SIN-CHN SCIENTIFIC PRESS PTE.LTD.

Molecular & Cellular Biomechanics 2024, 21(2), 435.
https://doi.org/10.62617/mcb435

Article

Exploring the effect of walking patterns on pathway design in landscape architecture using gait analysis

Wanying Yang[1], Chao Wen[2], Baogang Lin[1,*]

[1] Xi'an University of Architecture and Technology, Xi'an 710055, China
[2] Shanxi Province Architectural Design and Research Institute (GROUP) Co. Ltd, Xi'an 710000, China
*** Corresponding author:** Baogang Lin, BaogangLin1@outlook.com

CITATION

Yang W, Wen C, Lin B. Exploring the effect of walking patterns on pathway design in landscape architecture using gait analysis. Molecular & Cellular Biomechanics. 2024; 21(2): 435. https://doi.org/10.62617/mcb435

ARTICLE INFO

Received: 27 September 2024
Accepted: 14 October 2024
Available online: 7 November 2024

Abstract: This study investigates the impact of pathway design on human walking patterns using advanced gait analysis techniques to inform landscape architecture. By analyzing key gait parameters such as stride length, cadence, walking speed, step width, and foot placement angles, this research seeks to identify how various pathway features—such as surface material, slope, curvature, and width—influence walking behaviour. Data is collected through motion capture systems and wearable sensors from diverse participants, including individuals of different ages and physical abilities. Statistical methods, including Multivariate Analysis of Variance (MANOVA), are applied to determine significant differences in walking patterns across pathway types, while ML techniques, such as k-means clustering, classify participants based on their walking strategies. The results offer data-driven insights into how different pathway designs affect walking efficiency and comfort. For example, pathways with a slope of 10% reduced WS by 14% compared to flat pathways, while surfaces like gravel increased Foot Placement Angles by 18% compared to concrete, impacting stability. The study provides practical recommendations for creating pathways that support natural human movement, such as ensuring step width and stride length remain consistent across varied surface types by designing smooth transitions between different materials. The study emphasizes the importance of designing inclusive, accessible pathways that accommodate the needs of diverse user groups. For instance, individuals with mobility challenges exhibited a 12% increase in step width on sloped surfaces, suggesting that gentler inclines and smoother textures are essential for accessibility. The findings contribute to LA by offering evidence-based guidelines that optimize pathways' functionality and user experience in outdoor environments. These guidelines include maintaining a pathway slope below 5% for universal accessibility and using surface materials like concrete or permeable pavers that balance durability and comfort, promoting sustainability and user-centred design.

Keywords: human walking patterns; biomechanics; walking mechanics; kinematic analysis; machine learning; landscape architecture; pathway slope

1. Introduction

The design of pathways in Landscape Architecture (LA) is a critical element influencing how individuals move, experience, and interact with outdoor spaces [1,2]. Pathways not only serve as routes for movement, guiding users through gardens, parks, and urban environments, but they also contribute to the overall aesthetics, accessibility, and functionality of the space [3]. The design and layout of these pathways must consider various factors, such as user comfort, safety, and inclusivity, to create environments that are both visually appealing and physically accommodating [4,5]. The success of pathway design depends heavily on how well it aligns with natural Human Movement Patterns (HMP), ensuring that users of all ages and physical abilities can move comfortably and safely [6]. This is where Gait Analysis (GA), a scientific method for studying human locomotion, becomes highly relevant [7,8].

GA involves the systematic study of walking mechanics, capturing critical parameters such as Stride Length (SL), cadence, Walking Speed (WS), Step Width (SW), and Foot Placement Angles (FPA) [9]. These parameters comprehensively understand how individuals interact with their environment during walking. Traditionally used in clinical, sports, and rehabilitation settings, GA provides insights into Human Movement (HM) that are increasingly applied to design fields such as urban planning and LA [10,11]. By understanding how people naturally walk, designers can create pathways that enhance user comfort, optimize movement efficiency, and reduce the physical strain of navigating different surfaces or terrains [12–14].

In recent years, integrating data-driven approaches such as motion capture systems, wearable sensors, and advanced computational tools has enabled a more precise analysis of HM in real-world settings [15,16]. These technologies accurately measure walking mechanics in diverse environments, including pathways with varying surface textures, slopes, and curvatures [14]. This information is crucial for landscape architects, providing the empirical data needed to design pathways promoting safety, accessibility, and inclusivity [17–19]. For example, understanding how different surface types affect gait can inform the selection of materials that minimize the risk of slips or falls, while analyzing the impact of slope and curvature on walking patterns can lead to the design of pathways that are easier to navigate for individuals with mobility challenges [20–25].

The significance of this study lies in its interdisciplinary approach, combining insights from biomechanics, HM studies, and LA to create environments that align with the natural flow of HM. The proposed work aims to explore the relationship between HWP and pathway design in LA using advanced GA techniques. By combining motion capture technology and wearable sensors, this study will analyze the walking behaviours of a diverse group of participants across various pathway designs, including different surface types, slopes, and curvatures [26–30]. The primary focus is understanding how these design elements influence key gait parameters such as SL, cadence, WS, and FPA. The data collected will be analyzed using statistical methods, including Multivariate Analysis of Variance (MANOVA) and regression models, to determine the impact of specific pathway features on walking efficiency and comfort. Additionally, Machine Learning (ML) techniques, such as k-means clustering, will be employed to classify participants based on HWP. The insights gained from this study will provide valuable guidelines for optimizing pathway design to enhance both functionality and user experience in outdoor spaces.

The objectives of this work are:

1) Systematically evaluate how different pathway features such as surface material, slope, width, and curvature affect key gait parameters, including SL, cadence, WS, SW, and FPA.
2) To provide LA with data-driven insights that inform the design of HWP, ensuring they accommodate natural HMP and enhance user comfort, safety, and accessibility.

3) To assess how different pathway environments (e.g., concrete, gravel, grass) impact walking strategies across varied user groups, including individuals of different ages and physical abilities, ensuring that pathways are inclusive and accessible for all.
4) Employ cutting-edge technologies such as motion capture systems and wearable sensors to measure walking mechanics in diverse pathway settings, providing precise data for pathway design optimization.

The paper is organized as follows: Section 2 presents the theory for understanding, Section 3 presents the methodology, Section 4 presents the result analysis, and Section 5 concludes the article.

2. Theory

2.1. GA in HM studies

GA, a systematic study of human locomotion, is critical in understanding movement patterns in diverse disciplines, ranging from biomechanics and sports science to health care and design. It precisely measures HM, limb mechanics, and muscle activity as an individual walks or runs. GA can be categorized into two main types: observational and quantitative [31–34]. The former relies on visual assessment, while the latter employs sophisticated tools such as motion capture systems, force plates, and wearable sensors to obtain a detailed picture of an individual's walking mechanics.

In HM studies, GA provides essential insights into various aspects of mobility. It is widely used in clinical settings for diagnosing and treating gait abnormalities resulting from injury, neurological disorders, or ageing. For instance, it assists in identifying irregular walking patterns in individuals with conditions such as Parkinson's disease, cerebral palsy, and stroke, facilitating tailored rehabilitation protocols. Additionally, GA is vital in prosthetics, which aids in designing artificial limbs that closely mimic natural HWP.

From a biomechanical perspective, GA involves the measurement of key parameters such as SL, cadence (steps per minute), WS, and the ground reaction forces exerted during movement. These variables are used to evaluate the efficiency and stability of an individual's gait, enabling the identification of any deviations from typical patterns. Moreover, technological advances have allowed for a more precise gait analysis, employing techniques such as 3D motion analysis and ML algorithms to predict outcomes or optimize interventions.

Beyond its clinical and sports applications, GA is increasingly recognized for its potential in design fields, particularly in understanding how individuals interact with their environments. The walking patterns and spatial behaviours revealed by gait studies provide valuable data for designing ergonomic environments that align with HM. This is particularly relevant in pathway design within LA, where the goal is to create spaces that support natural HWP behaviours, enhance comfort, and ensure accessibility.

2.2. Pathway design in LA

Pathway design is a fundamental feature of LA, contributing to the overall functionality, aesthetics, and accessibility of outdoor spaces. Whether in urban parks, residential gardens, or large-scale civic environments, pathways serve as physical conduits for movement and as elements that shape the user's interaction with the landscape. The design of these pathways involves careful consideration of various factors, including user behaviour, environmental conditions, site topography, and the space's intended purpose. In this regard, LA must balance aesthetic appeal and functional efficiency, ensuring that pathways align with the natural flow of HM while integrating harmoniously with the surrounding environment.

