Effect of walking surface, late-cueing, physiological characteristics of aging, and gait parameters on turn style preference.

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Highlights

- Turning while walking can be performed using either a step or spin turn.
- Step turns were preferred during pre-planned turns.
- Steps turns were preferred as stride regularity and acceleration decreased.
- Turn strategy selection should be evaluated during gait analyses of older adults.

Abstract

Turning while walking is a crucial component of locomotion, often performed on irregular surfaces with little planning time. Turns can be difficult for some older adults due to physiological age-related changes. Two different turning strategies have been identified in the literature. During step turns, which are biomechanically stable, the body rotates about the outside limb, while for spin turns, generally performed with closer foot-to-foot distance, the inside limb is the main pivot point. Turning strategy preferences of older adults under challenging conditions remains unclear. The aim of this study was to determine how turning strategy preference in healthy older adults is modulated by surface features, cueing time, physiological characteristics of aging, and gait parameters. Seventeen healthy older adults (71.5 ± 4.2 years) performed 90 degree turns for two surfaces (flat, uneven) and two cue conditions (pre-planned, late-cue). Gait parameters were identified from kinematic data. Measures of lower-limb strength, balance, and reaction-time were also recorded. Generalized linear (logistic) regression mixed-effects models examined the effect of (1) surface and cuing, (2) physiological characteristics of ageing, and (3) gait parameters on turn strategy preference. Step turns were preferred when the condition was pre-planned ($p < 0.001$) (model 1) and when the gait parameters of stride regularity and maximum acceleration decreased ($p = 0.010$ and $p = 0.039$, respectively) (model 3). Differences in turn strategy selection under dynamic conditions ought to be evaluated in future fall-risk research and rehabilitation utilizing real-world activity monitoring.

1. Introduction

Turning is a common movement, representing up to 50% of steps during daily activities (Glaister, Bernatz, Klute, & Orendurff, 2007). The ability to negotiate an environment successfully by changing direction is therefore essential to functional mobility. Turning is also a risk factor associated with falls (Cumming & Klineberg, 1994), which is especially important with an aging population. Recent research has reported that future fallers take longer to turn and turn less frequently than non-fallers (Leach, Mellone, Palumbo, Bandinelli, & Chiari, 2018). Falls can be devastating, and this is amplified when performing a turn, which is 8 times more likely to result in a hip fracture compared to a fall when not turning (Cumming & Klineberg, 1994).

Different kinds of turns can be performed: standing turns, circular path turns, and turning while walking (turning gait)–defined as a transient turn during straight line walking. Two main turning strategies have been identified (Hase & Stein, 1999): step turns (turning away from the outside limb, e.g. landing on the right foot and turning to the left) and spin turns (turning toward the inside limb, e.g. landing on the right limb and turning to the right). There are stark differences in the biomechanics of these turning strategies which may have implications for turn success, turning preference, and falling in older adults. For example, the step turn, with its wider base of support, reduced muscular demand, and decreased joint angular displacements, suggests this is a less demanding, more stable, and simpler strategy (Taylor, Dabnichki, & Strike, 2005). Older adults may favor step turns (Justine, Manaf, Sulaiman, Razi, & Alias, 2014); however, context needs to be considered. In the work of Akram et al. (Akram, Frank, & Chenouri, 2010), older adults preferred step turns over spin turns through 45° and 90° at a comfortable walking speed (60 and 54%, respectively) and when turning 90° at faster than comfortable walking speed (61%). Spin turns were preferred for performing turns at a slower than normal pace through 45° (62%) and 90° (53%) and during fast turns of 45° (40%). Use of spin turns could explain a cause of falling in older adults as the foot-to-foot distance during the turn is closer (Taylor, et al., 2005). Why healthy older adults may prefer one strategy over another in different contexts is unclear; however, based on biomechanical considerations, it is possible that surface conditions, planning time, and physiological characteristics related to ageing may play a role in strategy choice.

