Enhancing Motor Learning in Cycling Tasks: The Role of Model Predictive Control and Training Sequence

L. Alizadehsaravi, S. Draukšas, J. K. Moore, R. Happee, L. Marchal-Crespo

Abstract— **We evaluated the impact of Model Predictive Control (MPC) robotic-assisted compared to unassisted training, and the effect of alternating between MPC-assisted and unassisted training sequences on motor learning of a complex bicycle steering task. This task involved participants steering and collecting virtual stars displayed on a screen riding a steer-by-wire bicycle on a treadmill. Ten participants were split into two groups, alternating between MPC-assisted and unassisted training.**

Tasks' motor skills were quantified by the distance to stars and its standard deviation (SD), while motor performance was determined by mean absolute and SD of steering rate across three evaluation time points: Baseline, Mid-Training, and Post-Training. The repeated-measures ANOVA indicated a significant improvement in task skill (SD of distance from stars) and steering performance (mean absolute and SD of steering rate) and an interaction effect of Group x Time Point on mean absolute and SD of steering rate. The group who initially trained without MPC exhibited a notable decrease in average and variation of steering rate, implying an advantage in starting training unassisted.

Our findings suggest that the strategy of starting the training unassisted could stimulate an internal focus (concentrating on one's own body movements) and intrinsic skill perception, which forms a basis for later integrating MPC assistance to further refining the gained motor skills. Such a sequential training approach may be beneficial in motor skill acquisition of complex dynamics tasks. MPC assistance could be advantageous for individuals with diminished internal model and skill perception, such as those with balance impairments, potentially allowing them to rely less on their impaired sensorimotor abilities.

I. INTRODUCTION

Learning to ride a bicycle is a complex daily-life skill that involves mastering balance and advanced techniques like cornering and steering [1]. In countries like the Netherlands, where bicycles are a primary mode of transportation, this skill is especially crucial [2]. Importantly, the emergence of electric bicycles (E-bikes) has added new dimensions to this task, offering higher speeds but also increased risks, especially for less skilled or elderly riders [3], [4].

Traditional bicycling training methods, such as the use of training wheels, while popular, come with limitations. Training wheels can mask the real dynamics of bicycle riding, potentially hindering the development of essential balancing skills [5], [6]. More advanced training approaches, like those proposed by Klein et al. [7] that replaced the bicycle wheels with rollers of varying radii, offer improvements but require continuous mechanical adjustments in the training setup. In contrast, robotic assistance, particularly Model Predictive Control (MPC), presents a promising alternative. MPC is an optimal control strategy that dynamically adjusts assisting forces based on the learner's performance, offering a tailored learning experience. This method is particularly advantageous as it potentially reduces the risk of learners becoming passively reliant on assistance and potentially preserving the perception of the task's dynamics [8], [9], [10].

Recent advancements in robotic motor learning have demonstrated the efficacy of MPC in learning dynamic tasks such as swinging a virtual pendulum [11], suggesting its potential applicability in more complex dynamic scenarios like bicycle steering. MPC could be particularly suitable for the task of steering & balancing a 2-wheeler since this task's generally unstable non-minimum phase dynamics requires an advanced control strategy. This could not be achieved by simply nudging the steer towards the on-road target, as in [12], but requires an initial countersteering, followed by steering towards the target while stabilizing. However, MPC while offering a potentially (personalized) learning experience of the dynamic task, must be carefully managed, e.g., it is unclear if it should be provided at the early phases of learning or in more advanced phases to avoid over-reliance on the assistance.

Our research investigates the effectiveness of MPC in training for complex bicycling tasks. We hypothesized that MPC-assisted training will significantly improve motor skill acquisition and performance compared to unassisted training in a steering and navigating bicycling task. Furthermore, we explored the impact of training sequence on skill acquisition and performance, evaluating the effectiveness of starting training with MPC assistance versus without it. This aspect of our study aims to provide insights into how the order of training modalities influences learning outcomes and performance in complex bicycling tasks, addressing a gap in current research and offering potential advancements in training methodologies for bicycling.

