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Evolving networks of human intelligence

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ABSTRACT

Twentieth century theory formation in human intelligence was dominated by factor theories; network theories will dominate the twenty first. Network theories answer a broad call for formal theories in psychological science, provide a strong approach to an idiographic science, and create an opportunity to study the developmental mechanisms of human's cognitive dynamics. Although the current century already delivered two formal stationary network theories of human intelligence—mutualism and wired intelligence—integrating dynamic mechanisms remains a serious challenge. This challenge translates into clear priorities: the identification of robust developmental phenomena, the study of the biological and cognitive mechanisms that drive these phenomena, the integration of these mechanisms into network theories of growth, the integration of network theories from different explanatory levels, and the empirical characterization of the structure of network theories.

Every future has a past. Looking back on a century of research in human intelligence, there is reason for optimism as well as pessimism. The previous century had a terrific start, with Spearman (1904) not only uncovering the positive manifold—the invariably positive correlations between scores on cognitive tests—but also intelligence's hierarchical organization. Today, these remain two of the most robust phenomena observed in psychological science, and litmus tests for theories of human intelligence.

One such theory has also stood the test of time, but with a more doubtful justification. The same Spearman that uncovered the positive manifold, introduced and developed a reflective factor theory of intelligence (Spearman, 1904, 1927). Such a factor theory has become today's most dominant theory, except that it is a much evolved variant. This Cattell–Horn–Carroll theory is argued to have "attained the status as the consensus psychometric model of the structure of human cognitive abilities" (Schneider & McGrew, 2012); a status that in politics is celebrated, but in scientific theory formation warrants caution (Borsboom & Wijsen, 2016; Ceci & Williams, 2020). Especially since factor theories tend to reduce individual differences to factor scores and fail to convincingly take into account education and cognitive development. At the end of the day we wonder which dynamics of human's mesmerizing cognitive complexity factor theories illuminate.

Factor theories did inspire decades of research into the genetic origin of intelligence. Although the one gene was never discovered, genetics research brought a crucial insight: complex traits require a polygenic and possibly omnigenic approach (Boyle, Li, & Pritchard, 2017). Contemporary theories of intelligence have embraced a compatible approach to target the shortcomings of the factor representation: networks (Colom, Karama, Jung, & Haier, 2010; van der Maas, Kan, Marsman, & Stevenson, 2017; van der Maas, Savi, Hofman, Kan, & Marsman, 2019). Network theories represent intelligence as an open complex system; open because the system interacts with its environment, complex because the system consists of many interacting parts. In such a system, *global* phenomena such as the positive manifold emerge from the *local* interactions, a process called self-organization. In doing so, networks obviate latent factors while capturing both structure and dynamics.

In this article for the Special Issue on The Future of Intelligence, we briefly discuss today's two formal network theories of intelligence. Crucially, we distinguish network *theory* (i.e., formal models) from network *analysis* (i.e., data models). The former models phenomena in order to explain intelligence, whereas the latter models data in order to detect phenomena. Then, we identify the most pressing problem of theories of intelligence in general (lack of developmental dynamics) and dissect how network theories can and must evolve to resolve that problem. We hope scholars of cognitive ability are as excited as we are to push theories of intelligence forward in the decades to come.

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1. Mutualism

van der Maas et al. (2006) were the first to introduce a network theory of human intelligence. This theory, *mutualism*, departs from the observation that many cognitive processes are fueled by positive reciprocal interactions. van der Maas et al. (2006), Peng and Kievit (2020), Peng et al. (2020), and Kievit (2020) review such *mutualistic* interactions, ranging from the reciprocal effects of motivation and performance to those of vocabulary and reading ability. Mutualism theory is formalized as a Lotka–Volterra model and describes how a network of exclusively mutualistic interactions explains key phenomena in intelligence, including the positive manifold and hierarchical organization. Also, it is consistent with heritability effects (increase of heritability with age), developmental patterns (age differentiation and dedifferentiation), and the Jensen effect. On top of the empirical evidence for the underlying mutualistic interactions among cognitive processes, there is a growing body of comparative evidence for mutualism theory over *g*-factor theory (Hofman et al., 2018; Kan, de Jonge, van der Maas, Levine, & Epskamp, 2020; Kan, van der Maas, & Levine, 2019; Kievit et al., 2017; Kievit, Hofman, & Nation, 2019; Ou et al., 2019). The extended mutualism model (van der Maas et al., 2017, 2019) distinguishes between fluid and crystallized abilities, and includes test sampling, internal (mutualistic) and external (multiplier) reciprocal effects, and central cognitive factors (such as working memory capacity). Figure 5.1 in van der Maas et al. (2019) provides a concise overview of the current state of mutualism theory.