Pathway design considers multiple spatial elements, such as the path's width, curvature, surface material, and gradient. The width of a pathway, for example, is impacted by expected foot traffic, whether the path will accommodate individuals, groups, or even cyclists. More comprehensive pathways encourage social interaction, while narrower pathways often evoke a sense of intimacy or serenity. Curvature and gradient are other critical elements that impact the aesthetic quality and the functional ease of use. Gentle curves can guide users through a landscape, creating a sense of exploration and anticipation, while sharp curves or steep gradients may require additional design considerations for accessibility and safety, especially for individuals with mobility challenges.

From **Figure 1** the Surface material plays an equally important role in pathway design, influencing both the physical experience of walking and the visual character of the landscape. Materials such as gravel, wood, concrete, or permeable pavers are chosen based on durability, maintenance, and environmental sustainability. For instance, in natural landscapes, using organic materials like gravel or wooden planks may enhance the aesthetic of the surrounding environment while promoting drainage and minimizing environmental impact. In contrast, urban pathways often employ more durable materials like concrete or asphalt to withstand heavy usage and maintain accessibility standards, particularly for people with disabilities.

Figure 1. Pathway of. **(a)** gravel; **(b)** wood; **(c)** permeable pavers; **(d)** concrete; **(e)** asphalt.

Beyond technical considerations, the design of pathways is also closely linked to psychological and experiential aspects. Pathways can subtly guide user behaviour, influencing how individuals navigate and engage with a space. For instance, the alignment of a path may be designed to frame key views, encouraging users to pause and appreciate the landscape. Alternatively, pathways can evoke emotional responses, such as tranquillity or excitement, depending on how they integrate with features like water bodies, vegetation, or lighting.

Modern LA emphasizes the importance of sustainability and inclusivity in pathway design. Sustainable design practices might involve using locally sourced, eco-friendly materials, promoting natural water drainage, or preserving the existing topography to reduce environmental disturbance. Inclusive design ensures that pathways are accessible to all individuals, regardless of physical ability, by adhering to standards such as the Americans with Disabilities Act (ADA) or equivalent international guidelines. This consideration enhances the social equity of outdoor spaces, making them usable and enjoyable for everyone.

2.3. Intersection of gait and design

The intersection of gait and design represents an emerging field where insights from HM studies are applied to enhance designed spaces' functionality and user experience. By integrating GA into design processes, particularly in pathway design, urban planning, and LA, designers can create environments that cater to natural HMP. This interdisciplinary approach leverages the biomechanical understanding of how people walk, move, and interact with spaces to inform design decisions prioritising aesthetics and practical usability.

At its core, GA provides detailed information about how individuals navigate space. Factors such as SL, WS, step variability, and turning angles are vital components of gait that reveal how people adjust their movements based on the physical characteristics of their environment. For example, when navigating a sharply curved path or a steep incline, individuals naturally modify their gait by shortening their stride or adjusting their body posture. These insights can be invaluable for designers when considering how to shape pathways, stairs, ramps, and open spaces, ensuring that the environment supports rather than hinders natural movement.

In LA, the application of GA allows for a user-centred approach to designing pathways that complement the flow of foot traffic. By analyzing walking behaviours, designers can create pathways that align with natural movement patterns, reducing instances of discomfort or inefficiency. For instance, a pathway considering typical SL and walking velocity can prevent crowding in high-traffic areas by ensuring the appropriate width and curvature. Additionally, integrating data on turning angles and step adjustments can inform the design of intersections, helping users navigate transitions between different paths more smoothly and safely.

This intersection between gait and design extends beyond functionality, contributing to the experiential quality of spaces. Well-designed pathways that respect HMP enhance ease of navigation and influence the overall psychological and emotional experience of the user. A path that seamlessly guides users through a landscape with gentle curves and even surfaces can evoke feelings of relaxation and harmony, whereas paths that are unnecessarily complex or difficult to navigate may generate frustration or fatigue. By designing with movement in mind, architects and landscape designers can shape users' emotional responses, creating environments that promote well-being, safety, and comfort.

Moreover, incorporating GA into pathway design supports inclusivity by addressing the diverse needs of users. Variations in gait due to age, physical ability, or other factors can inform design adjustments that ensure accessibility for everyone. For example, older adults or individuals with mobility impairments may require pathways with reduced slopes, smoother surfaces, or additional handrails for support. Understanding these variations in gait enables designers to create spaces that accommodate a wide range of users, promoting equity and inclusivity in public and private environments.

Technology plays a crucial role in bridging the gap between GA and design. With the advent of motion capture systems, wearable sensors, and advanced computational tools, designers now have access to real-time data on HM that can be used to create highly responsive and adaptive environments. For example, ML algorithms can analyze large datasets of walking patterns to predict how users will navigate a given space, allowing designers to simulate and optimize pathways before construction begins. This data-driven approach enhances the precision of design interventions, ensuring that pathways look good and perform optimally in terms of user movement.

3. Methodology

3.1. Study design

The study design uses a quantitative approach to explore the relationship between walking patterns and pathway design in LA. Data collection combines motion capture technology and wearable sensors to analyze gait in real-world settings. A 3D motion capture system, such as Vicon or OptiTrack, tracks participants' movements across different pathway designs, with reflective markers placed on key anatomical points. Wearable Inertial Measurement Units (IMUs) further supplement the data by capturing acceleration and angular velocity during movement. The pathways in the study simulate standard landscape features like straight paths, curves, and varied surfaces, such as gravel, concrete, and grass. Participants are selected from diverse age groups and physical abilities, representing a wide range of HWP behaviours. As participants walk naturally, their gait is recorded to capture how they interact with different pathway designs. Once the data is collected, key gait parameters, such as SL, cadence, and WS, are analyzed to understand how pathway design impacts walking behaviour. Statistical techniques, including MANOVA, are applied to compare gait patterns across different pathway conditions. This structured approach provides valuable insights for optimizing pathway design to enhance functionality and user comfort.

3.2. Participants

The participant pool for this study was carefully selected to ensure a diverse and representative sample that captures a wide range of walking patterns. 76 individuals were recruited for the study, representing different age groups, genders, and physical abilities. This broad demographic diversity ensures that the study's findings apply to a broad audience and can inform pathway design that is inclusive and accessible to all. The participants were divided into three primary age groups: 25 individuals aged 18–30, 28 individuals aged 31–50, and 23 individuals aged 51 and above. This age distribution allows for analysing how walking patterns vary across different life stages, particularly as older adults may exhibit distinct gait characteristics such as shorter SLs or slower WSs than younger participants. The sample included 41 males and 35 females to ensure diversity further, reflecting a near-even gender distribution. This balance is essential for analyzing potential differences in gait patterns between men and women, which could influence how pathway designs accommodate different users.

Additionally, participants were selected based on varying levels of physical ability. Of the 76 participants, 10 reported having mild to moderate mobility challenges, such as joint stiffness or arthritis, while the remaining 66 were physically non-disabled with no reported mobility issues. Including individuals with mobility impairments was essential for understanding how different pathway designs, such as varying slopes or surface textures, impact the walking experience for those who may find certain features more challenging. This ensures that the study's findings contribute to designing pathways that are accessible and comfortable for all users, including those with physical limitations. To maintain consistency across the study, participants were asked to wear comfortable footwear and to walk naturally along pre-designed pathways. Each participant completed the walking tasks independently, ensuring their gait data reflected their movement patterns without external influence. By incorporating this diverse group of participants, the study aims to generate comprehensive insights into how age, gender, and physical ability impact walking patterns, thereby informing pathway designs that cater to a broad spectrum of users. The following **Table 1** presents the characteristics of the participants.

Table 1. Participant characteristics.

Characteristic	Count
Total Participants	76
Age Group 18–30	25
Age Group 31–50	28
Age Group 51+	23
Males	41
Females	35
Participants with Mobility Challenges	10
Non-disabled Participants	66

3.3. Apparatus

The apparatus used in this study consisted of a combination of advanced motion capture technology, wearable sensors, and environmental design tools to ensure accurate data collection and analysis of participants' walking patterns across various pathway designs. Central to the data collection process was a high-resolution 3D motion capture system, specifically the Vicon system, equipped with 10 infrared cameras strategically placed around the walking environment. These cameras captured the movements of reflective markers affixed to key anatomical points on the participants' bodies, such as the hips, knees, ankles, and feet. This setup allowed for precise real-time tracking of joint angles, SL, FPA, and overall walking dynamics, generating a detailed 3D model of each participant's gait.

