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A Second-Order Adaptive Social-Behavioural Model for Individual and Duo Motor Learning

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Abstract. This paper addresses computational analysis by psychological knowledge in motor learning of how people with certain personalities, alone and in pairs, are being influenced by several factors during their motor learning processes. To this end a second-order adaptive network model was designed for the social and behavioural processes involved. Example simulations show how the model fits to different situations. Mathematical analysis was performed for verification and parameter tuning for validation.

1 Introduction

Motor learning can be regarded as a broad concept that involves many different phenomena, disciplines, and applications. The concept, for example, encompasses great theoretical and experimental interest among neuroscientists, psychologists, and physiologists (Krakauer et al. 2019). It enables humans and animals to gain new skills or it improves the accuracy and smoothness of a physical action (Wolpert and Flanagan 2010). Therefore, motor learning has tremendous practical relevance among babies, injured people who rehabilitate, dancers, musicians, drivers, sporters, or coaches and teachers (Krakauer et al. 2019).

Cano-De-La-Cuerda et al. (2015) propose several factors affecting motor learning. Among others, they mention the relevance of practice and motivation. Implying that the more someone practises or wants to learn something, the better someone gets good at something. These two factors imply a behavioural or psychological and personal influence and that is where the focus will be on in this paper. To build on that, other scientists have proposed related factors that may play a role in the behaviour of people in motor learning as well. Motivation, for example, can be divided into intrinsic and extrinsic motivation, each using different dynamics to influence the performance in the process of motor learning (Benabou and Tirole 2003). Additionally, personal dynamics such as self-confidence or the belief to acquire a certain skill appear to be relevant for motivation levels as well (Benabou and Tirole 2003; Wattie and Baker 2017). Lastly, particularly relevant in sports, different types of learning exist, such as auditory instructions, mental visualisation, or kinesthetically, which imply different behaviours in motor learning as well (Predoiu et al. 2020; Effenberg et al. 2007; Guillot and Collet 2008).

The aim of this research is to contribute to the psychological knowledge in motor learning by helping to understand how people with certain personalities, individually and

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in pairs, are being influenced by several factors during their motor learning process. Two research questions that adhere to this configurative approach are formulated as follows:

1. How do different individual dynamics influence the performance in motor learning of an individual?
2. How do duo dynamics influence the performance in motor learning of an individual?

To answer these research questions, a second-order adaptive mental model is designed. The model contains two persons each having their own mental model. Links between the two models are included to analyse duo dynamics. By means of this model, several scenarios are expounded based on a sports context through which three simulations are proposed that indicate the impact of individual dynamics on the performance in motor learning of an individual, and 2) three simulations are proposed that provide implications on how duo dynamics influence the performance in motor learning of an individual.

In this paper, after the current section, the second section provides a background of relevant literature regarding the main concepts. In the third section, the design of the network model is proposed which constitutes the base model in this paper. In the fourth section, the upper described simulations are presented as results. After that, in section five, verification and validation of the model are discussed. In the final section, a discussion is proposed in which the main findings are discussed, the research question is answered, the strengths and limitations of the paper are addressed and lastly, the implications for further research are provided.

2 Background Literature

This section discusses relevant concepts important in the dynamics of motor learning and provides an explanation and justification on why certain factors are incorporated in the design of the model this research applies.

As Wolpert and Flanagan (2010) imply in their paper, motor learning is about gaining new skills or improving the accuracy or smoothness of a movement. This encapsulation provides a rather simplistic description of what motor learning is about. To deepen the understanding around the concept, some formal definitions will be discussed and compared. Krakauer (2006) and Umphred and Lazaro (2012) both discuss the essentiality of practice. And second, "permanent changes' used by Krakauer (2006) compared to 'makes automatic the desired movement' used by Umphred and Lazaro (2012) both address a similarly long-lasting resolution of the process.

To elaborate on the concept of practice in light of this paper, one type of learning related to this research is used. Reviewed comprehensively by Ridderinkhof and Brass (2015) is Kinesthetic Motor Imaginary (KMI). This is a widely used technique among professional athletes to improve motor performance without overt motor output. This visual type of learning thus "enables one to practice movements without needing to physically perform them" (Ridderinkhof et al. 2002, p. 54).

As is described by Cano-De-La-Cuerda et al. (2015), motivation also plays a significant role in motor learning. Motivation is an explanation of why people perform certain behaviour. It provides reason, for example, to initiate, continue or terminate an action (Wasserman and Wasserman 2020). Benabou and Tirole (2003) discussed the distinction and interrelation between intrinsic and extrinsic motivation. Extrinsic motivation is described as motivation initiated by external rewards (Wasserman and Wasserman 2020; Benabou and Tirole 2003). Comparably, intrinsic motivation is "the individual's desire to perform the task for its own sake" (Benabou and Tirole 2003, p. 490). On top of that, they describe the phenomenon called the 'undermining effect'. This effect means that rewards are often counterproductive because they undermine "intrinsic motivation".

