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Bibliographie sur des questions de pointe en anglais

Motor Learning in the Age of AI

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I. Introduction

Over the last decades, with the development of artificial intelligence (AI), machine learning and deep learning have made high-accuracy human motion analysis possible (Vandevoorde et al., 2022 ; Lecun et al., 2015). By estimating human body and hand poses, detecting the objects and tools that are used or are visible in the surroundings and recognizing human actions, AI allows us to track human motion in dynamic and natural surroundings (Redmon et al., 2016 ; Zhang et al., 2019). It is increasingly used to support motor skill learning in areas such as sports, rehabilitation, education and industrial training. For example, AI-based systems can analyze athlete performance, guide physical exercises and provide real-time feedback at a level of precision and scale that was not possible before.

As these technologies expand, a set of fundamental scientific questions arises : Can people truly improve their motor skills with AI support training ? And if so, do these skills actually generalize to real-world performance, and what are the barriers of generalisation? To address this question, we focus specifically on AI systems that analyze human motion and provide adaptive or personalized feedback based on data-driven models.

In this review, we first examine AI-assisted motor learning and its underlying mechanisms. We then explore both the possibilities and limitations of learning transfer from AI-driven training environments to real world unassisted performance, through cognitive, neuroscientific, and human–computer interaction perspectives. Finally, we summarize the previous discussion and introduce a new perspective on AI supported learning : human–AI co-evolution.

II. Effectiveness of Motor Learning and Underlying Mechanisms

Krakauer et al. (2019) define motor learning as comprising two main components. The first is skill acquisition, the process by which individuals learn to identify movement goals, choose appropriate actions, and execute them with precision. The second is skill maintenance, which concerns the ability to maintain skilled performance over time.

2.1 Empirical Evidence of Effectiveness

Empirical works provide clear evidence that AI based training leads to measurable improvements during or after training across different types of skills.

In the context of physical skill learning, Ma et al.(2025) showed that a MediaPipe pose recognition system can improve the learning of Baduanjin, a traditional Chinese physical exercise. The system analyses video data, extracts kinematic information and compares it to a reference pattern, then provides real time feedback. Students who trained with the AI achieved higher scores in movement quality and execution Fluency than those in the control group. Moreover, AI-supported learners engaged in significantly longer practice durations and higher motivation.

AI driven applications also improve learning outcomes and student engagement in higher education sports courses. Ompoc & Aguinaldo (2025) examined a set of AI supported fitness applications designed to match four core components of physical fitness (cardiorespiratory endurance, upper body strength, core strength and lower body strength). The applications provided personalized and adaptive training plans. The experimental group showed a significant increase in post-test performance compared to both their own pre-test and to the control group, for all of these four components of physical fitness.

In the context of motor rehabilitation, Sharma et al.(2019) evaluated the effectiveness of the HoloPHAM prosthesis training system, which combines augmented reality with a pattern-recognition interface that translates physiological signals (e.g., electromyography) into control commands. Repeated practice with immediate feedback helped participants develop stable and precise control of the movement patterns. Across the training period, kinematic quality increased steadily and task completion time decreased. After ten days of practice, participants demonstrated more intuitive control of the virtual modular prosthetic limb and a significantly faster task execution. Although performance gains partially deteriorated after a five-day no-training period, they remained above baseline, indicating motor retention.

2.2 Mechanisms Supporting Successful Learning

These positive effects of AI on motor skill learning are not accidental. They can be explained through a framework that combines behavioral, cognitive and motivational factors.

First of all, for complex form dependent skills such as Baduanjin, which was mentioned earlier, effective learning depends on knowledge of performance (KP). KP refers to feedback that provides specific information about the quality and coordination of the movement itself. AI systems are well trained to deliver this feedback in real time. Research has shown that KP is more important than knowledge of results for improving such motor skills (Wulf et al., 2010). Secondly, from the perspective of cognitive load theory, AI reduces unnecessary cognitive load by automating error detection. It acts as a cognitive support. This allows learners to use their working memory for the deeper processing that is needed to internalize the skill. Finally, efficient learning also requires strong motivational support. According to self determination theory, intrinsic motivation comes from the satisfaction of basic psychological needs, especially competence and autonomy (Ryan & Deci, 2000). AI systems make error correction possible and make progress visible. This strengthens the learner's sense of competence. At the same time, the learner keeps full control over the practice process, which supports autonomy and promotes a sense of achievement.