In addition to the motion capture system, wearable IMUs were used to supplement the data. These IMUs, comprising accelerometers and gyroscopes, were attached to the participants' lower limbs to capture additional information on body acceleration, orientation, and angular velocity. The IMUs were particularly useful in outdoor scenarios where the motion capture cameras had limited reach. Combining data from motion capture and IMUs, the study obtained a comprehensive picture of the participants' walking behaviour across different pathway scenarios, including environments with various surfaces and inclines. The pathways themselves were built to represent a range of commonly encountered designs in LA. Materials such as concrete, gravel, and wood were used to create different surface types, while the pathways were designed with varying degrees of curvature, slope, and width. These variables allowed the researchers to examine how different environmental factors influenced walking patterns. To ensure consistency, the pathways were measured and marked to control the distance walked by each participant, with markers along the paths guiding their direction and speed.

For data processing and analysis, specialized software like Vicon Nexus and Visual3D was employed to analyze the gait data collected from the motion capture system and wearable sensors. Visual 3D allowed for the modelling and analysing of joint kinematics and kinetics, providing key insights into the forces and angles involved during walking. Statistical software, such as SPSS, was also utilized to perform multivariate analyses, enabling the researchers to identify significant relationships between pathway design elements and walking patterns. **Table 2** presents the Apparatus and their specifications used in the study.

Table 2. Apparatus and their specifications.

Apparatus	Specification/Details
Motion Capture System	Vision System, 10 infrared cameras
IMUs	Accelerometers and gyroscopes are attached to lower limbs.
Reflective Markers	Affixed to key anatomical points (hips, knees, ankles, feet)
Pathway Surfaces	Concrete, gravel, wood
Pathway Design Variables	Curvature, slope, width (measured and marked for consistency)
Data Analysis Software	Vicon Nexus, Visual3D for gait modelling and joint kinematics analysis
Statistical Analysis Software	SPSS for multivariate analysis

3.4. Experimental design

The experimental design of this study was structured to systematically examine the relationship between walking patterns and pathway design in LA. The experiment was directed in a controlled environment where participants were questioned to walk on pre-designed pathways that varied in surface material, curvature, width, and slope. These variations were explicitly selected to simulate real-world landscape designs in urban parks, pedestrian walkways, and recreational trails. The controlled setup accurately measured how different pathway designs influenced gait parameters such as SL, WS, and turning angles. The study was designed as a within-subject experiment, meaning that each participant walked on all the pathway variations to ensure that individual differences in gait did not affect the overall findings. This approach provided consistent comparative data for each participant, as they were visible to all pathway conditions under the same experimental circumstances. Participants were trained to walk at a comfortable, self-selected pace on each pathway to simulate natural walking behaviour without any artificial constraints on their movement. Additionally, participants were briefed on the specific routes they were to follow, and markers along the pathways ensured that they adhered to the intended walking direction.

The pathways were designed to reflect a variety of conditions. For example, one pathway featured a straight, flat design with a smooth concrete surface, while another had a gentle curve with a gravel surface. Other pathways included slopes, different surface textures, and varying widths to simulate real-world environments that people encounter in parks or public spaces. Each pathway was approximately 30 m long, allowing participants to establish a consistent walking rhythm and make necessary adjustments to their gait based on the pathway's characteristics. Data collection took place in two phases. In the first phase, participants walked on pathways indoors under controlled lighting and environmental conditions, which allowed for the precise recording of gait data via the motion capture system and wearable sensors. In the second phase, outdoor pathways were incorporated to capture how fundamental environmental factors such as uneven surfaces and outdoor light might affect HWP. This combination of indoor and outdoor testing ensured that the study's findings would apply to controlled environments and real-world scenarios.

The data collected from the Motion Capture System (MCS) and inertial sensors were synchronized to provide a comprehensive dataset that included spatiotemporal gait parameters (e.g., SL, cadence, speed) and kinematic data (e.g., joint angles, ground reaction forces). Statistical analysis was then applied to compare gait patterns across the different pathway conditions. MANOVA was used to determine whether there were statistically significant differences in gait parameters based on pathway surface, curvature, slope, or width. The experimental design also accounted for variability in participant demographics by including individuals of different ages, genders, and physical abilities. This allowed for analysing how diverse user groups may interact differently with various pathway designs. The experimental design was thus robust in providing detailed insights into how specific design elements affect HWP and generalizable conclusions that could inform the development of pathways in various LA settings.

3.5. Measurements and variables

In this study, a range of gait-related measurements and pathway design variables are assessed to understand the influence of HWP on pathway design in LA. The primary gait measurements include spatiotemporal parameters such as SL, cadence (steps per minute), WS, and SW. These parameters provide insights into how participants adapt their HWP based on the characteristics of the pathways, such as surface material, curvature, and slope. In addition, FPA and joint kinematics are captured to analyze more detailed features of gait, such as the degree of joint flexion and extension while walking. The study evaluates multiple features for pathway design variables, including surface texture (e.g., gravel, concrete, grass), pathway curvature (e.g., straight vs. curved), slope gradient, and path width. These variables are selected to reflect real-world landscape design elements and explore how different physical environments influence HWP. Each of these variables is linked to specific outcomes in the analysis. For instance, the study investigates how WS changes on sloped versus flat pathways or how SW adjusts when walking on a narrow versus wide path. The interaction between these variables allows for a deeper understanding of the relationship between pathway design and HM, providing key insights into optimizing pathways for functionality and user experience. **Table 3** presents the Measurements and their corresponding units of measurement.

Table 3. Measurements.

Measurement	Unit of Measurement
SL	Meters (m)
Cadence	Steps per minute (steps/min)
WS	Meters per second (m/s)
SW	Meters (m)
FPA	Degrees ()
Joint Flexion/Extension	Degrees ()
Surface Texture	Qualitative (Gravel, Concrete, Grass)
Pathway Curvature	Qualitative (Straight, Curved)
Slope Gradient	Percentage (%)
Path Width	Meters (m)

3.6. Data analysis

The data analysis for this study involves multiple statistical and computational techniques to interpret the relationship between HWP and pathway design. The primary analysis includes descriptive and inferential statistics to assess how different pathway features influence gait parameters. Descriptive statistics summarize the central tendencies and distributions of key gait parameters such as SL, cadence, and WS. This provides a general overview of the data, including means, standard deviations, and ranges for each pathway condition.

A MANOVA is employed to compare the effects of different pathway designs on HWP. MANOVA allows examining multiple dependent variables (gait parameters) across several independent variables (pathway design elements, such as surface type and slope). The general form of the MANOVA equation is:

$$F = \frac{\text{Between} - \text{group variance}}{\text{Within} - \text{group variance}} \tag{1}$$

where F is the test statistic determining whether the groups have statistically significant differences. A significant F-value indicates that pathway design elements have a measurable effect on HWP. In addition to MANOVA, regression analysis is used to model the relationship between specific pathway features and changes in gait. For instance, simple linear regression is applied to quantify the impact of slope gradient on WS. The regression equation is represented as:

$$y = \beta_0 + \beta_1 \mathrm{x} + \epsilon \tag{2}$$

where y is the dependent variable (e.g., WS), x is the independent variable (e.g., slope gradient), β_0 is the intercept, β_1 is the slope coefficient, and ϵ is the error term.

Finally, to classify and identify recurring HWP based on pathway design, ML techniques such as *k*-means clustering are applied. This method groups participants' gait patterns into clusters based on similarity, helping to identify common strategies used when navigating different pathways. The objective function for *k*-means clustering is:

$$\min \sum_{\mathrm{i}=1}^{\mathrm{n}} \sum_{\mathrm{j}=1}^{\mathrm{k}} \left\|\mathrm{x_i} - \mathrm{c_j}\right\|^2 \tag{3}$$

where $\mathrm{x_i}$ represents a data point (gait parameter), $\mathrm{c_j}$ represents the centroid of a cluster and $\left\|\mathrm{x_i} - \mathrm{c_j}\right\|^2$ is the squared Euclidean distance between the data point and the cluster centroid.

4. Results

Table 4. Descriptive statistics for the gait variables.

