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Artificial intelligence, 21st century competences, and socio-emotional learning in education: More than high-risk?

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Abstract

Over the last two decades, 21st century competences and socio-emotional skills have become a major focus in educational policy. In this article, skills for the 21st century, soft skills, as well as social and emotional skills, are contextualised in the context of technological change, machine learning, and the ethics of artificial intelligence. The use of data-driven AI technologies to model and measure these skills—in this article defined as non-epistemic competence components—can lead to major social challenges that have important implications for educational policies and practices. A moratorium on the use of data on these competence components in machine learning systems is proposed until the society-wide impact is better understood.

1 | INTRODUCTION

There exists now a strong policy-level agreement on the importance of 21st century competences and social and emotional skills for educational, social, economic, and other life outcomes (Chernyshenko et al., 2018; Kankaraš, 2017). The field, however, is also described using "*a dizzying array of terms, definitions, and measures*" (Soto et al., 2022, p. 193). A recent extensive review found 136 socio-emotional competence frameworks (Berg et al., 2017), and many alternative terms have been used to characterise these skills and competences, including 'noncognitive skills,' 'character skills,' 'transferable skills,' and 'soft skills' (Abrahams et al., 2019). The terms *competence* and *skill* are often used interchangeably in the literature, and the commonly used term *noncognitive skills*—intended to comprise personality traits, attitudes, and motivations—is acknowledged to be unfortunate because social, emotional, and other 'soft' skills are influenced and depend on human cognition (Borghans et al., 2008).

In contrast to skills and knowledge that have traditionally been the focus of education and training, 21st century competences and socio-emotional skills are closely related to individual personality traits and characteristics. For example, a recent major initiative in this area, the OECD Study on Social and Emotional Skills (Kankaraš &

Suarez-Alvarez, 2019), organises these skills based on the *Big Five* personality domains (John & Srivastava, 1999). The original Big Five model defined five top-level factors: (1) Openness to Experience, (2) Conscientiousness, (3) Extraversion, (4) Agreeableness, and (5) Neuroticism; and the resulting Five Factor Theory of personality was built on the postulate that personality traits are highly stable and biologically determined (McCrae & Costa Jr., 1999). Such a view, clearly, challenges policies and educational interventions that aim at developing these skills.

Recent research suggests that there are age and life-event-related changes in the average levels of these skills, and that educational interventions may have some limited impact on their change (Borghans et al., 2008; Heckman & Kautz, 2012). In fact, social, emotional, noncognitive, and soft skills are often defined as skills that are susceptible to interventions and policy measures, especially during the early years of life (Chernyshenko et al., 2018). Despite defining these skills as malleable, it is also known that they show predictable patterns of change across age groups (Roberts et al., 2006), and the relative arrangement of individuals along personality traits (known as rank-consistency) is surprisingly stable over time (Roberts & DelVecchio, 2000). Empirical studies, however, are also known to provide ambiguous evidence because these skills and personal qualities are measured in many different ways using varying conceptual frameworks (Duckworth & Yeager, 2015), and, despite hundreds of studies, high-quality scientific evidence is still rare (Smithers et al., 2018).

When the emerging possibilities of artificial intelligence (AI) are appropriated to model 21st century competences and social and emotional skills, important and qualitatively new ethical challenges emerge for education policy and practice. To understand these, in this article a new conceptual framing of 21st century competences and social and emotional skills is proposed that distinguishes epistemic and non-epistemic competence components. Non-epistemic competence components are shown to be related to personality characteristics that are, on average, highly stable and difficult or impossible to change after preschool age. Although it is now commonly claimed that, for example, social and emotional skills are malleable and can be influenced by interventions, in this article I adopt a more literal reading of existing research that emphasises the possibility to predict life outcomes using data on non-epistemic competence components. Deconstructing competence into its epistemic and non-epistemic components is useful from the point of education policy and learning theory, but it also makes explicit the social and technological dimensions of competence. Competent action requires integration of all these four components of competence.

Recent developments in artificial intelligence have shown that, given enough data, machine learning can recover often surprising associations that can effectively be used for prediction. The developments in AI over the last two decades have to a large extent been driven by commercial interests in modeling users and customers based on their online behaviour. A core technology for major AI-based platforms, such as Google, Amazon, Netflix, and Facebook, is social clustering based on behavioural similarity. Recent breakthroughs in data-driven AI, including in image processing and natural language processing, now provide novel ways to analyse and model personal characteristics. For example, a recent study successfully used colours in social media images to predict the Big Five personality traits (Khorrami et al., 2022). In learning analytics, students' interactions with the learning platform and the generated trace data have been used to map students to the Big Five traits, as well as to their characteristic learning strategies (Matcha et al., 2020). In general, there has been increasing interest in using AI in education (AIED) for the development of non-epistemic competence components (Joksimovic et al., 2020), including motivation (du Boulay, 2018), emotion (Harley et al., 2017), social interaction skills (Porayska-Pomsta et al., 2018), as well as metacognition and self-regulated learning (Azevedo et al., 2019).

The analysis presented in this article draws conclusions from research on personality psychology, economics of personal characteristics, and AI to show that the use of machine learning technologies to model and measure non-epistemic competence components may have important social consequences in the near future. Although the argument is based on existing research, the expected futures of AI and AIED are also considered, and the argument, therefore, is to some extent speculative. Although many caveats are necessary, the outline of the argument in this article is simple. Innovation, globalisation and access to knowledge—and information and communications technologies that underpin these—reduce the importance of epistemic competence components and increase the social and economic importance of non-epistemic ones (Tuomi, 2015). Various terms, such as 21st century competences, soft and noncognitive skills, and social and emotional skills have been used in the literature to capture the essence of these competence components that have now become important. Non-epistemic competence components, however, are closely related to personality characteristics that are, on average, highly stable and difficult or impossible to change after preschool age. Although important caveats remain—and will be discussed later in this paper—research further shows that non-epistemic competence components can be used to predict life outcomes. Machine learning models can potentially predict life outcomes better than current statistical models, also using personal data collected in the first years of life. Although these predictions may not always be accurate at the individual level, they may have a profound social impact. As the importance of non-epistemic competence components has been widely recognised, data on these are also increasingly collected in educational settings. The emerging technical opportunities to sort individuals using data on non-epistemic competence components, therefore, generate important challenges for education policy and the ethics of AI, in and beyond education.

