Capturing complex processes of human performance

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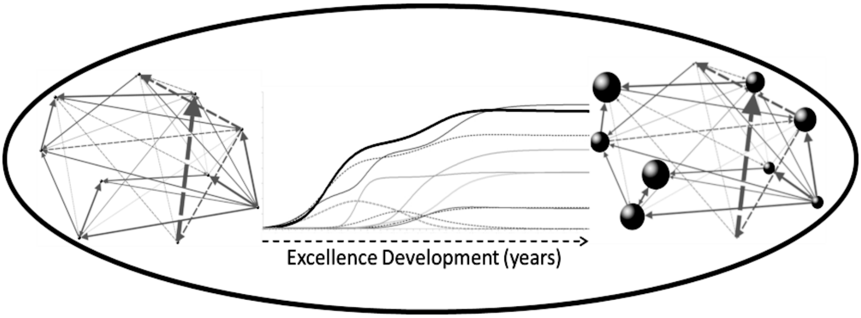
Chapter 6: Excellent Performance Likely Emerges Out of Dynamic Network Structures



This chapter is an adapted version of:

Van Geert, P. L. C., Den Hartigh, R. J. R., Steenbeek, H. W., & Van Dijk, M. W. G. (2014). *The* development of excellent human performance: A dynamic network model. Manuscript submitted for publication.

Abstract

For over a century, there exists an ongoing debate about the mechanism(s) explaining the development of excellent human performance. In the current chapter we demonstrate that excellence is likely to emerge out of individual dynamic network-structures. The nodes consist of personal and environmental variables relating to a particular ability domain, and the connections are supportive or competitive effects of one variable on another. The network model we propose predicts typical developmental properties such as idiosyncratic routes to excellence, and predictive indicators of later ability, the reliability of which increases with age. In addition, the model accurately predicts the highly right-skewed distributions of productivity across the population, which occur in virtually any achievement domain (e.g., publications of scientists, medals won by athletes, etc.). Finally, we illustrate how the model can be fine-tuned to generate plausible predictions in the domain of sports (i.e., soccer and tennis). The finding that excellence likely emerges from individual compositions of dynamic networks has implications for future approaches to the detection and stimulation of excellence in different achievement domains.

6.1 Introduction

Relatively few people develop excellence, and in rare instances individuals reach exceptional levels of success, such as Albert Einstein, Mozart, and Roger Federer. Excellence refers to domain-specific superiority, and is a topic that has been extensively studied in the domains of science, music, technological creativity, and sports (e.g., Ericsson & Charness, 1994; Howe, Davidson, & Sloboda, 1998; Kaufman, 2013; Macnamara et al., 2014; O'Boyle & Aguinis, 2012; Simonton, 1999, 2001). Ever since the topic was introduced, debate has existed on the origins of excellence. This debate already started in the 1860s, when Galton published his work on the genetics of genius, claiming that excellent performers are born (Galton, 1869). In 1873, following Galton's work, De Candolle wrote a book in which he stated that environmental resources (e.g., family, education, facilities) are the major factors explaining the development of excellence (De Candolle, 1873). In addition to these classical nature and nurture points of view, Ericsson and colleagues demonstrated more recently that prolonged and intensive practice, often more than 10 years, is necessary to reach excellent levels of performance (e.g., Ericsson, 2006; Ericsson & Charness, 1994; Ericsson et al., 1993).

While the debate on the exact role of nature and nurture continues (e.g., Detterman, 2014; Kaufman, 2013), most researchers agree that all such factors (genetic endowment, tenacity, parental support, help from coach or teacher, practice, etc.) contribute to the development of excellence (e.g., Abbott, Button, Pepping, & Collins, 2005; Abbott & Collins, 2004; Barab & Plucker, 2002; Gagné, 2004; Elferink-Gemser, Jordet, Coelho-E-Silva, & Visscher, 2011; Hambrick & Tucker-Drob, in press; Howe et al., 1998; Kaufman, 2013; Phillips et al., 2010; Simonton 1999, 2001, 2003; Vaeyens, Lenoir, Williams, & Philippaerts, 2008). However, how the different factors actually combine to shape excellence over time remains unknown. In the current chapter, we focus on the underlying model principles that explain, and predict, some major properties of excellence. That is, rather than attempting to determine the specific contribution of factors related to excellence across the population, we will focus on the kind of (generic) model that gives rise to typical characteristics of excellence as they are found in different achievement domains. We will propose that excellence is likely to emerge out of idiosyncratic networks of connected personal and environmental variables that are in continuous interaction. In addition, we will demonstrate how the network model can be fine-tuned to fit with a specific performance domain, namely sports.

Properties of Excellence Development

The emergence of excellence covers a developmental range from the moment that a domain-specific ability starts to grow (i.e., beginner level) until the point that superior performance is (repeatedly) demonstrated (e.g., Abbott & Collins, 2004; Howe et al., 1998; Simonton, 2001; Phillips et al., 2010). Recent literature stipulates that, across achievement domains, the developmental trajectories leading to excellence are characterized by a number of qualitative properties (for an overview, see Simonton, 2001). First, in different individuals a similar ability can emerge at different ages, evidence for which is found in the domains of music (e.g., Howe, Davidson, Moore, & Sloboda, 1995; McPherson & Williamon, 2006; Sosniak, 1985; 1990), arts (e.g., Sloane & Sosniak, 1985), mathematics (e.g., Gustin, 1985), and sports (e.g., Abbott et al., 2005; Abbott & Collins, 2004; Davids & Baker, 2007; Elferink-Gemser et al., 2011; Gulbin, Weissensteiner, Oldenziel, & Gagné, 2013; Phillips et al., 2010; Vaeyens et al., 2008). Second, the underlying constituents of a particular ability can change during the individual's life span (e.g., Abbott et al., 2005; Abbott & Collins, 2004; Davids & Baker, 2007; Elferink-Gemser, Huijgens, Coelho-E-Silva, Lemmink, & Visscher, 2012; Howe et al., 1998; Simonton, 1999, 2001; Phillips et al., 2010). Third, the level of domain-specific ability is not necessarily monotonically rising or stable: Its development can take a variety of forms including gradual, S-shaped, stepwise, and sudden changes (e.g., Abbott et al., 2005; Abbott & Collins, 2004; Dai & Renzulli, 2008; Davids & Baker, 2007; Elferink-Gemser et al., 2011; Gulbin et al., 2013; Simonton, 1999; 2001; Phillips et al., 2010; Simonton, 2000; Vaeyens et al., 2008). Fourth, early indicators of ultimate excellent abilities are often absent, which means that demonstrating better skills than peers at a young age is often weakly related to later excellent abilities (e.g., Abbott et al., 2005; Abbott & Collins, 2004; Ericsson & Charness, 1994; Howe et al., 1998; Phillips et al., 2010; Simonton, 1999, 2001; Vaeyens et al., 2008). In line with the latter three properties, research—particularly in the domain of sports and exercise—has shown that individuals may have diverse ways to achieve similar ability levels, thereby emphasizing the idiosyncratic nature of the pathways to excellence (e.g., Davids & Baker, 2007; Elferink-Gemser et al., 2011; Gulbin et al., 2013; Phillips et al., 2010; Simonton, 2000; Vaeyens et al., 2008).