II. METHODS

A. Experimental setup

The task was performed on a treadmill (Fig. 1) providing a safe and controllable environment with complimentary visual information (Fig. 2), while retaining realistic steering and balancing dynamics. Participants wore a safety harness connected to a fixed point on the ceiling, just above the center

L. Alizadehsaravi and J. K. Moore are with the Department of Biomechanical Engineering, Delft University of Technology, Delft, The Netherlands.

S. Draukšas, R. Happee, and L. Marchal-Crespo are with the Department of Cognitive Robotics, Delft University of Technology, Delft, The Netherlands.

L. Marchal-Crespo is also with the Department of Rehabilitation Medicine, Erasmus University Medical Center, Rotterdam, The Netherlands.

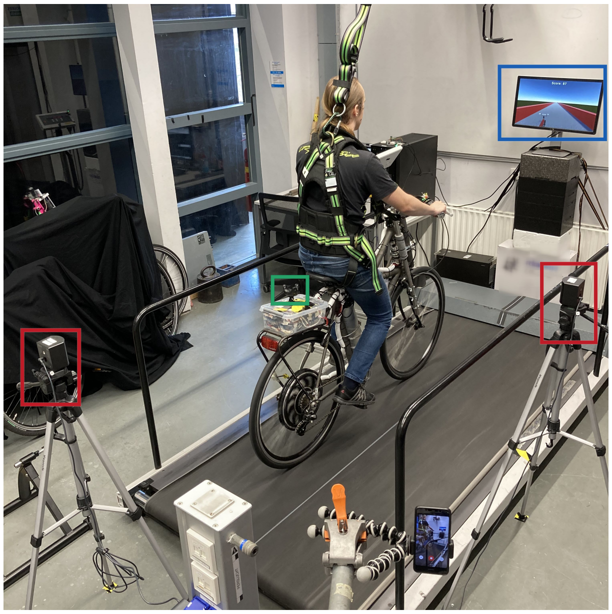

Fig. 1. Experimental setup with a participant riding the steer-by-wire bicycle on a treadmill. The participants wore a harness securely attached to the ceiling for safety. The width of the treadmill's usable space is 1.1 m. The display showing the virtual star-shaped targets from a first-person perspective is highlighted with a blue box. The locations of the SteamVR Base Stations 2.0 are shown within red rectangles. The location of the HTC Vive Tracker 3.0 is shown in green.

of the treadmill, to reduce the risk of injury. Note that due to the harness, participants did not need to pedal and thus could mainly focus on the steering and balancing task. We used a custom steer-by-wire bicycle previously developed at Delft University of Technology in The Netherlands, to provide steering assistance during bicycle riding [13]. This bicycle allows the provision of guiding torques to the handlebar using a motor (and encoder) attached to the handlebar stem.

The lateral position, yaw angle, and roll angle of the steer-by-wire bicycle were measured using an HTC Vive Tracker 3.0 (HTC, Taiwan) installed right above the rear wheel center (Fig. 1). Two SteamVR Base Stations 2.0 (HTC, Taiwan) were located on the back and side of the treadmill to enable this tracking. Tracker data was sent to the supplied USB dongle, which was connected to a Raspberry Pi 4 Model B 4 GB (Raspberry Pi Foundation, UK). This computer run a 32-bit Raspberry Pi OS Lite version in headless mode. `Libsurvive`'s [14] Simple Application Programming Interface (API) was used to read the data coming from the tracker, calculate the position and orientation of the tracker, and send the data using User Datagram Protocol (UDP) at 220 Hz to a Windows 10 desktop computer, which runs the MPC and virtual reality game. The desktop computer was equipped with Intel i7-7700K 4.2 GHz processor (Intel, US), running Simulink Desktop Real-Time (MathWorks, US). The desktop computer and the bicycle communicated wirelessly using Bluetooth at 200 Hz for the bicycle-to-computer communication, and 75 Hz for the computer-to-bicycle communication.