Where mutualism theory was formalized on the explanatory level of human's *psychological* system, Jung and Haier (2007) arrived at a similar perspective while departing from a *biological* one: the human nervous system. Their parieto-frontal integration theory (P-FIT) suggests a neurobiological network that explains variation in cognitive ability by variation in brain structure and function. Similar to mutualism theory, P-FIT theory stresses the importance of local interactions, be it between brain regions rather than psychological processes. Their idea resonates with other neuroscientists, evidenced by the various compatible theories introduced in recent years (for brief summaries, see Barbey, 2018; Deary, Cox, & Hill, 2021).

It follows that mutualism theory is not an isolated success. In fact, we believe it is at the root of a paradigm shift. The network perspective is not only greedily applied in empirical investigations—most notably in the field of psychopathology (Cramer et al., 2016; Fried et al., 2016; Robinaugh, Hoekstra, Toner, & Borsboom, 2019; Schmittmann et al., 2013)—it moreover inspired the formation of network theories across a range of other psychological constructs, including psychopathology (Borsboom, 2017), panic disorder (Robinaugh, Haslbeck, et al., 2019), attitudes (Dalege, Borsboom, van Harreveld, & van der Maas, 2018; Dalege et al., 2016; van der Maas, Dalege, & Waldorp, 2020), emotion (Lange, Dalege, Borsboom, van Kleef, & Fischer, 2020), interest (Sachisthal et al., 2019), and rational choice (Kruis, Maris, Marsman, Bolsinova, & van der Maas, 2020). These theoretical advances have sparked a renewed interest in formal psychological theory formation, reflected in a recent surge of studies that discuss and advocate the topic, and suggest best practices (Borsboom, van der Maas, Dalege, Kievit, & Haig, 2020; Eronen & Romeijn, 2020; Fried, 2020; Guest & Martin, 2020; Haslbeck, Ryan, Robinaugh, Waldorp, & Borsboom, 2019; Robinaugh, Haslbeck, Ryan, Fried, & Waldorp, 2020; van Rooij & Baggio, 2021).

The resemblance between the rise of network theories at the start of the current century, and the rise of factor theories at the start of the previous century, is striking. It is all the more interesting that mathematical equivalences of particular network models and factor models have repeatedly been established (Epskamp, Maris, Waldorp, & Borsboom, 2018; Kruis & Maris, 2016; Marsman, Maris, Bechger, & Glas, 2015; Waldorp & Marsman, 2020). Nevertheless, the current rise of network theories seems to be at the expense of factor theories. This may signal that although psychological constructs can sometimes be elegantly summarized in a latent factor, it is increasingly recognized that such factors obscure fundamental dynamics. That is, whereas a factor provides a convenient description of a system at the global level, it conceals the local interactions that drive the global phenomenon. Also, it may signal the increasing awareness of the risks of modeling and interpreting factors (van Bork, Epskamp, Rhemtulla, Borsboom, & van der Maas, 2017), the trap of (perfect) factor model fit (Rhemtulla, van Bork, & Borsboom, 2020), and the fact that mathematical equivalence does not imply that the suggested mechanisms that drive observed psychological phenomena are equally plausible (van Bork et al., 2019).

2. Wired intelligence

Following mutualism theory, Savi, Marsman, van der Maas, and Maris (2019) provided a completely new formal account of human intelligence. Where mutualism theory exploits the mutualistic interactions between cognitive processes during development, Savi et al.'s *wired intelligence* theory states that development of especially crystallized cognitive abilities can be described as growing networks of facts and procedures. This approach is analogous to various symbolic (Anderson & Lebiere, 2014), connectionist (Hoffman, McClelland, & Ralph, 2018), and hybrid (Sun & Alexandre, 2013) cognitive representations. In the wired intelligence formalization, every individual is described by its own unique cognitive network. Fig. 1a–c illustrate these networks for three individuals with varying network size. In a network, facts and procedures are represented by the nodes. The presence of a node reflects an observed fact or procedure, and has one of two states: mastered or not mastered. The actual state of a node is only observed when being used. That is, when an individual produces facts or employs procedures and receives feedback from the environment, for instance during practice. Moreover, wired intelligence theory demands that nodes can only be connected when in the same state. Correct strategies create connected cliques of mastered nodes, whereas incorrect strategies create connected cliques of not mastered nodes. While this is a strict assumption, deviations are expected to resolve during learning by means of a rewiring mechanism. This topic is dealt with in for instance harmony theory (Smolensky, 1968), and Savi et al. (2019) describe a rewiring mechanism for wired intelligence theory.