The argument presented in this article illustrates the point that existing AI ethics frameworks inadequately address developmental and society-wide concerns that are central to education. For example, the proposed EU AI Act (EC, 2021), which focuses on safety, security, human rights, and trustworthiness from an individual point of view, misses the long-term systemic challenges identified in this article.

A moratorium is proposed because theoretical understanding in this area is still evolving, and there are strong interests in using data on non-epistemic competence components in machine learning models. A call for a moratorium may sound dramatic or alarmist but is intended to allow researchers and policymakers time to stop and think about the potentially profound consequences of using machine learning in this domain. Social classification and categorisation provide the foundations for societies, and the effective use of data on personal characteristics imply a tectonic change in these foundations.[1] The combination of state-of-the-art machine learning approaches with data on personal characteristics is potentially leading to a 'Cambrian explosion' in the social sciences and psychological research. 21st century competences, and noncognitive, social and emotional skills are rapidly becoming a central topic in education and policy, and AI-based systems that use data on personal characteristics are now widely used, for example, in recruiting (Hunkenschroer & Luetge, 2022), counselling and guidance (Tuomi et al., 2021), and increasingly also in AIED (du Boulay, 2019; Joksimovic et al., 2020). If empirical research on personality psychology, life outcomes, and economics of personality traits is accurate, and a small number of measurable personal qualities can be used to characterise individuals, these qualities most probably are currently being recovered by data-driven AI systems used to predict user behaviour on the internet. Even if the genie has already been let out of the bottle, it is important to consider how the potential harms could be alleviated.

The resulting ethical challenges have little to do with technology design or intended use, for example, algorithmic fairness (Kizilcec & Lee, 2022; Mitchell et al., 2021), unacceptable biases (Baker & Hawn, 2021; Kirkpatrick, 2016), or explainability and transparency (AI HLEG, 2019; Barredo Arrieta et al., 2020; Biran & Cotton, 2017; Mittelstadt et al., 2019). Ethical challenges emerge here as a society-wide interaction of new information infrastructures and machine learning systems that use data available on these infrastructures. Personal characteristics have always been socially important; data-driven AI simply makes them more important than before as technology allows us to use knowledge and data more efficiently. The ethical challenge, therefore, cannot be found from the characteristics of any specific AI system; instead, it is rooted in the general predictive capacity of data-driven AI. In contrast to much research on how AI-based prediction can go wrong, the present case shows what can happen if the system works as intended.

The article is organised as follows. Section 2 discusses different conceptualisations of competence and skill and suggests that 21st century competences and social and emotional skills should be understood as non-epistemic competence components. Section 3 then focuses on the nature of these non-epistemic components building on Roberts' (2006) neo-socioanalytic model of personality. Section 4 reviews research on the malleability of non-epistemic competence components and notes the importance of the stable *core* personality for AI-based prediction. Section 5 discusses data-driven AI and non-epistemic competence components and highlights some limitations of the presented argument and current knowledge. Section 6 puts these discussions in the context of education policy and the ethics of AI. The article ends with a short concluding section with a suggestion that a new framing may be necessary to realise the potential of future AIED for non-epistemic learning.

2 | STRUCTURAL CHANGE IN COMPETENCES AND THE BIRTH OF 21ST CENTURY SKILLS

The use of the term *competence* has proliferated in different contexts during the last decades. One source of this popularity is its use in strategic management literature in the 1990s, from where it has spread to many *core competence* frameworks used in formulating capabilities that are needed in work and life. Such frameworks range from the OECD Core Competence Framework on financial literacy (OECD, 2015) to the UNESCO Core Competency Framework for its staff (UNESCO, 2016), and the EU Key Competence Framework for Lifelong Learning (Council of the European Union, 2018).

Despite the proliferation of the term, the nature of competences is often addressed only superficially. For example, the recent UNESCO Competence Framework for Cultural Heritage Management (UNESCO, 2020) explains parenthetically that the framework identifies areas of competence as skills and knowledge. UNESCO's Competency Framework for UNESCO employees (UNESCO, 2016) uses a slightly broader definition that constructs competences as a set of related knowledge, skills and abilities resulting in essential behaviours expected from those working for the organisation. OECD's internal Competency Framework (OECD, 2014) separates technical competences from core competences that are important across all OECD jobs. These, according to OECD, include competences such as analytical thinking, achievement focus, flexible thinking, teamwork and team leadership, diplomatic sensitivity, influencing, negotiation and strategic thinking. According to the European Commission, "*competences include more than knowledge and understanding and take into account the ability to apply that when performing a task (skill) as well as how – with what mind-set – the learner approaches that task (attitude)*" (EC, 2018, p. 4). In European Union literature, competence thus can often be understood as an intersection between knowledge and skill related components and attitudes.

The literature on skills and competences often distinguishes technical domain-specific skills and functional or generic skills. Skills have been associated with individuals, occupations and jobs, and also argued to be distributed among persons and technology (Attewell, 1990). Competence, in turn, has been conceptualised as a combination of cognitive, conative, and affective components (Snow et al., 1996). Cognitive elements include various forms of knowledge and intelligence. The conative dimension, in turn, captures motivational and intentional aspects such as attention, grit and executive control of behaviour, whereas the affective dimension of competence captures the emotional and temperamental aspects of competence.