A 24-inch computer monitor was placed around 2 m in

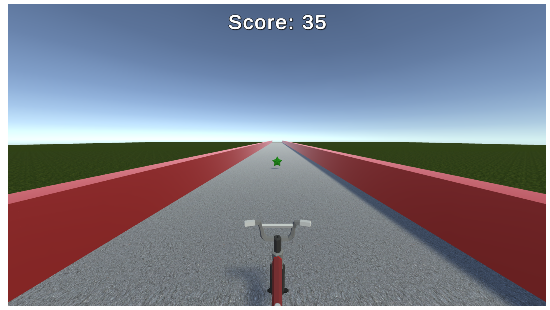

Fig. 2. The virtual environment shown to the participants. The participants controlled the lateral position of the virtual bicycle by steering the real bicycle on the treadmill. The task consisted of collecting green stars that appeared on the horizon and approaching the participant at 15 km/h (the same speed as the treadmill). After passing through each star, a score appeared on the top of the screen that depended on the distance between the virtual bicycle and the center of the star. The red walls correspond to the edges of the treadmill.

front of the participant (Fig. 1) to show the location of the virtual targets (see subsection B). The game was implemented using Unity (Unity Technologies, US) on the desktop computer.

B. Steering and Navigation Task: Collecting Virtual Stars

The steering task consisted of collecting virtual star-shaped targets approaching the rider at a constant velocity of 15 km/h (the same speed as the treadmill). To collect a star, the rider had to steer and navigate the real bicycle which in turn steered the virtual bicycle —shown on a screen in front of them— to place it in front of the star and pass through it. A first-person perspective of the virtual bicycle was shown on a road of the same width as the usable width of the treadmill (Fig. 2). The real bicycle acted as a Human Interface Device for the game, i.e., the virtual bicycle moved in the lateral direction mapping to the measured lateral position of the real bicycle on the treadmill.

To provide feedback to the participants about their navigational steering in the star collection task, a score was displayed each time a star was passed, calculated based on the distance between the lateral position of the bicycle's rear wheel contact point on the treadmill (y_P) and the lateral position of the star's center y_S, both in meters. Scores were assigned using three conditions: 100 points for distance $\leq$ 0.02 m, 0 for distance $>$ 0.22 m. For distances between 0.02 and 0.22 m, the score ranged linearly from 100 to 0, calculated as $500 \times (0.22 - \text{distance})$. The interval between the appearance of two consecutive stars was 6 s.

C. The MPC Robotic Assistance

Our MPC used a mathematical model of the bicycle lateral dynamics [15] to predict the system's behavior throughout a specified time horizon. We choose a control signal such that the predicted system state follows a given reference state. A cost function (and its weights) is specified —e.g., minimizing the assistance and minimizing the distance to the stars— which is then used by the controller to determine the control action at each time step t, through real-time optimization.

Several constraints can be put on the system to guarantee, e.g., safety.

The linear MPC problem employed in our study is stated in Equation 1, where J is the cost function to be minimized, t is the current time, N is the number of steps in the time horizon, x is the bicycle state, r is the reference state, u is the control input, and Q and R are designer-defined weighing matrices. The input varies stepwise across the N steps resulting in N input values to be optimized by the MPC. Only the first (next) input is applied and the following inputs are reoptimized at the next time step based on the updated system state. The subscripts lb and ub stand for *lower bound* and *upper bound*, respectively, and are used to enforce constraints on the controller, i.e., maximum and minimum values of lateral position (± 0.5 m), steering angle ($\pm 40\,deg$), roll angle ($\pm 20\,deg$), and assisting torque (± 10 Nm). The matrices A and B are linear time-invariant state-space matrices.

$$\begin{aligned} J = \sum_{k=t}^{t+N} (x_k - r_k)^T Q_k (x_k - r_k) + \sum_{k=t}^{t+N-1} u_k^T R_k u_k \\ \text{subject to } x_{k+1} = Ax_k + Bu_k \\ x_{lb,k} \leq x_k \leq x_{ub,k} \\ u_{lb,k} \leq u_k \leq u_{ub,k} \end{aligned} \tag{1}$$

