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EXPLORING NOVEL APPROACHES FOR QUANTIFYING LEVELS OF PHYSICAL ACTIVITY

PREUČEVANJE NOVIH PRISTOPOV UGOTAVLJANJA STOPNJE TELESNE DEJAVNOSTI

ABSTRACT

Physical inactivity worldwide poses a significant risk to public health. The use of modern technology-based methods for the evaluation and understanding of behaviours related to physical activity is essential for crafting interventions aimed at promoting a more active population. This scholarly article explores innovative methods for assessing physical activity levels, categorized into objective and subjective approaches. Objective techniques, including wearable activity monitors, mobile health apps, environmental sensors, and geospatial analysis, are crucial for generating reliable and valid data across different demographics. Conversely, subjective methods like self-reports and diaries, though useful for studying larger populations, offer less data reliability. The methods discussed in this study provide profound insights into the behaviors associated with physical activity and assist in devising strategies to counteract rising global inactivity.

Keywords: physical activity, public health, physical inactivity, objective measurements, subjective measurements, strategie

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IZVLEČEK

Globalna telesna nedejavnost predstavlja resno grožnjo celotnemu javno-zdravstvenemu sistemu. Sodobne metode, ki temeljijo na razvoju novih tehnologij, so za razumevanje značilnosti telesne dejavnosti posamezne populacije izjemnega pomena. Na ta način je možno oblikovati strategije in rešitve za bolj aktivno populacijo. Ta prispevek analizira novejše pristope za ugotavljanje stopnje telesne aktivnosti, ki se v grobem delijo na objektivne in subjektivne metode. Metode, s katerimi pridobivamo objektivne podatke sodijo meritve z napravami za nošenje (merilniki pospeškov), podatki pridobljeni z aplikacijami na mobilnih aparatih, meritve z okoljskimi senzorji, pomembne pa so tudi tehnike analize okolja. Te metode zagotavljajo veljavne in zanesljive podatke. Metode samoevalvacije ali pa dnevniki so primerne za preučevanje večjih populacij vendar pa zagotavljajo manjšo zanesljivost in veljavnost podatkov. Opisane metode zagotavljajo dober vpogled v značilnosti vedenj povezanih s telesno dejavnostjo populacije in omogočajo oblikovanje strategij in intervencij za zmanjševanje telesne nedejavnosti v prihodnje.

Ključne besede: telesna dejavnost, javno zdravje, telesna nedejavnost, objektivno merjenje, subjektivna ocena, strategije

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https://doi.org/10.52165/kinsi.30.1.120-126

INTRODUCTION

In recent years, the quest to understand and quantify physical activity (PA) levels has become paramount in the realms of public health and clinical research (Troiano, 2014). PA serves as a cornerstone of well-being, influencing various health outcomes ranging from cardiovascular fitness to mental health (Haskell et al., 1992; Leon & Sanchez, 2001; Mark and Janssen, 2008; Sasaki, 1987; Whalen, et al., 1988; Wellman et al., 2020). However, accurately measuring PA poses a significant challenge, with methods falling into two broad categories: objective and subjective assessments (Connor & Norman, 2017; Ferrari et al., 2020; O'Donoghue et al., 2018).

Objective measurements, such as those obtained through wearable activity monitors and mobile health applications, offer a direct and real-time measurement of PA. These methods utilize advanced sensors and algorithms to track movement patterns, providing quantifiable metrics like steps taken, distance traveled, and energy expended. Objective measurements are lauded for their validity and reliability, offering researchers precise data for analyzing individual behavior and informing personalized interventions (Jørgensen et al. 2022; Troiano, 2014).

Conversely, subjective assessments, typically gathered through self-report surveys or diaries, rely on individuals' perceptions and recollections of their PA levels. While subjective measures are less precise compared to objective methods and are susceptible to recall bias and social desirability bias, they can be administered to larger samples or populations more feasibly. Despite their limitations, subjective assessments remain valuable for capturing broader trends and patterns in PA across diverse demographics and settings (Armstrong & Welsman, 2006).