Validated tests to determine domain-specific excellence hardly exist, and researchers often focus on assumed correlates of a particular ability (e.g., dribbling test-scores of soccer players, Huijgen, Elferink-Gemser, Post, & Visscher, 2009). Here, we proceed from the argument that excellent abilities are domain-specific and that they are manifested in, and measured by, performance accomplishments (Aguinis & O'Boyle, 2014). In many domains (e.g., arts, science, sports, technology, music, etc.), performance accomplishments can be operationalized by individuals' productivity as defined by consensual expert assessment (e.g., Amabile, 1982, 1983, 1996). The consensual assessment technique implies that the quality of human performance can be judged by experts in a particular domain (e.g., reviewers of a research article, coaches of sport teams) and/or based on countable expressions of particular excellent abilities, such as produced scientific articles, musical compositions, and tournaments or medals won in sports (e.g., Aguinis & O'Boyle, 2014; Huber, 2000; O'Boyle & Aguinis, 2012; Simonton, 1999, 2003, 2014). A measure of productivity, based on consensual expert assessment, thus emphasizes what a performer has realized in a particular performance domain, and is a widely used operationalization of excellent abilities. In line with Ericsson and Lehman's (1996) definition of expertise, this measure reflects who displays (or has displayed) consistent superior performance. Productivity is also considered a valid indicator of domain-specific ability in practice, in that it is used as a selection criterion in job interviews, decisions about grant proposals, and national selection of athletes for international competitions. For instance, to select soccer players for the national team before the world cup, the coach will not let players perform a (standardized) test of an assumed soccer-ability correlate. Probably, the coach will select players based on relevant productivity indicators (e.g., number of matches played, number of goals scored).

Previous studies have shown that the distribution of performance productivity across the population is highly right-skewed in virtually any achievement domain (e.g., Huber, 2000; O'Boyle & Aguinis, 2012; Simonton, 1999, 2001, 2003). Earlier studies based on archival data have shown that the relationship between a particular number of products—e.g., medals won in sports, scientific publications in high-impact journals, patent inventions—and the number of individuals generating that number of products, approaches distributions described by power laws or stretched exponentials (e.g., Aguinis & O'Boyle, 2014; Davies, 2002; Huber, 2000; Huber & Wagner-Dobler, 2001; Laherrere & Sornette, 1998; Lotka, 1926; O'Boyle & Aguinis, 2012; Redner, 1998; Sutter & Kocher, 2001). This finding entails that the great majority of performers has few products (often only one), whereas the truly exceptional performers are in the extreme right tail of the asymmetric distribution. As an illustration, Figure 13 displays the distributions of two (historical) datasets, one of which concerns the number of international matches played by Dutch soccer players in the National team (retrieved from Voetbalstats.nl), and the other the number of ATP tennis tournaments won by tennis players (retrieved from ATP Performance Zone). In line with earlier literature, these distributions are highly skewed, and on a natural log-log scale they approach a linear plot (power law) or curved plot (stretched exponential).

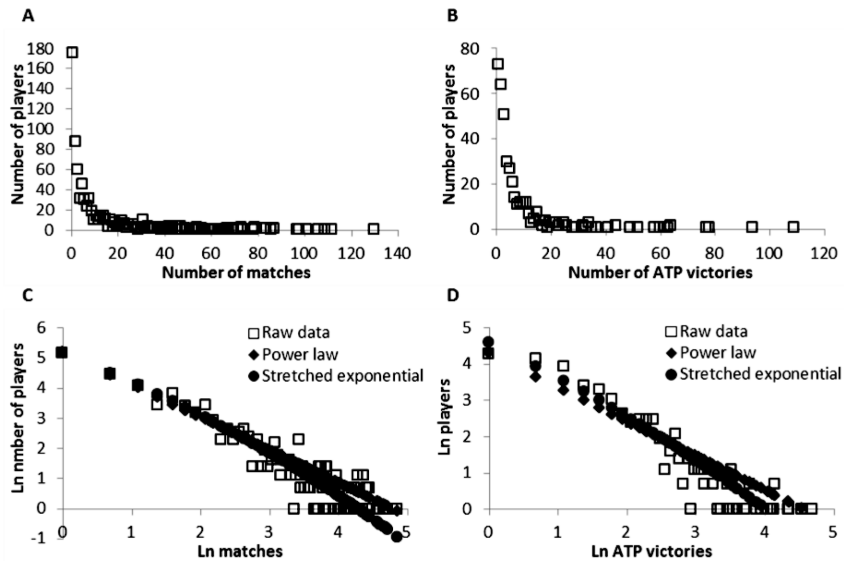


Figure 13. Distributions of the number of international matches a soccer player played in the national team (A), and the number of ATP tennis tournaments won by tennis players (B). The natural log-log plots of these datasets are displayed in Graph C and D.

Towards a Model of Excellent Human Performance

Based on the accumulated knowledge with regard to talent and excellence development, the challenge is to establish a model that is multidimensional (Abbott et al., 2005; Abbott & Collins, 2004; Barab & Plucker, 2002; Davids & Baker, 2007; Elferink-Gemser et al., 2011; Gagné, 2004; Kaufman, 2013; Phillips et al., 2010; Simonton, 2001), and able to predict and explain the growth of domain-specific abilities that lead to a level at which products are generated. Hence, our aim is to provide insights into what kind of model drives the emergence of the typical idiosyncratic developmental properties, as well as the highly skewed productivity distributions across the population, at the level of excellent human abilities and performance.

