, we proceeded to conduct mixed-model ANOVA to examine the effects of the intervention.

For Neighborhood-specific MSE, a significant main effect for the group was observed [$F_{(1,14)} = 5.342$, $p < 0.05$, $\eta^2 = 0.276$], indicating that the intervention had a targeted impact with a moderate effect size. Importantly, a significant group-by-time interaction [$F_{(1,14)} = 13.264$, $p < 0.01$, $\eta^2 = 0.487$] highlighted specific improvements in Neighborhood-specific MSE for the intervention group over the study period. However, the main effect for time was not significant [$F_{(1,14)} = 6.400$, $p > 0.05$], suggesting no overall temporal improvement across both groups. For Mobility Intentions, a significant main effect for the group was found [$F_{(1,14)} = 15.289$, $p < 0.01$, $\eta^2 = 0.522$], reflecting a substantial impact of the intervention with a large effect size. Additionally, a significant main effect for time [$F_{(1,14)} = 14.611$, $p < 0.01$, $\eta^2 = 0.511$] indicated notable improvements in mobility intentions over the study duration. A significant group-by-time interaction [$F_{(1,14)} = 30.232$, $p < 0.001$, $\eta^2 = 0.683$] further demonstrated that the intervention group experienced greater improvements in mobility intentions compared to the control group over time.

6. DISCUSSION

This study aimed to enhance Neighborhood-specific MSE among older adults through a wearable-based crowdsensing intervention. By developing and testing an age-friendly mobile application that previewed

environmental stressors and provided practical navigation tips, the study sought to empower older adults to navigate their neighborhoods with greater confidence. The findings demonstrate the effectiveness of this approach, with the intervention group showing significant improvements in Neighborhood-specific MSE (21.10% increase) and Mobility Intentions (28.76% increase) from pre- to post-intervention. These results support Bandura's theory that task-specific confidence is a critical determinant of behavior (Bandura, 1997). The significant group-by-time interaction for Neighborhood-specific MSE [F (1,14) = 13.264, $p < 0.01$, η^2 = 0.487] suggests that the intervention successfully enhanced participants' confidence in navigating their neighborhoods. This improvement is particularly noteworthy given the lack of significant temporal changes in the control group, reinforcing the intervention's role in addressing the MSE challenges faced by older adults. Similarly, the significant improvements in Mobility Intentions, supported by a large effect size (η^2 = 0.683), highlight the intervention's success in motivating older adults to engage in outdoor mobility activities. The strong group-by-time interaction [F (1,14) = 30.232, $p < 0.001$] indicates that the intervention not only boosted participants' confidence but also translated this confidence into actionable intentions. This resonates with the Theory of Planned Behavior (Ajzen, 1991), which identifies intentions as a key predictor of behavior.

These findings offer critical insights for urban planners and policymakers by demonstrating how technology-enhanced interventions can optimize neighborhood design and management for aging populations. By targeting Neighborhood-specific MSE, this study highlights an important dimension of sustainable community development: the imperative to address both physical and psychological dimensions of accessibility. This is especially relevant in the context of "aging in place," where fostering confidence in navigating local environments can significantly enhance independence and quality of life. Even when physical barriers are removed, psychological challenges often persist, limiting outdoor mobility and independence. This underscores the need for holistic approaches that tackle both environmental and perceptual obstacles. The approach developed in this study could transform how municipalities evaluate the effectiveness of age-friendly urban improvements, moving beyond traditional accessibility metrics. Such innovations in built environment monitoring could lead to more responsive and human-centered urban management practices that better serve aging populations.

Despite these promising results, the study is not without limitations. First, the sample size, though adequate for initial analysis, may limit the generalizability of the findings. Future research should include larger and more diverse populations to validate the results across different demographic and geographic contexts. Second, the study relied on self-reported measures for mobility levels, which may introduce response bias. Incorporating objective measures of mobility such as Global Positioning System (GPS) tracking or step counts could provide a more comprehensive assessment of intervention effectiveness. Finally, longitudinal studies are needed to determine whether the observed improvements persist over time and translate into sustained increases in outdoor mobility and quality of life.

7. CONCLUSION

The study demonstrates the effectiveness of wearable-based urban crowdsensing intervention to enhance Neighborhood-specific MSE and, consequently, the outdoor mobility of older adults. Through the development and deployment of an age-friendly mobile application that effectively previews environmental stressors and offers practical navigation tips, the intervention significantly improved participants' confidence in navigating their neighborhoods, as evidenced by a notable increase in both Neighborhood-specific MSE (21.10%) and Mobility Intentions (28.76%). These findings align with Bandura's theory of self-efficacy, emphasizing the importance of task-specific confidence in shaping behavioral intentions. The significant group-by-time interaction for neighborhood-specific MSE [F (1,14) = 13.264, $p < 0.01$, η^2 = 0.487] highlights the intervention's targeted impact. These findings carry important implications for sustainable community development, suggesting that technology-driven interventions can serve as valuable complements to traditional built environment modifications. By focusing on enhancing neighborhood-specific MSE, this study highlights the transformative potential of wearable biosensors and urban crowdsensing based interventions in enabling older adults to navigate their communities with greater confidence, thus supporting healthier aging and independent living.

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