An example from learning addition helps to clarify wired intelligence theory. First, think of a network that contains nodes that represent addition problems. When new addition problems are observed, new nodes appear in the network. An addition problem that is mastered through memorization will be disconnected from the existing addition nodes, whereas an addition problem that is mastered by using a specific procedure will be connected to the other addition nodes that are mastered by that procedure. Likely, not all observed addition problems are instantly mastered. One can think of a problem that is too advanced for the current state of the cognitive network, or a problem that is memorized incorrectly. Some of these nodes will remain unconnected until mastered, but systematic errors may create connected cliques of such nodes. Ideally, all problems are eventually mastered and a fully consistent arithmetic network is developed.

Savi et al. (2019) chose to formalize this theory in the form of a Fortuin–Kasteleyn model (Fortuin & Kasteleyn, 1972), which originates in statistical physics. The model has important advantages. First, it specifies the probability distributions of both the nodes and edges, such that a truly idiographic model is obtained (Fortuin & Kasteleyn, 1972; Savi et al., 2019). Second, it can be shown formally that any network sampled from these distributions gives rise to the positive manifold (Fortuin, Kasteleyn, & Ginibre, 1971; Savi et al., 2019). This feature is obtained by ensuring that two nodes only connect if they are in the same state (at the population level, if two nodes have a positive connection probability, their probability for having the same state is $>.5$; Grimmett, 2006). Third, generating data that is typically modeled with hierarchical factor models is straightforward (Savi et al., 2019). Finally, Savi et al. showed that the model produces the Matthew effect: a widening gap in