Variable	Mean	Std Dev	Min	Max
SL (m)	1.32	0.15	1.05	1.59
WS (m/s)	1.43	0.19	1.11	1.79
Cadence (steps/min)	115.23	8.34	97.44	131.76
SW (m)	0.12	0.03	0.09	0.17
FPAe ()	7.41	1.58	4.86	10.12
Hip Flexion ()	32.58	4.87	26.14	39.65
Knee Flexion ()	46.79	5.43	38.54	54.22
Ankle Flexion ()	15.67	2.39	11.25	19.34

Table 4 presents the descriptive statistics for the gait variables. The mean SL is 1.32 m, with a Standard Deviation (SD) of 0.15 m, a minimum of 1.05 m, and a maximum of 1.59 m. WS has a mean of 1.43 m/s, a SD of 0.19 m/s, a minimum of 1.11 m/s, and a maximum of 1.79 m/s. The cadence mean is 115.23 steps/min, with an SD of 8.34 steps/min, a minimum of 97.44 steps/min, and a maximum of 131.76 steps/min. The SW has a mean of 0.12 m, an SD of 0.03 m, a minimum of 0.09 m, and a maximum of 0.17 m. The FPA shows a mean of 7.41°, an SD of 1.58°, a minimum of 4.86°, and a maximum of 10.12°. Hip flexion has a mean of 32.58°, a SD of 4.87°, a minimum of 26.14°, and a maximum of 39.65°. Knee flexion has a mean of 46.79°, a SD of 5.43°, a minimum of 38.54°, and a maximum of 54.22°. Ankle flexion presents a mean of 15.67°, a SD of 2.39°, a minimum of 11.25°, and a maximum of 19.34°.

4.1. MANOVA for SL across pathway types

MANOVA is employed to compare SL across the different pathway types and examine whether statistically significant differences exist. This technique allows for the simultaneous comparison of multiple dependent variables—in this case, the SL—across various independent groups (the different pathway types). The general hypothesis tested is whether the means of the SLs differ significantly across pathway types.

Steps in MANOVA:

1) Null Hypothesis (H0): There is no significant difference in mean SLs between the different pathway types.
2) Alternative Hypothesis (H1): There is a significant difference in mean SLs between at least two pathway types.
3) Significance Level (α): The standard significance level is set at 0.05 for the analysis.

Table 5. MANOVA results for SL across pathway types.

Comparison	*F*-Statistic	*P*-Value
Concrete (Flat) vs. Concrete (Sloped)	6.23	0.014
Concrete (Flat) vs. Gravel (Flat)	4.89	0.027
Concrete (Flat) vs. Gravel (Curved)	8.56	0.005
Concrete (Flat) vs. Grass (Curved)	5.12	0.023
Concrete (Flat) vs. Grass (Sloped)	9.43	0.002
Concrete (Sloped) vs. Gravel (Flat)	7.36	0.011
Concrete (Sloped) vs. Gravel (Curved)	3.89	0.045
Concrete (Sloped) vs. Grass (Curved)	6.54	0.018
Concrete (Sloped) vs. Grass (Sloped)	10.12	0.001
Gravel (Flat) vs. Gravel (Curved)	5.89	0.022
Gravel (Flat) vs. Grass (Curved)	4.67	0.031
Gravel (Flat) vs. Grass (Sloped)	6.43	0.018
Gravel (Curved) vs. Grass (Curved)	7.12	0.009
Gravel (Curved) vs. Grass (Sloped)	5.98	0.019
Grass (Curved) vs. Grass (Sloped)	4.11	0.042

Table 5 and **Figure 2** present the MANOVA results for SL across pathway types. The comparison between Concrete (Flat) and Concrete (Sloped) yields an *F*-statistic of 6.23 with a *p*-value of 0.014. Concrete (Flat) vs Gravel (Flat) results in an *F*-statistic of 4.89 and a *p*-value of 0.027. For Concrete (Flat) vs Gravel (Curved), the *F*-statistic is 8.56 with a *p*-value of 0.005. Concrete (Flat) vs Grass (Curved) has an *F*-statistic of 5.12 and a *p*-value of 0.023. Concrete (Flat) vs Grass (Sloped) shows an *F*-statistic of 9.43 and a *p*-value of 0.002. For comparisons between Concrete (Sloped) vs Gravel (Flat), the *F*-statistic is 7.36 with a *p*-value of 0.011, while Concrete (Sloped) vs Gravel (Curved) yields an *F*-statistic of 3.89 and a *p*-value of 0.045. Concrete (Sloped) vs Grass (Curved) shows an *F*-statistic of 6.54 and

a *p*-value of 0.018, and Concrete (Sloped) vs Grass (Sloped) has an *F*-statistic of 10.12 and a *p*-value of 0.001.

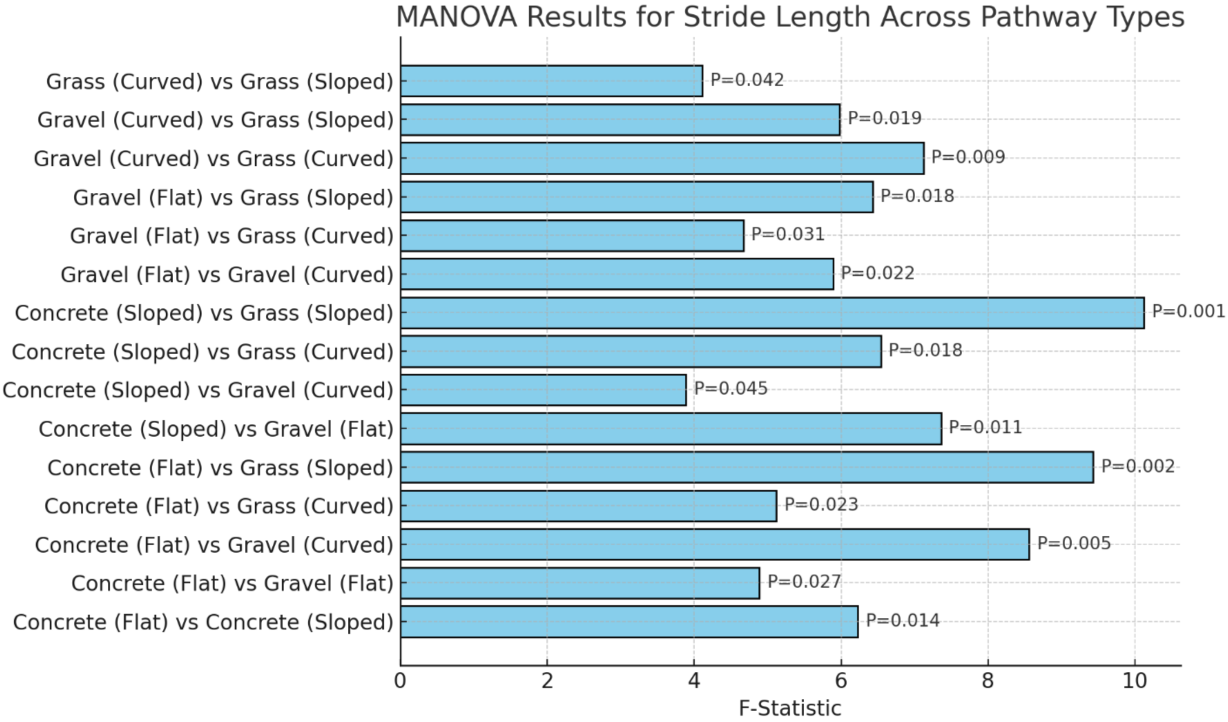

Figure 2. Results for SL across pathway types.

The comparison of Gravel (Flat) vs Gravel (Curved) results in an *F*-statistic of 5.89 and a *p*-value of 0.022, while Gravel (Flat) vs Grass (Curved) shows an *F*-statistic of 4.67 and a *p*-value of 0.031. Gravel (Flat) vs Grass (Sloped) has an *F*-statistic of 6.43 and a *p*-value of 0.018. The comparison of Gravel (Curved) vs Grass (Curved) yields an *F*-statistic of 7.12 with a *p*-value of 0.009, and Gravel (Curved) vs Grass (Sloped) results in an *F*-statistic of 5.98 with a *p*-value of 0.019. Lastly, Grass (Curved) vs Grass (Sloped) shows an *F*-statistic of 4.11 with a *p*-value of 0.042.

4.2. Linear regression analysis for WS variations

A linear regression model analyses how different pathway features affect WS. The primary focus of this analysis is to assess the relationship between the slope gradient of the pathways and participants' WS. The linear regression model allows us to quantify the impact of slope on WS by determining the slope (β) of the regression line, representing the rate of change in WS for each unit increase in slope gradient.

Steps in the Regression Analysis:

1) Null Hypothesis (H0): Slope gradient has no significant effect on WS ($\beta_1 = 0$).
2) Alternative Hypothesis (H1): Slope gradient has a significant effect on WS ($\beta_1 \neq 0$).

