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Measuring and Predicting Technical Fluency: How Knowledge, Skills, Abilities, and Other Behaviors Can Contribute to Technological Savviness

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14. ABSTRACT
Future operating environments will require humans to team with increasingly sophisticated and evolving technologies. These intelligent technologies will be required to keep pace with adversarial challenges. Operators and leaders in these domains will require increased technological aptitudes and skills to leverage their expertise and creativity to adapt technologies to evolving mission sets and avoid being overmatched by the adversary. This combination of aptitudes and skills is termed technological fluency (TF): the ability of operators to use and rapidly adapt new and intelligent technologies without formal training. With this new and evolving area of research, models of TF will be developed, as well as assessment approaches necessary to quantify TF in individuals for selection and assignment, and finally training protocols and in-field aids to enhance TF. These will modernize personnel selection and training methodologies, which will lead to a reduction in training costs, faster and more extensive technology fielding, and greater operational flexibility and effectiveness. To reach these goals, it is crucial to determine what necessary knowledge, skills, abilities, and other behaviors are required for individuals to become technologically fluent. This report outlines five preliminary categories relating to enhancing and maximizing TF within human-technology interaction domains.

15. SUBJECT TERMS
Humans in Complex Systems, technological fluency, technological adaptation, human-guided technological adaptation, technological literacy

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1. Introduction

The digital revolution is progressing exponentially (e.g., Ghobakhloo 2020). One of the most salient areas of growth in recent years, and perhaps the most impactful, has been in learning-capable artificial intelligence (AI). AI capabilities have demonstrated near-human, and sometimes superhuman, performance on highly complex tasks, thereby increasing productivity across almost every sector, especially for cognitive and computational tasks (Dwivedi et al. 2021). Although certain tasks currently performed by humans, and perhaps in some cases entire professions, may be delegated to AI (Huang and Rust 2018; Webb 2019), human-AI interactions will be critical for future operations (O'Neill et al. 2022).

1.1 Background

Before the advent of AI, many technological advances offered specific solutions to specific problems. Now, however, AI models are built upon vast quantities of information and use algorithms that enable users to train models that can perform disparate tasks. Even more recently, generative AI models can produce tailor-made responses to a user's requests and demonstrate powerful capabilities for being programmed on the fly. Moreover, users can program certain models using natural language, thus circumventing the need to train users in the complexities of fussy programming languages. Although this recent progress is built upon decades of tireless work, we have observed massive strides in performance in just a matter of years and sometimes even months.

1.2 Problem Space

One of the main challenges for human operators working with future AI technologies is that advances are poised to occur at increasingly faster rates, leaving little time for people to master novel functions and forcing people to confront a great deal of uncertainty. In this report, we are interested in examining whether some people are better equipped for navigating this rapidly advancing, and largely uncertain, technological landscape. Specifically, we seek to understand whether people differ in their abilities to instruct and operate these technologies to perform specific tasks, and, if so, how we can identify the attributes that facilitate better performance. We define technological fluency (TF) as a competency wherein people's knowledge, skills, and behaviors (KSBs) enable them to guide and operate with novel learning-capable systems toward near-optimal performance, with little-to-no formal training.

To begin laying the foundations for understanding TF, we conducted a vast literature review to understand the KSBs that contribute to people navigating similar challenges of the past, in addition to covering the burgeoning research in the domain of human-AI interactions. In Section 2, we provide an in-depth explanation of how we are defining TF, followed by an overview of closely related concepts. Subsequently, we use our theoretical definition of TF to describe different operational definitions for measuring TF. Then, using our understanding of TF's scope, we review KSBs that we believe will facilitate TF, framing each KSB into one of five categories: 1) Disposition and Motivation; 2) Cognitive Abilities; 3) Social and Teaming Skills; 4) Adaptability and Response to Change; and 5) AI-Relevant Knowledge and Experience. We then provide tools for measuring each of the KSBs described in the literature review before summarizing our findings and discussing future research directions.

2. What Does It Mean to Be Technologically Fluent?

In the Introduction, we established that the construct of TF is a crucial factor for successful future human-technology interactions. When discussing this construct, it is imperative that we also outline what it means to be technologically fluent. In other words, we identify what types of behaviors or objective performance metrics illustrate TF in more detail.

Let us first consider the nature of fluency more broadly. A simple Google search for a definition of "fluency" yields adjectives relating to ease, proficiency, and behaviors that are easily changed or adapted (depending on the context). Within the digital domain, we must ask ourselves what the qualitative shift from simple "technology user" to "technologically fluent user" looks like.

According to Bernstein (2010), this shift involves the simple matter of creativity. For example, on one hand, the *regular* technology user has likely mastered certain functions of their smartphone or laptop but tends to use the technology in prescribed ways. On the other hand, a *fluent* technology user is creative in their use and uses the technology in novel and appropriate ways (Amabile 1996). The key outcome of a fluent technology user is that they can use and adapt their technology use in different ways, according to individual needs, which can vary from situation to situation.

One example of creativity with technology is illustrated by an artistic, if somewhat adversarial, manipulation of the technology used in traffic mapping apps. In the 2020 Google Maps Hack (Barrett 2020), artist Simon Weckert filled a child's wagon with 99 mobile phones and proceeded to stroll around streets in the city of Berlin, Germany. Although there were very few cars on the road at the time, Weckert's wagon "tricked" the Google Maps navigation application into displaying a traffic jam. There were very few cars on the streets; however, the application depended primarily on sensing location data from the phones and displayed gridlock to anyone trying to drive the empty roads along which Weckert was strolling. In this case, Weckert exhibited a *creatively adaptive*, *contextually aware*, *technologically fluent use* of an advanced technological system.

Because technology is changing so rapidly, it is somewhat difficult to provide a one-size-fits-all definition for what an individual must have, understand, or convey to be considered technologically fluent; however, this notion of technological adaptability seems to address key aspects of this question. This would include learning foundational material that would enable the acquisition of new skills, which may or may not be independently obtained, after the "formal" education is complete. In fact, Hatano and Inagaki (1986) describe adaptable experts as those who are able (by virtue of experience and depth of knowledge) to come up with solutions to unexpected or novel problems. They also differentiate between adaptable and routine experts who simply perform skills in a procedural manner, in situations that are relatively consistent. Adaptable experts can, in their opinion, apply conceptual knowledge to understand "the meaning and nature of their object" (Hatano and Inagaki 1986, p. 263). This underlying conceptual knowledge denotes *procedural flexibility* in problem solving and new skill acquisition, with skills that enable them to succeed in situations that are new or present unexpected challenges. Similarly, Paletz et al (2013) built upon Hatano and Inagaki's (1986) work to show how adaptive expertise enables both individuals and teams to be both innovative and efficient in their operations. Therefore, when discussing TF as a construct, we argue that it should be considered a multidimensional construct that encompasses both "crystalized" digital intelligence (DQ) as well as a more "fluid" adaptable intelligence that can be observed as humans interact with technology.

Our use of adaptability as a core aspect for TF goes beyond more traditional interpretations of how humans adapt to new situations and/or technologies. VandenBos (2007, p. 17) defines adaptability as the "capacity to make appropriate responses to changed or changing situations," which included cognitive, behavioral, and affective responses to changes in existing situations and to new situations. To be effective users of technology (whether the 17th century printing press and book, or the 21st century smartphone and gesture interfaces), humans have had to adapt to ever-evolving information/technology contexts to be successful in society. This foundational view of adaptability includes transfer of learning, that is, the ability that experienced and expert users have to transfer knowledge and responsive behaviors across different situations (Paletz et al. 2013). This view of adaptability as a combination of expertise *and* the flexibility to transfer that expertise across contexts is the basis for being technology savvy (tech-savvy). A tech-savvy individual not only uses and adapts with evolving technologies, but they also drive and guide the technology to adapt to new situations and work goals. Weckert's ability to use his knowledge of the underlying data driving the navigation tool interface to pose a creative problem for others is a canonical example of the level of human-guided adaptability, or adaptive expertise, that we aim to characterize. This human-guided adaptation of technology can be visualized as a sort of feedback loop in which the process of interacting with technology inherently calls for and changes the way we live and work. These actions are then fed forward into how technology becomes more pervasive and evolves over time.

3. The Broad Landscape of Technological Fluency Concepts

As noted in the first section, we refer to TF as the ability for individuals and teams to rapidly use and adapt to new technology without the need for formal training. However, another related term that has also been used is "tech-savviness", which we define as "a competency, consisting of cognitive and noncognitive attributes, that enables individuals to creatively use, synthesize, and adapt with novel technologies to enhance performance." However, our definitions do not operate in isolation, but rather they exist within and build upon a vast landscape of similar concepts and definitions in the scientific literature.

The general concept of people's facility with technology has been explored by many groups of researchers using a vast array of terms and definitions. Early researchers in this area coined various literacy-related terms around this topic including "digital literacy", "computer literacy", and even "information literacy". For example, the term digital literacy (DL) has been defined in several ways as 1) "the ability to understand and use information in multiple formats from a wide range of sources when it is presented via computers" (Gilster 1997, p. 1), 2) "the ability to find, utilize, share, and create content using information technologies from the Internet" (Cornell University 2009), and 3) "the ability to use information and communication technologies to find, evaluate create, and communicate information, requiring both cognitive and technical skills" (American Library Association 2013).