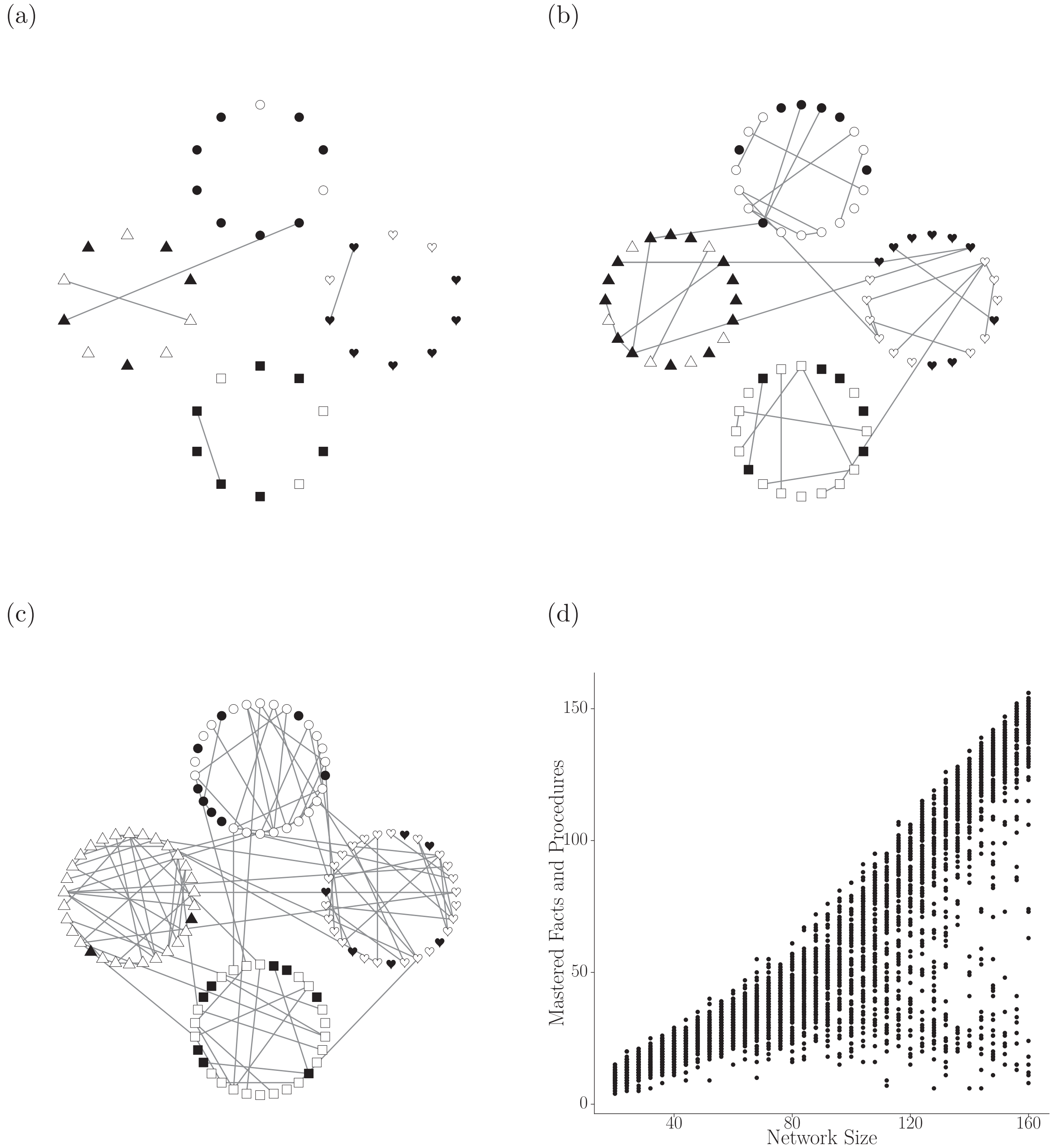

Fig. 1. Network evolution in wired intelligence theory. Note. (a, b, c) Three individuals' wired intelligence networks containing respectively 40, 80, and 120 facts and procedures (white nodes are *mastered*, black nodes are *not mastered*). Shapes represent different cognitive domains. (d) Matthew effect in a population of wired intelligence networks. Points represent the total number of mastered nodes (*y*-axis) for independent individuals with differently sized cognitive networks (*x*-axis).

cognitive ability across individuals (evidenced in Fig. 1d). On the other hand, a disadvantage of the Fortuin–Kasteleyn formalization is that the model is static. Bringing the implied developmental mechanisms into being, by adding and removing nodes and edges over time, introduces the risk that the Fortuin–Kasteleyn formalization is not maintained and the positive manifold can no longer be guaranteed. Savi et al. introduced three strategies to circumvent this issue. However, all strategies have their limitations and the issue might only be mitigated by new formalisms.

Mutualism theory and wired intelligence theory are set apart by their explanations of human intelligence. Nevertheless, there is a lot that unites them. Both provide explanations that are formal, both model cognitive ability as networks, both imply developmental mechanisms that drive the phenomena, and both allow individuals to be modeled by distinct networks. As such, both answer the call for an idiographic science (Molenaar, 2004) and bridge psychology's division of disciplines (Cronbach, 1957). However, both theories are at present formalized by static models; they reflect cognitive systems in equilibrium. Whereas cognitive ability is evidently dynamic, the models are not, and the implied developmental mechanisms are, indeed, implied. We believe that to date the most significant challenge for intelligence research is to make truly dynamic theories of intelligence. That is, to make those theories evolve, literally.

3. The dynamics of development

3.1. Phenomena

On the path toward dynamic theories of intelligence, robust phenomena provide the lampposts. Stationary phenomena illuminate where the network should grow to, and developmental phenomena provide stills along the way. Putting it differently, phenomena constrain theory. In psychological science, the identification of robust phenomena is fraught with difficulties (Eronen & Bringmann, 2021). Intelligence researchers have the luxury that they can build upon a few robust stationary phenomena, such as the positive manifold and the hierarchical organization of intelligence. However, to understand the dynamics of cognitive development, developmental phenomena must be identified. Rather than the mostly cross-sectional data that factor theories are built upon, developmental phenomenon detection demands intensive longitudinal data. Many statistical methods facilitate phenomenon detection, such as latent change score modeling, or network analysis for longitudinal binary data (Marsman & Huth, 2019) and longitudinal continuous data (Epskamp, 2020).