Many AI-based systems now use extensive skill taxonomies built using natural language processing of on-line job advertisements (e.g., Australian Government, 2019; CEDEFOP, 2019; ILO, 2020; Squicciarini & Nachtigall, 2021). At the time of writing, the European Skills, Competences, Qualifications and Occupations (ESCO) skills pillar includes some 14,000 skills (EC, 2022). The widely used US government sponsored occupational information resource website O*Net OnLine (O*NET, 2022) provides data on job-related basic content skills, basic process skills, such as critical thinking and active learning, and cross-functional skills, including social skills, complex problem-solving skills and technical skills.

Simplifying this complex picture, we can depict competence as a combination of two qualitatively different components. One is the *epistemic component* that includes knowledge, domain specific skill and experience. This can be summarised using the term *expertise*. As new knowledge and domain-specific skills can be learned and experience gained, this competence component has been the traditional focus of education, vocational training, and intelligent tutoring systems in AIED.

To become realised as an expressed capability to get things done, this epistemic component needs to be complemented with non-epistemic elements. These include the 'attitudes,' 'dispositions,' and 'noncognitive', 'soft' and '21st century' skills that have also been called the "behavioural repertoire" (Hoekstra & Van Slujis, 2003). More broadly, as discussed in more detail in the next section, they also include *cognitive* aptitudes and capacities. These non-epistemic elements capture many of the things commonly called transversal, generic, or *core* competences and skills, including analytical and critical thinking, communication skills, emotional intelligence, leadership skills, curiosity, openness to experience, grit, and learning skills. The list is long. It can be shortened by labelling it as '21st century skills,' or 'social and emotional skills.' In this article, an attempt is made to capture the essence of such skills, and how they differ from the focus of mainstream 20th century education, by terming these skills the *non-epistemic components of competence*.

Competent action often occurs in situations where the current material and cultural contexts can be taken for granted. Historically, social institutions—including education, the organisation of work, and stocks of knowledge and expertise—have been able to stabilise after new key technologies have been introduced (Freeman & Louçã, 2001); in effect, becoming the invisible background where skills and competences are distinguished. Domain-specific skills and knowledge, therefore, can often be viewed as a reflection of the prevailing technological and material context (Tuomi, 2020; for an example, see Kotamraju, 1999). In this sense, a car generates the skills of a car-mechanic, a programmable computer generates the skills of a software programmer and computational thinking, and an anvil creates a blacksmith. In the industrial era, the resulting skill sets were stable enough to be associated with professions, areas of expertise, and educational qualifications. Occupational skills, as listed in taxonomies—such as provided for the US on the O*Net website and for Europe by ESCO—therefore, are conceptually mirror images of current technology. When technology changes, many of these skills become obsolete, and policy focus shifts to '21st century competences,' now commonly understood as social, emotional, and transversal skills.

The capability of getting things done depends on the material and technical environment as well as human collaboration and coordination. At one extreme, actor-network theory and science and technology studies argued for the symmetry between human and non-human actors (Callon et al., 1986).[2] Research on socially distributed and situated cognition (e.g., Brown et al., 1989; Hutchins, 1995) and cultural-historical activity theory (e.g., Engeström et al., 1999; Leont'ev, 1978), in turn, emphasised the interactions between human cognition, culture, and tools and technologies used in action. In general, a sociological and organisation theoretic view on competence would highlight the social and cultural constraints, norms, rules, and resources that are necessary for human action and agency, whereas sociology of technology and science would align with Vygotsky (Vygotsky & Luria, 1994), and point out that—beyond socially shared conceptual systems—the capability to get things done depends on instruments, tools, and technology.

Both in activity theory and in general sociology, the cultural context provides systems of value that make action meaningful and socially intelligible and useful. It is easy to see that in a world where cultural contexts lose their stability and activities become connected across cultures, the importance of communication, collaboration, and intercultural skills increases. Such a cultural change, of course, is deeply linked to technical change and, in particular, communications technology. In contrast to the classical sociological theories of modernisation, intercultural collaboration cannot anymore be reduced to transactions across geographies (Durkheim, 1933), or even global flows of information (Castells, 1996). To be able to act competently, actors need to mobilise social resources across cultural boundaries and systems of meaning. As a result of this process, and the continuous innovation that results from it, also the technological and cultural contexts, previously taken for granted, now become visible.

The above overview shows that there are important social, economic, and historical reasons for the increasing attention to the non-epistemic components of competence. In this sense, the focus on 21st century competences was a reaction to a global social transformation, commonly known as the information or knowledge society, that described a disruptive historical period before recent advances in AI. The following elaborates on non-epistemic competence components that can be associated with personal characteristics. However, for education and policy it is important to note that competence emerges at the intersection of changing social, technological, epistemic, and non-epistemic components.

It is therefore no accident that the non-epistemic components have been characterised as '21st century competences.' Labelling these as *skills*, however, is bound to generate confusion as skills are commonly understood as domain-specific or practice-oriented competence components, and often associated with 'know-how,' and procedural and tacit knowing (Polanyi, 1967; Ryle, 1949). Similarly, calling these person-related elements 'competences' contributes to a disregard of the cultural and technological contexts, and makes it difficult to understand how the ongoing changes in these contexts generate the need to address these non-epistemic components of competence.

In a graphical form, the domains of competence can be depicted as in Figure 1. The left-hand side consists of expertise that can be defined as a combination of knowledge, skill and experience. The right-hand side includes various dispositions, characteristics and generic capacities that are needed to realise competent action. The realisation of action requires social and material resources and is constrained and enabled by technology and culturally shared norms and values. In general terms, the shift from 20th century competences towards 21st century competences can be viewed as a shift from the left to right, accompanied by the increasing visibility of the changing cultural and material contexts.