However, "computer literacy" comprises both user and technical computing skills and denotes a deeper understanding of digital technology, according to Techataweewan and Prasertsin (2018). Furthermore, Norman (1984) proposed four specific levels of computer literacy that included the following: 1) understanding the general principles and concepts of computation, 2) understanding how to use computers, 3) understanding how to program computers, and 4) understanding the science of computation. According to Norman (1984), the average person would only need to master the first two levels, whereas the last two levels would require a specific domain of expertise.

Finally, the term "information literacy" refers to the "ability to locate, identify, retrieve, evaluate, process, and use digital information optimally (Techataweewan and Prasertsin 2018, p. 216), whereas "cyber literacy" includes competency in using the Internet in general and for communication purposes (Leahy and Dolan 2010; Karpati 2023). For ease of use, Table 1 outlines examples of terms used, conceptual definitions and scope, and references to gauge how others in the field are interpreting this construct.

Table 1 Terms, definitions, and citations of several constructs relating to TF from the literature

Term	Definition	Citation
Adaptation	The cognitive and behavioral efforts performed by users to cope with significant information technology events that occur in their work environment.	Beaudry and Pinsonneault (2005)
Computer Literacy	The ability to use a few computer applications. For example, computer literacy often refers to the ability to use a spreadsheet and a word processor and to search the World Wide Web (Web) for information.	Lin (2000)
Digital Fluency	Dynamic, evolving, and graduated aptitude which empowers the users of digital technologies to reach high levels of digital expertise and produce works of significance by exploring, accessing, organizing, interpreting, evaluating, realizing, and creating digital information and ideas to enhance learning in other domains and participate successfully in society.	Sinay and Graikinis (2018)
Fluent with Information Technology (FIT)	The National Research Council's report, "Being Fluent with Information Technology," advocates for developing technological fluency, defining it as "the ability to creatively express ideas, reformulate knowledge, and synthesize new information". This fluency is a lifelong learning process in which individuals continually adapt to change, acquire more knowledge, and effectively apply information technology to their professional and personal lives. It encompasses intellectual capabilities, fundamental IT concepts, and contemporary IT skills, emphasizing both skills and a deep understanding of foundational concepts (Lin 2000).	National Research Council (1999)

Table 1 Terms, definitions, and citations of several constructs relating to TF from the literature (continued)

Term	Definition	Citation
Information and Communication Technology (ICT) literacy	ICT literacy encompasses the proficient use of digital technologies, including computers and communication tools, to access, manage, create, and communicate information for both personal and societal purposes. It involves activities like data analysis, information generation, problem-solving, and effective communication. When integrated into higher education, various forms of ICTs can enhance digital literacy, self-efficacy, collaborative learning, conceptual understanding, and higher-order thinking skills.	Ananiadou and Claro (2009); Barak et al. (2018); National Research Council (2012); Organization for Economic Cooperation and Development ([OECD] 2009)
Technological Fluency	The ability of Soldiers and units to use and rapidly adapt new and intelligent technologies without formal training on these technologies.	DEVCOM Army Research Laboratory Definition
Technology Fluency	Technological fluency, as defined by scholars like Lin (2000) and Baker and O'Neil (2002), goes beyond mere technology expertise or in-depth knowledge. Instead, it signifies an orientation toward technology that prioritizes its role in enhancing content and context for student learning. This fluency encompasses the ability to creatively reformulate knowledge, generate information, and apply, adapt, or create technology to improve various aspects of life.	Baker and O'Neil (2002); National Research Council (1999); Lin (2000)

4. Measuring Technological Fluency

The desire to understand TF has grown and is reflected in the increasing number of initiatives from which several frameworks and methods of assessments have been proposed and developed. Because technology manifests in a multitude of forms, research on technology can be wide—being approached from several angles—or narrower and more bounded by focus on types of technology or particular use contexts. Thus, just as there is a wide range of terms and definitions for TF, the measurement of TF is not unified and comes from a wide array of approaches, paradigms, and methodologies. Furthermore, the nature of technology is face-paced and continually evolving, changing, and adapting, making its definition and related constructs a moving target.

To provide a comprehensive understanding, we offer an overview of the frameworks associated with technical fluency, outlining the foundational concepts and dimensions underpinning this multifaceted construct. Subsequently, we explore the existing measurement approaches designed to gauge an individual's level of technical fluency. This exploration encompasses performance-based measures, which evaluate practical skills in actual or simulated technological environments, and self-report measures that rely on individuals' self-assessment of their technical capabilities. As we navigate this assessment landscape, we also consider the critiques and challenges inherent in measuring technical fluency, shedding light on the complexities and limitations of existing evaluation methodologies. By synthesizing these key insights, we aim to better understand how to assess and quantify technical fluency.

As we discuss prior measurements of TF, the reader should keep in mind that although each discipline, or even researcher, may have their own definition of what it means to be technologically fluent, what may differentiate or bind the various notions of technology fluency is how the construct is measured. In other words, although two different research groups may come up with variations in their definition of technology fluency, the overlap will be based on what measurements they use and the theory they believe these measurements reflect.

4.1 Developing Constructs

The existing literature uses a variety of terminologies to describe these related constructs, as shown in Table 1 in Section 3, "The Broad Landscape of Technological Fluency Concepts". However, there are some emergent themes among them. In a review by Ala-Mutka (2011), these terminologies are conceptually grouped into five major key concepts. We show this in Table 2.

Table 2 Grouping of terminology in technology fluency literature into key concepts and their descriptions that are based on Ala-Mutka (2011)

Key concept	Description
Computer Literacy, ICT Literacy	Concepts are typically centered around being able to use a computer and its related software.
Internet Literacy, Network Literacy	Concepts are typically centered around being able to use the Internet.
Information Literacy	Concepts are typically centered around the user's ability to locate, gather, and evaluate information from the use of computers and other multimedia technologies.
Media Literacy	Concepts are like information literacy but extend to include information coming from more traditional sources of media such as radio and television.
Digital Literacy	Concepts are centered around a broader notion of literacy around technology and digital tools and more explicitly include elements of digital citizenship, ethics, and societal implications.

One can imagine that the key concepts lay on a continuum representing centricity or scope. On one end is ICT literacy, being narrower in scope, and on the other end of the continuum is DL, which attempts to be all encompassing and broad. This makes sense because the start of the rise of common household technology was computer, email, and web centric. Thus, the natural tendency was to first understand technology use and efficacy in the context of computer use (computer, ICT literacy). Technology has now taken on many forms, such as our mobile devices, smart home devices, apps, and social networks. Thus, the concept of TF has evolved to incorporate such devices or "digital tools" while also attempting to be general enough to be "future proof" or in step with technological advances. As we gain understanding, the focus turns into a deeper, more systemic viewpoint that may involve matters such as ethics and societal implications, with further construct building. These frameworks may also include things such as "judgment" and "quality of use" as metrics of TF; that is, instead of having questions as to whether an individual can use a certain technology (i.e., does the individual know how to search for information), the questions become more about the process and way of use (i.e., can the individual search for high-quality information).

The discussion is complicated by the fact that many of the frameworks and the assessments that arise from them are not necessarily linearly progressive, although retroactively they may seem that way. Many of them overlap or exist in parallel, focusing on particular aspects of technology and use. This is made more explicit by examining how public initiatives and research studies have assessed these concepts. In an effort to establish a global reference point for technology and digital competencies, a division within the United Nations Educational, Scientific, and Cultural Organization (UNESCO) has attempted to keep track of some digital competency frameworks on their website (https://unevoc.unesco.org/home/Digital+Competence+Frameworks). Table 3 is a modified version of this that includes competency areas and demonstrates the many facets of TF that are being captured.

Table 3 Selected frameworks and their areas of competencies

Framework	Number of indicators/elements	Areas of competencies
21st Century Skills: Information, Media, and Technology Skills	5	Information Literacy; Media Literacy; ICT Literacy
Artificial Intelligence and Digital Transformation Framework	14 + 5 complimentary attitudes	Digital Planning and Design; Data Use and Governance; Digital Management and Execution (+Attitudes)
British Columbia's Digital Literacy Framework	20	Research and Information Literacy; Critical Thinking, Problem Solving, and Decision Making; Creativity and Innovation; Digital Citizenship; Communication and Collaboration; Technology Operations and Concepts
Center for Media Literacy	10	Five Core Concepts; Five Key Questions

Table 3 Selected frameworks and their areas of competencies (continued)

Framework	Number of indicators/elements	Areas of competencies
Common Digital Competence Framework for Teachers (CDCFT)	21	Information and Data Literacy; Communication and Collaboration; Digital Content Creation; Safety; Problem Solving
Common Framework of Reference for Intercultural Digital Literacies	14	Multimodal Orchestration; Digital Technologies; Intercultural Communication; Transversal Skills
Competency Framework: Digital Skills[a]		Information and Digital Literacy; Digital Content Creation; Problem Solving; Data Strategy and Planning; Data Analytics; Data Visualization
Digital Competence (DIGCOMP) Framework	21	Information and Data Literacy; Communication and Collaboration; Digital Content Creation; Safety; Problem Solving
Digital Competence Framework (United Kingdom)	12	Citizenship, Interacting and Collaborating, Producing, Data and Computational Thinking
DigCompEdu	22	Professional Engagement; Digital Resources; Teaching and Learning; Assessment; Empowering Learners; Facilitating Learners' Digital Competence
DQ Framework	24	Digital Rights; Digital Literacy; Digital Communication; Digital Emotional Intelligence; Digital Security; Digital Safety; Digital Use; Digital Identity
Educational Testing Service Framework for ICT Literacy	15	Define, Access, Evaluate, Manage, Integrate, Create, Communicate
GSMA's Developing Mobile Digital Skills in Low- and Middle-Income Countries		Set-up and Configuration; Information Management; Digital Communication; Digital Content Creation; Safety and Security; Problem Solving
McKinsey & Company's Foundational Skills for Citizens: Digital[a]	11	Digital Fluency and Citizenship; Software Use and Development; Understanding Digital Systems
UNESCO ICT Competency Framework for Teachers (ICT-CFT)	18	Policy; Curriculum and Assessment; Pedagogy; Application of Digital Skills; Organization and Administration; Professional Development

[a] Reflects a subset of a larger framework.
Note: Adapted from *UNESCO-UNEVOC's Digital Competence Framework Database*, UNESCO, https://unevoc.unesco.org/home/Digital+Competence+Frameworks.