Because excellence typically develops over time (often over more than 10 years; Ericsson, 2006; Ericsson et al., 1993; Ericsson, Roring, & Nandagopal, 2007), we propose a dynamic model of growth to account for a performer's ability development (cf. Van Geert, 1991, 1994). Such models have not yet been applied to talent and excellence development, although some authors already hinted toward their value (e.g., Aguinis & O'Boyle, 2014; Abbott et al., 2005; Abbott & Collins, 2004; Araújo & Davids, 2011; Ceci, Barnett, & Kanaya, 2003; Dai, 2005; Dai & Renzulli, 2008; Davids & Baker, 2007; Phillips et al., 2010). In line with the consensus that excellence is shaped by various (interacting) personal and environmental variables, we will demonstrate a dynamic network model, according to which excellent abilities emerge from the iterative interactions among sparsely—and across the population randomly—connected network variables, which may correspond to domain-specific ability, motivation, parental support, teaching and coaching, practice, and so forth.

A Dynamic Network Model Representation of Ability Development

An ability network consists of one node (i.e., variable) representing the domain-specific ability, and other nodes consisting of components that positively or negatively affect the ability (and each other). In line with the existing models in the field of talent and excellence development (e.g., the Differentiated Model of Giftedness and Talent; Gagné, 2004), the nodes can be of an internal or of an external nature, such as domain-specific interest and family support, respectively.

Connections between the variables may be supportive or competitive, symmetric or asymmetric, and direct or indirect. An example of a direct, symmetric connection is the positive feedback-loop between the growth of an ability (e.g., tennis ability), and the amount of practice (Figure 14A). However, connections can also be indirect or asymmetric, for instance when the coach positively affects the tennis ability, which in turn positively affects parental-support; in this case the support of the coach and the support of the parents are indirectly connected (Figure 14B). We propose that any variable in the network is directly connected with a relatively small number of other variables and indirectly connected with a considerably greater number of other variables (cf. Watts & Strogatz, 1998).

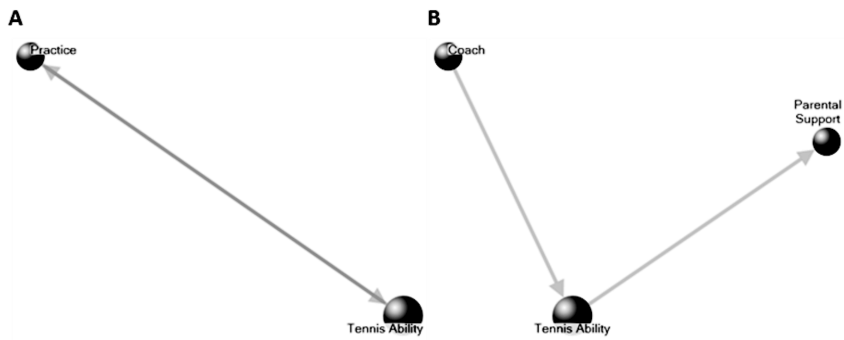


Figure 14. Examples of a direct, symmetric connection between two variables (Graph A) and an indirect asymmetric connection (Graph B). Such compositions form the building blocks of the entire dynamic network.

The network is dynamic in the sense that the values of the nodes (the levels) change, among others as a consequence of the interactions with other nodes, and nodes may appear or disappear over developmental time (cf. Barabási, 2009). The nature and strength of the relationships between the ability component, the internal components, and the external (environmental) components are assumed to be idiosyncratic and characteristic of a particular person's dynamic network profile (specificity of ability profile and individual differences are characteristic of excellent performance in general, e.g., Achter, Lubinski, & Benbow, 1996; Elferink-Gemser et al., 2011; Phillips et al., 2010;

Robertson, Smeets, Lubinski, & Benbow, 2010; Vaeyens et al., 2008; Webb, Lubinski, & Benbow, 2002; for a general discussion of the importance of idiosyncratic models, see Molenaar, 2004; Molenaar & Campbell, 2009).

To provide an example, a dynamic ability network can be visualized as follows. Imagine that a particular child has a particular interest in tennis. The parents of the child recognize this and strongly stimulate this interest. To the extent that their child shows more interest, the parents tend to buy a new racket, take the child to the tennis court, pay his training/coaching, etc. The child’s practice and tennis ability are reciprocally related: As the child's tennis level increases, practice increases and vice versa. Furthermore, the child also experiences considerable pleasure because of playing tennis, and is very persistent. This pleasure and tenacity increase as the tennis ability increases. Then, at secondary school, the child meets new friends who like to hang out after school. After having joined once, the child obtains more support from the friends, for instance in the form of increasing popularity in the group. In this particular network, hanging out with friends competes with tennis ability development, for instance through a competition for available time or through a competition between motivation for gaining popularity and motivation for playing tennis.

If we now take a look at this individual’s tennis ability network, the interconnected variables can be displayed in the form of a directed graph consisting of nodes and arrows (Figure 15). The nodes specify the relevant variables, such as the child’s motivation to hang out with friends after school or the pleasure it experiences when playing tennis, that influence or are influenced by other variables in the network. The sizes of the nodes reflect the levels (or strength) of the variables. Each directed edge between two nodes represents a supportive (solid) or competitive effect (dashed) of one variable on another. The strength of the relationships between the variables is reflected in the thickness of the edges.

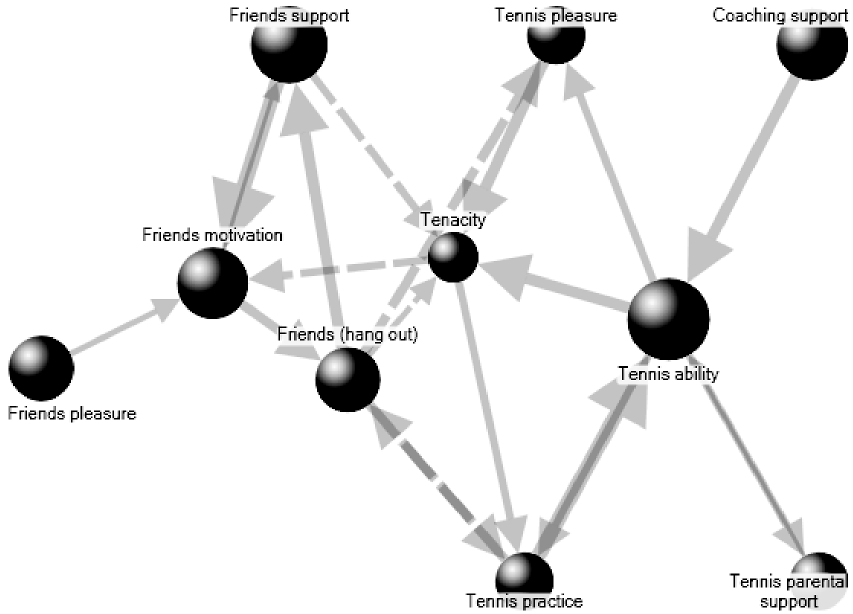


Figure 15. Graphical representation of an individual's tennis ability network structure.