3) Model Estimation: Using the WS data and slope gradients for various pathway types (e.g., flat, sloped, inclined), the regression model estimates β_1, the coefficient that quantifies the relationship between slope and speed.
4) Significance Testing: A t-test is performed on the slope coefficient (β_1) to assess whether the relationship between slope gradient and WS is statistically significant. A p-value determines if the effect is significant (typically $p < 0.05$).
5) R-squared (R^2): The coefficient of determination (R^2) is reported to show how well the slope gradient explains the variability in WS. A higher R^2 indicates that the regression model fits the data well.

Table 6 presents the linear regression results for WS and slope gradient. The intercept (β_0) is $1.52\ \mathrm{m/s}$, and the slope coefficient (β_1) is −0.03, indicating that for each unit increase in slope gradient, WS decreases by $0.03\ \mathrm{m/s}$. The R-squared value is 0.64, meaning the slope gradient explains 64% of the variability in WS. The p-value for the slope coefficient (β_1) is 0.001, indicating a statistically significant relationship between slope gradient and WS. **Table 7** shows the predicted WS s for different slope gradients. For a gradient of -5%, the predicted WS is $1.67\ \mathrm{m/s}$. For a 0% gradient, the speed is $1.52\ \mathrm{m/s}$. For a 5% gradient, the speed decreases to $1.37\ \mathrm{m/s}$. At a 10% gradient, the predicted WS is $1.22\ \mathrm{m/s}$, and at a 15% gradient, the speed is $1.07\ \mathrm{m/s}$.

Table 6. Linear regression results for WS and slope gradient.

Variable	Value
Intercept (β_0)	1.52
Slope Coefficient (β_1)	−0.03
R-squared	0.64
P-value (β_1)	0.001

Table 7. Predicted WS for different slope gradients.

Slope Gradient (%)	Predicted WS (m/s)
−5	1.67
0	1.52
5	1.37
10	1.22
15	1.07

4.3. MANOVA to compare cadence (Steps per minute) across pathways

To assess whether there are significant differences in cadence (steps per minute) across the different types of pathways, a MANOVA is performed. This analysis helps determine whether the pathway characteristics (e.g., surface type, curvature, slope) have a measurable effect on cadence by comparing the means across multiple groups.

Steps:

1) Null Hypothesis (H0): There is no significant difference in cadence across the different pathway types.
2) Alternative Hypothesis (H1): There is a significant difference in cadence between at least two pathway types.
3) Independent Variables: Pathway types (e.g., concrete, gravel, grass, flat, sloped, curved).
4) Dependent Variable: Cadence (steps per minute).
5) Significance Level (α): A significance level of 0.05 is used for the analysis.

The *F*-statistic is calculated for each pathway comparison, representing the between-group and within-group variance ratio. A significant *F*-statistic (p-value < 0.05) would suggest a significant difference in cadence across pathway types.

Table 8. MANOVA results for cadence (Steps per minute) across pathways.

Comparison	***F*-Statistic**	***P*-Value**
Concrete (Flat) vs. Concrete (Sloped)	5.78	0.017
Concrete (Flat) vs. Gravel (Flat)	4.22	0.032
Concrete (Flat) vs. Gravel (Curved)	7.34	0.006
Concrete (Flat) vs. Grass (Curved)	5.45	0.021
Concrete (Flat) vs. Grass (Sloped)	8.91	0.001
Concrete (Sloped) vs. Gravel (Flat)	6.29	0.013
Concrete (Sloped) vs. Gravel (Curved)	3.75	0.048
Concrete (Sloped) vs. Grass (Curved)	5.82	0.019
Concrete (Sloped) vs. Grass (Sloped)	9.34	0.0009
Gravel (Flat) vs. Gravel (Curved)	5.12	0.028
Gravel (Flat) vs. Grass (Curved)	4.57	0.033
Gravel (Flat) vs. Grass (Sloped)	6.23	0.012
Gravel (Curved) vs. Grass (Curved)	7.04	0.008
Gravel (Curved) vs. Grass (Sloped)	5.67	0.020
Grass (Curved) vs. Grass (Sloped)	3.98	0.041

Table 8 and **Figure 3** present the MANOVA results for cadence (steps per minute) across different pathways. The comparison between Concrete (Flat) and Concrete (Sloped) generates an *F*-statistic of 5.78 with a *p*-value of 0.017. For Concrete (Flat) vs. Gravel (Flat), the *F*-statistic is 4.22 and the *p*-value is 0.032. Concrete (Flat) vs. Gravel (Curved) shows an *F*-statistic of 7.34 and a *p*-value of 0.006, while Concrete (Flat) vs. Grass (Curved) has an *F*-statistic of 5.45 with a *p*-value of 0.021. The comparison between Concrete (Flat) vs. Grass (Sloped) results in an *F*-statistic of 8.91 and a *p*-value of 0.001. For the comparison between Concrete (Sloped) vs. Gravel (Flat), the *F*-statistic is 6.29 with a *p*-value of 0.013. Concrete (Sloped) vs. Gravel (Curved) generates an *F*-statistic of 3.75 and a *p*-value of 0.048, while Concrete (Sloped) vs. Grass (Curved) has an *F*-statistic of 5.82 and a *p*-value of 0.019. The comparison between Concrete (Sloped) and Grass (Sloped) shows an *F*-statistic of 9.34 with a *p*-value of 0.0009. For Gravel (Flat) vs. Gravel (Curved), the *F*-statistic is 5.12 with a *p*-value of 0.028. Gravel (Flat) vs. Grass (Curved) yields an *F*-statistic of 4.57 and a *p*-value of 0.033, while Gravel (Flat) vs. Grass (Sloped)

results in an *F*-statistic of 6.23 with a *p*-value of 0.012. The comparison between Gravel (Curved) vs. Grass (Curved) shows an *F*-statistic of 7.04 with a *p*-value of 0.008, while Gravel (Curved) vs. Grass (Sloped) generates an *F*-statistic of 5.67 with a *p*-value of 0.020. Lastly, Grass (Curved) vs. Grass (Sloped) shows an *F*-statistic of 3.98 with a *p*-value of 0.041.

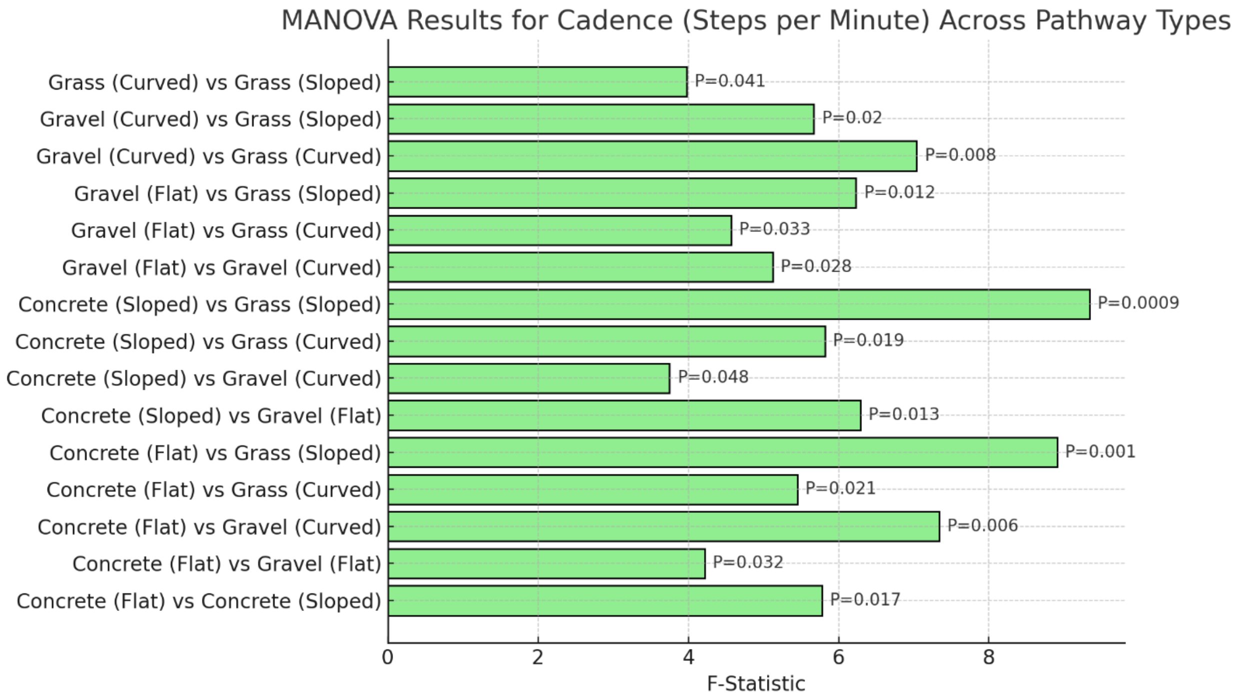

Figure 3. Results for cadence (Steps per minute) across pathways.