The ability to accommodate uneven or irregular terrains while maintaining balance is imperative for functional mobility in the “real” environment with 24% of falls in older adults occurring while walking on uneven ground (Berg, Alessio, Mills, & Tong, 1997). A potential mechanism to adapt to this challenge are through kinematic changes. Gates et al. (2012) reported kinematic changes during straight walking on an uneven, compared to flat, surface in young adults, consistent with a lowering of the center of mass (COM) to increase stability. Dixon et al. (2018) reported corroborative findings during straight walking with respect to the COM movement and additionally revealed a decrease in overall COM movement smoothness in older adults. Marigold et al. (2008) showed that, compared to young adults, older adults walk over multi-surface terrains with greater medial-lateral trunk accelerations. The enhanced acceleration and variability of the trunk/COM suggest that medial-lateral balance may be compromised, which is likely to be further exacerbated when turning on an uneven surface and may influence the preferred turning strategy. With respect to turning on an uneven, compared to flat, surface, older adults increase maximum COM acceleration, while decreasing COM movement smoothness (jerk-based metric) (Dixon, Jacobs, Dennerlein, & Schiffman, 2018); however, these results were reported independently of turning style and require further investigation in the context of turning strategy preference.

When negotiating an environment, it is possible that turns need to be performed in response to a stimulus, such as responding to instructions or unexpected movements of objects or people. A successful turn must be planned to allow time to reduce the acceleration of the COM toward the stance (turning) foot. If a cue to turn is given during the stance phase, then it is very unlikely that a turn will be performed in the following step (Patla, Adkin, & Ballard, 1999). When a cue to turn is given in the preceding step, there is time to decelerate the COM and most (> 70%) participants can initiate a turning maneuver (Patla, Prentice, Robinson, & Neufeld, 1991). During late-cued turns, increased maximum COM acceleration concomitant with decreased stride regularity and step regularity was observed in older adults (Dixon, Jacobs, et al., 2018). These changes may reflect decreased control of movement patterns under challenging conditions. The preferred turning strategy for older adults when reacting to a turning stimulus has yet to be reported.

In summary, turning is associated with fall risk. The biomechanics of turning are compromised in persons at risk of falls and affected by the turning strategy. It is unclear whether older adults display a turn strategy preference and whether turn preference is further affected by the environment where the turn occurs or physiological characteristics. Thus, the aim of this study was to determine if turn style preference correlated with: surface features in the built-environment and late-cueing paradigms; physiological characteristics of aging; or gait parameters in healthy older adults during 90° turning gait at self-selected speed. We hypothesized that (1) surface irregularity and late-cueing conditions are associated with a preference for the more biomechanically stable step turn, (2) increased balance, strength, and reaction-time are associated with a preference for the more dynamic spin turn, and (3) gait parameters related to COM movement control and stepping patterns could predict turning strategy.

2. Methods

2.1. *Participants*

Twenty-six community-dwelling older adults were asked to participate in this study. A medical screen, revealing neurological impairments, musculoskeletal abnormalities, diabetes, or elevated body mass indexes, resulted in the exclusion of eight participants. An additional participant was excluded after the balance assessment phase of the study. Thus, a group of seventeen older healthy adults completed all components of the experimental session (Table 1). Screening procedures have been described in detail previously (Dixon, Schutte, et al., 2018). The Harvard University Institutional Review Board approved this study. All participants provided informed written consent before the start of the study procedures.

Table 1: Participant demographic and physiological assessment results

F:M	Age (years)	Mass (kg)	Height (cm)	BMI (kg/m^2)	balance	Reaction time (s)	Lower-limb strength (Nmm/kg)
12:5	71.5 [69.4, 73.7]	67.6 [61.1, 74.1]	165.7 [160.9, 170.5]	24.5 [22.8, 26.2]	24.1 [22.9, 25.3]	0.53 [0.48, 0.58]	1.00 [0.87, 1.13]

Patient demographics (Age, Mass, Height, BMI) and results from physiological assessments (balance, reaction time, strength). Balance, reaction time, and lower-limb strength were measured using the miniBESTest, the mean response time to a keyboard-based reaction time test, and an instrumented dynamometer, respectively (see section 2.2 for more details). Mean [95% confidence interval] shown. Abbreviations: Female (F), male (M), body mass index (BMI).