Mathematical Principles of the Dynamic Network Model

When focusing on the mathematical principles of the network structure, the various nodes and their connections are expressed in the form of equations. The domain-specific ability corresponds to one equation, and its growth depends on: (1) the ability level (*L*) already attained, (2) available resources that remain relatively constant during ability development (*K*) such as genetic endowment of the ability, (3) resources that vary on the time scale of ability development (*V*), such as parental, teaching or coaching support, practice, and tenacity, (4) the degree in which an ability profits from the constant resources (*r*), (5) the positive, negative, or zero weights of the connections (*s*) with the variable resources, and (6) a general limiting factor (*C*) (Van Geert, 1991; 1994). The *C*-parameter is the carrying capacity, which specifies the ultimate or physical limits of growth of a particular variable. In other words, the *C*-parameter keeps the variables within (physically) realistic limits, in the relatively unlikely case that too many relationships are strongly positive and drive a variable (e.g., ability) into an exponential explosion (e.g., Van der Maas et al., 2006). Within the ability network, the variable resources (*V*) are potentially co-dependent on the ability and on any arbitrary subset of all other variables. Taken together, our model thus implicitly follows a gene × environment approach, that is, the model specifies a multiplicative relationship between the ability-specific *K*-parameter (genetic endowment), and the influence of the support-competition factors in terms of the variable resources (*V*).

The dynamic network model can be mathematically defined as a set of (sparsely coupled) logistic growth equations, each of which represents the growth of a single variable (*A*, *B*, *C*, and so forth), and one of which is the domain-specific ability. The number of variables to which a particular variable is connected, is represented by *i*, *j*, etc:

$$\begin{Bmatrix} \frac{\Delta L_A}{\Delta t} = \left(r_{L_A} L_A \left(1 - \frac{L_A}{K_{L_A}}\right) + \sum_{v=1}^{v=i} s_v \ L_A V_v \right) \left(1 - \frac{L_A}{C_A}\right) \\ \frac{\Delta L_B}{\Delta t} = \left(r_{L_B} L_B \left(1 - \frac{L_B}{K_{L_B}}\right) + \sum_{v=1}^{v=j} s_v \ L_B V_v \right) \left(1 - \frac{L_B}{C_B}\right) \\ \dots \\ \dots \\ \dots \end{Bmatrix} \qquad (3)$$

From a model building perspective, we asked ourselves what are the minimal properties the network model should have for it to generate the qualitative features of the trajectories, as well as the highly skewed product distributions. To cover the structure of realistic domain-specific networks, our model has the following properties (note that a person's entire network may consist of multiple clusters, each representing a different performance domain, connected by variables functioning as hubs). In order to mathematically simulate individual's domain-specific networks, we start with a set of 10 nodes.[5] Within this network the nodes are sparsely connected with an average degree of connectivity of 25%, and the connections are randomly distributed over the nodes. This means that excellent abilities could emerge from different network configurations. For simplicity, for each simulation of an individual the initial parameter values are randomly drawn from symmetric distributions. The weights of the edges *s* are

[5] Network simulations based on up to 50 nodes reveal qualitatively similar results as simulations based on 10 nodes.

variable and randomly distributed with an average of zero. We identified one node (node 3) as the target variable whose change reflects the ability-development over time (for information about the specific parameter settings, see Method section).

The Current Study

In this study we aimed to test whether the typical properties of excellence emerge out of the dynamic network model described above, in order to discover the underlying principles of talent and excellence development. More specifically, if excellence emerges out of dynamic network structures, simulations of individual performers would reveal that: (a) similar ability levels can develop at different ages, (b) the underlying constituents of a the ability can change during the individual's life span, (c) the ability-development can take a variety of forms (e.g., gradual, S-shaped, stepwise, abrupt), and (d) early indicators of ultimate excellent abilities are often absent (e.g., Abbott et al., 2005; Abbott & Collins, 2004; Howe et al., 1998; Phillips et al., 2010; Simonton, 1999, 2001). Furthermore, ever since the topic of excellent human performance was introduced, debate has existed on the contribution of heredity (for a recent intensive debate, see Ericsson, 2013; Ericsson, Roring, & Nandagopal, 2013; Gagné, 2013). Given that our model implicitly follows a gene × environment approach, in addition to examining the qualitative properties described above we also tested what the model predicts with regard to the role of genetic endowment.

Apart from testing the above-mentioned qualitative properties, by simulating many individuals we tested whether our dynamic network model predicts a major quantitative property of excellent performance, namely the highly skewed—power law and stretched exponential—distributions of productivity that are demonstrated by empirical data across many achievement domains (e.g., Aguinis & O'Boyle, 2014; Davies, 2002; Huber, 2000; Huber & Wagner-Dobler, 2001; Laherrere & Sornette, 1998; Lotka, 1926; O'Boyle & Aguinis, 2012; Redner, 1998; Sutter & Kocher, 2001). Additionally, we determined whether the distributions of excellent performance productivity can be (or are better) predicted by a null-hypothesis model based on the standard statistical assumption that abilities are normally distributed across the population, and are supported by the additive effects of *all* supporting variables.

Finally, apart from a general test of the dynamic network model, we considered it worthwhile to test the applicability of the model to a specific performance domain. For this aim, we took the empirical data that are displayed in Figure 13, and we tested whether the dynamic network model is able to predict the productivity distributions in the domain of sports (i.e., soccer and tennis).

6.2 Method

Default Model Settings

Each model simulation consists of 500 steps. The specific real-time duration of a single step thus depends on the domain of interest (e.g., a step length of about five weeks could be chosen for the domain of arts or science, in which ability growth and maintenance may cover a duration of about 50 years—around 2500 weeks—, whereas the step length can cover a shorter period in sports). For each simulation we defined the values of the parameters specified in the equations, by randomly drawing from predefined distributions. The actual parameter *values* have no intrinsic or absolute meaning, but are chosen in such a way that the total set of parameters allows us to run feasible simulations of lifespan trajectories, given the chosen number of simulation steps (e.g., Netoff, Clewley, Arno, Keck, & White, 2004; Van der Maas et al., 2006). Accordingly, the values of the parameters have their meaning in relation to each other, rather than to some absolute standard (Van Geert, 2014). This rationale follows from our aim to discover the general underlying model principles—such as the general connection structure of the network of components—from which excellence emerges, rather than already specifying the more or less exact values of the components as they may exist in domain-specific populations of excellent performers. Table 6 displays the default distributions from which the parameter values were drawn for each variable in the network.