3 | NON-EPISTEMIC COMPETENCE COMPONENTS AS TRAITS, ABILITIES, INTERESTS AND NARRATIVES

A useful model of the dimensions of personality can be represented as in Figure 2, derived from Roberts' neo-socioanalytic model of personality (Roberts, 2006). The four segments in the figure correspond to the domains that make up the core of personality: traits, motives, abilities, and narratives. These four domains, according to Roberts, subsume most of the important categories of individual differences. In Figure 2 these different domains are also associated with common constructs that are used to characterise these domains.

The lower left segment of Figure 2 consists of *abilities*. These are often conceptualised and measured as 'intelligences.' Much scientific debate exists on what these intelligences are and how they should be modelled. A widely used model is Carroll's three-stratum model (Carroll, 2005). In this hierarchical model, the top-level construct of general mental ability, denoted as *g*, explains variance across all types of cognitive ability tests, second-level constructs, such as fluid intelligence, crystallised intelligence, broad visual perception, and processing speed, explain variance across different task domains, and the bottom level consists of factors that are most specific.

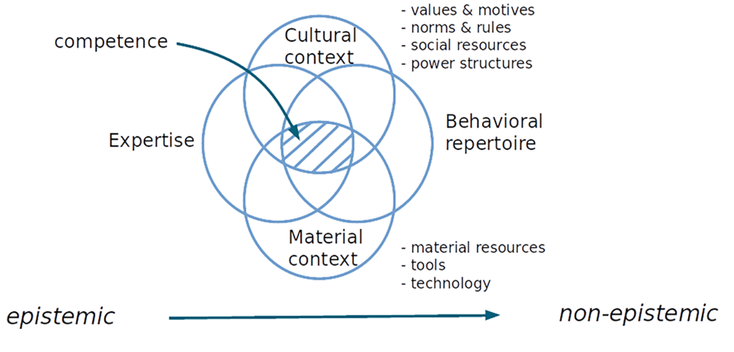

FIGURE 1 Competence components. *Source*: Author.

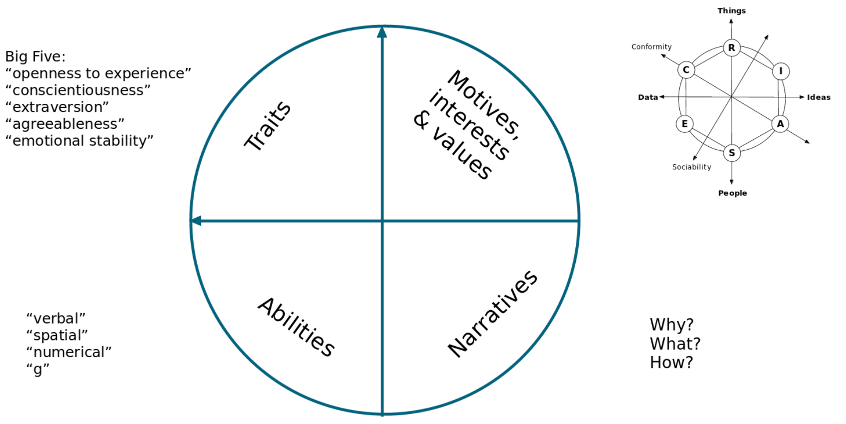

FIGURE 2 The four domains of personality. *Source*: Figure constructed by author using concepts from Roberts (2006, pp. 5–10).

Personality *traits* are commonly defined as the enduring patterns of thoughts, feelings, and behaviour that people exhibit (Roberts, 2006). These are most often measured using psychometric tests that map personality to the Big Five factors of extraversion, agreeableness, conscientiousness, emotional stability/neuroticism, and openness to experience (e.g., McCrae & John, 1992).

The third segment in Figure 2 is aimed to cover the domain of *motives* and the structure of *interests*. For the purposes of this article, I use Holland's theory of career choice as a basis for measuring motives and interests (cf. Nauta, 2010)—which of course, is a simplification.[3] Holland's character description factors, Realistic, Investigative, Artistic, Social, Enterprising, and Conventional (RIASEC), however, are widely used in educational and career guidance, counselling, recruiting and occupational research. At present, RIASEC tests, or their variants, also underpin many public-sector and commercial web-based career and educational guidance services in countries around the world, including Singapore, Australia, the US, the UK, the Netherlands, Denmark, and in a multitude of other countries (Tuomi et al., 2021).

In contrast to the neo-socioanalytic model that groups values and motives, Figure 2 implicitly locates values in the *narrative* segment. Although the term is used in many ways in existing literature, the assumption here is that values are a fundamentally social phenomenon, grounded in making good-bad or right-wrong distinctions in the context of cultural systems of meaning.[4] Research on cultural categorisation suggests that systems of values are culture-specific (Douglas, 1966; Lakoff, 1987). Narrative accounts of personality, thus, rely on existing socially shared value systems.[5] In this interpretation, values are part of the tacit context in Polanyi's (1967) original sense, and the narrative elements of personality consist of accounts that, for example, explain who the person is (McAdams, 1993; Taylor, 1989) and where the person is located in the culturally constituted world (Eliade, 1991). These narratives have both an internal aspect, for example, self-generated accounts of how the person came to be what she is, who she is, and where she is going, but also external accounts about the person and her social roles. In Roberts' neo-socioanalytic model, internal assessment forms the source of identity, whereas external observation and assessment forms the reputational aspect of personality.

4 | STABILITY AND MALLEABILITY OF NON-EPISTEMIC COMPETENCE COMPONENTS

The concept of personality rests on the assumption of stability across time. In everyday discourse, we use the concept of personality to describe those generalisable and relatively stable characteristics that differentiate individuals and make prediction, expectation, and explanation possible. The sources of this stability have been actively debated over the centuries. In the last decades there have been major shifts in these debates. The idea that personality can be characterised using a small set of stable person-related traits was strongly rejected towards the end of the 1960s, when it was argued that personality reflects situational factors, and personality 'traits' should be understood as artifacts generated by personality tests (Mischel, 1968). In reaction to this situational view, in the 1990's it was increasingly argued that five situation-independent universal factors (The Big Five) consistently characterise personality across cultures (e.g., McCrae & Costa Jr., 1997). In the last two decades, many empirical studies have argued that personality traits exist, are largely genetically determined, but also change over the lifetime due to maturation, social pressure, and major life events, such as becoming a parent (Almlund et al., 2011; Heckman & Kautz, 2012; Roberts & DelVecchio, 2000; Specht et al., 2014).