As described by Benabou and Tirole (2003), a concept closely related to intrinsic motivation, and therefore interesting to integrate into this research, is confidence. They describe the relationship as that when people have higher self-esteem they are more motivated to start, continue or terminate certain behaviour. What is interesting, however, is that in the case that confidence reaches too high, this would negatively affect the intrinsic motivation of someone (Benabou and Tirole 2003).

A final compounding factor influencing the dynamics between intrinsic motivation and practice, in order to improve performance in motor learning, is based on the belief that skills are predominantly acquirable and attributes poor performance to a lack of effort or insufficient preparation. This contrasts with the belief of 'inherent ability', which encapsulates that skills are predominantly unchangeable (Wattie and Baker 2017). As we believe skills are acquirable, the model described in the following section incorporates the acquirable skill belief as an influencing factor in motor learning.

Research questions. Based on this background, several sub-questions are formulated which contribute to answering the two research questions proposed in the introduction:

1. How do different individual dynamics influence the performance in motor learning of an individual?

    - To what extent do acquirable skill beliefs influence intrinsic motivation, and what does that imply for the performance in motor learning?
    - How does visualising influence confidence, and what does that imply for the performance in motor learning?
    - To what extent does overconfidence influence the performance in motor learning of an individual?
    - How do intrinsic and extrinsic motivation each influence the performance in motor learning?

2. How do duo dynamics influence the performance in motor learning of an individual?

    - How do different motivation levels in duo-learning influence the performance in motor learning?
    - How does competitiveness influence the performance in motor learning?

3 Method Used

In this section, we will elaborate on our model. We will explain how we have built the model, which decisions we made based on the previous sections, and eventually show the resulting model which we will use for analysis. In the first part of this section, the network-oriented modeling approach used is briefly explained. Next, a one-person model will be explained, and in the last part we will add a second person to this model and we will explain how the persons work together.

The conceptual representation of the causal network model consists of states and connections between the states. These connections can represent a causal impact. It is assumed that the states have activation levels that vary over time. Adaptation of causal relations and other network characteristics are incorporated in the approach too (Treur 2020). The network structure characteristics used are as follows:

Connectivity of the network Connection weights $\boldsymbol{\omega}_{X,Y}$ for each connection from a state (or node) X to a state Y.
Aggregation of multiple impacts A combination function $\mathbf{c}_Y(..)$ for each state Y to determine the aggregation of incoming causal impacts.
Timing in the network A speed factor $\boldsymbol{\eta}_Y$ for each state.

In Table 1 the combination functions used are explained. The way in which these network characteristics define the dynamics of a network model is explained as follows.

$$\begin{aligned}\mathbf{impact}_{X_i,Y}(t) &= \boldsymbol{\omega}_{X_i,Y}X(t)\\ \mathbf{aggimpact}_Y(t) &= \mathbf{c}_Y(\mathbf{impact}_{X_1,Y}(t),\ldots,\ \mathbf{impact}_{X_k,Y}(t))\end{aligned} \tag{1}$$

Here $X_1,\ldots, X_k$ are the states from which state Y gets incoming connections. This is assembled in the following canonical differential equation used for all states:

$$\mathrm{d}Y(t)/\mathrm{d}t = \boldsymbol{\eta}_Y\,[\mathbf{aggimpact}_Y(t)\ - Y(t)] \tag{2}$$

This differential equation can be rewritten into difference equation format to determine the state values with regard to the change in time Δt:

$$\begin{aligned}Y(t+\Delta t) &= Y(t) + \boldsymbol{\eta}_Y\,[\mathbf{aggimpact}_Y(t)\ - Y(t)]\Delta t\\ &= Y(t) + \boldsymbol{\eta}_Y\,[\mathbf{c}_Y(\boldsymbol{\omega}_{X_1,Y}X(t),\ \ldots.,\ \boldsymbol{\omega}_{X_k,Y}X(t)) - Y(t)]\Delta t\end{aligned} \tag{3}$$

Moreover, self-model states (also called reification states) were added to the network to make some of the network characteristics adaptive. For this model, these self-model states are of type $\mathbf{W}_{X,Y}$ and $\mathbf{H}_{X,Y}$. The $\mathbf{W}$-states $\mathbf{W}_{X,Y}$ are first-order self-model states; they represent their corresponding connection weight $\boldsymbol{\omega}_{X,Y}$. These states are used for plasticity by Hebbian learning (Hebb 1949; Shatz 1992). Additionally, in this model there are five second-order self-model states $\mathbf{H}_{\mathbf{W}_{X,Y}}$ representing the timing (speed factor) characteristic $\boldsymbol{\eta}_{\mathbf{W}_{X,Y}}$ for the mentioned first-order self model states $\mathbf{W}_{X,Y}$. Adding these speed factors allowed for determining the moment when each of the learning activities would take place. In this way, metaplasticity (Abraham and Bear 1996) of the model was ensured.