Network Model Predictions of Developmental Properties

First, we ran network simulations of individual performers to examine the developmental patterns, including the growth curves (e.g., linear, S-shaped, stepwise growth; Van Geert, 1994) and the (changing) values of the network variables. This would provide information about the fit with the first three properties of excellence: Similar ability levels can develop at different ages; the underlying constituents of a specific ability can change over the individual's life span; and the ability-development can take a variety of forms. To test the fourth property—early indicators of ultimate excellent abilities are rare—, we determined the correlation between the end-ability levels and earlier levels. More specifically, we simulated 1,000 individuals and calculated correlation coefficients (Pearson *r*) between the end-level of node 3 (the ability component) and the level of node 3 at earlier simulation steps.

Finally, to explore the role of genetic endowment, we simulated 1,000 individuals and calculated the correlation (Pearson *r*) between the *K*-parameter of node 3 (the ability) and the actual ability level, during the simulated life-span of ability development.

Table 6. Default parameter values used for the dynamic model simulations.

Parameter	**Average**	**Standard deviation**
r (resource consumption rate)	.05	.01
Connection strength with other variables	0	.02
K (stable resources)	1.00	.15
Connection probability with other variables	.25	-
	Minimum	**Maximum**
L (initial level)	0	.05
Time of initial emergence of a variable	1.00	350.00
C (carrying capacity)	10.00	25.00

Network Model Predictions of Productivity Distributions

We assume that the domain-specific productivity of a performer is a function of the performer's (developing) ability level. However, apart from the ability level, a myriad of accidental events can occur with highly variable probabilities, which may or may not result in a product (e.g., Elferink-Gemser et al., 2011; Simonton, 2003). For instance, Steven Bradbury won the gold medal at the 2002 Olympic games, because the other competitors fell before the finish line, or imagine a researcher who finds unexpected results that lead to a high-impact publication (Simonton, 2003). Thus, in order to examine what the network model predicts concerning the productivity distributions we not only need a model of the underlying abilities, but also a model of how abilities lead to the products, which takes into account the stochastic nature of product generation.

The simplest model in this regard is the Poisson model, which states that the probability P that a particular product (e.g., a scientific paper or a tournament victory) will occur during a fixed time interval t, is the mathematical product of a domain-specific Poisson parameter (φ) and the individual's current level of the underlying ability L (Huber, 2000; Huber & Wagner-Dobler, 2001; Simonton, 2003). Hence, for each step in the simulation, there is a small probability that a product will be generated, and the number of products generated will accumulate across the simulated life spans. Because, in accordance with the empirical distributions, the majority of (excellent) performers in a specific domain has one product (e.g., Davies, 2002; Huber, 2000; Lotka, 1926; O'Boyle & Aguinis, 2012; Sutter & Kocher, 2001), the probability that a product is released during each time step is chosen in such a way that the average productivity during an entire life span is 1. The Poisson parameter that corresponds with this lifetime average is .002, since the simulation length was set at 500 steps. At a particular moment during ability development, the probability of generating a product is thus predicted based on the following equation:

$$P_t = 0.002 \times L_t. \tag{4}$$

To determine the validity of the dynamic network model, we compared the simulation results with the properties of the empirical product distributions as found across domains (i.e., sports, science, music, etc.).

Null-Hypothesis Predictions of Productivity Distributions

To provide an additional test of the dynamic network model, we compared the network model predictions with predictions based on simulations of a null-hypothesis model. If the null-hypothesis model generates a comparable (or better) fit with the empirical data, we should opt for the null-hypothesis model in view of its greater simplicity. The null-hypothesis model rests on the standard statistical assumptions that abilities are normally distributed across the population, and are supported by the additive effects of all supporting variables, such as tenacity, coaching, and practice. We therefore reduced the connection strength with other variables in the network to 0, and we treated the *K*-parameter of the ability variable as the parameter including *all* resources to develop excellence:

$$\frac{\Delta L}{\Delta t} = r\, L\, (1 - \frac{L}{K}) \tag{5}$$

Network Model Predictions of Domain-Specific Distributions

In order to test the applicability of the dynamic network model in a specific performance domain, we focus on the domain of sports. In sports, support resources (e.g., parental and coaching support, facilities) play a relatively large role in athletes' developments (e.g., Baker, Horton, Robertson-Wilson, & Wall, 2003). Moreover, apart from the ability component, the tenacity component (goal commitment, perseverance in a specific sport) is assumed to be a major determinant of productivity (Abbott et al., 2005; Abbot & Collins, 2004; Van Yperen, 2009). Accordingly, we adapted the default parameter settings displayed in Table 6 by reducing the *K*-parameter from 1.00 to 0.50 (*SD* = 0.15) and extending the range of the variable support contribution (*SD* = 0.10). This means that we increased the influence of the variable support resources relative to the stable resources (e.g., genetic endowment). Furthermore, in the network model we selected one node (node 4) as the tenacity component, and we used an ability (L) × tenacity (T) product model (Huber, 2000; Huber & Wagner-Dobler, 2001). This means that the probability of generating a product at time t is a function of the *combination* of ability (L) and tenacity (T):

$$P_t = \varphi L_t T_t, \tag{6}$$

where the Poisson parameter was set at 0.005.

We focused on productivity measures in two major sports: Soccer and tennis. In both sports we assessed historical productivity data based on consensual expert assessment, namely the number of matches played in the Dutch national team by soccer players, and the number of ATP tournaments won by tennis players, which are displayed in Figure 13. To optimally compare the generated distributions, we plotted the data on natural log-log scales, and we set the number of players with one product equal to 1.

6.3 Results

Developmental Trajectories towards Excellence

Figure 16 provides a representative illustration of two simulated individuals who reach high ability levels. The Figure illustrates that the same type of ability can emerge at different ages, and that the same ability can be the product of different (changing levels of) underlying variables. In addition, we can observe that the ability levels are not monotonically rising or stable. Note, however, that the ability levels are latent variables here, which cannot be observed directly. As noted earlier, levels of (excellent) ability that individuals attain are manifested stochastically via the number of products they are associated with (see next section).

In Figure 16, Graph A displays an individual's simulated ability network in which the ability level reaches a value of 3.91 (2.85 standard deviations above the average simulated population ability level of 1.26), and Graph B shows an individual's ability network in which the ability level reaches a value of 4.48 (3.46 standard deviations above the average simulated population ability level). The simulated individual in Graph A displays a clear increase in ability level early in development, which stabilizes around step 320, whereas the ability level of the individual in Graph B starts to rise slowly, and shows a steep increase around step 320. In addition, the simulations revealed that new variables can emerge at various moments during development, which may influence the trajectory of ability development. For instance, variable 10 emerges relatively late in individual B, and seems to contribute to an abrupt increase in the ability in this specific individual. Finally, the growth curve of individual A resembles a gradual stepwise growth, whereas individual B displays an S-shaped growth including abrupt change.