Two relevant developmental phenomena are the Matthew effect and age dedifferentiation: a widening gap in cognitive ability across individuals and an increase in the strength of the positive manifold with age. Unfortunately, these phenomena are not as uncomplicated as their stationary relatives. As discussed by van der Maas et al. (2006) and Savi et al. (2019), both phenomena have an antagonist—the compensation effect (a *closing* gap) and age differentiation (a *decrease* in strength)—and there is no unambiguous evidence for either one of them. Moreover, challenges such as inadequate measurement scales, ceiling and floor effects, and regression to the mean hinder accurate estimation of the phenomena (Protopapas, Parrila, & Simos, 2014). Interactions between the mechanisms that drive the opposing phenomena—dampening or even canceling out the effects—would pose intelligence researchers to the fundamental challenge of separating the two. And the effects may ultimately turn out to be spurious (Hartung, Doebler, Schroeders, & Wilhelm, 2018). Finally, stationary phenomena may not be as uncomplicated as they seem, and be the product of developmental mechanisms: the existence of age differentiation and dedifferentation would prove that the positive manifold is a dynamic phenomenon, and hierarchically organized systems can emerge during network growth (Bunimovich, Smith, & Webb, 2018).

Developmental phenomena not only provide the lampposts for theory formation, they signify the pivotal importance of studying developmental mechanisms in the first place. The Matthew effect, for instance, demonstrates a sensitivity to initial conditions: small differences in initial conditions can have significant effects over time. Such a sensitivity demonstrates that simple projections of initial conditions to future states, such as genetic endowment to adult IQ, are problematic and demand an understanding of the intermediate dynamics. Savi et al. (2019) explore the dynamics underlying Matthew and compensation effects by means of Pólya's urn models. In a Pólya's urn model, marbles are randomly gathered from an urn and replaced with other marbles, following simple rules, to simulate developmental patterns. Crucially, these models prove that future states may differ significantly, even when initial states and developmental mechanisms are *identical*. In doing so, Pólya's urn models illuminate a third source of developmental differences (Molenaar, Boomsma, & Dolan, 1993) by means of a developmental mechanisms that is often overlooked: chance (Pluchino, Biondo, & Rapisarda, 2018).

3.2. Mechanisms

It may be the two disciplines of psychology to blame, the seemingly intransgressible gap between experimental and correlational psychology (Cronbach, 1957; Ferguson, 1954), but formal theorists of intelligence—mesmerized by the cross-sectional positive manifold—have largely neglected the fundamental progress in the field of human learning. There is much to catch up on. Cognitive psychologists identified various large learning effects, such as testing, spacing, and feedback effects (Karpicke & Roediger, 2008). More importantly, the mechanisms that drive such effects are actively studied, not only for the mentioned practice effects (e.g., Toppino & Gerbier, 2014), but also for generalisation and transfer (e.g., Barnett & Ceci, 2002), forgetting (e.g., Anderson & Hulbert, 2021), and so forth. Such advances must be integrated into network theories.

Also in genetics and neuroscience, Deary et al. (2021) discuss promising directions for the search of mechanisms that connect genetic variation to variation in intelligence. However, the authors warn that many biological systems may be involved and that phenotypic variance may be explained by many small effects, which could impede progress in constructing a mechanistic account of intelligence. In mutualism theory, the cumulation of small effects by means mutualistic interactions provides such a mechanistic account, be it at a different explanatory level. Mutualistic interactions are consistently identified in cognitive science. Symbiosis, the umbrella term for such close and long term interactions, describes more mechanisms, including commensalistic and parasitic interactions. In a commensalistic interaction, the one cognitive aspect is positively affected and the other is neither positively nor negatively affected, whereas in a parasitic interaction, the one cognitive aspect is positively affected at the expense of the other. On top of mutualistic interactions, such other symbiotic interactions can likewise play a role in the emergence of intelligence.

These interactions are not necessarily isolated within the individual. In sociological science, DiPrete and Eirich (2006) identified various developmental mechanisms that produce Matthew effects. Under the umbrella term cumulative advantage, they distinguished path-dependent, time-dependent, and status-dependent mechanisms. Whereas path-dependent mechanisms describe mutualistic interactions, time- and status-dependent mechanisms describe commensalistic interactions. An example of such a time-dependency that drives developmental differences is the relative age effect: the persistent developmental advantage of relatively older individuals in a particular cohort over their younger peers. Similarly, critical periods such as in language acquisition (e.g., Hartshorne, Tenenbaum, & Pinker, 2018) create time-dependencies. An example of a status-dependency that drives developmental differences is socioeconomic status. Baumert, Nagy, and Lehmann (2012) explain that these commensalistic interactions can be part of mutualistic interactions, which once more illustrates the previously discussed challenge of separating various mechanisms.