Table 1. Combination functions used

Name	Description	Formula	Parameters	Used for
id(V_1, …, V_k)	Identity function	V_1	-	X_6, X_{14}, X_{18}
comp-id(V_1, …, V_k)	Complementary identity function	1- V_1	-	X_7, X_{11}, X_{19}, X_{23}
ssum$_\lambda$(V_1, …, V_k)	Scaled sum	$(V_1 + \cdots + V_k)/\lambda$	Scaling factor λ	X_1, X_2, X_4, X_5, X_{13}, X_{16}, X_{17}
alogistic$_{\sigma,\tau}$(V_1, …, V_k)	Advanced logistic sum	$[\frac{1}{1+\mathrm{e}^{-\sigma(V_1+\cdots+V_k-\tau)}} - \frac{1}{1+\mathrm{e}^{\sigma\tau}}](1+\mathrm{e}^{-\sigma\tau})$	Steepness σ Threshold τ	X_3, X_9, X_{15}, X_{21}
hebb$_\mu$(V_1, V_2, W)	Hebbian learning: positive weights	$V_1V_2(1-W) + \mu W$ V_1,V_2 activation levels of connected states; W activation level of **W**-state	Persistence factor μ	**W**-states X_{12}, X_{24}
hebbneg$_\mu$(V_1, V_2, W)	Hebbian learning: negative weights	$-V_1(1- V_2)(1+W) + \mu W$ V_1,V_2 activation levels of connected states; W activation level of **W**-state	Persistence factor μ	**W**-states X_{10}, X_{22}
stepmod$_{\rho,\delta}$(…)	Repeated activation	1 if t mod $\rho \geq \delta$, else 0 (time t)	Repetition ρ Duration δ	X_8, X_{20}

A total of 12 states are used in the second-order model for one person, thereby using seven different combination functions for them as shown in Table 1, last column. The full specification of the connections, weights, speed factors, and combination functions can be found in the tables in the Appendix available as Linked Data at URL https://www.researchgate.net/publication/357648578.

The central aspect in our model is the performance (X_6) in motor learning of the person. As mentioned before, the amount of practice is important for performance. Therefore, a state is added which represents the practice (X_5). This state has a connection to the performance and an incoming connection from motivation (X_4). This is the state which represents the general amount of motivation a person has in this particular skill, and it is dependent on two different types of motivation.

At first, there is extrinsic motivation (X_2), which is motivation coming from external rewards. Secondly, there is intrinsic motivation (X_3), which is the direct satisfaction this particular skill brings to the person. Both of these motivations connect to motivation, and there is a connection from extrinsic to intrinsic motivation as well. This is the previously mentioned undermining effect, therefore this connection has a negative weight. Extrinsic motivation has a direct incoming connection from performance, the higher the performance the more extrinsic motivation there is. Intrinsic motivation has an incoming connection from confidence (X_1), which in turn has an incoming connection from performance. There are three other states to be mentioned. At first, there is acquirable skill belief (X_7). This state has an incoming connection from performance, but it is inversely proportional to it. The worse the performance is, the more there is to gain in this particular skill. And when the performance is at its highest, there is no skill to be acquired anymore. This acquirable skill belief has a direct connection to intrinsic motivation. There is also a state representing visualising (X_8). This is a context state which can be either turned on or off, and it influences both confidence and practice directly. Lastly, there is a state representing overconfidence (X_9), which only activates when confidence becomes too low. It represents the general idea of overconfidence, where too much confidence can cause the person to be lazy and therefore less motivated.

Lastly, there are a few self-model states of first- and second-order. There is a first-order self-model **W**-state (X_{10}) which represents a Hebbian learning process for the negative connection from extrinsic motivation to intrinsic motivation. It uses the negative Hebbian function **hebbneg**, which makes that the weight becomes stronger negative over time when extrinsic motivation is high while intrinsic motivation is low. A higher-order self-model $\mathbf{H_W}$-state (X_{12}) manages the speed of this **W**-state. The more performance someone has at a particular motor learning skill, the harder it becomes to improve upon this skill. Therefore, a first-order self-model **H**-state X_{11} was added which is the inverse of the performance and controls the speed factor of performance.

All states with only one incoming connection use an id function. Confidence, motivation and practice use a scaled sum function, while intrinsic motivation and overconfidence use an alogistic function. Overconfidence has a high steepness and threshold value, it should not increase immediately but it should increase fast. Table 2 contains an overview of the states for the one-person model with their explanations.

Table 2. States of the single person model with their explanation.

State	State name	State explanation
X_1	C1	Confidence of the person
X_2	EM1	Extrinsic motivation of the person
X_3	IM1	Intrinsic motivation of the person
X_4	M1	Weighted average of the motivation
X_5	Pr1	(Amount and type of) Practice of the person
X_6	Pe1	Performance of the person
X_7	Asb1	Acquirable skill belief of the person
X_8	V1	Visualizing
X_9	O1	Overconfidence of the person
X_{10}	$\mathbf{W}_{EM1,IM1}$	First-order self-model state for the weight of the connection from X_2 (EM1) to X_3 (IM1)
X_{11}	$\mathbf{H}_{Pe1}$	First-order self-model state for the speed factor of X_6 (Pe1)
X_{12}	$\mathbf{H}_{\mathbf{W}_{EM1,IM1}}$	Second-order self-model state for the speed factor of X_{10} ($\mathbf{W}_{EM1,IM1}$)

For the two-person model, context states will be used for the second person. The two context states represent the second person's intrinsic motivation and performance. The second person's intrinsic motivation influences the intrinsic motivation of the first person, and the second person's performance influences both the intrinsic and extrinsic motivation of the first person.