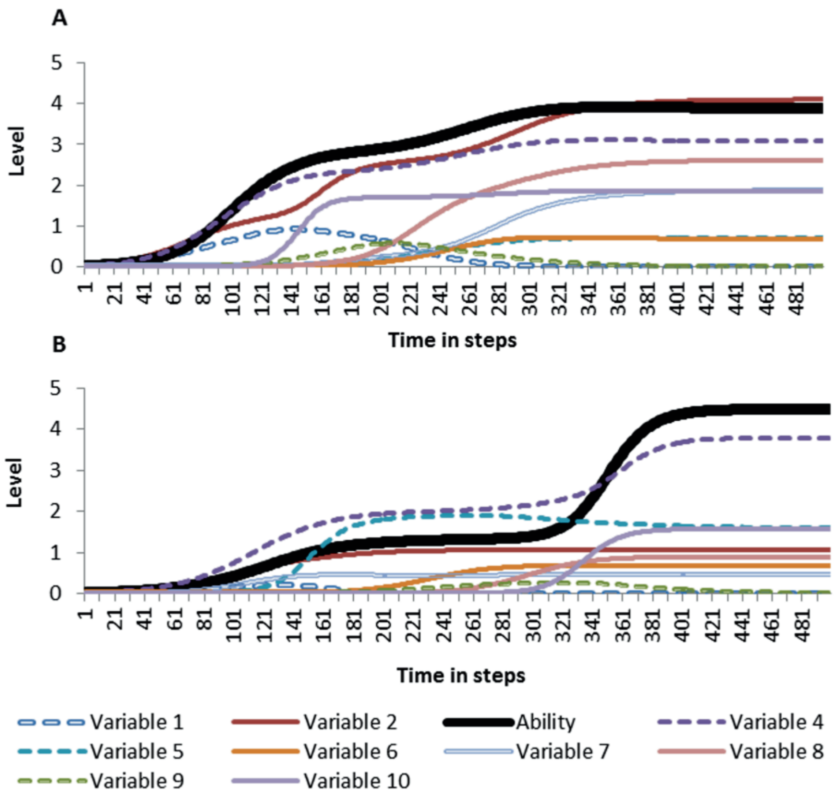


Figure 16. Simulations of the ability networks of two individuals (A and B). The black solid lines in the graphs represent the abilities, the other lines reflect the dynamic network variables that have supportive, competitive, or neutral relationships with the ability.

To test what the model predicts with regard to early indicators of later performance, we simulated 1,000 different individuals. For simplicity, we expressed the simulation steps in terms of age (i.e., an age range from 0 to 44 years, which is typical for domains such as science and arts). Results show that the correlation between the end-level of the ability and its level in early childhood is virtually absent (Figure 17). However, we can also observe that around the simulated age of 12, the correlation has increased to 0.5, after which it further increases to approximately 1. Thus, although we find a low correlation between the end level and early levels of ability, we also find that the correlation between the end ability-level and earlier levels increases with age.

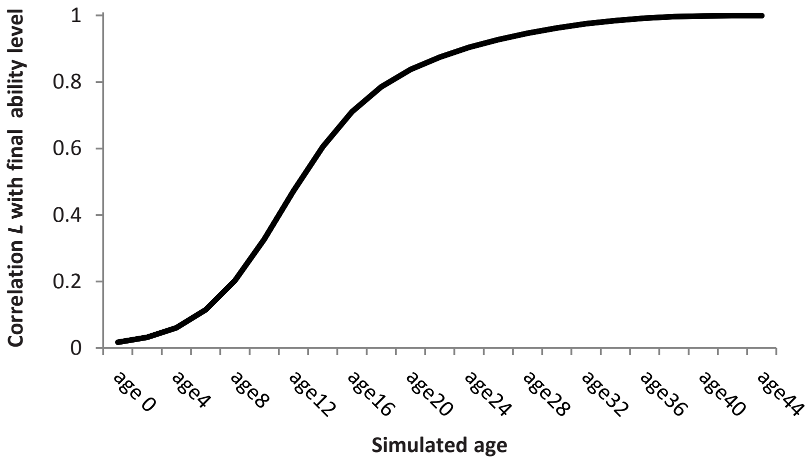


Figure 17. Correlations between the final ability level and earlier levels.

Finally, to determine the model predictions with regard to the role of genetic endowment, we calculated the correlations (Pearson *r*) between the *K*-parameter of node 3 and the ability level. Simulation results revealed that the correlation is around 0 at the beginning, increases to about 0.5, and then falls back to stabilize around 0.4 (Figure 18).

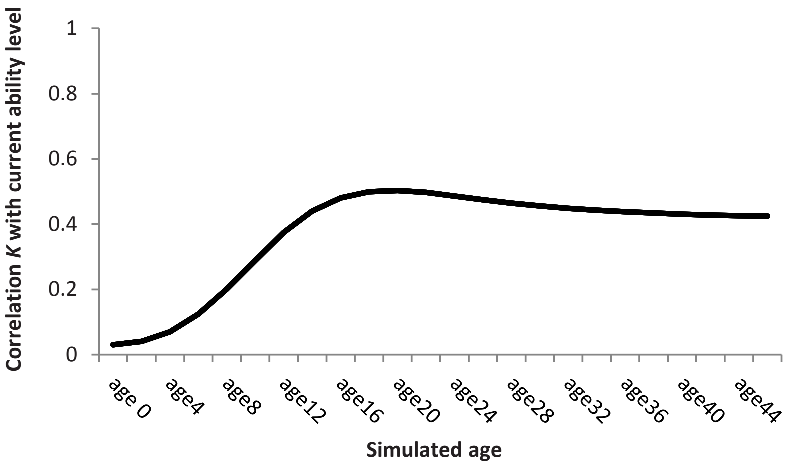


Figure 18. Correlations between the *K*-parameter and the ability level at different simulated age-steps.