Despite the difficulties in tracking, categorizing, and/or merging all the related literature and approaches, gaining a sense of how some of the major initiatives and frameworks view and assess the construct of TF may help provide some binding context. Finally, the language around and the specific types of knowledge, skills, and attitudes vary between research groups. Rather than attempting to force the differing approaches into a single representation, we selected frameworks that may highlight various parts of the key concepts.

4.2 Example Frameworks and Assessments

To date, many frameworks have evolved to include factors that extend past basic computer use. However, several of these frameworks were initially built around computer and ICT literacy. This implies a "flavor" or "variant" of technology fluency frameworks whose language and indicators tend to be more "use" centric. As mentioned in Section 4, ICT literacy can be viewed as being narrower in scope. Although that may be the case, there was still difficulty in defining what ICT and computer literacy means. The desire to come to a common language around technology literacy was mostly driven by the education domain, where much of the research aims were to understand what factors improve students' ability to learn and use as well as teachers' ability to teach technology. In 2001, the International ICT Literacy Panel defined ICT literacy as follows:

> "…using technology, communications tools, and/or networks to access, manage, integrate, evaluate and create information in order to function in a knowledge society…" (International ICT Literacy Panel 2002).

They came up with an organizational model of ICT literacy that is composed of three components: 1) *cognitive proficiency*, defined as foundational skills of everyday life at school and home; 2) *technical proficiency*, defined as foundational knowledge of basic components of DL; and 3) *ICT proficiency*, the integration and application of both cognitive and technical proficiency. Their provided example was that an individual who can successfully perform an ICT task, such as searching the Internet, must apply cognitive skills (e.g., reading and problem solving) and technical skills (e.g., knowing how to access the Internet and using a search engine). The basic idea is that ICT literacy is complex and not a unidimensional model, and assessments to measure the construct should start from a model that reflects this. Furthermore, at the time of this panel meeting, there were no large-scale assessments on ICT literacy that were computer based, and such a model would allow for flexibility and accommodation in large-scale test development. That is, the panel recognized that for some constituents, their interest may be on gaining a sense of an individual or group's overall ICT literacy (holistic assessment), and for others, their best interest may be to assess the components of ICT literacy (e.g., access, manage, integrate, evaluate, and create) (International ICT Literacy Panel 2002).

In 2003, the National Higher Education ICT Literacy Initiative was established by the Educational Testing Service (ETS) in the United States. This initiative was a collaboration between representatives of colleges and universities that agreed with the need and urgency to develop ICT literacy assessments for higher education (Katz 2007). Building off of the International ICT Literacy Panel's (2002) definition, the consortium defined ICT literacy as follows:

> "ICT literacy is the ability to appropriately use digital technology, communication tools, and/or networks to solve information problems in order to function in an information society. This includes having the ability to use technology as a tool to research, organize, and communicate information and having a fundamental understanding of the ethical/legal issues surrounding accessing and using information." (Katz et al. 2004)

Upon arriving on a definition of ICT literacy, in concert with the Association of College and Research Libraries, ETS expanded and identified seven elements or performance areas of ICT Literacy. These components, their definitions, and indicators are shown in Table 4.

Table 4 ETS's ICT framework components and indicators

Component	Definition	Indicators
Define	Understanding and articulating the scope of a problem to facilitate electronic search for information.	• Distinguishing a clear, concise, and topical research question from poorly framed questions • Asking questions of a "professor" that help disambiguate vague research assignment • Conducting effective preliminary information searches to help frame research statement
Access	Knowing about and knowing how to collect and/or retrieve information.	• Generating and combining search terms to satisfy the requirements of a particular research task • Efficiently browsing one or more research to locate pertinent information • Deciding what types of resources might yield the most useful information for a particular need
Evaluate	Judging whether information satisfies the problem.	• Judging the relative usefulness of provided Web pages and online journal articles • Evaluating whether a database contains appropriately current and pertinent information • Deciding the extent to which a collection of resources sufficiently covers a research area
Manage	Applying an existing organizational or classification scheme.	• Categorizing emails into appropriate folders based on a critical view of its contents • Arranging personnel information into an organizational chart • Sorting files, emails, or database returns to clarify clusters of related information

Table 4 ETS's ICT framework components and indicators (continued)

Component	Definition	Indicators
Integrate	Interpreting and representing information.	• Comparing advertisements, emails, or websites from competing vendors by summarizing information into a table • Summarizing and synthesizing information from a variety of types of sources according to specific criteria to compare information and make a decision • Re-representing results from an academic or sports tournament into a spreadsheet to clarify standings and decide the need for playoffs
Create	Generating information by adapting, applying, designing, inventing, or authorizing information.	• Editing and formatting a document according to a set of editorial specifications • Creating a presentation slide to support a position on a controversial topic • Creating a data display to clarify the relationship between academic and economic variables
Communicate	Disseminate information effectively for particular target audiences in digital format.	• Formatting a document to make it more useful to a particular group • Transforming an email into a succinct presentation to meet an audience's needs • Selecting and organizing slides for distinct presentations to different audiences • Designing a flier to advertise to a distinct group of users

ETS developed the *iSkills* assessment, which is an Internet-delivered assessment focusing on both cognitive problem-solving and critical thinking skills that are associated with technology in the seven performance areas referenced in Table 4. Although there were existing measures related to cognitive and technical proficiency (e.g., problem-solving, numeracy, technical knowledge, etc.), there were no computer-based tasks, which ETS argued would limit the ability to measure the full interactive domain of ICT literacy. Thus, the uniqueness of the *iSkills* assessment was that it provided students with an *interactive* digital environment based on real-world scenarios. For example, one of the tasks is to research earthquakes and requires students to develop a search query through interaction with simulated software (Katz 2007).

In parallel, UNESCO and the European Union were also working toward standards of defining and measuring ICT literacy. They defined ICT competency as follows:

> "…the confident and critical use of electronic media for work, leisure, and communication. These competencies are related to logical and critical thinking, to high-level information management skills, and well-developed communication skills." (European Commission 2003; Pernia 2008)

Their framework can be described as an integrated framework that characterizes factors that are associated with the ability to use technology into three dimensions:

knowledge, skills, and attitudes. The *Knowledge* dimension denotes to the user's awareness and appreciation of the relevance of ICT in their personal and professional life. The *Skills* dimension is the result of "use of or experience with" the technologies. The *Attitudes* dimension pertains to the product or process of a person's critical assessment of his/her ICT use of ICT for information and knowledge. Table 5 lists the dimensions and their associated competencies.

Table 5 UNESCO's ICT framework dimensions and indicators

Dimension	Description	Indicators
Knowledge	Awareness of technologies and appreciation of their relevance.	• Familiarity with mobile phones, computers, the Internet, and other ICTs • Ability to identify ICTs • Appreciation of actual and potential functions of these technologies in everyday life (i.e., personal fulfillment, social inclusion, and employability) • Understanding basic features/uses of ICTs (e.g., for mobile phones: voice calls and SMS; for computers: word processing, spreadsheet, database, information storage; for Internet: web browsing, email, and instant messaging) • Ability to distinguish between the virtual and real world • Awareness of need for "phonethics" or "netiquette"
Skills	Use of technology for information and knowledge encompassing skills or abilities to access, retrieve, store, manage, integrate, evaluate, create, and communicate information and knowledge, and participate in networks via the Internet.	• Ability to use ICT features and applications (e.g., for mobile phones: voice calls, SMS, still camera, video recorder and/or player, voice recorder and/or player, radio, music player, multimedia service, word processing, spreadsheet, presentation, infrared, Bluetooth, and Internet connectivity; for computers: word processing, spreadsheet, database, information storage; for Internet: web browsing, email, and instant messaging • Ability to access and search websites (e.g., log on to the Internet, use search engines, refine search using keywords, etc.) • Ability to use Internet-based services (e.g., create an account, compose email, attach and download files, participate in discussion forums, Ims, and social networking sites, create blogs, etc.) • Ability to collect and process (e.g., create database, organize, store, filter out irrelevant, etc.) electronic data for immediate or later use • Ability to convert data into graphic presentation and other visual formats • Using ICTs to support critical thinking, creativity, and innovation for educational, work-related, and leisure purposes (e.g., make the most of multimedia information, cross-reference information across websites, dealing with spam and fraud, etc.) • Ability to distinguish credibility (e.g., differentiate relevant vs. irrelevant, subjective vs. objective, real vs. virtual, filter out pornography and other offensive content, check for and guard against plagiarism, etc.)