In our study, N was set to 150, which is equal to a time horizon of 2 s with a sample rate of 75 Hz. The control input u is the steering torque applied by the handlebar motor. The bicycle and reference states, x and r, consist of the lateral position of the rear wheel of the bicycle y_P, the yaw angle ψ, the roll angle ϕ, the steering angle δ, the roll rate $\dot{\phi}$ and the steering rate $\dot{\delta}$. Thus, the cost function stabilizes the bicycle in steer and roll while both minimizing deviation from the target and motor steer effort. The target tracking task is represented by the lateral position relative to the target at the time needed to reach the target. Thus, the MPC derives an optimal steering sequence to reach the target. The state-space matrices A and B were obtained using the `HumanControl` software [16], which can convert the equations of motion of a linear Whipple-Carvallo bicycle model to a state-space representation. Bicycle parameters of the *Davis Instrumented Bicycle* (specified under *Rigid* in pages 91-92 of [17]) were used due to its physical similarity to the bicycle used in this study. A forward speed of 15 km/h (4.17 m/s), equal to the treadmill's speed, was chosen.

D. Study Protocol

Ten healthy adult participants divided into two groups (9 between 25-39 years old, and 1 between 60-64 years old; 3 female) gave written consent to participate in the experiment. The study was approved by the TU Delft Human Research Ethics Committee (HREC).

The study protocol is depicted in Fig. 3. The experiment consisted of six blocks: Familiarization (*Free riding*), Baseline (*BL*), Training 1 (*T1*), Mid-Training evaluation (*MT*), Training 2 (*T2*), and Post-Training evaluation (*PT*). Participants were randomly assigned to one of two groups. The five participants allocated to Group 1 (MPC first) trained with MPC assistance during T1 and without assistance during T2, while the order was reversed for Group 2 (MPC second).

In the Free riding (Familiarization) session participants spent 5 minutes bicycling on the treadmill without any assistance and were verbally encouraged to carry out lane change maneuvers of varying amplitudes.

Baseline, Mid-Training and Post-Training blocks were designed to evaluate the skill acquisition and steering performance of the participants before, after the first, and after the second training block, respectively. During these evaluation blocks, no MPC assistance was provided and riders cycled for 2 x 1-min trials trying to collect the stars appearing on the screen by steering the bike. Each (1-min) trial contained 10 stars to be collected. The location of the 10 stars was pseudo-randomized but similar for all participants with varied placements on the virtual road.

The training blocks T1 and T2 were started right after the Baseline and Mid-Training blocks, respectively. Participants were informed that they may be assisted during the training. Two-minute breaks were enforced between T1 and Mid-Training blocks, and between T2 and Post-Training blocks.

E. Data Analyses

1) Skill Acquisition and Performance Measures: To evaluate the skill acquisition in the stars collecting task, the average and standard deviation (SD) of the distance (m) from the bike position to targeted stars averaged over 20 stars per evaluation time point (BL, MT, and PT) was obtained. This measure aims to indicate changes in the **accuracy (average distance)** and **consistency (standard deviation distance)** in the steering and navigation task compared to the baseline measurement. A decreased average and standard deviation indicate higher precision (accuracy) and repeatability (consistency) in task execution, respectively, associated with an improved skill acquisition. [18].

For evaluating the participants' navigation and steering performance, the **average steering rate (rad/s)** quantified by mean absolute value of the steering rate [19] and the standard deviation of steering rate (**SD of steering rate (rad/s)**) in a 6-second time frame from appearing until hitting the stars were calculated. These values provide insights into how smoothly the riders maneuver the bicycle within each 6-second interval between star appearances. For statistical analysis, the average and standard deviation of the steering rate across 20 stars (2 x 10 stars) for each evaluation time point (BL, MT, and PT) were calculated, reflecting the participants' average performance over a total of 120 seconds (2 x 1-min trial). The standard deviation of the steering rate serves as an indicator of consistency or variability in the steering rate, where a decreased SD of steering rate implies a more consistent and refined motor control in steering behaviour.