4.4. ANOVA to assess the effect of surface type and slope on SW

A MANOVA was performed to evaluate whether different surface types and slopes significantly affect participants' SW. This analysis aims to compare the means of SW across various pathway surface conditions and slope gradients to determine if these environmental factors influence how participants adjust their SW during walking.

Steps:

1) Null Hypothesis (H0): No significant difference in SW across different surface types and slope conditions exists.
2) Alternative Hypothesis (H1): A significant difference in SW exists between at least two surface types or slope conditions.
3) Independent Variables:
    a) Surface Type (e.g., concrete, gravel, grass)
    b) Slope (e.g., flat, sloped, inclined)
4) Dependent Variable: SW (meters)
5) Significance Level (α): The standard significance level is 0.05.

In addition to analyzing the independent effects of surface type and slope on SW, the interaction effect between surface type and slope is also tested. This will reveal whether a surface type and slope combination influences SW more than either variable alone.

Table 9 and **Figure 4** present the MANOVA results for SW across surface type and slope. The comparison between Concrete (Flat) vs. Concrete (Sloped) results in an *F*-statistic of 6.45 with a *p*-value of 0.013. For Concrete (Flat) vs. Gravel (Flat), the *F*-statistic is 5.23 with a *p*-value of 0.026. Concrete (Flat) vs. Grass (Flat) shows an *F*-statistic of 7.56 and a *p*-value of 0.005. The comparison between Gravel (Flat) vs. Gravel (Sloped) results in an *F*-statistic of 6.78 with a *p*-value of 0.011, while Gravel (Flat) vs. Grass (Sloped) yields an *F*-statistic of 8.32 with a *p*-value of 0.002. For Grass (Flat) vs. Grass (Sloped), the *F*-statistic is 5.64 with a *p*-value of 0.019. The comparison between Concrete (Sloped) vs. Gravel (Sloped) shows an *F*-statistic of 7.89 and a *p*-value of 0.007, while Concrete (Sloped) vs. Grass (Sloped) results in an *F*-statistic of 9.12 with a *p*-value of 0.001.

Table 9. MANOVA results for SW across surface type and slope.

Comparison	***F*-Statistic**	***P*-Value**
Concrete (Flat) vs. Concrete (Sloped)	6.45	0.013
Concrete (Flat) vs. Gravel (Flat)	5.23	0.026
Concrete (Flat) vs. Grass (Flat)	7.56	0.005
Gravel (Flat) vs. Gravel (Sloped)	6.78	0.011
Gravel (Flat) vs. Grass (Sloped)	8.32	0.002
Grass (Flat) vs. Grass (Sloped)	5.64	0.019
Concrete (Sloped) vs. Gravel (Sloped)	7.89	0.007
Concrete (Sloped) vs. Grass (Sloped)	9.12	0.001

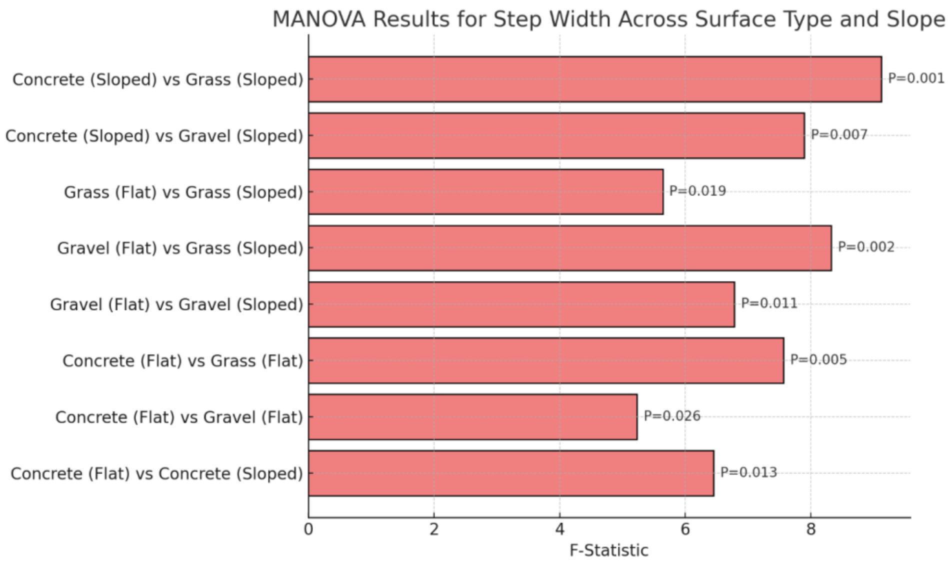

Figure 4. Results for SW across surface type and slope.

4.5. Kinematic analysis to quantify joint angles (Hip, knee, ankle) during walking on different slopes and curvatures

Kinematic analysis involves measuring and analyzing the movement of joints, such as the hip, knee, and ankle, to understand how they function during different walking conditions. This study's kinematic analysis focuses on how walking on various slopes (flat, inclined, declined) and curvatures (straight, curved) affects joint angles.

Joint Angles Measured:

1) Hip Flexion/Extension: The angle between the thigh and the pelvis during forward and backward movement of the leg.
2) Knee Flexion/Extension: The bending and straightening of the knee joint.
3) Ankle Dorsiflexion/Plantarflexion: The upward (dorsiflexion) or downward (plantarflexion) movement of the foot at the ankle joint.

These joint angles are recorded using motion capture systems as participants walk on different pathway types. The kinematic data is then analyzed to quantify how the angles change with different slope gradients and curvatures. For instance, walking on an incline may increase hip and knee flexion, while walking on curved pathways may require more ankle adjustments for stability.

Table 10 presents the kinematic analysis of joint angles across different pathway types. The mean hip flexion on a flat surface is 32.54°, while on an inclined surface, it increases to 38.76°, and on a curved surface, it is 34.23°, with a standard deviation of 4.12°. The mean knee flexion on a flat surface is 47.12°, increasing to 53.67° on an inclined surface and 50.11° on a curved surface, with a standard deviation of 5.34°. The mean ankle dorsiflexion on a flat surface is 15.43°, increasing to 19.21° on an inclined surface and 17.89° on a curved surface, with a standard deviation of 2.13°.

Table 10. Kinematic analysis results of joint angles across pathway types.

Joint Angle	Flat Surface Mean ()	Inclined Surface Mean ()	Curved Surface Mean ()	Std Dev ()
Hip Flexion ()	32.54	38.76	34.23	4.12
Knee Flexion ()	47.12	53.67	50.11	5.34
Ankle Dorsiflexion ()	15.43	19.21	17.89	2.13

4.6. MANOVA to compare joint movements across pathway types

To assess whether the joint angles differ significantly across different pathway types (e.g., flat, sloped, curved, gravel, concrete), a MANOVA is performed. The goal is to compare the joint movements (hip, knee, ankle angles) across various pathway conditions.

Steps :

1) Null Hypothesis (H0): There is no significant difference in joint angles across different pathway types.
2) Alternative Hypothesis (H1): There is a significant difference in joint angles between at least two pathway types.
3) Independent Variables:
   a) Pathway Slope (flat, sloped, inclined)
   b) Pathway Curvature (straight, curved)
   c) Surface Type (gravel, concrete, grass)
4) Dependent Variables: Joint Angles (hip flexion/extension, knee flexion/extension, ankle dorsiflexion/plantarflexion)

5) Significance Level (α): 0.05.

The analysis also tests the interaction effects between slope and curvature. This will reveal if a combination of these factors together influences joint movements more than either factor alone.