Table 5 UNESCO's ICT framework dimensions and indicators (continued)

Dimension	Description	Indicators
Attitudes	Understanding that ICT acquisition and use has an impact on personal and social development, including perception of values and responsibilities, communication practices, and other behaviors. Social and ethical competencies developed as a result of this critical assessment and reflection.	• Ability to use ICTs to work individually or in teams, complying with agreements and helping each other in case problems occur • Judicious/responsible use of technology: sensitivity to safe and responsible use of the Internet • Critical and reflective attitude when assessing information: awareness of the motives of technology companies and ability to judge the truthfulness of advertisements regarding technologies • Interest in using ICT to broaden horizons by taking part in communities and networks for various causes • Understanding the consequences of acquiring and using technology: ability to understand that use of ICTs affects formation of values and responsibilities, communication practices, and other behaviors • Ability to critically assess the effects of the technology on values

Just as important as the need for large-scale assessments targeted towards *students* in higher education, this ICT literacy framework has served as a foundation in several initiatives centered around identifying *teaching and training needs*. For example, UNESCO, in collaboration with ISTE, CISCO, INTEL, and Microsoft, developed the ICT-CFT (UNESCO 2018). The National Institute of Educational Technologies and Teacher Training developed the CDCFT (INTEF 2017). These frameworks provide teachers and trainers with curriculum materials and learning resources to meet the working standards of teaching technology competencies. Teachers and schools may use an online self-reflective tool, SELFIE (European Commission 2019b), to gain a sense of their strengths and weaknesses in their use of technology through gathering anonymous reports from students (or teachers if done at a school level). In Australia, the National Assessment Program (NAP) developed an online test (Information and Communication Technology Literacy NAP) that allows schools, education ministers, and their community to get information on year 6 and year 10 student's ICT literacy to inform them on how to improve teaching and learning (ACARA 2020).

More recently, recognition that the lack of technology literacy could impede one's quality of life outside of educational activities and, thus, should be seen as a critical skill of the future is reflected in frameworks such as the Joint Research Committee's DIGCOMP framework (Ferrari 2013) and the DQ Framework (https://www.dqinstitute.org/wp-content/uploads/2017/08/DQ-Framework-White-Paper-Ver1-31Aug17.pdf). The DIGCOMP framework was developed to provide a common language around digital competence to aid in policy making that supports the enhancement of digital skills in Europe, who had set a target of reaching 80% of its population with basic digital skills and having 20 million ICT specialist by 2030 (Vuorikari et al. 2022). The DIGCOMP framework considers digital competence development as part of a set of key competencies *necessary* for personal and professional lifelong learning. DIGCOMP's definition of digital competence is as follows:

> "Digital competence involves the confident, critical and responsible use of, and engagement with, digital technologies for learning, at work, and for participation in society. It includes information and data literacy, communication and collaboration, media literacy, digital content creation (including programming), safety (including digital well-being and competences related to cybersecurity), intellectual property related questions, problem solving and critical thinking." (European Commission 2019a)

The framework identifies 21 competencies grouped into 5 areas shown in Table 6.

Table 6 DIGCOMP framework dimensions and key competencies

Dimension	Description	Key competencies
Information	Identify, locate, retrieve, store, organize, and analyze digital information, judging its relevance and purpose.	• Browsing, searching, and filtering information • Evaluating information • Storing and retrieving information
Communication	Communicate in digital environments, share resources through online tools, link with others and collaborate through digital tools, interact with and participate in communities and networks, cross-cultural awareness.	• Interacting through technologies • Sharing information and content • Engaging in online citizenships • Collaborating through digital channels • Netiquette • Managing digital identity
Content creation	Create and edit new content (from word processing to images and video); integrate and re-elaborate previous knowledge and content; produce creative expressions, media outputs, and programming; deal with and apply intellectual property rights and licenses.	• Developing content • Integrating and re-elaborating • Copyright and licenses • Programming
Safety	Personal protection, data protection, digital identity protection, security measures, safe and sustainable use.	• Protecting devices • Protecting personal data • Protecting health • Protecting the environment
Problem solving	Identify digital needs and resources, make informed decisions as to which are the most appropriate digital tools according to the purpose or need, solve conceptual problems through digital means, creative use technologies, solve technologies, solve technical problems, update one's own and other's competencies.	• Solving technical problems • Identifying needs and technological responses • Innovating and creatively using technology • Identifying digital competence gaps

There are various tools that can be used to assess an individual's digital competence. The DIGCOMP Self-Assessment grid provides individuals with examples of how one can gauge their current competency levels (foundation, intermediate, or advanced) in each of the five areas. For example, in the competency area of information, exemplars of each level are as follows: 1) foundation, "I can do some online searches through search engines"; 2) intermediate, "I can browse the Internet for information, and I can search for information online"; and 3) advanced, "I can use a wide range of strategies for information and browsing on the Internet." They also developed an online version of the test that upon completion, users receive a report that contains course suggestions and a learning roadmap.

The DigCompSat is a self-reflection tool that allows users to assess all 21 DigComp competencies, and, based on the user's responses to the 82 questions, the tool measures current area levels, identifies competence gaps, and brings awareness of what digital competence means to date for each test taker (Clifford et al. 2020).

The DigCompEDU is a tool targeted toward DL educators that measures 22 competencies grouped into six areas: professional engagement, digital resources, teaching and learning, assessment, empowering learners, and facilitating learners' digital competence (Punie 2017). Finally, individuals looking to express their digital competency skills for the workforce may use the Europass CV online tool, which organizes self-reported digital skills and organizes them in a form of a CV under the DigComp model (European Commission 2019b).

Consequently, the DQ framework seeks to set a global standard to promote digital competencies for all (DQ Institute, https://www.dqinstitute.org/wp-content/uploads/2017/08/DQ-Framework-White-Paper-Ver1-31Aug17.pdf). This includes the assessment of digital competence for individuals, organizations, and nations. They define DQ as follows:

> "…a comprehensive set of technical, cognitive, meta-cognitive, and socio-emotional competencies that are grounded in universal moral values and that enable individuals to face the challenges and harness the opportunities of digital life." (DQInstitute.org, https://www.dqinstitute.org/collaborative-rd/)

Their D24 framework comprises 24 competencies, grouped into 8 "critical areas of digital life" (DQ Institute, https://www.dqinstitute.org/global-standards/#contentblock1). The eight critical areas are as follows: 1) digital use, 2) digital identity, 3) digital rights, 4) DL, 5) digital communication, 6) digital emotional intelligence, 7) digital security, and 8) digital safety. The D24 framework with the critical areas and their competencies can be seen in Fig. 1 (DQ Institute, https://www.dqinstitute.org/global-standards/#contentblock1).