In studying the dynamics of a developing intelligence, it is tempting to concentrate on growth. However, a significant part of development is adverse. Such adverse development occurs during aging, but just as well during (early) development. Two examples are forgetting and the formation of misconceptions. In their discussion, Savi et al. (2019) elaborate on both phenomena and illustrate how these can be captured in a network theory of intelligence. Possibly, some aspects of forgetting and misconception formation can be modeled by parasitic interactions. In memory formation, old memories are sometimes distorted to accommodate new information (Bridge & Voss, 2014), a process in which a new experience is at the expense of the image of an old experience. Similarly, misconceptions may form at the expense of valid knowledge. A striking example is a correct explanation that reinforces an individual's misconception, which is for instance observed in science learning (Muller, Bewes, Sharma, & Reimann, 2007).

3.3. Dynamics

Network theories formalize the mechanisms from which phenomena emerge. In *developmental* theories of intelligence, these networks must capture both structure and dynamics. The structure (topology) describes the system in terms of nodes and their connections (edges). Then, the dynamics describe network changes as a function of time, which is commonly termed network *evolution*. Networks allow different characterizations of such evolutionary dynamics, from very elementary to more sophisticated. Elementary dynamics are observed when the network runs towards its equilibrium state, are captured by direct changes to the state parameters that describe the network, or by considering successive static snapshots of the network (Borgnat et al., 2018). Formal models of cognitive development predominantly study such elementary dynamics, including mutualism theory, wired intelligence theory, and logistic growth models (e.g., van Geert, 1991).

Such elementary dynamics hardly model the actual mechanisms that drive network evolution. As such, they effectively signal that those mechanisms, such as underlying a parameter change, are not well understood. This is analogous to psychological *g*, the reflective factor that obscures the complex dynamics that form psychometric *g*. More sophisticated dynamics may model the actual mechanisms that drive network evolution. To begin with, the number of nodes may be fixed, while mechanisms describe changes in the edges. Such dynamics are exemplified by the Watts–Strogatz model (Watts & Strogatz, 1998). This model has a fixed number of nodes and is designed to exhibit small world properties. Also, connectionist approaches to development employ such dynamics (e.g., Elman et al., 1996; Munakata & McClelland, 2003). In the field of intelligence, these dynamics seem a natural companion to neurobiological theories, as brain regions are virtually fixed but connections are subject to continuous change.

Ultimately, the dynamics may describe changes in both the edges and the number of nodes. Such dynamics are exemplified by the Barabási–Albert model (Barabási & Albert, 1999). This model has no fixed structure and is designed to exhibit scale free properties. Notably, the Barabási–Albert model grows by means of preferential attachment, a mechanism that produces the previously discussed Matthew effect. In the field of intelligence, wired intelligence theory describes development by means of growth dynamics. However, contrary to the Barabási–Albert model, the exact mechanism that enables growth is currently not formalized in wired intelligence theory, for reasons we previously discussed. In theoretical biology on the other hand, network growth mechanisms are actively studied (van Ooyen, 2011). The identification of mechanisms and refinement of network dynamics is key to advancing network theories.

4. Advancing theories of human intelligence

Network theories of intelligence represent a mature scientific field that are already reshaping intelligence research, and that will continue to do so. Networks provide an ideal method to study developmental aspects of intelligence, and their versatility provides ample advantages. van der Maas et al. (2006) and Savi et al. (2019) show that theories of intelligence can be truly idiographic: individuals' intelligence is captured by local interactions in distinct networks. They show that these networks obviate the need for latent factors: global phenomena across individuals, such as the positive manifold and hierarchical organization, emerge from the manifest local interactions within the individual networks. Moreover, networks demonstrate that there is no *or* in nature *and* nurture. The *wired intelligence* theory provides clear leads for both and can help expose their possible interactions. Nature may set the boundaries for nurture—which is not to say that those boundaries are ever reached—and nurture may aim for reaching the upper one. This brings us to the first priority for the decades to come: the integration of theories at different explanatory levels (Savi, van der Maas, Maris, & Marsman, 2020). The genetic, neurobiological, psychological, educational, and societal systems that underpin human intelligence do not function in isolation, and networks provide the means to connect the different levels.