2.2. *Data Collection*

The study comprised four assessments: balance, gait analysis, reaction-time, and lower-limb strength. Order of assessments were as are listed in this section, except for reaction-time which was performed half way through the gait analysis.

For the balance assessment, the miniBESTest was selected for its high dynamic balance construct validity (Franchignoni, Horak, Godi, Nardone, & Giordano, 2010). The miniBESTest comprises 14-items such as compensatory lateral stepping and walking with turns. The gait tests were conducted using an eighteen-camera three-dimensional motion capture system (Motion Analysis Corp., Santa Rosa, USA) (Fig. 1). Participants performed a series of straight walking and 90° turning gait trials under pre-planned and late-cued conditions while fitted with a Plug-in Gait marker set (Vicon Motion Systems Ltd., Oxford, UK) with additional foot tracking markers (not used in this study) and a three-dimensional accelerometer (OPAL, APDM, Inc. Portland, USA) placed about the L5 vertebra, approximating the COM position. A minimum of four trials per condition / surface / direction were collected. For the pre-planned turns, participants were told before the trial which maneuver to perform (left turn, right turn, or straight walking). For the late-cued turns, participants were unaware whether to walk straight, turn left, or turn right before the start of the trial. As participants approached the middle of the walkway, they triggered an audio cue which emitted instructions (in random order) to turn right (“Right”) or turn left (“Left”). If no cue was emitted/heard, participants were instructed to keep walking straight.

Participants were tethered to a safety harness during all trials. Flat and uneven brick surfaces were interchanged half way through the data collection (counter-balanced presentation of surface across participants). Pre-planned turns were performed first. Straight walking trials were performed on an 8.4 x 2.0 m main portion of the walkway. Additional 2.0 x 2.0 m perpendicular sections in the middle of the walkway were used for the turning trials. Participants completed approximately 4-6 steps prior to reaching the turning zone. Marker and accelerometer data were captured at 100 and 128 Hz, respectively. Participants performed trials wearing a pair of standardized athletic shoes. Reaction time was measured in a seated position using a custom LabVIEW (v2017, National Instruments, Texas, USA) program that recorded the time delay between 10 audio-cues (randomly generated “Right” or “Left”). Participants pressed the corresponding right or left arrow keys, respectively, on a computer keyboard. The mean response time served as the generalized choice-reaction-time measure. Lower-limb strength was measured via three isokinetic maximal effort knee extensions (Biodex Medical Systems Inc., Shirley, USA). Measurements were recorded for a single leg (participant counter-balanced) at 60°/s after a standardized warm-up. In the case of poor reliability between trials (coefficient of variation >15%), an additional trial was performed.

2.3. *Data processing and analyses*

The first data processing step was to label and gap fill the marker trajectories via cubic spline interpolation using Cortex (Motion Analysis Corp., Santa Rosa, USA) software. Due to marker occlusions data were analyzed for between 26-33 trials/participant, for a total of 520 out of 576 collected trials analyzed in this study. Then, these data were imported into Matlab (v2016b, The Mathworks Inc., Natick, USA) along with the accelerometer data for further processing using the biomechZoo toolbox (Dixon, Loh, Michaud-Paquette, & Pearsall, 2017) and custom code.

Marker data were filtered via a 4th-order low-pass Butterworth filter (8 Hz cutoff frequency). The timing of foot-strike and foot-off events was determined based on markers (Zeni, Richards, & Higginson, 2008). Turning strategy (step or spin) was identified as the single-limb stance phase in which the greatest amount of pelvis rotation was observed (Dixon, Stebbins, Theologis, & Zavatsky, 2013) (see Fig. 2 for schematic representation of step and spin turns). This approach was favored over potentially bias-prone visual assessment. Data were partitioned from foot strike three steps prior to the turn apex to foot-off of the second step after the turn apex.