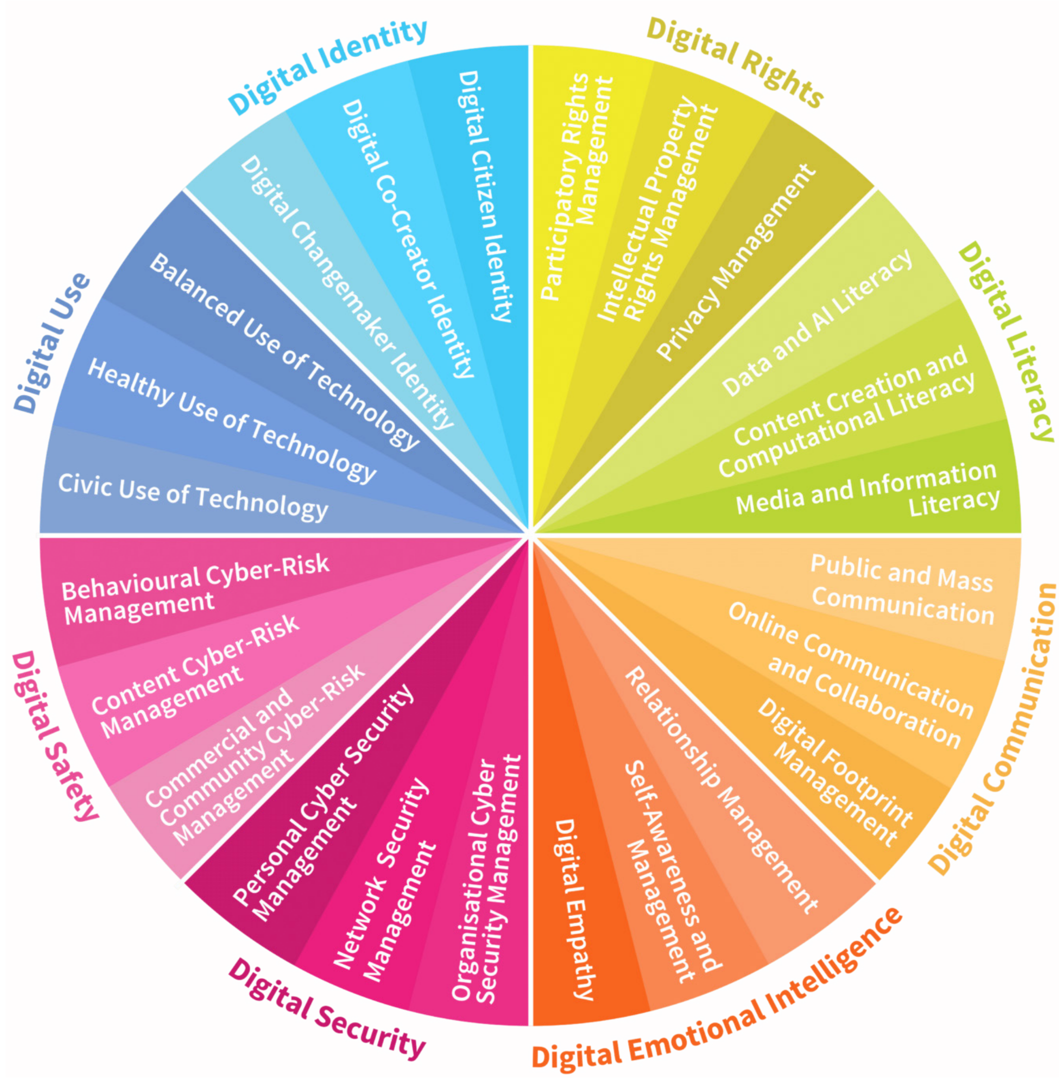

Fig. 1 DQ (Digital Intelligence) Framework from What is the DQ Framework? Global Standards for Digital Literacy, Skills, and Readiness by DQ Institute, (n.d.), Online https://www.dqinstitute.org/global-standards/#contentblock1. ©2023 DQ Institute. All Rights Reserved.

The standards set by the DQ Institute seen in Fig. 1 have been endorsed by the IEEE Standards Association of Organization for Economic Co-operation and the Coalition for Digital Intelligence. For individuals, particularly children and teens, the assessment of DQ can be done by taking their Digital Citizenship Test, which allows test takers to see their "digital citizenship" score compared to national and global averages (DQ Institute, https://www.dqinstitute.org/news-post/digital-citizenship-test-cyber-risk-and-digital-skills-assessment-launch/). Nations looking to assess their digital transformation progress (i.e., the digital competence of stakeholders in that nation's ecosystem) can look forward to the DQ Index, which is currently being developed (DQ Institute, https://www.dqindex.org/). It aims to provide indicators for three dimensions (digital competence areas, stakeholders, and levels) for each of seven thematic pillars (DQ Institute, https://www.dqinstitute.org/collaborative-rd/). The dimension *digital competence areas* are the eight critical areas of the DQ framework: digital identity, digital rights, DL, digital communication, digital emotional intelligence, digital security, digital safety, and digital use. The dimension *stakeholders* include individuals, families and communities, schools and organizations, service providers (EdTech, non-governmental organizations, etc.), ICT companies, and government ministries/agencies. The dimension *levels* include citizenship, creativity, and competitiveness. The DQ Index's thematic pillars and the questions they attempt to measure for each of the three dimensions are shown in Fig. 2 (DQ Institute, https://www.dqinstitute.org/collaborative-rd/).

THEMATIC PILLARS	QUESTIONS THAT ARE BEING MEASURED
Child Online Safety	Are children able to use technology safely, responsibly, and ethically with proper protection and guidance from their caregivers, schools, and society?
Digital Enablement and Resilience	Are citizens equipped with basic digital skills to use technology successfully while being resilient to various cyber-threats and risks?
Digital Education for Life-Long Learning	Do nations have formal and informal education systems that provide quality digital intelligence education and training for life-long learning?
Digital Wellbeing	Are citizens able to maintain their wellbeing in the digitized society?
Workforce Digital Skills	Is labour equipped with the right mindset and skills to welcome technological changes in the workplace, and to maximize the benefits of the digital workplace?
Digital Equity	Do women and individuals from underserved communities have access to full digital participation and digital skills to make meaningful change through technology?
Digital Infrastructure	Do nations have hard- and soft- infra structure that ensure technology adoption and advancement?

Fig. 2 **DQ Index's Thematic Pillars from Co-Creation of the DQ Index by DQ Institute, (n.d.), Online https://www.dqinstitute.org/collaborative-rd/. ©2023 DQ Institute. All Rights Reserved.**

The example frameworks discussed provide a look into the landscape of the evolving construct and continued efforts in assessing and measuring aspects of technology literacy. In Table 2, frameworks such as ETS's ICT Literacy Framework and UNESCO's ICT Competency frameworks mostly center around ICT/Computer Literacy with some extension to Information Literacy, as reflected by their framework's indicators. Frameworks such as DIGCOMP and DQ Framework extend further out, looking at digital competency as part of a set of key competencies for the future, and aim to create indicators and assess these competencies not only in the classroom but for all citizens, organizations, and nations.

4.2.1 Existing Measurement Approaches for Technology Fluency

Section 4.2 discussed some assessments oriented toward initiatives aiming to gain a sense of TF at a larger scale. The remainder of this section will focus on measurement approaches in the academic research literature on TF.

4.2.1.1 Categories of Measurement

We loosely categorized the measurements into four broad categories: 1) knowledge/literacy; 2) skills/operational use; 3) general attitudes towards technology; and 4) other characteristics. Furthermore, for some categories, we grouped assessments based on whether they were self-report measures or performance-based measures. However, the reader should note that much of the content within these assessments are highly contextual. Thus, in the following elaborations of each category, we discuss the general purpose of these assessments and then provide some exemplars.

- *Knowledge-Based Measurements.* Knowledge-based measures are those that generally attempt to assess or test for basic computer and/or technology knowledge.
- *Skills/Operational Use.* Skills/operational-based measures are those that attempt to assess a particular functional task (or set of tasks).
- *General Attitudes.* Measures of general attitudes are those that attempt to assess how the user perceives or relates to technology.
- *Common Cofactors.* Common measures that do not necessarily directly relate to TF but are frequently assessed along with TF measures. We grouped these into two subcategories: those about the individual (age, sex/gender identity, socioeconomic status, learning style, and motivation) and those about the environment (technology support and availability).

4.2.1.2 Self-Report Measures

Self-report measures of TF are valuable tools to assess individuals' self-perceived competencies and confidence in digital technologies (Table 7). Self-report measures are commonly used in gauging individuals' ICT literacy, because they allow participants to evaluate their performance on certain ICT-related tasks, capturing their self-confidence or self-efficacy (Bandura 1986; Aesaert et al. 2014).

Table 7 Self-report measures of constructs related to TF

Measure name	Description	Citation	Dimensions/constructs
ICT Self-Efficacy Scale	Measures individuals' beliefs in their ability to effectively use information and communication technologies.	Musharraf et al. (2019)	Confidence in solving basic computer-related tasks (e.g., finding files, editing photos, creating documents, Internet search, multimedia presentations, and uploading content).
CEW Fluency Scale	Assesses computer skills, email usage, web navigation, and web editing through self-ratings.	Bunz (2004), Bunz et al. (2007)	Proficiency in computer-related tasks (e.g., printing on different printers), self-rated on a five-point Likert scale.
Digital Fluency Scale	Measures creativity, communication, research, critical thinking, and digital citizenship fluency.	Chou and Chiu (2020)	Proficiency in digital technology use across dimensions (e.g., planning strategies and collaboration attitude), rated on a seven-point Likert scale.
Digital Media Literacy Scale	Assesses technical skills, critical understanding, creation, communication abilities, and citizenship participation related to digital media.	Zhang and Zhu (2016)	Capabilities in various digital tasks (e.g., sending emails, detecting information differences, and creating flash files), rated on a five-point Likert scale.
AI Concepts Inventory	Assesses comprehension of AI concepts	Zhang et al. (2021)	Multiple-choice and true/false questions evaluating AI concepts, processes, and specific topics (e.g., neural networks, GANs).
AI Literacy Scale (AILS)	Measures awareness, usage, evaluation, and ethics in AI	Wang et al. (2022)	Participants' agreement with statements regarding their AI-related behavior, ability, and comfort in tasks.
Self-Assessment of Nursing Informatics	Evaluates nursing students' competencies in informatics.	Yoon et al. (2009)	Self-rated nursing informatics competencies in various areas (e.g., clinical informatics role, computer skills, and wireless device skills).
Internet Self-Efficacy Scale	Assesses self-perceived abilities in using the Internet for exploration and communication.	Joyce and Kirakowski (2014)	Self-perceived abilities in online exploration and communication (e.g., making nicknames and presenting ideas), rated on a four-point Likert scale.

Overall, these self-report measures offer valuable insights into individuals' perceptions of their TF, DL, and competency with digital technologies. They provide researchers and educators with useful information for understanding and enhancing individuals' technological capabilities. However, it is important to recognize that self-reports only provide rough proxies for actual competencies and may not accurately reflect individuals' true abilities (Van Laar et al., 2017). Self-reports are prone to bias and may primarily represent competence beliefs rather than actual abilities (Ross 2006; Kaasbøll 2012). Several studies comparing self-reported levels of ICT competence with actual performance have reported low correlations, raising concerns about the reliability and validity of self-report measures (Hakkarainen et al. 2000; Larres et al. 2003; Ballantine et al. 2007). This discrepancy highlights the need for caution when interpreting self-report data as indicators of true technical abilities.