A total of 14 states are used in the second-order model, and seven combination functions are used. A full overview of the model can be seen in Fig. 1, and the values used for the connections, weights, speed factors and combination functions can be seen in the tables in the Appendix (Linked Data) at https://www.researchgate.net/publication/357648578. The speed factors and combination function variables remain the same compared to the single-person model.

In next section, we will investigate this model, show the base result and answer the research questions.

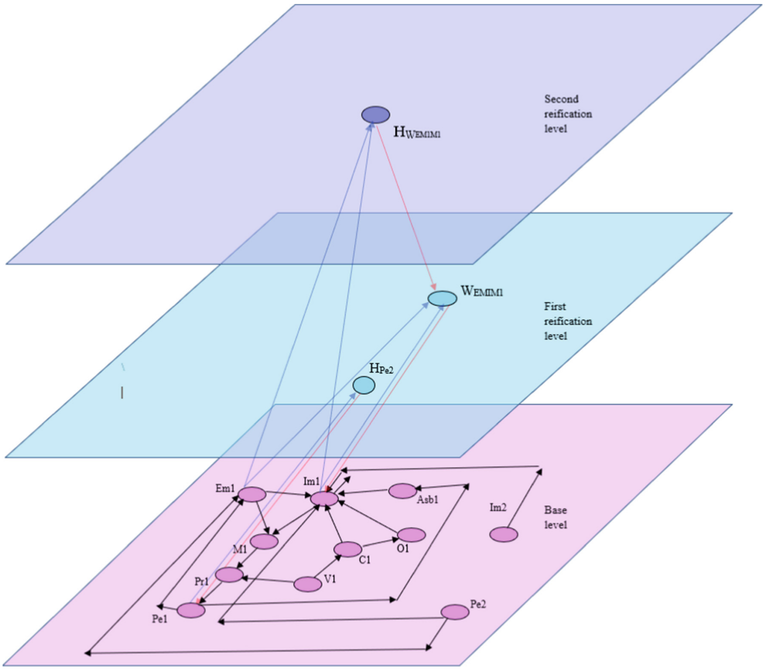

Fig. 1. 3D figure of the connectivity of the full two-person model.

4 Simulation Results

In Fig. 2 the base of the single-person model is shown; in such graphs, time *t* from formulaa (1), (2), (3) is on the horizontal axis and activation level *Y(t)* on the vertical axis. This is the result of running the model with the parameters shown in the tables in the Appendix available as Linked Data at https://www.researchgate.net/publication/357648578. All values are initially 0.5, except for X_9 (overconfidence) and all higher-order states, which are all initially 0. The state for performance, X_6, initially increases to around 0.9, and after a few timesteps, it converges to a value of around 0.85.

That the value is going up and down for a while is due to some factors. At some point, it is going down because X_9 (overconfidence) increases. Moreover, X_3 (intrinsic motivation) decreases because the strength of the connection between X_2 (extrinsic motivation) and X_3 increases due to Hebbian learning, and X_2 itself is also increasing.

Performance still converges at a high value due to an increase of intrinsic motivation, which is caused by a stabilising X_7 (acquirable skill belief). This effect of acquirable skill belief can be seen in Fig. 3, upper graphs. Two graphs are shown wherein the graph on the left everything is initially set to 0, and in the graph on the right, there is no effect of acquirable skill belief. This means that X_7 does not have an effect on intrinsic motivation. The connection weight value from X_7 to X_3 is put to 0, and a decrease in performance can be noticed in the graph. On the other hand, overconfidence has a negative effect on performance. This can be seen in Fig. 3, left under. In this scenario, X_9 does not have an effect on intrinsic motivation anymore which eventually leads to an increase of performance in comparison with the base model.

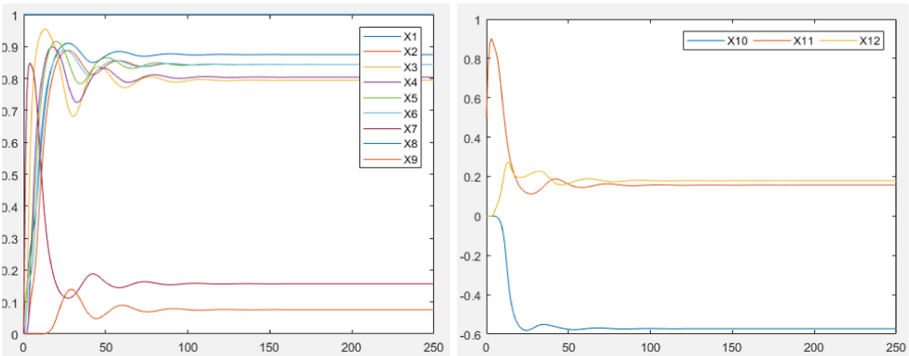

Fig. 2. Base model simulation for base states (left) and self-model states (right).