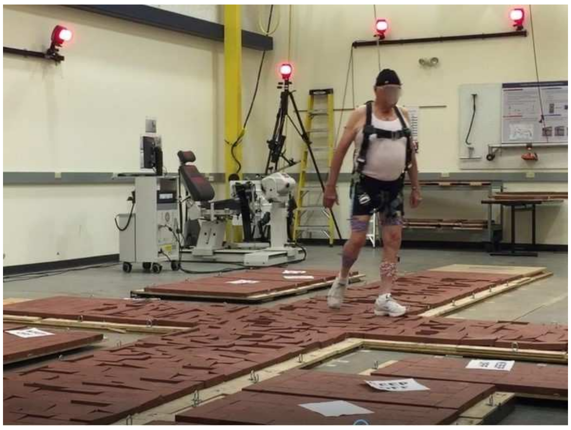

Fig. 1: Experimental setup for gait trial data collection showing an older adult participant performing a 90° online turn to the left. Interchangeable flat surface panels and strength testing equipment also shown.

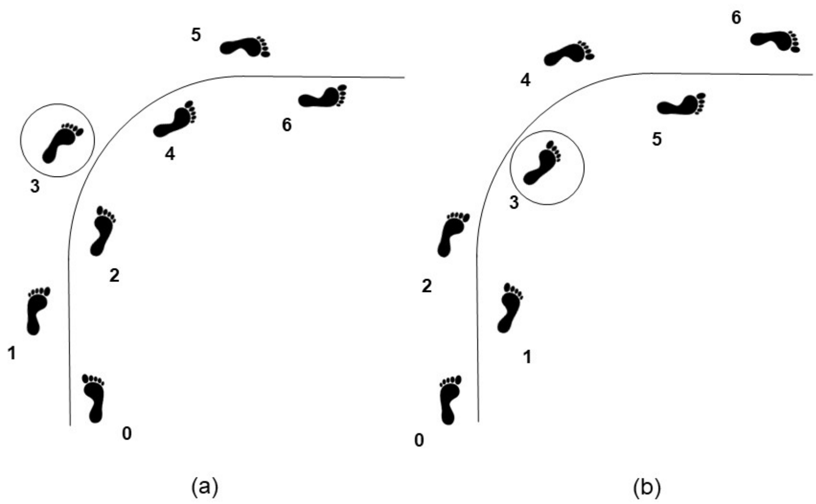

Fig. 2: Schematic representation of the 90° (a) step (outside step) and (b) spin (inside step) turn. Data were analyzed from foot-strike of step 0 to foot-off of step 5. Step 3 is circled and considered the main (apex) turn step of a turning cycle.

Accelerometer data were down-sampled to match marker data and the resultant acceleration vector was used to extract four parameters previously shown to be affected by the uneven surface or late-cueing during turning (Dixon, Jacobs, et al., 2018): Maximum COM acceleration, step regularity, stride regularity, and smoothness (Table 2). Briefly, step and stride regularity estimate gait symmetry and consistency, respectively (Moe-Nilssen & Helbostad, 2004), while smoothness measures changes in the acceleration signal (jerk) using the spectral arc-length (SPARC) (Balasubramanian, Melendez-Calderon, Roby-Brami, & Burdet, 2015).

2.4. *Statistical analyses*

To test our three hypotheses related to participants' turn style preferences, three generalized mixed-effect linear (logistic) regression models with subject as random factor (random intercept only) were implemented. For all models, turn type (step, spin) was identified as a binary outcome variable (true for step). Predictor variables were: surface (uneven, flat) and condition (pre-planned, late-cued) (model 1); balance, strength, and reaction time (model 2); and maximum acceleration, step regularity, stride regularity, and SPARC (model 3). Odds ratios and 95% confidence intervals were calculated for significant categorical predictor variables. Data were missing for the strength test for two of the participants and therefore model 2 included 15 participants. The significance level was set at $\alpha = 0.05$. The statistical analyses were conducted using the statistics toolbox in Matlab (r2017b, The Mathworks Inc., Natick, USA). The m-file script and data table are included in an online repository (github.com/PhilD001/Turning-Strategy) and as supplementary material.