Through this multi-level of mechanisms and coordinated process, together with the personalization and adaptivity of AI systems, AI increases behavioral engagement. A mediation analysis in Baduanjin learning showed that the effect of AI training was fully mediated by increases in total practice time. This means that AI systems were effective because they transformed learner motivation into sustained and guided practice (Ma et al., 2025).

The next question is whether these improvements extend beyond the training environment.

III. Learning Transfer and Constraints

Learning transferts or generalizations refer to the application of skills acquired in one context to new contexts (Barnett & Ceci, 2002).

3.1 Empirical Evidence of Successful Transfer

Several studies show that skills acquired with AI assistance can transfer to daily functional activities without support, particularly in the context of rehabilitation.

Murakami et al.(2023) tested an AI integrated electromyography driven robotic hand for upper limb rehabilitation after chronic stroke. Upper limb function was assessed with the Fugl Meyer scale. Scores improved significantly after the intervention and remained improved at the four week follow up. Most importantly, daily functional use of the affected limb, measured with the Motor activity log-14 scale, also improved. This confirms a transfer of the trained skill to real life activity.

Srivastava et al.(2014) examined whether AI-driven robot assisted gait training could transfer to over ground walking in stroke patients. During training, the system provided visual feedback on ankle movement and delivered physical assistance only when needed. Assistance was reduced over time to encourage independent control. After training, participants showed significant improvements in over ground walking speed and in clinical mobility scores such as the Dynamic Gait Index (DGI) and the Timed Up and Go (TUG). These gains were still present six months later, which demonstrates both successful transfer and long term retention.

These findings show that transfer is possible, but there exists a deeper question: why does transfer succeed or fail?

3.2 Barriers to Transfer: a neuroscientific perspective

Research shows that transfer is often specific and limited. For example, the characteristics of the training environment influence how well a skill transfers (Smith & Vela, 2001), performance can decline when testing takes place in an environment that differs from the one used during training (Kim, Schweighofer & Finley, 2019). This behavioral limitation observed in transfer has a neural basis.

From a neuroscientific perspective, transfer of motor learning depends on how the brain encodes and consolidates motor skills (Krakauer et al., 2019). The brain uses several parallel encoding strategies, such as coordinate-frame encoding, effector transfer and effector-independent representations. Each strategy has a distinct representation in the neural system and supports different demands of motor learning. For coordinate frame encoding strategy, studies suggest that visuomotor adaptation relies on an extrinsic coordinate frame who relative to the outside world, whereas force-field adaptation adaptation is more intrinsic, relative to the body’s own joints and muscles (Krakauer et al., 2000 ; Shadmehr et Moussavi, 2000). Because these coordinate frames differ, transfer tends to be constrained and difficult to generalize across tasks. Effector-independent representations is another encoding strategy. Instead of representing the specific kinematics of each movement element, it encodes the order in which actions should be selected. This allows improvements to transfer to other effectors, such as the opposite hand, or to novel but structurally similar sequences (Grafton et al., 2002). This pattern of generalization suggests that abstract and effector-independent representations provide a more flexible and broadly applicable solution to our brain.

Besides, motor learning is organized into several core stages, including goal selection, action selection, and action execution. Different learning mechanisms, such as adaptation, sequence learning, de novo learning, and improvements in motor acuity, primarily target one or more of these stages. These mechanisms depend on distinct neural subsystems and therefore lead to different types of skills, each with its own speed of acquisition, capacity for transfer and retention profile. For example, motor adaptation relies heavily on the cerebellum (Cullen & Brooks, 2015 ; Shadmehr et al., 2010). Cerebellum-dependent implicit adaptation is often viewed as a temporary adjustment that is short-lived and reversible, which limits the transfers to new contexts.