An influential study by McGue et al. (1993), for example, showed that over 80% of the observed stability in personality characteristics in late adolescence and early adulthood can be explained by genetic factors. Close to two thirds of the individual differences in openness to experience—the most important Big Five factor for educational achievement along with conscientiousness—can be explained by hereditary factors (Kankaraš, 2017, p. 15). The maturation of personality and the resulting changes in the Big Five traits have a strong hereditary component, in particular for agreeableness, conscientiousness, and neuroticism (Bleidorn et al., 2009). Although linkages and causalities between hereditary factors, the environment, and personality characteristics are not well understood, this means that also the possibilities for change in personality traits is constrained and enabled by hereditary factors. After hereditary and early childhood influences, apparently only limited space is left for individually differentiated personality change when children enter formal education.

Although life events, environment, and, for example, education may influence the development of personality, it is generally believed that personality traits have substantial predictive value across time. For example, in his review on non-cognitive skills, Zhou (2016) suggests that the Big Five traits have to be separated from non-cognitive skills because they are shown to be relatively stable and not easily improved by training or education.

Similarly, large bodies of empirical research suggest that interest structures are relatively stable (Nauta, 2010). As Holland's influential RIASEC model was developed in the context of occupational choice, studies on interest stability have mainly focused on adolescents and adults. Research, however, indicates that there is moderate rank-order stability in the interest structure already among elementary school children (Tracey & Sodano, 2008). Strong rank-order stability, i.e., the ordering of people along this dimension, means that the relative future location of a person on this scale can be well predicted using historical data.

Extant psychometric research suggests that the most stable personality factor is general mental ability, or *g*. Although components of *g*, such as fluid intelligence and crystallised intelligence change with age—the first peaking in young adulthood, and the second accumulating through the life-time—the relative order of people on these scales remains fairly stable (Heckman & Kautz, 2012). The reasons for this stability are not clear, but genetic factors and early childhood experiences apparently play an important role. Research suggests that about half of the variance in *g* has genetic origin (Plomin & Spinath, 2002). Large bodies of empirical literature have shown that cognitive capacity, temperament, and, for example, social capabilities show continuity and predictability from the first months of age, and sometimes already from prenatal developmental stages (Bornstein, 2014). Some cognitive capacities, such as language performance at eight years, can be predicted by brain activity of newborn infants (Molfese, 2000).

There are different forms of consistency of personality that need to be distinguished. Consistency can mean continuity, for example time invariance or predictable patterns of maturation. Consistency, however, can also mean relative stability and rank-order consistency. Strong rank-order stability has been observed in many empirical studies on personality traits (Roberts & DelVecchio, 2000). Although recent research has started to focus on the more fine-grained facets of personality that underpin the general Big Five factors and related cognitive abilities (e.g., Rammstedt et al., 2018), and alternative models, such as the Big Six (Ashton et al., 2004), may better describe personality across cultures, there is a general agreement that personality characteristics are relatively rank-order stable after the early childhood (Bornstein, 2014). Individuals can, therefore, be sorted using information on traits, abilities, and interests, and future orderings of individuals along these characteristics can be predicted using this information.

For educators, a critical question is to what extent educational interventions can impact the level or development of personality characteristics. For example, there exists much work on Social and Emotional Learning (SEL) and mindset interventions (Abrahams et al., 2019; Chernyshenko et al., 2018; Durlak et al., 2011; Taylor et al., 2017). In policy-related literature, non-epistemic competence components are usually defined as malleable skills. The term skill, in itself, suggests that it can be developed and that the result is useful and valuable, and the additional attribute *malleable* emphasises that these skills, indeed, can intentionally be changed. At the same time, the existing evidence on stability and predictability of many capacities that could well be labelled social and emotional skills and 21st century competences, is considered by definition largely irrelevant.

Summarising the vast literature on personality change in terms relevant for the present analysis, there is now strong evidence that there exists a *core* personality that is stable enough to make predictions across time and environmental conditions. McGue et al. (1993) showed that, on average, over 80% of the variance in this stable component was associated with genetic factors. They also showed that, although also hereditary factors play a role, about half of the change in the 'residual' elements of personality can be associated with environmental influences. This particular longitudinal twin-study focused on changes in early adulthood but is consistent with the claim that *core personality* is formed by the first years of childhood. Reversing the logic commonly used in discussions on 21st century skills that focus on the residual and potentially changing 'noncognitive' parts of personality, for AI-related prediction, the stable core and the non-epistemic competence components associated with it are a more natural starting point.

From a practical point of view, the changing social demand for education puts educators in a challenging position. For example, the top three most requested skills in CEDEFOP's job market monitoring system include (1) working in teams, (2) planning and scheduling events, and (3) accessing and analysing digital data (CEDEFOP, 2022). These can in a straightforward way be mapped to, for example, the taxonomy of behavioural, emotional, and social skills recently proposed by Soto et al. (2022). Although research suggests that social contexts and environmental influences have an impact on measured personality characteristics, the induced changes seem to be temporary. There is a long history of claims of the effectivity of "brain training" interventions (Katz et al., 2018), but, despite many popular claims, the evidence remains particularly weak for short-term interventions such as growth mindset (Moreau, 2022).

Discussion on the malleability of life-determining personal characteristics is bound to create controversy. Education is traditionally based on the fundamental belief that it can change and develop individuals.[6] For epistemic competence components, this clearly is the case. It also seems intuitively clear that life experiences and maturation can change personality. It would be natural, for example, to expect that studying abroad could increase openness to experience. Recent research, however, suggests that whereas students with high openness often choose to study abroad, this does not seem to have noticeable impact on their personality (Niehoff et al., 2017; Nissen et al., 2022).