3. Results

Summary physiological characteristics collected are presented in Table 1. Representative acceleration curves for one of the participants are shown in Fig 3.

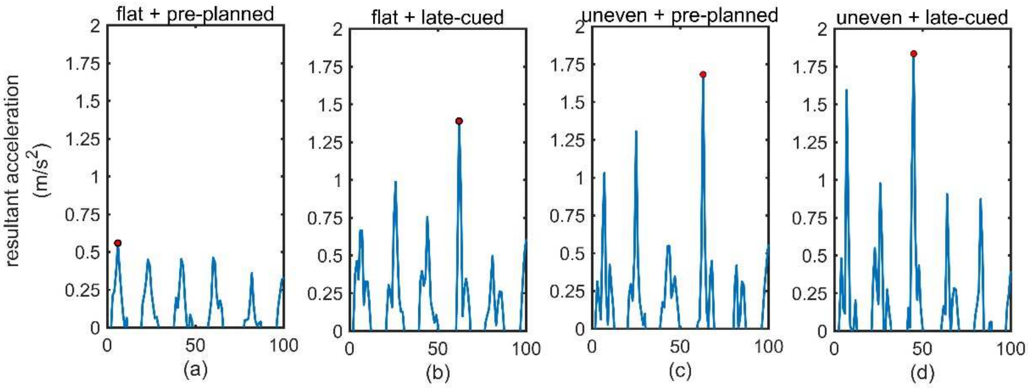

Fig. 3: Representative graphs of the acceleration magnitude (m/s^2) for each surface and turn condition: (a) flat + pre-planned, (b) flat + late-cued, (c) uneven + pre-planned, and (d) uneven + late-cued. Data are presented from foot strike three steps prior to the turn apex to foot-off of the second step after the turn apex as a percentage (0-100%). Instant of maximum acceleration annotated.

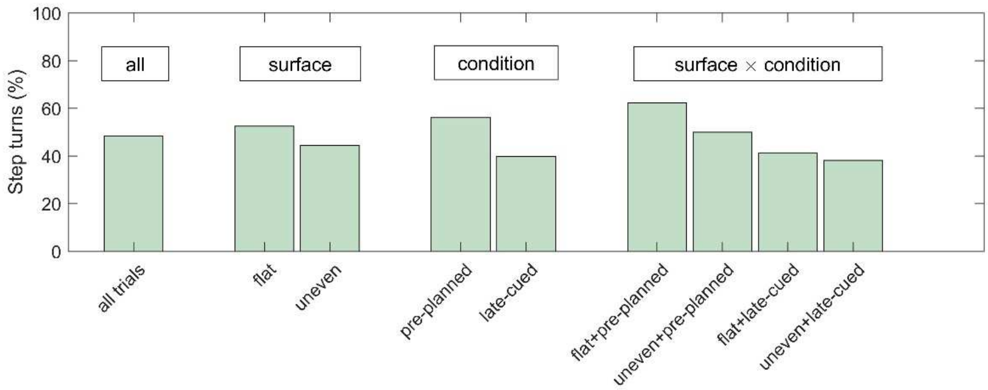

Fig. 4: Percentage of step turns performed for all experimental trials, by surface, by condition, and for surface × condition.