General Predictions of Productivity Distributions

Our simulations based on 100,000 runs with the default parameter values show that the network model generates highly right-skewed product distributions. In order to determine whether the predictions are specific to the dynamic network model, we compared the results with simulation results of the null hypothesis model. To guarantee that the null hypothesis model would produce the same average ability level as the network model, the level of *K* was augmented to 1.26, which equals the average ability level resulting from the network model (note that the average ability level resulting from the network model simulations was 26% higher than what would be genotypically expected based on the settings of the *K*-parameter; a value of 1). Although the simulations based on the null-hypothesis model also produced skewed product distributions, they did not generate the typical power law or stretched exponential distributions that were generated by the dynamic network model. Figure 19 also shows that the right tail of the product distribution generated by the network model is considerably longer than that of the null hypothesis model (a maximum of 25 versus 8 products).

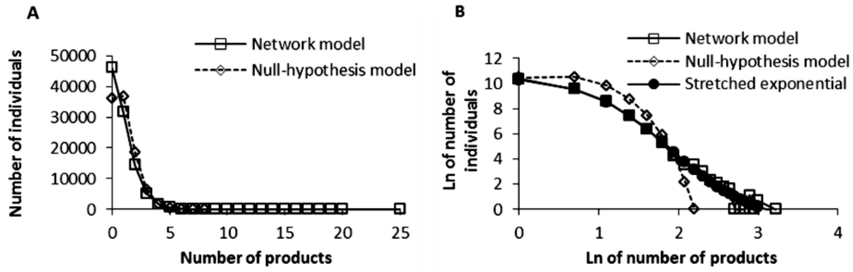


Figure 19. Simulated product distributions of the network model and the null-hypothesis model. Graph A displays the raw frequencies; in Graph B the data are plotted according to the natural logarithmic scales.

Additionally, we tested whether the parameters of the null-hypothesis can be adapted in a way that it would also produce the highly skewed distribution in line with the empirical data. In order for the null hypothesis model to generate maximum number of products comparable to that of the network model, we had to set a seven-times bigger Poisson parameter, but also an average value of the K parameter that is 25% higher, and a standard deviation of the K parameter that is twice as big. However, with these parameter settings the average number of products in the population would be about 10 times bigger than generated by the network model, with a distribution that is almost symmetrical.

Domain-Specific Predictions of Productivity Distributions

Figure 20 displays the log-log plot of the empirical productivity measures in soccer and tennis and the predictions of the network model simulation, as based on the adapted parameter values (see Method section). In line with the empirical data of the number of matches played in the Dutch national team (soccer) and the number of ATP tournaments won (tennis), the simulation revealed a highly comparable distribution that approaches a straight line (i.e., a power law).

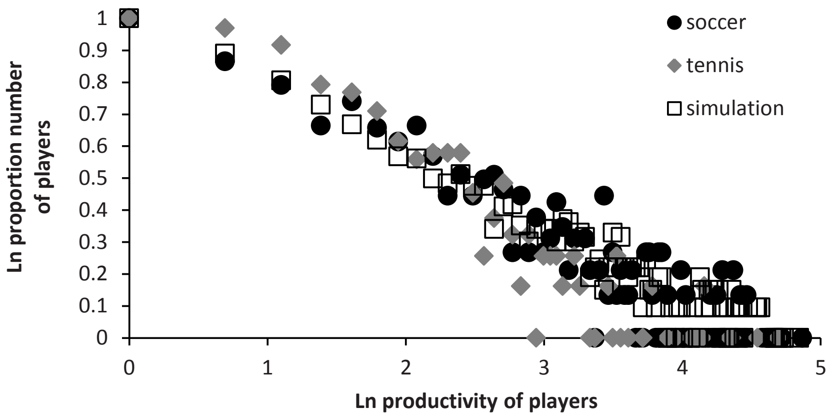


Figure 20. Ln-Ln graph of productivity in soccer, tennis, and according to simulation.

6.4 Discussion

Since the 1860s, philosophers, researchers, and policy makers have been intrigued by the question how excellent human performance can be explained and predicted (Kaufman, 2013). Although research has advanced insights into the components (i.e., nature, nurture) that contribute to excellence (e.g., Abbott et al., 2005; Abbott & Collins, 2004; Barab & Plucker, 2002; Davids & Baker, 2007; Ericsson & Charness, 1994; Ericsson et al., 1993; Howe et al., 1998; Kaufman, 2013; Phillips et al., 2010; Simonton, 1999; 2001; 2003; Vaeyens et al., 2008), debate continues to exist on the exact role of nature and nurture (Kaufman, 2013). Related to this, the dominant research practice has been based on finding associations between individual and environmental predictor variables on the one hand and performance on the other, as they statistically exist within the population (Abbott et al., 2005; Abbott & Collins, 2004; Barab & Plucker, 2002; Elferink-Gemser et al., 2011; Howe et al., 1998; Kaufman, 2013; Simonton, 1999; 2001; 2003; Vaeyens et al., 2008). As yet, however, researchers have not been able to capture and explain the time serial, individual-based developments towards excellence. Here, we propose a dynamic network model to explain the qualitative properties of excellence development, which are (a) in different individuals a similar ability can emerge at different ages; (b) the underlying constituents of a particular ability can change during the individual's life span; (c) the level of domain-specific ability is not necessarily monotonically rising or stable: Its development can take a variety of forms; and (d) early indicators of ultimate excellent abilities are often absent (e.g., Abbott et al., 2005; Abbott & Collins, 2004; Simonton, 1999; 2001; Phillips et al., 2010; Vaeyens et al., 2008). In addition, we tested whether the network model predicts a typical quantitative property, namely the highly right-skewed distribution of productivity that occurs in virtually any achievement domain, and that can be described by power laws and stretched exponentials (e.g., Huber, 2000; O'Boyle & Aguinis, 2012; Simonton et al., 1999; 2001; 2003).

Developmental Properties of Excellence

The model simulations revealed idiosyncratic routes to excellence, and more specifically that the same ability level can be attained in different ways; that the values of the (in)directly coupled (supportive or competing) variables change over time; and that the ability growth curve can take different forms for different simulated individuals. These model predictions correspond exactly to the first three properties of excellence development (e.g., Abbott et al., 2005; Abbott & Collins, 2004; Simonton, 1999; 2001; Phillips et al., 2010; Vaeyens et al., 2008). Furthermore, we found that the relationship between early ability levels and the end level was virtually absent, which supports the fourth property of a lack of early predictors of later excellence (Abbott et al., 2005; Abbott & Collins, 2004; Ericsson & Charness, 1994; Howe et al., 1998; Phillips et al., 2010; Simonton, 1999; 2001; Vaeyens et al., 2008). However, the simulations also revealed that the relationship increases with age, and is around 0.5 at the simulated age of 12. This is in accordance with several studies, mostly in the domain of scientific talent, that showed at least moderate to good predictability of later excellence around adolescence (e.g., Lubinski, Benbow, Webb, & Bleske-Rechek, 2006; Lubinski, Webb, Morelock, & Benbow, 2001; Wai, Lubinski, & Benbow, 2005).