Three of the segments of Figure 2—abilities; traits; motives and interests—provide key elements of the stable core personality. It should be noted that the fourth *narrative* segment has a very different dynamic. The stories we tell about ourselves and others have a fundamental impact on how we interpret the world and make sense of it, and how we act. The socialising function of education (Biesta, 2015) can in many ways be understood as a process that generates shared inter-generational stories, understanding, and systems of value that make social life possible. The creation of new stories and reframing existing ones, therefore, may be an important source of personality change. Culturally shared narratives do not only enable us to make sense of ourselves, but also define the social relevance and meaning of concepts such as *ability*, *personality traits*, and *motives and interests*. In this sense, the narrative component of personality may both be seen as the most malleable component of personality and its most fundamental layer on top of which abilities, traits and motives are constructed. From a point of view of sociology of knowledge and social learning theories, however, narratives are fundamental elements of the prevailing systems of knowledge. The narrative component of personality in Figure 2 should therefore be located among the epistemic competence components.

5 | AI AND NON-EPISTEMIC COMPETENCE DATA

For the present analysis, it is not necessary to make strong claims about the possibility of useful educational interventions in the non-epistemic domain. In fact, education theorists and practitioners agree that education has important social functions that are not epistemic (e.g., Biesta, 2010). Instead, the argument is that whatever regularities, stabilities, and continuities there may exist in human personality, current machine learning systems will be able to find them and use them for prediction. Whereas empirical studies on personal characteristics have struggled to find statistically valid associations that predict future life outcomes, AI-based models can skip most concerns about statistical validity and conceptual and theoretical immaturity. The approach in machine learning is different. The development and training of machine learning models stops when the system works well enough, and its predictions can be generalised. At that point, the system has generated an internal representation of the domain in question and a predictive model that embeds as much information on relevant distinctions it can. There is no guarantee that the representation would be based on the Big Five, Big Six, or any other proposed factors or their facets.

Many studies on personality factors, for example, have been based on collecting words used to describe personality, and clustering them into a manageable set of factors. In contrast, common representations of input data in AI natural language applications based on machine learning usually represent words in 300 or 500-dimensional spaces (e.g., Mikolov et al., 2013). Psychometric research is strongly limited by its aim to find a relatively small set of factors that can have intuitive human interpretations. AI systems are not restricted by this requirement.

Data published by the OECD Survey on Social and Emotional Skills (OECD, 2022), for example, can in a straightforward way be used to generate models of social and emotional skills that with high probability make more accurate predictions than the best existing factor models. Whereas the intent of the OECD study is to fit collected data into a predefined descriptive theoretical frame, machine learning can use these data to construct a new implicit theory of the domain. Although survey instruments used to collect these data are based on existing theories and hierarchical models—thus implicitly supporting the chosen theoretical model—machine learning systems can easily complement such data from other sources. After a model that associates patterns of personality characteristics with life outcomes is trained, it can predict these outcomes also for individuals. There remain many technical challenges, for example, in transferring models trained with specific datasets in new application domains and complementing and augmenting their data, but these are typical engineering challenges in machine learning.[7]

Borghans et al. (2008) list five limitations of current evidence on predictive validity that may have underestimated the impact of personality traits for socioeconomic outcomes including job performance, health, and academic achievement. First, the optimal level of a trait is not necessarily the maximal one, and the curvilinear relationships are not well represented by correlation coefficients. Second, the top-level factors of Big Five are probably too blunt an instrument to capture relationships between personality and outcomes, and more narrowly defined facets of personality can predict outcomes better. Third, personality is often measured using self-report questionnaires that are not very reliable. Fourth, interaction effects, for example, between cognitive abilities and personality traits may be important. Fifth, standard measures of predictive power, such as effect size and variance explained, may not be the most useful ones, for example, when causal effects are studied. Machine learning systems can avoid all these sources of potential error and could therefore have more predictive power than existing research.

Many data-driven AI systems are now used, for example, to predict school drop-out (Del Bonifro et al., 2020) and to select applicants for jobs and job-related training (Aspan, 2020; HR Research Institute, 2019; Hunkenschroer

& Luetge, 2022). Although there is no guarantee that a prediction would be correct for a specific individual, by definition the predictions will be statistically robust. For example, state-of-the-art generative language models in AI, such as the famous GPT-3 from OpenAI (Brown et al., 2020), can use data on personality characteristics as an input and, with a relatively minor retraining, write the expected life story of the person. If this can be done using data from a very early age, the personal and social consequences deserve further study. Similarly, if preschool children can be sorted based on their ability to *work in teams*, capacity for *problem solving* and *planning*, and characteristics such as *creativity*, *curiosity*, *ability to work under pressure* and *willingness to constantly learn new things*, it should be clear that data on personality has social consequences.

An extreme claim that data collected in the first years of life can predict life outcomes can only be made with important caveats. First, despite the broad agreement that social and emotional skills, personality traits, and cognitive abilities have a clear impact on various life outcomes (Heckman & Kautz, 2012; Kankaraš, 2017), there is very little robust scientific evidence to support or reject these claims. Smithers et al. (2018) reviewed 554 publications that have reported the relationship between childhood noncognitive skills, such as attention, self-regulation, and perseverance, and later outcomes. About 40% of these empirical studies were judged to present better-quality scientific evidence, 21% were classified as studies that provided weak evidence, and 38% classified as providing poor evidence as there was effectively no attempt to control confounding (Smithers et al., 2018, p. 869). The observed effects have been heterogeneous, and the 95% prediction interval includes negative, null, and positive effects. Overall, this meta-analysis of existing research, that also considers the methodological quality of the reported results, suggests that there is some evidence supporting a role for non-cognitive skills in better academic achievement, but the reported effects are highly heterogeneous, and a true null effect of noncognitive skills on outcomes cannot be ruled out.