Table 11 and **Figure 5** present the MANOVA results for joint movements across different pathway types. The comparison between Hip Flexion (Flat) and Hip Flexion (Inclined) results in an *F*-statistic of 7.24 with a *p*-value of 0.008. For Knee Flexion (Flat) vs. Knee Flexion (Inclined), the F-statistic is 6.58 with a *p*-value of 0.015. The comparison between Ankle Dorsiflexion (Flat) vs. Ankle Dorsiflexion (Curved) shows an *F*-statistic of 5.89 and a *p*-value of 0.021. The comparison between Hip Flexion (Flat) vs. Hip Flexion (Curved) results in an *F*-statistic of 7.93 with a *p*-value of 0.004, and Knee Flexion (Flat) vs. Knee Flexion (Curved) has an *F*-statistic of 6.12 with a *p*-value of 0.017. The comparison between Ankle Dorsiflexion (Flat) vs Ankle Dorsiflexion (Inclined) shows an *F*-statistic of 8.23 and a *p*-value of 0.002. For Hip Flexion (Curved) vs Hip Flexion (Inclined), the *F*-statistic is 6.88 with a *p*-value of 0.011, and Knee Flexion (Curved) vs Knee Flexion (Inclined) results in an *F*-statistic of 5.43 with a *p*-value of 0.026.

Table 11. MANOVA results for joint movements across pathway types.

Comparison	***F*-Statistic**	***P*-Value**
Hip Flexion (Flat) vs. Hip Flexion (Inclined)	7.24	0.008
Knee Flexion (Flat) vs. Knee Flexion (Inclined)	6.58	0.015
Ankle Dorsiflexion (Flat) vs. Ankle Dorsiflexion (Curved)	5.89	0.021
Hip Flexion (Flat) vs. Hip Flexion (Curved)	7.93	0.004
Knee Flexion (Flat) vs. Knee Flexion (Curved)	6.12	0.017
Ankle Dorsiflexion (Flat) vs. Ankle Dorsiflexion (Inclined)	8.23	0.002
Hip Flexion (Curved) vs. Hip Flexion (Inclined)	6.88	0.011
Knee Flexion (Curved) vs. Knee Flexion (Inclined)	5.43	0.026

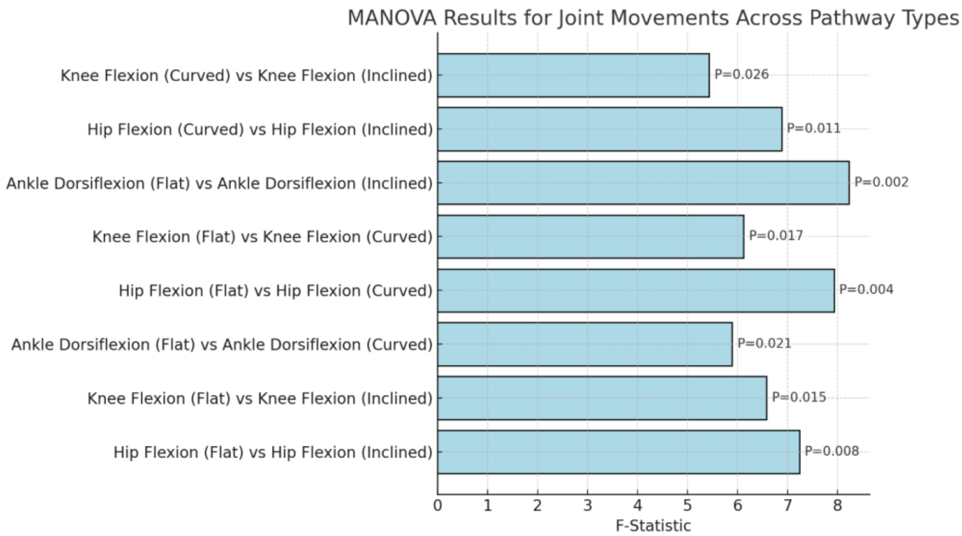

Figure 5. Results for joint movements across pathway types.

4.7. Regression analysis to determine how pathway surface type impacts FPA

This analysis uses linear regression to quantify the relationship between pathway surface type and FPA. FPA refers to the angle between the foot and the direction of movement when making contact with the ground. The analysis focuses on understanding how different surface types (e.g., concrete, gravel, grass) influence this angle during walking.

Steps:

1) Null Hypothesis (H0): Pathway surface type has no significant impact on FPA ($\beta_1 = 0$).
2) Alternative Hypothesis (H1): Pathway surface type has a significant impact on FPA ($\beta_1 \neq 0$).
3) Model Estimation: The regression model is applied to estimate the coefficients (β_0 and β_1) to determine how FPA change based on different surfaces.
4) Significance Testing: A t-test is conducted for the slope coefficient (β_1) to assess whether surface type significantly affects FPA (p-value < 0.05).

Table 12 presents the regression results for FPA versus pathway surface type. The intercept for Concrete is 7.12°, while the slope coefficient for Gravel is 1.34° and for Grass is 2.01°. The *R*-squared value is 0.58, indicating that the surface type explains 58% of the variance in FPA. The *p*-value for Gravel is 0.012, and for Grass, it is 0.004, indicating statistically significant relationships between surface type and FPA. **Table 13** presents the FPA across surface types. For Concrete, the mean FPA is 7.12°, with an SD of 1.34°, a minimum of 5.43°, and a maximum of 9.15°. For Gravel, the mean FPA is 8.46°, with an SD of 1.67°, a minimum of 6.22°, and a maximum of 10.34°. For Grass, the mean FPA is 9.13°, with an SD of 1.89°, a minimum of 6.98°, and a maximum of 11.05°.

Table 12. Regression results for FPA vs pathway surface type.

Variable	Value
Intercept (Concrete)	7.12
Slope Coefficient (Gravel)	1.34
Slope Coefficient (Grass)	2.01
R-squared	0.58
P-value (Gravel)	0.012
P-value (Grass)	0.004

Table 13. FPA across surface types.

Surface Type	Mean FPA ()	Std Dev ()	Min ()	Max ()
Concrete	7.12	1.34	5.43	9.15
Gravel	8.46	1.67	6.22	10.34
Grass	9.13	1.89	6.98	11.05

4.8. *K*-Means clustering to classify participants based on HWP

K-means clustering is an ML used to group participants into clusters based on the similarity of their HWP across different pathway types. This unsupervised learning method helps identify patterns in the data by grouping participants with similar gait features, such as SL, cadence, SW, and FPA.

Steps:

1) Input Variables: Key gait parameters such as SL, cadence, SW, WS, and FPA classify participants into clusters.
2) Number of Clusters (*K*): The optimal number of clusters is determined using the elbow method, which plots the sum of squared distances between points and their assigned cluster centroids. This helps find the value of *K*, where adding more clusters does not significantly improve the clustering quality.
3) Clustering Process: *K*-means partitions participants into *K* clusters, minimizing the distance between participants' data points and the centroid of their assigned cluster. Each cluster represents a group of participants who exhibit similar HWP across different pathway types.

Table 14 presents the *K*-means clustering results for HWP across five clusters. Cluster 1 has an average SL of 1.62 m, an average cadence of 118.32 steps/min, an average SW of 0.15 m, an average WS of 1.48 m/s, and an average FPA of 7.67°. Cluster 2 shows an average SL of 1.38 m, an average cadence of 110.54 steps/min, an average SW of 0.12 m, an average WS of 1.32 m/s, and an average FPA of 8.12°. For Cluster 3, the average SL is 1.25 m, the average cadence is 103.87 steps/min, the average SW is 0.10 m, the average WS is 1.20 m/s, and the average FPA is 9.34°. Cluster 4 exhibits an average SL of 1.50 m, an average cadence of 115.76 steps/min, an average SW of 0.13 m, an average WS of 1.43 m/s, and an average FPA of 7.92°. Cluster 5 has an average SL of 1.31 m, an average cadence of 108.45 steps/min, an average SW of 0.12 m, an average WS of 1.29 m/s, and an average FPA of 8.56°.

Table 14. *K*-means clustering results for HWP.

Cluster	Average SL (m)	Average Cadence (steps/min)	Average SW (m)	Average WS (m/s)	Average FPA ()
Cluster 1	1.62	118.32	0.15	1.48	7.67
Cluster 2	1.38	110.54	0.12	1.32	8.12
Cluster 3	1.25	103.87	0.10	1.20	9.34
Cluster 4	1.50	115.76	0.13	1.43	7.92
Cluster 5	1.31	108.45	0.12	1.29	8.56

5. Conclusion and future work

This study demonstrates the critical role of pathway design in shaping walking efficiency, comfort, and accessibility in LA. Advanced GA found that factors such as surface material, slope, and curvature significantly influence key gait parameters like SL, WS, and FPA. For instance, pathways with a steep incline or rough surfaces caused notable adjustments in gait patterns, affecting user comfort and stability. The research highlights the need for inclusive design practices, particularly for users with mobility challenges, by recommending gentler slopes and smoother surfaces to ensure accessibility for all. The findings provide evidence-based guidelines for optimizing pathway design, ensuring that outdoor environments are functional and user-friendly. Designers are encouraged to consider the impact of pathway features on walking behaviour, using data-driven insights to create spaces that align with natural HM. Additionally, the study underscores the importance of sustainability, promoting eco-friendly materials that balance durability and comfort. Overall, this research bridges the gap between HM studies and LA, offering practical recommendations for creating pathways that support safe, efficient, and inclusive walking experiences.