When examining the role of genetic endowment, we found that the relationship between the genetic (K) component and ability first increased to a value around 0.5, after which it decreased and stabilized around 0.4 during the remainder of ability development. This model prediction is qualitatively in line with several studies, mostly on cognitive and scientific talent, having demonstrated an increase in heritability during childhood (Devlin, Daniels, & Roeder, 1997; Haworth, Dale, & Plomin, 2009). A recent extensive twin-study found that the heritability of scientific performance increases to 64% around the age of 9, after which it decreases to 47% around the age of 12 (Haworth et al., 2006). The authors suggested that the drop is caused by the increase in environmental effects on performance over time. This finding and the suggested explanation are consistent with the network model, in which potentially competitive or supportive variables are added to the network as age increases (see Table 6).

Thus, based on model simulations, we find that the characteristic developmental properties of excellence emerge out of idiosyncratic networks of mutually supporting or competing variables, such as abilities, tenacity, external support, and practice. Furthermore, as the network-model predictions suggest, internal, environmental, and practice components should not be considered as separate mechanisms to explain excellence, but as factors whose functional role is embedded in a network consisting of multiple dynamic and sparsely connected variables. Although our simulation results thus support the plausibility of the dynamic network model to explain excellence development, we shall also discuss the extent to which the network model predicts existing empirical data on population distributions of excellent performance in different domains.

Distributions of Excellent Performance Across the Population

A major property of excellence at population-level, is that the distributions of performance productivity are highly right-skewed. Simulating a population of (excellent) performers, the network model predictions revealed a highly-skewed productivity distribution that can be fitted by power law and stretched exponential functions, and is qualitatively similar to the distributions found in wide variety of domains, including science, music, arts, technology, and sports (e.g., Aguinis & O'Boyle, 2014; Davies, 2002; Huber, 2000; Laherrere & Sornette, 1998; Lotka, 1926; O'Boyle & Aguinis, 2012; Redner, 1998; Simonton, 1999; 2003; Sutter & Kocher, 2001). The simulations of a null-hypothesis model, based on the assumptions that abilities are normally distributed across the population, and are supported by the addition of relevant resources (e.g., teaching and coaching, practice, tenacity), generated productivity distributions that did not come near the distributions of the empirical data. Moreover, the parameter settings could not be adapted in a way that also the null-hypothesis model revealed the highly skewed product distributions. These results provide strong additional indications for the validity of our dynamic network model of excellence.

In addition to testing the dynamic model predictions based on the default parameter settings, we also fine-tuned the settings to the domain of sports. In line with the universality of highly right-skewed distributions of performance productivity across domains, the product distributions—based on consensual expert assessment—in soccer and tennis were also highly skewed. To predict the distributions of the number of matches played in the national team (soccer) and the number of ATP tournaments won (tennis), we adapted the model settings according to the sports literature (e.g., Abbott et al., 2005; Abbott & Collins, 2004; Baker et al., 2003; Van Yperen, 2009). With an ability – tenacity Poisson model connected to the network model, the predictions closely corresponded to the empirical data. This suggests that the dynamic network model not only qualitatively fits across domains, but is also applicable within specific performance domains, including sports.

Conclusion and Future Directions

The relatively simple dynamic network model we propose seems to provide a comprehensive framework to understand the kind of principles, or mechanism, underlying the development of excellence across different domains, such as science, arts, music, and sports. The model suggests that excellence emerges from intra- and inter-individual variations in the composition of idiosyncratic dynamic networks. Although we departed from a general foundational model, the model can be used and fine-tuned to discover the more specific dynamic principles underlying excellent performance in one particular domain of interest (e.g., sports).

The discovery that excellence likely emerges from idiosyncratic network structures may have widespread implications for theory and practice. For instance, it casts doubt on the assumption that the ability to reach excellence can be detected ‘in the individual’, and must be discovered at an early age. This perspective still dominates the talent detection programs in research and practice around the world (for comparable accounts, see Abbott et al., 2005; Abbott & Collins, 2004; Ericsson et al., 1993; Howe et al., 1998; Phillips et al., 2010; Vaeyens et al., 2008). However, in line with several authors' propositions (Abbott et al., 2005; Abbott & Collins, 2004; Ericsson & Charness, 1994; Howe et al., 1998; Lubinski et al., 2006; Lubinski et al., 2001; Simonton, 1999; 2001; Vaeyens et al., 2008; Wai et al., 2005), our network model predictions show that early indicators of later performance are virtually absent (yet increase with age), and that various kinds of direct and indirect multiplicative relationships between dynamic variables may exist and lead to idiosyncratic routes to excellence.

Although empirical studies that focus on individual developmental patterns toward excellence are scarce, researchers start to acknowledge that idiosyncratic patterns are the rule rather than the exception (e.g., Elferink-Gemser et al., 2011; Gulbin et al., 2013). For instance, in the Groningen talent studies, athletes have been longitudinally followed to study the development of several ability-related variables. Various papers based on this research program reported average differences between ultimately successful (professional) and non-successful athletes. To give an illustration, ultimately successful soccer players would outperform their non-successful counterparts on dribbling skills by the age of 14 (Huijgen et al., 2009), on interval endurance capacity from the age of 15 (Roescher, Elferink-Gemser, Huijgen, & Visscher, 2010), and on tactical skills at the age of 17 (Kannekens, Elferink-Gemser, & Visscher, 2011). However, the researchers acknowledge that the athletes had their own unique patterns toward successful (excellent) performance, which should not be omitted (Elferink-Gemser et al., 2011). In order to advance research on excellent performance, future studies should thus focus on the individual developmental patterns (see Gulbin et al., 2013), and acknowledge that these emerge from continuous mutual interactions between network variables, rather than from the addition of causal variables that explain a significant portion of performance variance at the sample level.

Finally, from a practical standpoint, although it is not easy to detect (or manipulate) what is inherently complex, it is possible to create conditions under which the probability of developing excellence can be increased. Accordingly, the basic practice of the 'sowers of excellent performers' (e.g., coaches, teachers, parents) should reside in: (a) their creativity of combining possibilities into a pattern that is optimally excellence-eliciting, such as by providing appropriate support (e.g., Van Geert & Steenbeek, 2005) and (b) their ability to see the signs in the individual, and in the individual's environment—e.g., enthusiasm, goal commitment, social support—that signal the opportunities for creating the (network) conditions under which excellence may develop.