This, of course, does not mean that non-epistemic competence components would have a negligible impact on life outcomes. It simply means that researchers have not been able to produce good scientific evidence for that. This also means that machine learning may be able to drill through the prevailing conceptual confusion and data limitations and find the true personal characteristics that predict future outcomes.

Second, it is always possible to question the indicators used to measure outcomes. Given, for example, that many successful entrepreneurs are school dropouts, educational achievement is not necessarily the best indicator for a positive outcome. In employment contexts, Bartram (2005), for example, suggested a criterion-based Big Eight model of work-related competence that was based on analysing factors that underpin on-the-job performance as judged by the superiors of the employee. In this approach, the question to ask is *What factors can best predict job performance?*, instead of the conventional *What performance personality trait X predicts?* A theoretically more robust approach might be to link outcome measures to capabilities that are important for development and well-being; for example, by using the capability-based approach as a starting point (Sen, 1993).

Third, reported experiments with machine learning have so far been unable to make accurate predictions about life outcomes. A large experiment in scientific mass collaboration, the Fragile Families Challenge (Salganik et al., 2020), used data from birth to age nine from 4,242 US families to predict outcomes at age fifteen. From the 160 competing teams of machine learning experts, no one was able to make very accurate predictions about the selected six outcomes, including a child's grade point average and grit. Although the Fragile Families data used in this experiment is highly selective and do not include detailed data on non-epistemic competence components or sophisticated measures for the outcome variables, the result supports the view that life events, in general, are difficult to predict. As life increasingly has a digital representation, it can be expected, however, that prediction accuracy is higher when online trace data can be used for prediction.

Based on existing research, it is possible to make contradicting claims; for example, that non-epistemic competence components are malleable skills amenable to interventions, to a large extent stable but malleable in some critical early stages of development, or largely fixed at birth. It is easy to select one alternative over the others based on personal beliefs and anecdotal evidence. In this article, I have emphasised predictability and generalisability that underpin the concept of *personality* as a relatively stable phenomenon. Whether this stability at the end can be reduced to the Big Five personality domains or its lower-level facets remains an empirical question. It is highly probable that lower-level facets can more effectively be used for prediction, and it is also probable that contextual factors not accounted for in conventional personality instruments, such as motives, incentives, and social roles (Almlund et al., 2011; Borghans et al., 2008; Roberts, 2006), have an important role. For the developers of data-driven AI systems, these are practical engineering challenges. When the system makes accurate enough predictions, it works. Somewhat paradoxically, however, there is no proof that past success will accurately predict the future in individual cases as the predictions will always be based on the statistical characteristics of past data.

6 | DISCUSSION

For education policy, it is important to know what factors influence social, economic, and educational outcomes. There is now extensive evidence that social and emotional skills and personality characteristics predict educational and broader life outcomes. Social and emotional skills are closely related to personality, and interventions aimed at the development of social and emotional skills are therefore associated with personality change. Although prediction does not mean that life outcomes would be determined by personal characteristics, the existing associations are statistically significant.

A core functionality in machine learning systems is prediction. This is not only prediction as an outcome; prediction also underpins the adaptation and learning of these systems. *Learning* in these systems is purely associative and *training* these systems is based on reducing errors in prediction.[8] Instead of *artificial intelligence*, these systems could therefore better be called “artificial instincts” (Tuomi, 2018a).

Despite fundamental differences between machine learning and human learning, these systems are in many domains able to outperform human cognitive capabilities (Zhang et al., 2022). Although not based on existing research, it can be expected that data-driven AI systems will be able to model personal characteristics in novel ways that lead to better predictions than traditional methods. Most importantly, the data do not have to be collected from personality surveys. Although, for example, the infamous Cambridge Analytica system (Isaak & Hanna, 2018) used a personality test based on the Big Five factors as an entry point to user data, the implicit connections among social network users became the main source of social impact.

From an ethical point of view, wrong predictions about individuals are an important problem, already widely debated also in educational contexts (Baker & Hawn, 2021; Holmes & Porayska-Pomsta, 2023). From a social point of view, social groupings and categorisations are important, and they also underpin concepts of fairness, equality, equity, discrimination, and equal treatment (Tuomi, in press). The ethical challenge of using personality characteristics in machine learning, therefore, is not as much about unfair algorithmic decision-making at the individual level as it is about society-wide amplification of social sorting in many domains of life, including education. Information and communications technologies generated what now is called the knowledge and information society, and AI will have similar tendencies to reorganise the foundations of society, including its systems of knowledge creation, learning, and education. Such a social impact is orthogonal, or extraneous, to the conventional ethical concerns based on assessing individual risks. Therefore, it remains outside the scope of, for example, the proposed EU AI Act (Smuha, 2021) and checklists aimed to support the developers of ethical AI applications (e.g., AI HLEG, 2020). Highlighting the potential adverse impact of AI-enabled profiling, Yeung (2019) notes that:

> These observations alert us to the collective and cumulative impacts of contemporary applications of data-driven technologies which, when undertaken systematically and at scale may, over time, seriously erode and destabilise the social and moral foundations that are necessary for flourishing democratic societies in which individual rights and freedoms can be meaningfully exercised. (Yeung, 2019, pp. 37–38)

Education is a building block of societies. The turn toward non-epistemic learning and competence development is motivated by profound changes in the ways societies organise their activities. AI will play an important role in shaping this change, because prediction and expectations are fundamental factors of social life. The quest for the development of 21st century competences may look attractive in the post-industrial knowledge society, but we may want to think where this road leads in a world where machine learning systems are widely used.