4.2.2 Performance-Based Measures of Technological Fluency

Performance-based measures of technical fluency assess individuals' actual abilities and skills in using digital tools and technologies (Table 8). These measures go beyond self-reported perceptions and provide a more objective assessment of participants' proficiency in various tasks related to technology use. Performance-based measures directly evaluate participants' real-world technical competencies, providing a more accurate reflection of their actual skills. They are less prone to biases and social desirability because they focus on objective task completion rather than self-perceived abilities. These measures allow for assessing specific technical skills, enabling researchers to pinpoint areas in which participants may need further development.

Although performance-based measures offer more accurate assessments of technical skills, they can be time consuming and resource intensive to administer and score. Creating and evaluating performance tasks can be challenging and require careful design to ensure they align with the intended skills. In addition, performance-based measures may not capture participants' confidence or attitudes toward technology, which can also influence their overall digital fluency.

Table 8 Performance measures of constructs related to TF

Measure name	Description	Assessment method	Skills/competencies assessed
ICT Competency Measure	Evaluates higher-order competencies and technical ICT skills.	Aesaert et al. (2014)	Task-based assessment: efficient use of search engines, file management, basic software commands
Digital Literacy Measure	Includes tasks assessing photo-visual, reproduction, branching, and information thinking skills.	Eshet-Alkalai and Chajut (2009)	Task-based assessment: photo-visual thinking, planning using multimedia software, utilizing Internet resources
IT Fluency	Assesses basic computer skills including hardware and software knowledge.	Sardone (2011)	Standardized test: knowledge of computer hardware and software
Digital Literacy Skills	Real-time thinking literacy evaluated through a challenging digital game.	Cihak et al. (2015)	Digital Game: multitasking, emailing, bookmarking, cloud storage usage
ICT Literacy	Basic Computer Skills Test assesses tasks requiring access, collection, and provision of information.	Goldhammer et al. (2013)	Task-based assessment: information access, collection, and provision using software environments
ICT Literacy	ST2 L is a performance-based assessment evaluating ICT literacy in technology, communication, collaboration, and citizenship.	Huggins et al. (2014)	Performance-based assessment: technology operations, communication, collaboration, digital citizenship
Digital Skills	Assesses searching and processing skills, Internet usage, email communication, and software proficiency (Kuhlemeier and Hemker, 2007).	Kuhlemeier and Hemker (2007)	Skill assessment: information searching and processing, email communication, general Windows and word processing skills
ICT Literacy	Comprises 140 multiple-choice items assessing computer-based tasks.	Senkbeil et al. (2013)	Multiple-choice questions: ability to accomplish tasks using software applications such as Internet browsers, electronic databases, spreadsheets
Learning in Digital Networks-ICT Literacy	Comprises 4 interconnected strands aimed to assess 3 main skill sets related to operation, collaboration, and learning.	Siddiq et al. (2017)	Task-based assessments: information literacy, ICT literacy, and personal and social responsibility through social media.

4.2.3 Critiques and Challenges in Technological Fluency Measurement

The TF measurement faces several potential critiques and challenges that can impact the accuracy and usefulness of assessments. One significant critique is the rapidly evolving nature of technology, making it challenging to create standardized and up-to-date measurement tools encompassing all relevant digital competencies. As new technologies emerge and existing ones evolve, the assessment instruments may quickly become outdated and fail to capture the latest skills required for technical proficiency. In addition, the complexity and breadth of TF pose challenges in developing comprehensive assessments encompassing all construct aspects. TF encompasses practical skills, critical thinking, problem solving, and adaptability in digital environments, making it difficult to design assessments that adequately represent these multifaceted dimensions.

Moreover, cultural and contextual differences can affect individuals' technology fluency, leading to potential biases in measurement instruments that may not account for diverse backgrounds and technological environments. Ensuring cross-cultural validity and adaptability of assessments is crucial to avoid disadvantaging certain groups. Furthermore, self-reported measures of technology fluency, which rely on individuals' perceptions of their skills, can be subject to social desirability bias and may not accurately reflect actual competencies. Performance-based assessments offer more direct evidence of technical skills, but they can be resource intensive and may only capture some aspects of technology fluency. Addressing these critiques and challenges is essential to develop robust and reliable measures of technology fluency that can inform educational practices and policy making in the digital era.

The validity of any measurement is crucial in determining whether it accurately reflects the construct it intends to measure (Trochim et al. 2001). The following validity issues are particularly important in the context of technology fluency measurement:

1) Construct Validity: Construct validity refers to the extent to which a measurement accurately represents the underlying construct of interest (Messick 1989). In the case of technology fluency, the construct encompasses a broad range of skills, competencies, and cognitive abilities related to using digital technologies effectively. Ensuring that measurement instruments comprehensively capture all the dimensions of technology fluency is essential for construct validity. Researchers and educators must carefully design assessments that encompass technical skills, critical thinking, problem solving, and adaptability in digital environments, as emphasized by comprehensive DL frameworks (Eshet-Alkalai 2004; Eshet-Alkalai and Soffer 2012).

2) Criterion-Related Validity: Criterion-related validity refers to how a measurement correlates with a relevant external criterion (Trochim et al. 2001). In technology fluency, criterion-related validity involves determining whether performance in the measurement tasks corresponds to real-world outcomes and success in digital environments. Performance-based assessments that allow individuals to demonstrate their technical

skills and competencies in authentic tasks provide more direct evidence of criterion-related validity, reflecting how well individuals can apply their knowledge and skills in practical settings (Darling-Hammond and Adamson 2010).

3) Convergent and Discriminant Validity: Convergent validity is the degree to which a measurement correlates positively with other measures that assess similar constructs. In contrast, discriminant validity is the degree to which a measurement correlates less strongly with measures of different constructs (Campbell and Fiske 1959). For technology fluency measurement, it is essential to demonstrate that the assessment instrument is distinct from other related constructs, such as DL or general ICT competencies. Ensuring that the measurement captures unique aspects of technology fluency will establish its discriminant validity and differentiate it from other digital competencies.

4) Cross-Cultural Validity (Applicability across Various Technical Domains): Cross-cultural validity refers to the extent to which a measurement can be applied consistently and meaningfully across diverse cultural and technical contexts (DiCerbo and Behrens 2014). Because technology fluency is a broad construct with applications in various technical domains, the assessment should be adaptable and relevant to different cultural and technological settings. Validation studies should include diverse populations to ensure the measurement maintains validity across different cultural backgrounds and technological landscapes.

Addressing these validity issues will contribute to developing robust and reliable measures of technology fluency, which are essential for guiding educational practices and policy making in the digital age. By designing assessments encompassing a comprehensive set of competencies, aligning with real-world outcomes, differentiating from related constructs, and being adaptable across cultural contexts, researchers can advance the measurement of technology fluency and its implications for individuals' success in digital environments. Addressing these critiques and challenges is essential to develop robust and reliable measures of technology fluency that can inform educational practices and policy making in the digital era.

4.2.4 Concluding Remarks on the Measurement of Technological Fluency

In conclusion, in the digital age, we have witnessed the rapid expansion of digital technologies, which presented individuals with new cognitive, social, and ergonomic challenges that are crucial to master for effective performance. Measuring technology fluency in the digital age is crucial for understanding individuals' abilities to effectively navigate and use digital technologies. Existing measurement approaches, including self-report and performance-based tests, provide insights into technology fluency. Enhancing the reliability and validity of measurement methods will contribute to a better understanding of individuals' competencies in the digital era, facilitating targeted interventions and strategies to promote technology fluency and digital inclusion.

5. KSBs That Contribute to Technological Fluency

If TF is a desired outcome for individuals or organizations, it would be valuable to understand what fundamental underlying KSBs contribute to TF. KSBs can include abilities, attitudes, tendencies, preferences, experience, or forms of knowledge. Understanding which KSBs are predictive of TF can facilitate recruitment efforts for technologically involved positions or inform individually focused teaching strategies. This understanding can also help guide technology developers in recognizing and meeting the needs of users with different KSBs.

However, before discussing the relevant KSBs that relate to TF, it may be beneficial to discuss work outlining the process of skill and competency development, as well as the difference between the two concepts. According to several researchers in this area, a skill is defined as "the combination of abilities, knowledge, and experience that enables an individual to complete a task well" (Carlton and Levy 2017, p. 17). It is generally acknowledged that skill acquisition occurs in three incremental stages (Anderson 1982; Gravill et al. 2006). The first stage, or the declarative knowledge stage, comprises initial skill acquisition and prompting of the learning process. Here, instruction and information are acquired by the individual (Fitts 1964; Anderson 1982), and it is then internalized to become the foundation for later learning (Gravill et al. 2006). During the second stage, knowledge becomes organized in systematic ways to better accomplish task goals (Gravill et al. 2006). Finally, in stage three, skills become automatic (Fitts 1964; Marcolin et al. 2000), wherein increases in experience level allow the individual to move past the initial skills acquisition phase to an organized, autonomous phase of skill execution (Anderson 1982). In the specific domain of TF, research has shown that an individual's experience with technology usage positively influences and helps establish the required knowledge of the skill itself (Gravill et al. 2006). Therefore, the three phases of skill acquisition mentioned above will allow technologically fluent individuals to not only know and understand how to use technology effectively but, more importantly, to generalize this knowledge to new tasks and procedures, which may increase performance and allow for more fluidity of competence progression.