While both objective and subjective assessments have their place in PA research, objective measurements are generally considered superior in terms of accuracy and reliability (O'Neil et al., 2016). However, the scalability and accessibility of subjective measures make them indispensable for large-scale epidemiological studies and population-level interventions (Armstorng et al., 2006). As such, the integration of both objective and subjective approaches allows researchers to obtain a comprehensive understanding of PA behavior, facilitating evidence-based strategies to promote active lifestyles and combat sedentary living-related health issues (O'Donoghue et al., 2018; Connor & Norman, 2017). In recent years, the landscape of measuring physical activity levels has evolved dramatically, with innovative technologies offering diverse approaches such as wearable activity monitors, mobile health applications, machine learning algorithms, and environmental sensors; presented in the following text (Sabry et al. 2022).

Wearable activity monitors

Wearable activity monitors, such as fitness trackers and smartwatches, have gained popularity due to their convenience and ability to continuously capture data (Shei et al., 2022). These devices utilize built-in sensors, such as accelerometers and gyroscopes, to track movements and quantify PA metrics, including steps taken, distance traveled, and calories burned. Additionally, some advanced wearable devices can detect specific activities, such as walking, running, or cycling, providing researchers with more detailed insights into activity patterns (Storm et al., 2015). The widespread adoption of wearable activity monitors offers researchers a wealth of real-time, objective data for analyzing PA levels across diverse populations and settings (Fuller et al., 2020; Evenson et al., 2015).

Mobile health applications

Mobile health applications, commonly known as "apps", present another promising avenue for measuring PA levels (Rathbone & Prescott, 2017). These apps leverage the sensors embedded in smartphones, such as accelerometers and GPS, to monitor activity levels and provide users with personalized feedback and goal-setting features. Moreover, many mobile health apps incorporate social networking elements, allowing users to share their progress with friends and participate in challenges or competitions (Petkovic et.al., 2021). From a research perspective, mobile health apps offer a cost-effective and scalable solution for collecting large-scale PA data and conducting intervention studies aimed at promoting active lifestyles (Ueno et.al., 2022; Schoeppe et.al., 2016).

Machine learning and artificial intelligence

Advancements in machine learning and artificial intelligence (AI) have revolutionized the analysis of PA data. Researchers can now employ sophisticated algorithms to process raw sensor data from wearable devices or mobile apps and extract meaningful insights regarding activity patterns, sedentary behavior, and energy expenditure (Biró et al., 2023). Furthermore, machine learning algorithms can identify activity type and intensity with high accuracy, enabling researchers to classify physical activities automatically without the need for manual annotation (Fuller et al., 2021). By leveraging machine learning techniques, researchers can uncover complex relationships between PA levels, health outcomes, and environmental factors, paving the way for more targeted interventions and personalized recommendations (Bates et al., 2023).

Environmental sensors and geospatial analysis

In addition to individual-level measurements, researchers are increasingly interested in understanding the contextual factors influencing PA, such as the built environment and neighborhood characteristics (Troped et al., 2010). Environmental sensors, including GPS devices and environmental monitors, can capture data on location, terrain, air quality, and weather conditions, providing valuable contextual information for analyzing activity patterns (Kamel Boulos & Koh, 2021). Geospatial analysis techniques allow researchers to integrate environmental data with individual-level PA data to investigate how environmental factors impact activity levels and inform urban planning and policy interventions aimed at creating more activity-friendly environments (Smith et al., 2022).

CHALLENGES AND FUTURE DIRECTIONS

While these novel methods offer exciting opportunities for advancing our understanding of PA behavior, several challenges remain. Privacy concerns, data security issues, and disparities in access to technology are critical considerations that need to be addressed. Moreover, the validation and standardization of measurement protocols across different devices and platforms are essential for ensuring the reliability and comparability of PA data. Looking ahead, interdisciplinary collaborations between researchers, technologists, policymakers, and public health practitioners will be crucial for harnessing the full potential of these innovative approaches and translating research findings into effective strategies for promoting PA and improving population health outcomes.

CONCLUSION

The emergence of new methods for measuring PA levels represents a paradigm shift in how researchers collect, analyze, and interpret data in the field of public health. Wearable activity monitors, mobile health apps, machine learning algorithms, environmental sensors, and geospatial analysis techniques offer unprecedented opportunities for capturing rich, objective data on PA behavior across diverse populations and contexts. By embracing these innovative approaches and addressing associated challenges, researchers can gain deeper insights into the determinants of PA and develop evidence-based interventions to encourage active lifestyles and combat the global burden of physical inactivity-related diseases.

DECLARATION OF CONFLICTING INTERESTS

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

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