In all the above-mentioned scenarios, X_8 (visualising) is set at a constant value of 1. To which puts visualising at 1 between time points 100 and 300, and otherwise at 0. The result of this model can be seen in Fig. 3 lower right, where we can clearly see that visualising has a positive effect on performance.

Motivation, both intrinsic and extrinsic, have an important influence on the model. Different ratios of intrinsic and extrinsic motivation do influence the model. In the base model, motivation has a ratio of 80% intrinsic and 20% extrinsic motivation, as we assumed this person values intrinsic motivation more than extrinsic motivation. In Fig. 3 we experimented with two other ratios. In the first figure, motivation is 100% intrinsic motivation, and in the third figure motivation is 100% extrinsic motivation. From the figures, we can see that the performance is better when extrinsic motivation has a higher share. This is due to the fact that extrinsic motivation has a negative effect on intrinsic motivation. Therefore, when performance is at its highest, extrinsic motivation will also be high, causing intrinsic motivation to decrease. There is no negative influence on extrinsic motivation, so when motivation only consists of extrinsic motivation, both performance and extrinsic motivation will eventually rise to a value of 1.

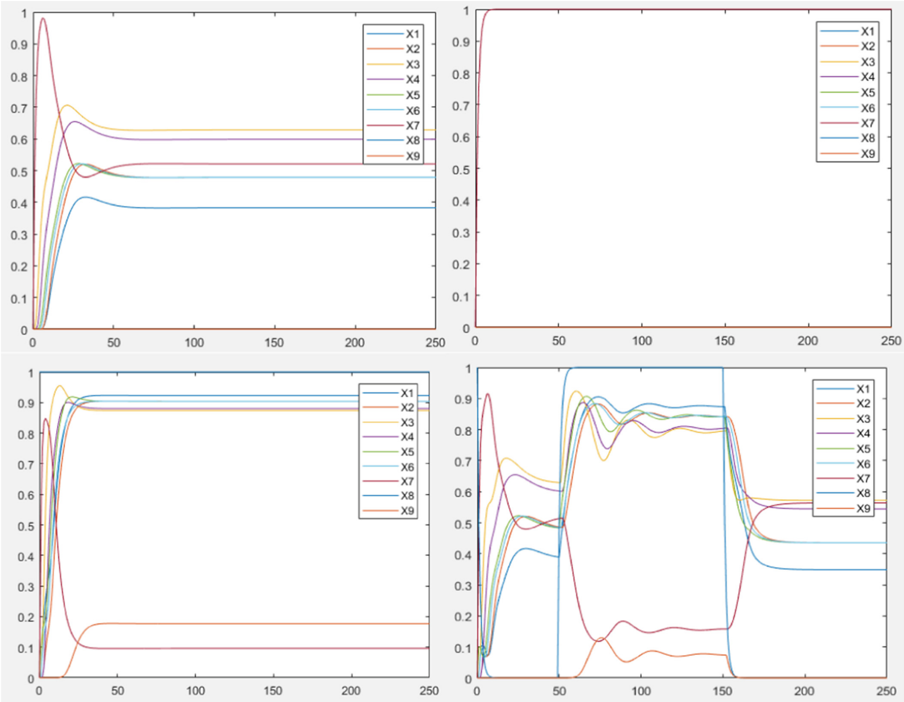

Fig. 3. Upper graphs: effect for removing acquirable skill belief when everything is initially 0. Lower left: without the effect of overconfidence. Lower right: effect of visualising

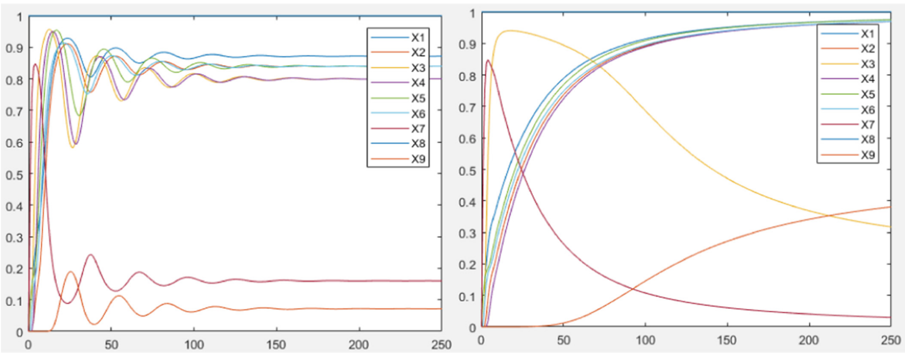

Fig. 4. Left: Motivation = 100% intrinsic motivation. Right: Motivation = 100% extrinsic motivation

That extrinsic motivation has a negative effect on intrinsic motivation is due to the previously mentioned undermining effect. The strength of this effect can be seen in Fig. 5. Here extrinsic motivation has more influence on intrinsic motivation. To be precise, in the model we lowered the weights of all incoming connections of intrinsic motivation, except for extrinsic motivation. It can be seen that a higher undermining effect causes a worse overall performance.