The discussion presented in this article on the potential uses of AI in education, highlights the point that a proper analysis of risks and social consequences may require studying long-term structural impacts. Structural change is often disruptive and its consequences inherently unpredictable—and difficult to study with methods traditionally used in empirical psychology, economy, and sociology. Somewhat paradoxically, as data-driven AI relies on historical data, it will have considerable difficulties in predicting the impact of the social change that it influences. Future-oriented thinking and imagination, therefore, is an important element in detecting and assessing challenges and opportunities, but also in creating anticipatory capabilities that allow the society and its members to appreciate the emerging challenges and opportunities (Miller, 2018; Poli, 2017).

The first metric intelligence tests were created in 1905 by Alfred Binet and Théodore Simon when a minister of public instruction in France tasked a special commission to identify pupils in need of specialised education programs. The need to sort children based on their mental ability emerged as France had in the previous decades introduced compulsory education for all children and extended the role of central government in education.

Since then, research on intelligence and personality traits is known for the many heated controversies it has generated. Whereas Binet was looking for ways to improve education (Cicciola et al., 2014), the history of IQ testing is also associated with eugenics and claims about scientific racism (e.g., Fraser, 1995). Similarly, any claim that non-epistemic competence components are difficult to change after children enter formal education, is bound to create controversy. Although this potential for controversy exists, the main message of this article is that, to the extent difficult to change individual differences exist, machine learning systems can profoundly amplify the social consequences of these differences. Ethics of AI in education, and beyond, therefore, also needs to revisit the ethics of education (Holmes et al., 2021).

Empirical research on non-epistemic competence components has been struggling with measurement challenges, methodological issues, and lack of coherent conceptualisations. It is possible to use existing research selectively to make contradicting claims about research findings. One reason is that the lack of shared coherent theoretical frameworks makes it difficult to synthesise existing research results. This is the case for social and emotional skills, noncognitive skills, soft skills, and 21st century competences. Therefore, there is a need for further conceptual work in this area. In contrast, machine learning systems can avoid these conceptual and empirical challenges, as they do not need domain-specific theory. Machine learning systems simply extract regularities from the data used for their training, and optimise predictions based on criteria given by the system designers. This is both their strength and their weakness.

Binet's research was driven by the belief that comparatively lower-ability students can benefit from their own classrooms and specialised education. A similar belief underpins mastery learning approaches that underpin many influential AIED applications.[9] These applications build on the assumption that—given enough time and practice—students with different abilities can achieve similar levels of mastery. The expectation that AI can transform education by personalising learning (see e.g., European Parliament, 2021) is often at least implicitly based on the idea that AI can tailor instruction at the individual level. These systems have typically been based on models of human cognition and domain-specific knowledge, although there has been increasing interest in supporting the development of non-cognitive 21st century skills, emotional and social skills, and, for example, metacognition and self-regulated learning. This shift towards non-epistemic learning has been driven both by the new technical possibilities of data-driven AI and the recognition of the importance of non-epistemic components of competence.

On the background of this analysis, I recommend a moratorium on the use of data on non-epistemic competence components in data-driven AI systems. A moratorium is a temporary halt and suspension of activity, intended to give time for adequate consideration. Temporarily postponing the commercial and public sector uses of AI systems that rely on personal characteristics is proposed. This policy decision is important for facilitating research and debate on the society-level impact of AI use in education. It is possible that many existing uses of AI implicitly or explicitly rely on data on personal characteristics. The proposed moratorium would help to surface such uses and allow the current and future users to consider possible consequences—including adverse effects that can be avoided.

7 | CONCLUSION

The observations presented above, of course, do not mean that we should stop studying non-epistemic competence components, their development, or AI as a tool to detect and support non-cognitive learning. We are, indeed, in the 21st century. AI-supported non-epistemic learning is a highly promising area of possible future uses for AI in education.

A new framing of the problem, however, might be useful. Vygotsky's empirical work in the 1920's on the role of artifacts and tools in cognition (Luria & Vygotsky, 1992) suggested that technology can augment human thinking. AI has successfully been used to support students with special needs, and from the point of view of unique personality, each of us is special.

For the use of AI in education (AIED), the proper unit of analysis for research and development of future AIED could well be a hybrid person-technology complex. If it is difficult to change person-related 21st century competences, it may well be possible to augment and complement social and emotional skills with AI-based systems when needed. We live, think, and learn in a technological context, and currently AI technologies are changing this context. In many ways, technology has become a part of our personality and, perhaps, should be studied as such.

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ENDNOTES

[1] Classification and categorisation are central topics, for example, in sociology of knowledge, sociocultural psychology, research on cultural cognition, as well as in mainstream social theory. Here I simply note that the use of data on personal characteristics in machine learning systems can structure societies in novel ways.

[2] Latour (1996), however, emphasises that actor-network theory has no model of human competence.

[3] The conceptualisation of motives varies widely across different disciplines, also within the different traditions of psychology. For example, in activity theory motive is the culturally constituted object of activity (Harré et al., 1985; Stetsenko, 1995).

[4] It can be argued that values become increasingly culturally determined as a child develops "higher forms" of thought (Tuomi, 2018b). In economics, values are often understood as preferences (Sen, 2009), and in sociological literature, typically associated with norms and social legitimation structures (e.g., Giddens, 1984).

[5] All personality characteristics, of course, have this narrative element. Hogan (1996, p. 173), for example, argued that personality traits are "categories that people use to evaluate one another."

[6] The history of education is, of course, more complicated as there have been many pedagogic traditions. For example, in critical pedagogy and activity theory social change plays an important role.

[7] Data-driven AI models require that training data and data used for predictions have similar structures. It is not possible to directly use OECD data to predict outcomes if data on outcomes is not available or if input data are structurally different from data used for model training. In practice, the OECD data would need to be augmented.

[8] More accurately, data-driven AI systems define a 'loss function' and learning occurs by reducing this loss until the system optimally generalises predictions to examples that it has not seen before.

[9] I have collaborated on another article that further elaborates on this point, in this issue of the European Journal of Education.

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