2) Statistical Analyses: We applied a repeated measures ANOVA on the average and standard deviation of the distance to stars, and on the average and standard deviation of the steering rate. The analysis specifically focused on two factors and their interaction that might influence participants' skill acquisition and performance: evaluation Time Points

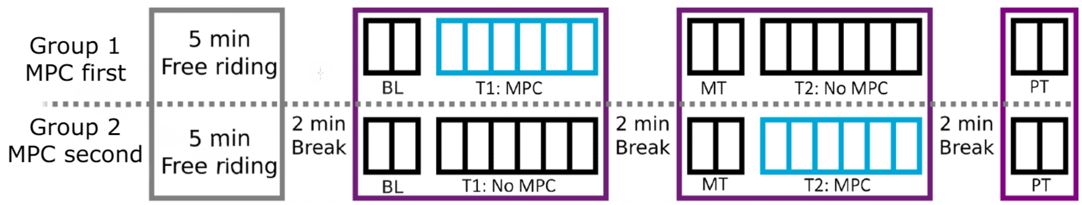

Fig. 3. Study protocol. Participants were randomly assigned to one of two groups. Each trial was 1 minute long and contained 10 stars. *BL*: Baseline evaluation, *MT*: Mid-training evaluation, *PT*: Post-Training evaluation, *MPC*: training with MPC, *No MPC*: training without MPC

(Baseline [BL], Mid-Training [MT], and Post-Training [PT]), and Group, denoting the different participant groups subjected to varying training sequences, enabling a detailed evaluation of how the timing and sequence of training interventions influenced participants' task skill acquisition and steering performance.

The statistical analyses were performed in Jasp (version 0.16) and the significance level was determined at p-values < 0.05.

III. Results

All participants were able to complete all conditions without falling and there were no reports of motion sickness. The analysis focused on changes in accuracy and consistency of collecting stars (Fig. 4) by evaluating the average and standard deviation of the distance to virtual stars, respectively, together with the average and standard deviation of steering rate (Fig. 5, and Fig 6). Results from the statistical analyses are summarized in Table I.

A significant improvement in skill was evidenced by a decrease in the standard deviation of the distance to stars (improved consistency/repeatability), with no effects of Group or interaction of Time Point X Group (Table I, Fig.4). We did not find a significant effect of evaluation Time Point or Group on the average distance to the stars (Table I).

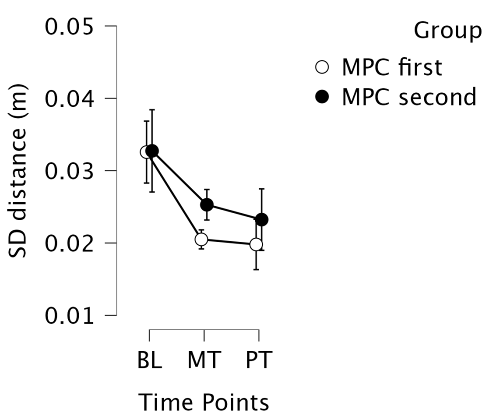

Fig. 4. The standard deviation of the lateral distance to stars at Baseline (BL), Mid-Training (MT) and Post-Training (PT) for each training group. Error bars indicate the standard errors.

We found a significant effect of the evaluation Time Points on average steering rate and a significant interaction between Time Points and Group, as shown in Table

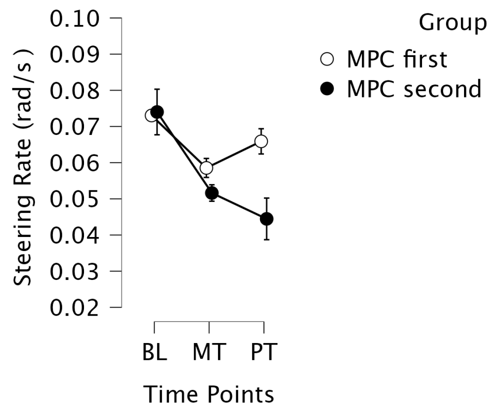

Fig. 5. The average of steering rate in (rad/s) at Baseline (BL), Mid-Training (MT) and Post-Training (PT) time points for each training group. Error bars indicate the standard errors.