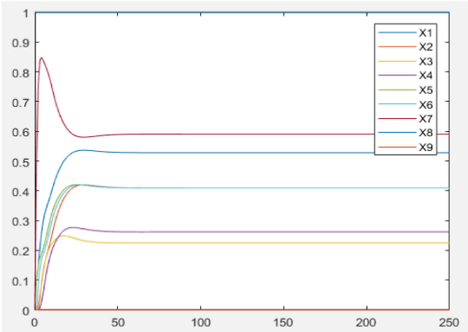

Fig. 5. Extrinsic motivation has more influence on intrinsic motivation

We also created a model for the two-person scenario, with the context states described in the previous section. Figure 6 shows the result of running the simulator of person 1, where every value is initially 0 and the weight values of the connections from the context states are also 0. This figure represents the base model and we will build upon this model. In the first experiment, we investigate how a strong connection from the context states to person 1's intrinsic motivation influence its performance, and this will represent the "friend" model. In Fig. 7 on the left, we see what happens in that case if both context states, performance and intrinsic motivation, are high, and in Fig. 7 on the right, we see what happens if only performance is high and intrinsic motivation is low. There is a clear difference in performance, where the first case has a higher performance.

In our second experiment, we show how a strong connection from the context's performance state to person 1's extrinsic motivation influences person 1's performance. This represents the "rival" model, where the person is only extrinsically motivated by the other person's performance. Here we investigate two cases where we make a difference between how important extrinsic and intrinsic motivation is for person 1. We do this by changing the weights of extrinsic and intrinsic motivation to the motivation of person 1. In the first case it is the same as the base model and the result can be seen in Fig. 8 on the left, in the second case we switch the ratio to 80% extrinsic motivation and 20% intrinsic motivation and the result can be seen in Fig. 8 on the right. In this competitive setting, it is clearly visible that the performance is higher when extrinsic motivation is more important.

Finally, we look into what a balance in connections can do for a person's learning. All the connections from the context states are now activated and both context states are set to 1. Moreover, motivation now is 50% extrinsic and 50% intrinsic motivation and the result of this model can be seen in Fig. 9. In comparison with all other models of the simplified 2 person model, this one scores the best.

The models, for both the single and two-person models, show interesting results which give an insight into how different aspects influence a person's motoric learning ability. In the next section, we will use these results to answer our research questions.

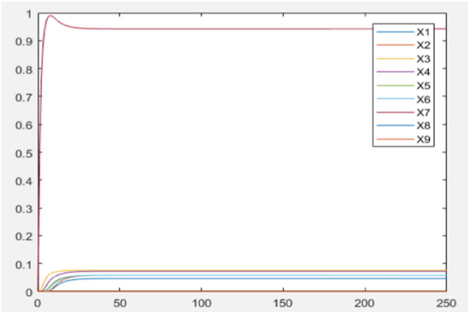

Fig. 6. Base result simplified two-person model

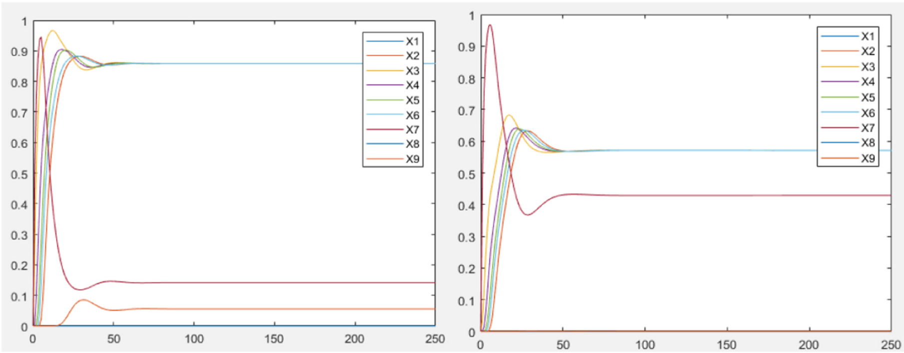

Fig. 7. Friend model, Left: second person high intrinsic motivation, Right: second person low intrinsic motivation.

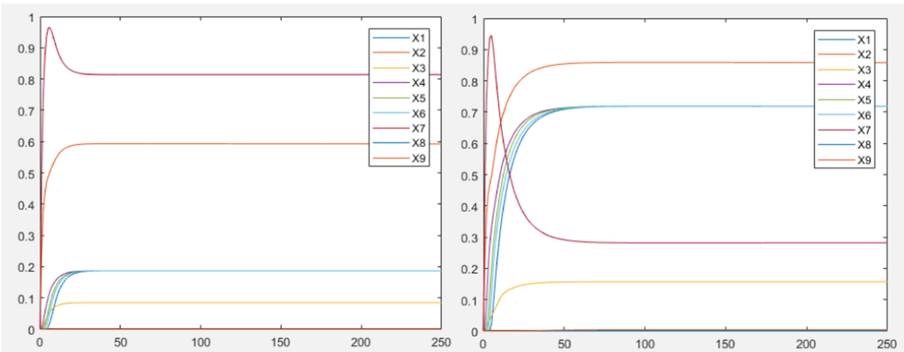

Fig. 8. Competitive model, Left: Intrinsic motivation is more important to person 1, Right: Extrinsic motivation is more important to person 1.