Overall, the brain's multiple learning systems impose limits on how far a skill can transfer. These limits interact with the structure of the training environment, which will be examined from an HCI perspective in the following section.

3.3 From Barriers to Opportunities : A Human–Computer Interaction (HCI) Perspective

A human–computer interaction perspective helps clarify how design choices in AI-assisted training systems can shape, and sometimes constrain, the conditions under which motor skills are learned and later transferred.

One major barrier is oversimplification. Many AI-based training systems rely on simplified or selectively emphasized sensory cues to reduce cognitive load and facilitate early performance gains. However, from the perspective of distributed cognition (Hollan, Hutchins & Kirsh, 2000), skilled performance emerges from the coordination between internal resources and external structures. This implies that altering or impoverishing the external structures during AI-supported training changes the informational constraints under which skills are learned. Consequently, the learner acquires motor skills that are adapted to the simplified environment but fail to generalize when the external cues or task dynamics differ in real-world settings.

A second barrier is over-assistance. Ronsse et al. (2011) showed that participants who received continuous visual feedback during a bimanual coordination task became strongly dependent on the guidance. Once the feedback was removed, their performance dropped sharply. The fMRI data further confirmed a shift toward reliance on external cues. Although this system does not involve AI, it illustrates a general principle highly relevant to AI-supported training : overly frequent or precise guidance reduces learners' autonomy and suppresses engagement in internal error detection and correction. This limits error-based learning, which is a central mechanism supporting long-term retention and generalization. This pattern echoes Bainbridge's 'Ironies of Automation' (Bainbridge, 1983), which emphasizes that excessive external support erodes human competence by removing the very opportunities needed to maintain independent skill. Over-assistance can also reduce the learner's sense of agency. When learners begin to attribute successful performance to the AI rather than to their own abilities, their self-efficacy decreases. This reduced confidence makes them less willing to attempt movements independently, thereby limiting further transfer to real conditions

Finally, a third barrier concerns system design processes. A recent review of AI-driven virtual rehabilitation platforms found that most studies did not involve patients or clinicians in the co-design of the training interface (Abedi et al., 2024). Limited involvement of users during design can reduce usability, personalization, and engagement. These are crucial factors for both learning and transfer.

Overall, these findings suggest that transfer failures often arise not from insufficient learning, but from mismatches between the informational, assistive, and interactional conditions present during training and during real-world performance.

IV. Conclusion and Perspective

With support of theoretical and empirical findings, we can conclude that AI supported training can significantly enhance motor skill acquisition. While certain neural constraints exist, effective transfer remains possible, particularly when systems are well designed from a HCI perspective.

Perspective: From Transfer to Transformation: Human–AI Co-Adaptation

What we discussed focuses on transfer because we assume that a person should perform what they learned without help in the real world. However, recent work suggests that human performance in AI-supported contexts may be better understood through the vision of co-adaptation. A recent study on personalized exoskeleton assistance used a logistic regression model to determine the control law that produced the greatest reduction in metabolic energy expenditure. The entire optimization ran on the exoskeleton's microcontroller, allowing real-time optimization in real-world settings such as public sidewalks (Slade et al., 2022). Such findings suggest that the concept of transfer changes: instead of learning a skill alone and then performing independently, the human and the AI system learn to work together and to create an interaction loop. This is described as human–AI co-adaptation.

In conclusion, current evidence shows that AI-assisted systems can meaningfully enhance motor learning, yet the conditions under which these gains generalize remain tightly constrained by the mechanisms and environments in which they are acquired. As AI technologies continue to evolve, rather than viewing transfer as the ultimate benchmark of success, future work may need to consider how humans and AI systems learn to adapt to one another, how control and autonomy should be negotiated, and how training environments can be designed to support these new forms of partnership. Addressing these questions will require theoretical and methodological contributions from neuroscience, HCI, and motor learning research. The future challenge is not only to improve performance, but also to understand what it means to learn and to perform in a world where human skill and artificial assistance are increasingly intertwined.

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