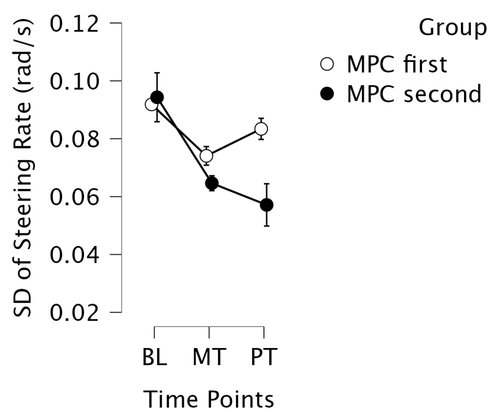

Fig. 6. The standard deviation of steering rate in (rad/s) at Baseline (BL), Mid-Training (MT) and Post-Training (PT) time points for each training group. Error bars indicate the standard errors.

I and Fig. 5. Posthoc analysis for Group 1 (MPC first) revealed no significant improvement in average steering rate between the Baseline (BL) and Mid-Training (MT) or BL and Post-Training (PT) evaluation time points ($t = 2.535$, $p = 0.171$, Mean Difference $= 0.015$ and $t = 1.251$, $p = 0.806$, Mean Difference $= 0.007$, respectively). In contrast, significant differences in average steering rate were observed within Group 2 (MPC second). Specifically, a significant improvement was noted between BL and MT ($t = 3.914$, $p = 0.013$, Mean Difference $= 0.022$), indicating enhanced steering performance (decreased steering rate) during this training period. Furthermore, a significant improvement from BL to PT was also observed ($t = 5.165$, $p = 0.001$, Mean Difference $= 0.030$) in Group 2.

Similarly, we found a significant effect of the evaluation Time Points on the standard deviation of steering rate and a significant interaction between Time Points and Group as shown in Table I and Fig. 6. Posthoc analysis for Group 1 (MPC first) revealed no significant improvement in SD of steering rate between the Baseline (BL) and Mid-Training (MT) or BL and Post-Training (PT) evaluation time points ($t = 2.463$, $p = 0.193$, Mean Difference $= 0.018$ and $t = 1.171$, $p = 0.844$, Mean Difference $= 0.008$, respectively). However, potshoc analysis revealed a significant difference in SD of steering rate within Group 2 (MPC second) between the Baseline (BL) and Mid-Training (MT) evaluation time points ($t = 4.113$, $p = 0.009$, Mean Difference $= 0.030$), indicating a significant improvement in steering performance (decreased variation of steering rate) during this training period. Furthermore, a significant improvement was also noted from the Baseline to Post-Training (PT) time point in Group 2 (MPC second) ($t = 5.1005$, $p = 0.001$, Mean Difference $= 0.037$). These results suggest that Group 2 (MPC second), which started training without MPC assistance, experienced substantial improvements in steering performance over the course of the training, something that was not observed in Group 1 (MPC first). These findings suggest that the introduction of MPC assistance at the beginning of the training did not significantly impact the average and variation of steering actions for Group 1. However, Group 2, which started training without MPC assistance, experienced significant improvements in the steering actions average and variation over the course of the training, highlighting the potential benefits of gradually introducing MPC assistance to enhance learning and adaptation processes, something that was not observed in Group 1 (MPC first).

TABLE I
REPEATED MEASURES ANOVA RESULTS

Variable	F-value	p-value	η_p^2
Average of Distance to Stars			
Time Points (Level)	2.775	0.109	0.258
Group (MPC Order)	1.785	0.218	0.182
Level*Group Interaction	0.061	0.903	0.008
SD of Distance to Stars			
Time Points (Level)	**5.083**	**0.048**	**0.389**
Group (MPC Order)	0.213	0.657	0.026
Level*Group Interaction	0.195	0.697	0.024
Average of Steering Rate			
Time Points (Level)	**13.791**	**<.001**	**0.633**
Group (MPC Order)	0.359	0.566	0.043
Level*Group Interaction	**3.942**	**0.041**	**0.330**
SD of Steering Rate			
Time Points (Level)	**13.876**	**<.001**	**0.634**
Group (MPC Order)	0.365	0.563	0.044
Level*Group Interaction	**3.998**	**0.039**	**0.333**

IV. DISCUSSION

We investigated the impact of MPC assistance on motor skill acquisition and steering performance in a complex bicycling task, with a particular focus on the timing of MPC introduction during training. Contrary to our initial hypothesis that training with MPC assistance would be inherently superior, the results revealed that both training methods led to improvements in motor skill, yet the sequence of training without MPC followed by training with MPC proved to be more effective in improving the steering performance. This finding is particularly intriguing as it suggests the importance of mastering fundamental skills before introducing technological assistance in this particular task.