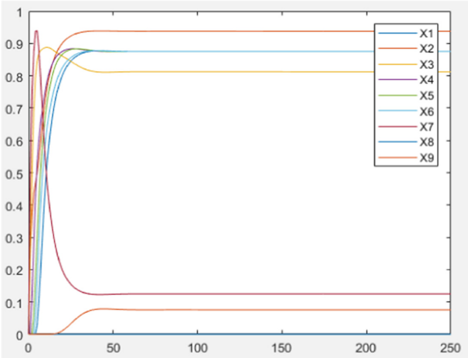

Fig. 9. Competition and cooperation are both important for person 1.

5 Verification and Validation of the Model

This section is meant for the verification of our model. At first, the model is analysed mathematically, where we verify that the stationary points are as expected. Secondly, we generate our own data based on the literature and tune several parameters to fit our model to the data.

For mathematical verification, a state Y has a stationary point if $\mathrm{d}Y(t)/\mathrm{d}t = 0$. According to (1) and (2), this is equivalent to the following criterion:

$$\boldsymbol{\eta}_Y = 0 \quad \text{or} \quad \mathbf{c}_Y(\boldsymbol{\omega}_{X_1,Y}X(t),\ \ldots.,\ \boldsymbol{\omega}_{X_k,Y}X(t)) = Y(t) \tag{4}$$

For the mathematical analysis, we looked at the one-person model and see whether the resulting model is accurate. We took the final time point, namely 400, as the stationary point for all states, because it is clearly visible that all states do not change anymore. To calculate the aggregated impact for the states, per state we summed over all the weighted incoming connections and used that value as input for the combination function of the state. The formulas used can be seen in Table 1. The result of this for every base state can be seen in Table 2. For all states, we get a correct aggregated impact with an accuracy of $<10^{-4}$. We also did the analysis on the two-person model, and this result can be seen in Table 3. Again, the accuracy for all states is $<10^{-4}$.

For the validation by parameter tuning, we used the one-person model. We could not find data online we could use, so we generated our own data based on scores for results found in the literature. In our data, we will take several factors into account. At first, the intrinsic motivation is increased due to a high acquirable skill belief (Wattie and Baker 2017).

This increase in motivation will also increase performance (Wasserman and Wasserman 2020), though it will increase slower. With the performance increasing, two things will happen. Firstly, due to the performance increase, extrinsic motivation will also increase. This will cause an undermining effect, which will decrease intrinsic motivation (Benabou and Tirole 2003, p. 490). Moreover, the confidence will increase at such a level that its effect on intrinsic motivation will be less, or even make it decrease (Benabou and Tirole 2003). But eventually, the model will find a stationary point where the

Table 3. Aggregated impact for all base states in the single person model, with their accuracy.

State X_i	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9
Time point t	400	400	400	400	400	400	400	400	400
$X_i(t)$	0.8747	0.8434	0.7945	0.8043	0.8434	0.8434	0.1566	1	0.0755
$\text{aggimpact}_{X_i}(t)$	0.8747	0.8434	0.7945	0.8043	0.8434	0.8434	0.1566	1	0.0755
deviation	$<10^{-4}$	$<10^{-4}$	$<10^{-4}$	$<10^{-4}$	$<10^{-4}$	$<10^{-4}$	$<10^{-4}$	$<10^{-4}$	$< 10^{-4}$

performance will still have increased. The resulting data can be found in the mentioned Appendix.

The parameters which were tuned are all (non-adaptive) speed factors, the weights of the incoming connections of intrinsic motivation, the combination function parameters of intrinsic motivation, and the Hebbian function parameter. All initial values are set to 0 and visualising has no effect on confidence and practice. We ran the simulated annealing algorithm, and after 7000 iterations the best RMSE was 0.08793. An overview of the parameters with their values can be seen in the Appendix, and the resulting model can be seen in Fig. 10.

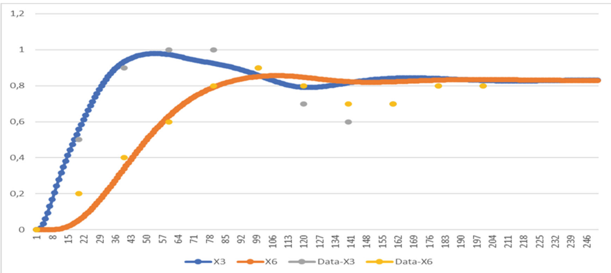

Fig. 10. Simulation of the model with the tuned parameters.

The fit is decent, but it is not as curvy as was expected in the data. The differences between the chosen values for the parameters and the values we used in the previous sections are mostly visible in the speed factors and alogistic parameters. Firstly, almost all speed factors are much lower, except for confidence and the second-order state for the Hebbian weight between extrinsic motivation and intrinsic motivation. Secondly, the values for the alogistic parameters of intrinsic motivation are completely different, the steepness almost doubled and the threshold is much lower. This has also caused the incoming connection weight values for intrinsic motivation to be lower than our original model. Finally, there is a difference in the Hebbian parameter. It has increased causing the weight of the connection from extrinsic to intrinsic motivation to be higher.