Table 2: Accelerometry-derived gait parameters

		Step Regularity	Stride Regularity	Maximum acceleration	SPARC
Flat	pre-planned	0.49 [0.47, 0.51]	0.43 [0.41, 0.45]	0.80 [0.76, 0.85]	-3.53 [-3.59 -3.46]
	Late-cue	0.40 [0.38, 0.42]	0.37 [0.34, 0.39]	1.14 [1.05, 1.23]	-3.57 [-3.64, -3.51]
Uneven	pre-planned	0.42 [0.41, 0.44]	0.41 [0.39, 0.43]	1.40 [1.33, 1.47]	-4.05 [-4.13, -3.98]
	Late-cue	0.38 [0.36, 0.40]	0.41 [0.39, 0.43]	1.53 [1.43, 1.63]	-4.03 [-4.13, -3.94]

Gait parameters derived from the resultant acceleration data captured by the inertial sensor device placed on the lower-back of the participants (see section 2.2 for more details). Mean [95% confidence interval shown]. Abbreviations: spectral arc length (SPARC)

Table 3: Summary results of fitting the generalised linear (logistic) regression mixed effect models

Model	Parameters	Estimate	Standard Error	p-value
1	Surface	-0.329	0.183	0.073
	Condition	0.714	0.184	**< 0.001***
2	Balance	0.144	0.096	0.136
	Reaction	2.545	2.169	0.241
	Strength	0.188	0.783	0.811
3	Step Regularity	1.234	1.000	0.218
	Stride Regularity	-2.381	0.926	**0.010***
	Maximum Acceleration	-0.453	0.219	**0.039***
	SPARC	0.355	0.219	0.105

Significant effects are bolded with star symbol (*)

On average, participants took an additional 1.2 steps after the turning cue to perform the turn (turn step). Turn style preferences for all experimental trials, by surface, by condition, and for surface × condition are shown in Fig. 4. For all trials, 48% of turns were completed using a step turn. Step turns increased to 53% on the flat surface and reduced to 44% when turning on the uneven surface. For turns that were pre-planned, step turns were preferred 56% of the time; however, for the late-cued condition, 40% of turns were performed using step turns. For the surface × condition combinations, preference for step turns decreased from 62% (flat / pre-planned) to 50% (uneven / pre-planned) to 41% (flat / late-cued) to 38% (uneven / late-cued).

Two models showed significant predictors (Table 3). A significant main effect of condition on whether a step turn was performed was observed ($p < 0.001$) (Table 3, model 1). The positive coefficient for condition indicates that when turning condition was pre-planned, a step turn was more likely. When the condition is pre-planned, the odds of performing a step turn are 1.93 (1.36, 2.74) times greater than the odds of performing a step turn when the condition is late-cued.

There were no significant predictors in the physiological characteristics model. Changes in balance, reaction-time, and strength were not associated with turn strategy selection (Table 3, model 2).

There were two significant predictors in the gait parameter model. Both stride regularity ($p = 0.010$) and maximum COM acceleration ($p = 0.039$) were associated with turn strategy. As stride regularity and maximum acceleration decreased, participants were more likely to perform step turns (Table 3, model 3).

4. Discussion

This study investigated whether 90° turn style preferences (step vs spin) of older adults were influenced by walking surface (uneven, flat) and / or turn condition (pre-planned, late-cued) and whether preference was modulated by physical constraints related to aging and gait parameters. The models show a preference for step turns when performing pre-planned turns and that COM maximum acceleration and stride regularity can be used to predict turn strategy.

4.1. Turn style preference

Our results for step turn preference in older adults during flat-surface, pre-planned turns (62%) agree with Akram et al. (2010) (60% preference for step turns during comfortable-speed 90° turns) and those of Justine et al. (2014) (preference for step turns during 90° corner turning).

Our first hypothesis was not confirmed. The regression model revealed increased odds of performing a step turn during the pre-planned, compared to late-cued, condition (1.9 times more). These results suggest that under challenging conditions i.e. late-cued conditions, older adults may move from the “safer” step turn to the “riskier” spin turn strategy. It is unclear why spin turns are preferred: closer foot-to-foot distance (Taylor, et al., 2005) and greater muscular effort, observed through increased peak ankle power generation (Taylor, 2006) should make spin turns unattractive. In a multi-target stepping study, Yamada et al. (2012) showed that spin turns were preferred more frequently by older adults at risk of falls, compared to healthy older adults. Potentially, older adults feel comfortable utilizing spin turns as they allow for immediate initiation of turns to meet task demands; however, it is unclear if this strategy is safe. Also, the uneven surface did not influence turn strategy selection. It appears that the uneven surface paradigm was insufficient to elicit a strategy change. Future research ought to consider investigating turn strategy selection using the methodology of the current study in frail older adults or adults with a known history of falls. Also, replicating “riskier” surface deviations to characterize further “real-world” turning adaptations that may impose greater functional demands (e.g. larger surface irregularities, decreased surface friction) is warranted.