However, simple skill acquisition is not enough. Developing and maturing knowledge through improved skill acquisition over time generally results in what is known as competency acquisition (Eschenbrenner and Nah 2014). In general, competencies are defined as a range of knowledge, abilities, and commitments required to accomplish a task well and efficiently, or to achieve professional goals (Teodorescu 2006). These also include attitudes and beliefs that are driving factors for competent behaviors. According to Toth and Klein (2014), competencies are developed over time, as individuals gather knowledge and hone skills, and as the individual's depth and knowledge of that skill increases through direct experience or on experience to related tasks (Eschenbrenner and Nah 2014; Benilian 2015). In fact, competency development of a particular skill is so crucial, it has been found to relate to an individual's professional satisfaction level (Havelka and Merhout 2009; Levy and Ramim 2015) and sense of empowerment (Marcolin et al. 2000), as well as organization productivity, safety, and employee fit (Downey and Smith 2011; Adomßent and Hoffman 2013). Therefore, to accomplish tasks efficiently, responsibly, and safely, competencies within individuals are needed (Beaudoin et al. 2009).

Figure 3 was inspired by the work of Carlton and Levy (2017) and illustrates how skill level increases through acquiring and developing abilities, knowledge, and experience. Practiced over time, these develop into competencies in those areas.

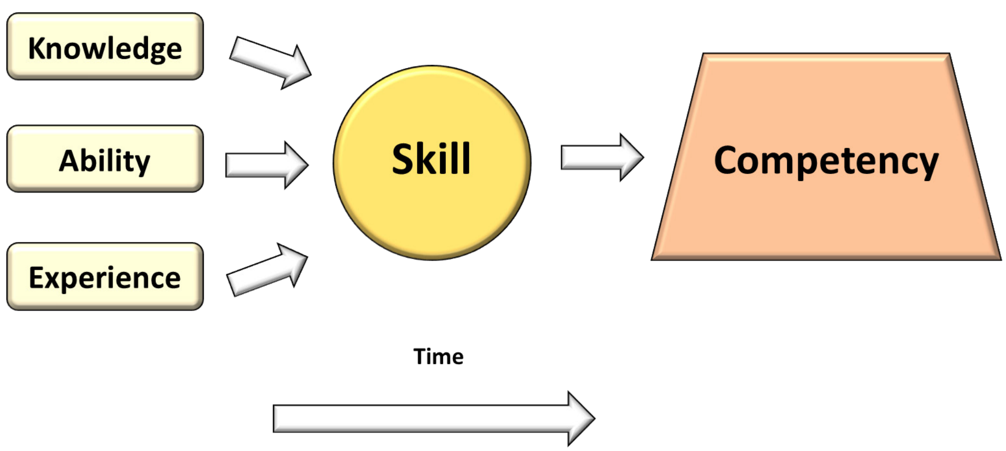

Fig. 3 Graphic representation of how skills are acquired over time to develop into competency.

Modeling specific skills and competencies requires understanding how these are acquired and developed over time. Such competency models also outline the specific collection of KSBs and other characteristics that are required for effective performance in specific domains and job areas (e.g., Mansfield 1996; Parry 1996; Kochanski 1997; Mirabile 1997; Lucia and Lepsinger 1999; Schippmann et al. 2000; Rodriguez et al. 2002). As such, Section 6 is divided into five higher-order categories of KSBs that we expect to be related to the development of TF. Further empirical testing and evaluation are needed to determine which of these KSBs are most predictive of TF with highly advanced technologies such as learning-enabled AI. Further empirical testing is also needed to uncover which of these KSBs are most broadly predictive of TF across domains. We anticipate that identifying, and perhaps even training, some of these KSBs can help ensure competency development in TF.

5.1 Why We Care About KSBs and the KSB Breakdown

AI and other advanced technologies have become increasingly important in various fields such as healthcare, education, and business. Such technologies can process vast amounts of data, make accurate predictions, and automate complex tasks. However, the effectiveness of AI and advanced technology systems largely depends on the characteristics and qualities of the individuals using them; in other words, the various combinations of KSBs or other behaviors an individual possesses. In fact, certain predictors of TF (e.g., KSBs) may be critical components of skill acquisition and competency development in these areas. For example, Green (2005) measured self-reported IT skill and found that factors such as younger age, greater education, openness, extraversion, positive constructions of the earliest technological experience, and the belief in the flexibility of one's computer skill significantly predicted digital fluency in a diverse sample. Here, having negative beliefs about themselves (e.g., being unlucky or incapable), or about computers/digital technology (e.g., mysterious or too complex), was a KSB that hindered development of digital fluency skills (Green 2005). Therefore, to begin to understand TF, and various ways to measure, assess, and enhance this ability in individuals, it is crucial to first understand what those various KSBs might be and what evidence there is that they relate to TF.

Other research groups have proposed models of important KSBs that contribute to TF-related constructs. For example, Eshet-Alakali and Amichai-Hamburger (2004) proposed a DL model that included four main predictors relating to cognitive, motoric, sociological, and emotional skills that allow an individual to use both digital software and hardware. Others, such as the International Society for Technology in Education (2007), claim that DL indicators comprise creativity and innovation, communication, collaboration, research and information fluency, critical thinking, and problem solving.

Bawden (2008) claimed that DL skills consist of information literacy regarding information evaluation, media literacy, and Internet/network literacy. Similarly, Law et al. (2018) defined six basic competencies relating to DL that include accessing, managing, evaluating, integrating, creating, and communicating information, skills that must be used individually or within one's collaborative, networked environment. Furthermore, researchers argue that it is the integration of technological, cognitive, and ethical skills that predict DL (Calvani et al. 2009).

Finally, Techataweewan and Prasertsin (2018) developed a model of DL that comprised four different skill groups and is like the overall structure and outline described in Section 6 and beyond. Specifically, these researchers claim that the following KSB clusters are predictive of DL:

1. Operation Skills such as cognition (e.g., understanding digital media, including selecting and using technology according to various needs and in appropriate ways), invention (e.g., the ability to integrate digital media for work, to create knowledge, or make innovations), and presentation (e.g., ability to present digital content in an appropriate format to a specific audience);

2. Thinking Skills such as analysis (i.e., consideration, interpretation, and relational finding of content in digital information), evaluation (i.e., assessing information for necessity, accuracy, timeliness, and reliability), and creativity (i.e., problem solving and flexibility);

3. Collaboration Skills such as teamwork, networking, and sharing;

4. Awareness Skills that revolve around ethics (i.e., acceptable social practices, netiquette within digital technology communications), legal literacy (i.e., knowledge, understanding, and complication of laws and regulations with usage and access to IT and digital media), and safeguarding of self (i.e., managing personal information and understanding the inherent risks associated with the Internet).

Although Section 5's breakdown of prior research in this area is useful, it consists of information and modeling attempts at similar but somewhat different constructs relating to DL, media literacy, or fluency in information technology. However, for the purposes of this paper, we have decided to focus specifically on our definition of TF and the specific KSBs or predictors that we anticipate would enhance or augment an individual's ability to use and adapt technology without the need for formal training. In Section 6, we explore these KSBs, grouped by the following five categories: 1) Disposition and Motivation, 2) Cognitive Abilities, 3) Social and Teaming Skills, 4) Adaptability and Response to Change, and 5) AI-Relevant

Knowledge and Experience. However, it should be noted that this is a preliminary list of what we consider to be promising predictors of TF, based on theory and current literature. We are not asserting that this list is exhaustive, nor that each KSB on the list is entirely free of overlap with other KSBs. Many of the KSBs discussed are related to one another. This list of KSBs will of course need to be empirically validated within experimental settings to determine whether they do indeed predict TF or whether the list needs to be adjusted. The Appendix provides a summary table of these KSBs along with their definitions, reasons they may relate to TF, and any relevant caveats to note.

6. Category 1: Disposition and Motivation

Disposition and motivation refer to patterns of thoughts, feelings, drives, and tendencies that define an individual's unique character or viewpoint. These qualities are generally relatively stable across long periods but can be influenced by situational factors (some more than others). Here, we review candidate constructs and explore the literature that describes how these constructs might relate to TF. The following KSBs fall within the *Disposition and Motivation* category.

The Big Five Personality Traits: The Big Five personality traits include extraversion, agreeableness, conscientiousness, neuroticism, and openness to experience (John and Srivastava 1999; Gosling et al. 2003). Extraversion is characterized by sociability, assertiveness, and a preference for excitement and stimulation. Agreeableness refers to a person's inclination towards cooperation, empathy, and trust in others. Conscientiousness describes the degree to which a person is dependable, organized, and goal oriented. Neuroticism reflects an individual's tendency towards negative emotions such as anxiety, depression, and vulnerability. Finally, openness to experience indicates the extent to which a person is open-minded, curious, and creative.

Extraversion: Extraversion has been linked to the effective use of AI technologies in various ways. Researchers have found that extraverts are more likely to be early adopters of new technologies, including AI (Behrenbruch 2013). Extraverts also tend to have a more positive attitude towards technology and are more likely to engage with it (Gefen et al. 2003). In addition, extraverts are better at multitasking, which may be an advantage when using AI technologies that require multiple inputs or managing multiple tasks simultaneously (Ushashree et al. 2016). Extraversion refers to an individual's tendency to be outgoing, sociable, and assertive. In the context of AI technologies, extraversion has been found to be positively related to the use of social robots (Gockley et al. 2005). Similarly, a study by Khan et al.