6 Discussion

The aim of this research was to contribute to the psychological knowledge in motor learning by helping to understand how people with certain personalities, alone and in pairs, are being influenced by several factors during their motor learning process. This was done by addressing several research questions. In this section, these questions are addressed and answered by means of a discussion based on our results. Subsequently, we reflect on our choices and results and give several options for future research.

First of all, with regard to individual motor learning, we did observe a difference in performance when acquirable skill belief is mitigated, namely the performance will decrease. However, the biggest difference can be seen when every other value is initially set to 0. Then we can really see the effect of acquirable skill belief, which makes a lot of sense. When everything is initially low, there is a lot of skill to be acquired. And when the person believes in this acquirable skill, it will motivate him or her to practice.

In addition, visualising appears to have a positive effect on confidence. Moreover, it also positively affects practice, and both these effects cause an increase in performance. In our results, we however do not observe a long-term influence of visualising. When visualising increases we see a clear increase in performance, but when visualising decreases again the performance decreases to its previous value.

Regarding overconfidence, this has a negative effect on performance. Confidence definitely is beneficial for the performance, however, when there is too much confidence, a negative influence on performance is established. Though there is a negative influence of overconfidence, this influence is rather small.

To continue, intrinsic and extrinsic motivation both have a positive influence on performance. However, due to the undermining effect, extrinsic motivation also has a negative effect on intrinsic motivation and therefore a small negative effect on performance. In the results, we can see this clearly. When we totally mitigate the effect of intrinsic motivation on motivation, the performance of the person increases. This is because there is no negative effect of extrinsic motivation on performance anymore. Moreover, when extrinsic motivation has a bigger influence on intrinsic motivation, making the undermining effect more prominent, this clearly has a negative effect on the performance.

Regarding the influence of duo learning on the performance of an individual; the best motivation level of a person in duo learning depends on the setting. In a teamwork setting, the person performs best when the other person is not only performing well but motivated as well. This is a nice representation of how empathy works, where a person performs well when it feels that the other is intrinsically motivated. In a competitive setting, where the person is solely motivated by performing better than the opponent, the best mindset is also a competitive mindset. There is no intrinsic motivation to be gained by the other person performing well, and getting the motivation only from extrinsic motivation will then increase the performance.

From the results, we can also conclude that a person thrives when there is a balance of competitiveness and cooperation. As previously mentioned, in a competitive setting a competitive mindset does perform better than a non-competitive mindset. But the performance is still worse than when the people are cooperating well. The best performance can be achieved when there is cooperation, but also including some competitiveness. This competitiveness is needed to keep the person on edge to perform better.

Altogether, the performance in motor learning on an individual is influenced by several individual dynamics. The acquirable skill belief appears to have influence when everything is initially zero, as when the person believes in this acquirable skill, it will motivate him or her to practice and therefore increase the performance in motor learning. Regarding visual learning, it appears to have an influence on confidence and practice and therefore increases the performance in motor learning. However, no long-term influence was indicated. To continue, too much confidence seems to have a small negative effect on the performance in motor learning. Lastly, both intrinsic and extrinsic motivation have a positive influence on performance. However, due to the undermining effect, extrinsic motivation also has a negative effect on intrinsic motivation and therefore a small negative effect on performance. On top of that, the performance in motor learning of an individual is also influenced by several duo dynamics. In a teamwork setting, the individual performs best in motor learning when the other person is not only performing well but also motivated. In a competitive setting, where the person is solely motivated by performing better than the opponent, the best mindset to reach the highest performance in motor learning is a competitive mindset. Lastly, someone's performance in motor learning thrives when there is a balance between competitiveness and cooperation.

To briefly reflect on this research, a non-adaptive state is used to incorporate the influence of the acquirable skill belief on the performance in motor learning. However, by doing this, the state of acquirable skill belief increases immediately without any performance, because this is modelled as such. By making the state adaptive, the acquirable skill belief remains zero at the beginning of the simulation, resulting in a more realistic representation. Future research could explore this line of thought.

In addition, this research incorporated several factors of influence regarding the performance in motor learning. However, many other factors of influence exist. To name a few social factors, the way someone gets instructed or how someone receives feedback might be important. But also the memory of someone or the possibility of errors with regard to the motoric activity are valuable for consideration (Cano-De-La-Cuerda et al. (2015). Further research could focus on enhancing the breadth of this model by incorporating those factors of influence as well. Moreover, further research could also centre its attention towards a deeper understanding of the factors which are incorporated. Extrinsic motivation, for example, is not just influenced by the performance of him or herself, or of someone else. The extrinsic motivation assumingly is, for example, also influenced by the type of reward someone gets offered. Lastly, this research indicated that it is quite difficult to compare the single-person model with the two-person model, as both models are distinguishable. Further research may also focus on designing an integrated model which enables a comparison of both.

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