Our second hypothesis was not confirmed, as changes in balance, strength, and reaction time did not influence turn strategy. This result was unexpected because decreases in strength were associated with altered kinematic patterns on an uneven surface during straight walking (Dixon, Schutte, et al., 2018), and during pre-planned turning, strength, balance, and reaction-time deficits could explain some characteristics of movement (Dixon, Jacobs, et al., 2018). Here, these physiological characteristics did not significantly influence strategy selection, suggesting that changes in overt limb selection to initiate a turn are less sensitive to changes in physiological characteristics than other kinematic parameters of gait and turning.

Our third hypothesis was partially confirmed with two out of four gait parameters (stride regularity and COM maximum acceleration) related to turn strategy preference. These results are expected because spin and step turns are performed with kinematically different movement patterns reflected in COM acceleration patterns. Moreover, COM maximum acceleration may be functionally related to turn strategy. Perhaps COM acceleration patterns could be used to identify turning strategy in real-world settings using wearables with embedded accelerometers such as shirts and wrist-worn devices.

4.2. Identification of turning style

There are no established methods to identify turning style in the literature. We selected a method based on pelvis movement in the transverse plane computed based on pelvis marker data (single-limb-stance phase corresponding to greatest rotation of pelvis identified as turning limb (Dixon, et al., 2013). This method differs from the approach of Akram et al. (2010) in which the onset of foot medial-lateral displacement was used to detect turning style. A comparison of results between these two methods showed agreement for 510/520 trials, suggesting these two approaches result in similar classification. These approaches possess stronger validity than visual assessment (either real-time or through video playback). Future work could compare performance of algorithmic approaches against expert visual assessment.

4.3. Limitations

Five limitations warrant discussion. First, comparison with the work of Akram et al. (2010) is difficult due to different statistical methods. Based on our understanding, Akram et al. (2010) did not account for repeated trials across participants, potentially violating the assumption of independence, whereas we implemented a generalized linear (logistic) mixed-effect regression analysis with subject as a random factor. Second, it is known that humans possess preferential turning directions (Taylor & Strike, 2016; Yazgan, Leckman, & Wexler, 1996); however, here, left and right turns were combined for analysis as no differences were observed during visual inspection of graphs. Third, we presented the audio cue (late-cued condition) at a fixed point near the turning zone. Therefore, cue-timing was irrespective of the gait cycle phase. Previous work by Patla et al. (1999) synchronized an electrical stimulus turning cue with a phase of the gait cycle. We believe our approach leads to a more general representation of turning strategy after receiving a cue; however, our choice makes comparison with the previous work difficult. All participants were healthy older adults with little variability in physiological parameters. It is unknown how various pathologies and falling history may affect turn style preference during late-cued turns on uneven surfaces. Analysis of participants with musculo-skeletal impairments, gait deviations, impaired balance, fall-risk, or frailty may result in different turning style preferences. Finally, the reaction time task employed in the current study involved the upper limbs. Further research may consider using lower limb reaction time tasks to more fully understand if reaction time distinguishes turn strategy.

4.4. *Conclusion*

Step turns were preferred when turns were pre-planned and when stride regularity and maximum COM acceleration decreased. It remains unclear if turn strategy preferences observed here are optimal for older adults. Performing turns using a step strategy could be an attempt to minimize the threat to balance and reduce the occurrence of a fall. Conversely, the ability to implement spin turns may be an appropriate response of healthy older adults to task goals. Regardless, differences in turn strategy selection under dynamic conditions ought to be evaluated in future fall-risk research utilizing real-world activity monitoring.

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