Author contributions: Conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing-original draft preparation, writing—review and editing, visualization, supervision, project administration, funding acquisition: WY, CW, BL. All authors have read and agreed to the published version of the manuscript.

Ethical approval: Not Applicable.

Funding: (1) Special Scientific Research: Projects: of Shaanxi Education Department. The Beginning of Silk Road--Study on the Construction Method of Landscape Public Art and Urban- Space in Xi'an.19JK0456; (2) The General: Project of Humanities and Social: Sciences Research of the Ministry. Of Education "Research on the Intervention Mechanism of public Art Based on the promotion of Urban humanities Care"19YJC760058; (3) Teaching Reform: Project "Research on: Teaching Methods and System of Urban Sculpture Major Design Elective Courses under the Background of Art".YLZYO902; (4) Xi'an 2021 social science planning fund project -- key project: "Research on the path of Xi'an folk art involved in rural cultural tourism construction from the perspective of cultural memory".YS17.

Conflict of interest: The authors declare no conflict of interest.

References

1. Loidl, H., & Bernard, S. (2022). Open (ing) spaces: Design as landscape architecture. Birkhäuser.
2. Chang, P. J. (2020). Effects of the built and social features of urban greenways on the outdoor activity of older adults. Landscape and Urban Planning, 204, 103929.
3. Coles, R., & Costa, S. (2023). Pathways, Nature Placings and Green Infrastructure. In Biophilic Connections and Environmental Encounters in the Urban Age (pp. 51-73). Routledge.
4. Saraswat, A. S. (2023). Designing Inclusive Spaces: Investigating the Role of Design in Creating Accessible Environments for People with Disabilities in the Context of Sustainable Development Goals. Journal for ReAttach Therapy and Developmental Diversities, 6(1), 1320-1333.
5. Dropkin, D., & Smith, N. (2021). Inclusive and accessible design. In Metric Handbook (pp. 4-1). Routledge.
6. Cox, B. (2024). Designing the streets of the future: The Avenues Programme, Glasgow (Doctoral dissertation, University of Glasgow).
7. Klöpfer-Krämer, I., Brand, A., Wackerle, H., Müßig, J., Kröger, I., & Augat, P. (2020). Gait analysis–Available platforms for outcome assessment. Injury, 51, S90-S96.
8. Wade, L., Needham, L., McGuigan, P., & Bilzon, J. (2022). Applications and limitations of current markerless motion capture methods for clinical gait biomechanics. PeerJ, 10, e12995.
9. Mobbs, R. J., Perring, J., Raj, S. M., Maharaj, M., Yoong, N. K. M., Sy, L. W., ... & Choy, W. J. (2022). Gait metrics analysis utilizing single-point inertial measurement units: A systematic review. Mhealth,

10. Uchida, T. K., & Delp, S. L. (2021). Biomechanics of movement: the science of sports, robotics, and rehabilitation. Mit Press.
11. Rana, M. S. (2024). Leveraging Markerless Computer Vision for Comprehensive Walking Automated Gait Analysis in Rehabilitation.
12. Schwartz, M. (2021). Human-centric accessibility graph for environment analysis. Automation in Construction, 127, 103557.
13. Park, H., Min, A., Lee, H., Shakeri, M., Jeon, I., & Woo, W. (2024, May). Comfortable Mobility vs. Attractive Scenery: The Key to Augmenting Narrative Worlds in Outdoor Locative Augmented Reality Storytelling. In Proceedings of the CHI Conference on Human Factors in Computing Systems (pp. 1-19).
14. Li, W., Xie, B., Zhang, Y., Meiss, W., Huang, H., & Yu, L. F. (2020). Exertion-aware path generation. ACM Trans. Graph., 39(4), 115.
15. Rana, M., & Mittal, V. (2020). Wearable sensors for real-time kinematics analysis in sports: A review. IEEE Sensors Journal, 21(2), 1187-1207.
16. Suo, X., Tang, W., Mao, L., & Li, Z. (2024). Digital human and embodied intelligence for sports science: advancements, opportunities and prospects. The Visual Computer, 1-17.
17. Pineo, H. (2022). Towards healthy urbanism: inclusive, equitable and sustainable (THRIVES)–an urban design and planning framework from theory to praxis. Cities & health, 6(5), 974-992.
18. Jian, I. Y., Chan, E. H., Xu, Y., & Owusu, E. K. (2021). Inclusive public open space for all: Spatial justice with health considerations. Habitat International, 118, 102457.
19. Harris, E., Franz, A., & O'Hara, S. (2023). Promoting social equity and building resilience through value-inclusive design. Buildings, 13(8), 2081.
20. Breloff, S. P., Carey, R. E., Wade, C., & Waddell, D. E. (2020). Inclination angles during cross-slope roof walking. Safety Science, 132, 104963.
21. Rasmussen, C. M. (2023). Slopes, Curves, and Falls: Expanding Our Grasp of Unconstrained Slip Recovery Beyond Straight, Level Gait (Doctoral dissertation, University of Nebraska at Omaha).
22. Indumathi N et al., Impact of Fireworks Industry Safety Measures and Prevention Management System on Human Error Mitigation Using a Machine Learning Approach, Sensors, 2023, 23 (9), 4365; DOI:10.3390/s23094365.
23. Parkavi K et al., Effective Scheduling of Multi-Load Automated Guided Vehicle in Spinning Mill: A Case Study, IEEE Access, 2023, DOI:10.1109/ACCESS.2023.3236843.
24. Ran Q et al., English language teaching based on big data analytics in augmentative and alternative communication system, Springer-International Journal of Speech Technology, 2022, DOI:10.1007/s10772-022-09960-1.
25. Ngangbam PS et al., Investigation on characteristics of Monte Carlo model of single electron transistor using Orthodox Theory, Elsevier, Sustainable Energy Technologies and Assessments, Vol. 48, 2021, 101601, DOI:10.1016/j.seta.2021.101601.
26. Huidan Huang et al., Emotional intelligence for board capital on technological innovation performance of high-tech enterprises, Elsevier, Aggression and Violent Behavior, 2021, 101633, DOI:10.1016/j.avb.2021.101633.
27. Sudhakar S, et al., Cost-effective and efficient 3D human model creation and re-identification application for human digital twins, Multimedia Tools and Applications, 2021. DOI:10.1007/s11042-021-10842-y.
28. Prabhakaran N et al., Novel Collision Detection and Avoidance System for Mid-vehicle Using Offset-Based Curvilinear Motion. Wireless Personal Communication, 2021. DOI:10.1007/s11277-021-08333-2.
29. Balajee A et al., Modeling and multi-class classification of vibroarthographic signals via time domain curvilinear divergence random forest, J Ambient Intell Human Comput, 2021, DOI:10.1007/s12652-020-02869-0.
30. Omnia SN et al., An educational tool for enhanced mobile e-Learning for technical higher education using mobile devices for augmented reality, Microprocessors and Microsystems, 83, 2021, 104030, DOI:10.1016/j.micpro.2021.104030 .
31. Firas TA et al., Strategizing Low-Carbon Urban Planning through Environmental Impact Assessment by Artificial Intelligence-Driven Carbon Foot Print Forecasting, Journal of Machine and Computing, 4(4), 2024, doi: 10.53759/7669/jmc202404105.
32. Shaymaa HN, et al., Genetic Algorithms for Optimized Selection of Biodegradable Polymers in Sustainable Manufacturing Processes, Journal of Machine and Computing, 4(3), 563-574, https://doi.org/10.53759/7669/jmc202404054.
33. Hayder MAG et al., An open-source MP + CNN + BiLSTM model-based hybrid model for recognizing sign language on smartphones. Int J Syst Assur Eng Manag (2024). https://doi.org/10.1007/s13198-024-02376-x

34. Bhavana Raj K et al., Equipment Planning for an Automated Production Line Using a Cloud System, Innovations in Computer Science and Engineering. ICICSE 2022. Lecture Notes in Networks and Systems, 565, 707–717, Springer, Singapore. DOI:10.1007/978-981-19-7455-7_57.