The sequence of training significantly influenced steering performance in this complex bicycling task. Group 2 (MPC second), which began without MPC, exhibited more pronounced improvements in steering rate average and variation compared to Group 1 (MPC first), highlighting the impact of training sequence on motor learning. This is aligned with the principles of motor learning, particularly the Guidance Hypothesis, which states that too much augmented feedback during training, i.e., additional to the natural feedback mechanisms inherent in performing a task, guides learners but can cause dependency (slaking) if used too frequently [5]. MPC provided additional information to the participants, augmenting their natural sensory feedback with predictive data about future states of the system. Thus, in line with the Guidance Hypothesis, our results suggest that MPC use might disrupt the development of intrinsic motor skills, especially during the early stages of learning, necessitating a balanced approach with unassisted training in its application to prevent over-reliance.

A potential problem of providing robotic assistance while learning to interact with environments with complex dynamics is that the assistance could inadvertently mask the perception of the dynamics of the environment just as adding training wheels disturbs the perception of the bicycle dynamics. The study by Wähnert and Müller-Plath (2021) states the functionality hypothesis in motor learning of a balancing task, indicating that an internal focus, emphasizing body-internal senses, is more beneficial in tasks where external feedback could add cognitive load [20], or in our study, hinder the perception of the task dynamics through body-internal senses. Our findings support the functionality hypothesis in motor learning suggesting that training initially without MPC likely fostered an internal focus, enabling participants to develop a deeper intrinsic understanding of the navigating and steering through their body-internal senses in this bicycling task. This phase of self-reliance in learning appears to be crucial for establishing a solid foundation upon which technological assistance can build.

Furthermore, the study on audio-motor coordination in learning piano performance skills provides relevant insights into our findings [21]. Their research demonstrates that predictive motor control mechanisms, essential for determining the sequence and timing of actions, play a crucial role even in the early stages of learning complex motor skills. In our study, the initial training phase without MPC might have similarly encouraged the development of internal predictive motor control skills, allowing participants to independently navigate the task and refine their ability to anticipate and respond to the bicycling dynamics. The subsequent introduction of MPC then provided targeted feedback and assistance, leading to further refined motor control and enhancing the skills developed during the initial phase.

In practical terms, our study suggests potential applications of MPC for individuals with impaired internal models, such as those caused by aging or balance disorders. MPC's efficacy may be heightened in scenarios where learners fully rely on this technology, thereby minimizing reliance on their compromised internal models [5].

Future studies could benefit from a larger, more diverse participant group and the addition of two focused groups, one training exclusively with MPC and the other solely without it, to strengthen our conclusion. Moreover, the MPC model could be enhanced to adjust to individual rider characteristics. This includes calibrating the weights in the MPC cost function to align with each rider's responsiveness and control preferences, modifying constraints to match their specific steering abilities, and fine-tuning the feedback mechanism to offer customized guidance based on the rider's skill level. These targeted modifications aim to optimize the MPC system for each individual rider, potentially increasing the training effectiveness.

V. Conclusion

Our study highlights the feasibility and effectiveness of Model Predictive Control in complex steering and bicycling tasks, with a focus on the training sequence. We found that unassisted learning strategies beginning with the development of intrinsic predictive motor control, followed by the integration of MPC-assisted learning, led to more refined motor control. This highlights the importance of mastering fundamental skills before introducing robotic assistance and the need for well-structured training sequences.

Future research should focus on exploring the long-term impacts of various training sequences and the optimal and tailored integration of technological aids like MPC in enhancing motor performance.

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