Let us illustrate such a connection. We start with Juune, a Dutch toddler at the very beginning of building her cognitive network of facts and procedures. One of the facts is the word *ball*, representing an object in the shape of a globe that is often taken along outside to play. At the psychological level, the wired intelligence model formalizes this fact as a node, connected to facts like grass and procedures like kicking. At the neurobiological level, the activation of the node is modelled using sensory input, such as Juune's mom telling her to find the ball when going outside or the smell of the freshly mowed lawn. At the educational level, a model describes the pedagogical effect of the daycare supervisor's response to Juune kicking and chasing a mandarin orange. Ideally, she learns that although some properties of the mandarin overlap with those of a ball, the mandarin is best consumed (as opposed to a ball, which she had probably already found out by that time), and her cognitive network adapts accordingly. Naturally, the fact that these explanatory levels can in principle be connected, does not imply that it is easily done (Parker & Srivastava, 2013). And expected dynamic interactions between various explanatory levels only add to the complexity. Advances in estimating networks from data of these different levels (Simpson-Kent et al., 2021; Tio, Waldorp, & VanDeun, 2020) is an important first step. On the other hand, factor theories thwart such connections by modeling *g* as a causal entity that bars complex interactions both within the construct of intelligence itself and with its adjacent systems.

Then, we showed that whereas factor theories of intelligence may have reached "a preliminary endpoint in theory building" (Hartung et al., 2018), theory formation is not finished. On the contrary, the network approach demonstrates that the gaps in cognitive ability across individuals are nothing in comparison to the gaps in a complete understanding of human intelligence. We discussed how developmental phenomena, developmental mechanisms, and developmental models, not only signify the challenges in understanding the dynamics of intelligence, but signify the opportunities just as much. This brings us to the second priority for the decades to come: identifying developmental phenomena and mechanisms, and building dynamic models. The current lack of lampposts should not halt theory formation. Intelligence research must identify the many local interactions—or mechanisms—that drive the emergence of both the well-identified global stationary phenomena, and the to-be-identified global developmental phenomena. Network models must be developed to facilitate the mechanisms.

Finally, we showed that network theories of intelligence answer the call to formalize psychological theory. Formal theories demand precise descriptions of the hypothesized mechanisms, and provide falsifiable predictions. However, despite their superiority in exposing possible mechanisms, network theories of intelligence have thus far failed to concretely characterize the exact substance of the nodes and edges. Substantiation of the nodes and edges is not trivial, and certainly not necessary for gaining insight from network models. However, theories like wired intelligence do enable connections to manifest measures (such as responses to educational problems), and the endeavour is expected to deliver new insights. This brings us to the third priority for the decades to come: substantiating the structure of the proposed networks. The marriage of formal theories and substantial theories provides one opportunity to fill this gap. This effort comes with many challenges, including the specification of how central cognitive processes, such as working memory, manifest themselves in the structure and dynamics of a network. In wired intelligence theory, cognitive processes may for instance play a role in network formation and growth. Also, network theories will direct the collection of preferably intensive longitudinal data to both corroborate and substantiate theory. As intelligence is the product of human's hierarchical cognitive system, this type of data must come from its various levels, such as the neural (e.g., Simpson-Kent et al., 2020; Yuan, Voelkle, & Raz, 2018) and the educational (e.g., Klinkenberg, Straatemeier, & van der Maas, 2011).

The discussed priorities are not uniquely tied to intelligence research. The priorities and accompanying challenges reflect current developments in psychological theory formation. This is evidenced by their alignment with efforts in neighbouring fields such as neuropsychopharmacology (Lydon-Staley, Cornblath, Blevins, & Bassett, 2020). Ultimately, progress on each of the priorities will contribute to an understanding of human's mesmerizing cognitive complexity.

5. Closing remark

In the introduction we suggested that the Spearman (1904) that introduced a factor theory of intelligence and the Spearman (1927) that further developed it, are one and the same. To be precise, that is what the factor perspective would suggest. The network perspective on the other hand, demonstrates that one cannot be so sure. Humans are dynamic, and so is human intelligence.

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