(2014) found that extraversion was a predictor of perceived ease of use in technology acceptance models.

Agreeableness: Agreeableness may also play a role in the effective use of AI technologies. Research has found that agreeable individuals are more likely to value social interaction and cooperation, which may translate to their interactions with AI systems that have a social component, such as chatbots (Purington et al. 2017). Agreeable individuals may also be better at collaborating with others, which may be important when working with a team to develop or implement AI systems (Tost et al. 2013). Agreeableness refers to an individual's tendency to be cooperative, empathetic, and caring. In the context of AI technologies, agreeableness has been found to be positively related to the acceptance of social robots (Nomura et al. 2008). Similarly, a study by Brandtzaeg and Følstad (2017) found that agreeableness was positively related to the perceived usefulness of an AI-based personal assistant for elderly care.

Conscientiousness: Conscientiousness has been identified as an important factor in the effective use of AI technologies. Conscientiousness also refers to an individual's tendency to be organized, responsible, and goal oriented. Conscientiousness has also been found to be an important predictor of individual behavior in a variety of settings, including technology-mediated settings. Research suggests that conscientious individuals are more likely to trust technology (Bawack et al. 2021). Conscientious individuals are also more likely to engage in proactive behavior, such as seeking out information or help when they encounter a problem (Zhang et al. 2021). In addition, conscientiousness has been linked to ethical decision making, which may be important when designing or implementing AI systems that have ethical implications (Rogers et al. 2006).

Neuroticism: may have a negative impact on the effective use of AI technologies. Neuroticism has also been linked to a greater likelihood of experiencing technostress, which may affect performance and job satisfaction when using AI technologies (Jung et al. 2020). Neuroticism refers to an individual's tendency to experience negative emotions, such as anxiety and depression. Several studies have investigated the relationship between neuroticism and the use of AI technologies and reported negative correlations with trust in AI (Kraus et al. 2020; Sharan and Romano 2020; Riedl 2022). Together this suggests that lower levels of neuroticism may lead to higher trust and adoption of novel technologies.

Openness to Experience: Openness to experience refers to an individual's willingness to explore new ideas and experiences. In several studies, researchers have investigated the relationship between openness and the effective use of AI technologies (Zywica and Danowski 2017; Oksanen et al. 2020; Sharan and

Romano 2020). For example, a study (Oksanen et al. 2020) found that individuals high in openness were more likely to trust AI robots. Another study by Zywica and Danowski (2017) found that openness was positively related to the perceived usefulness of an AI-based recommender system for music. Brandtzaeg and Folstad (2017) reported a positive relationship between the perceived usefulness of an AI-based personal assistant for elderly care in the context of a chatbot.

Stress Tolerance: Stress-tolerant individuals exhibit resilience and tend to engage in effective coping mechanisms (e.g., remaining calm, focused, and composed) in response to stressful or challenging situations. These individuals may be more likely to persevere and thrive when faced with obstacles and setbacks, which is a crucial component for success in the unpredictable, rapidly evolving world of technological evolution. Key characteristics of stress tolerance include emotional regulation, effective problem solving and decision making (despite being required to perform in potentially distracting, unpredictable, or challenging situations), innovative thinking, resilience, and dealing with uncertainty to name a few (Gaillard 2017). Being high in stress tolerance may also help individuals in unpredictable or uncertain situations. For example, stress tolerance tends to help individuals maintain composure and adapt to uncertain situations. It facilitates flexibility and openness to change, which allows individuals to adjust to new circumstances as well as engage in adaptive responses when individuals must adjust their strategies to meet task demands. Furthermore, stress tolerance also relates to task-focused coping (Matthews and Campbell 1998) and can be a buffer against poor communication. For example, high stress responses typically result in emotion-focused coping, which is characterized by distress and intrusive worry-related thoughts while appraising and coping with task demands (Lazarus and Folkman 1984; Matthews and Campbell 1998). These traits can interfere with effective communication. In addition, stress tolerance also relates to feelings of self-efficacy (i.e., maintaining the belief in one's own abilities to handle stressful situations) and better time management skills in complex environments. These skills and abilities will be crucial for someone who hopes to embrace emerging technologies; however, the important caveat to note with stress tolerance is that effective coping involves not simply avoiding stress, but it is more specifically concerned with effectively managing and even adapting when stress states do emerge.

Within many workplace settings, technology plays a crucial role, and thus individuals and teams are expected to be able to effectively work with and manage various digital tools and software. They must also embrace innovation and experimentation and push the boundaries of what technology can achieve. Here, stress tolerance may play a key role because technology-related roles and careers are rapidly changing, and they will require quick and effective decision making, as well as exploring new possibilities and innovative solutions. Furthermore, interactions with technology present relatively new human-technology interactions and (to some) may be inherently challenging because, overall, decision making may be stressful to those who fear making the wrong or inappropriate decision (Gati and Tal 2008). Therefore, to be "tech savvy", individuals must be tolerant to these situations to perform well in technology-relevant environments, accept and effectively cope with the uncertainty that will inevitably arise in these domains, and possess the skills to adapt and promote problem solving, while avoiding being overcome by the stress or anxiety that may result during these interactions (Sinkkonen et al. 2018). Here, stress-tolerant individuals may make better decisions under pressure and are better equipped to cope with unpredictable task demands and adjustment that these roles and work conditions may demand (Savickas 2014). The need for continuous learning also relates to stress tolerance due to the inherent stress associated with acquiring new skills while simultaneously staying abreast of changes and technological adaptations. Those who are higher in stress tolerance may be able to engage much more effectively, and exhibit task-focused coping mechanisms (Matthews et al. 1998), despite the potential challenges that arise when acquiring new skills, and thus are more likely to thrive in technology-related roles.

In addition, various combinations of assessments can be used to measure stress tolerance and include subjective measures (e.g., asking questions to gauge an individual's ability to handle technological challenges under pressure), behavioral observations, and experimental testing. One subjective measure is the Coping Inventory for Task Stress ([CITS] Matthews and Campbell 1998), which differentiates three different types of coping mechanisms in response to stressful task demands and includes the following: (1) task-focused coping (e.g., individual attempts to formulate and execute a plan of action); (2) emotion-focused coping (individual attempts to deal with the stressor by changing one's feelings or thoughts about it, by engaging in positive thinking or self-criticism and worry); and (3) avoidance (individual copes by diverting attention away from the problem by distracting oneself).

The CITS is now more commonly used via the post-task Dundee Stress State Questionnaire (Matthews et al. 1999), which measures subjective responses to stress and includes an embedded version of the CITS. Subjective stress responses may also be captured via the State-Trait Anxiety Inventory, which is a commonly used measure of trait and state anxiety (Spielberger et al. 1989). State anxiety items include the following: "I am tense; I am worried" and "I feel calm; I feel secure." Trait anxiety items include the following: "I worry too much over something that really doesn't matter" and "I am content; I am a steady person." All items are rated on a four-point scale (e.g., from "Almost Never" to "Almost Always"). Higher scores indicate greater anxiety.

Experimental outcomes can also be measured in conjunction with performance. For example, it may be useful to observe how individuals cope with unexpected challenges, specifically with technology usage. These effects could be further enhanced by suddenly changing task requirements or imposing time constraints to further enhance stress, which would allow researchers to understand how the individual maintained composure and focus while engaging in effective (or ineffective) decision making to complete a technology-driven task. However, it is important to note that stress tolerance is a complex, multifaceted trait and may be best assessed using a variety of methods to gain the most robust, comprehensive understanding of an individual's ability in relation to their technological savviness. In addition, stress tolerance is not static and can be developed or enhanced through training and personal growth efforts. Stress tolerance overlaps, and it is concomitant, with a wide range of psychological factors and skills that may be valuable in technology-related domains. Ultimately, managing and effectively coping with stress while maintaining composure seems to be a key component when individuals are faced with new or unpredictable challenges and fast-paced dynamic roles or expectations, all of which are reflective of future human technology interactions.

Self-Efficacy and Self-Confidence: People who believe that they will do well on tasks tend to perform better than people who believe they will fail (Gist and Mitchell 1992); therefore, we posit that people who believe they can adapt novel technologies will, on average, be more successful at adapting novel technologies than those who believe they will fail. Self-beliefs regarding future success or failure can be characterized by two closely related, and often confused, constructs: self-efficacy and self-confidence. Although self-efficacy and self-confidence are often defined interchangeably in the literature (Cramer et al. 2009; Samuel et al. 2020), scholars often distinguish between them on theoretical and empirical grounds. Theoretically, self-efficacy is the belief in one's ability to achieve a desired effect (Bandura 1993), whereas self-confidence reflects a person's degree of certainty in their self-assessments (Cramer et al. 2009). In some empirical studies, researchers have found that self-efficacy tends to be domain-specific, in that one's self-efficacy in one domain (e.g., mathematics) is not necessarily related to one's self-efficacy in a distinct domain (e.g., sports); in fact, Fetlz (1988) defines self-efficacy as domain-specific self-confidence. Self-confidence, by contrast, seems to be domain-general, meaning that people with high degrees of certainty in their self-assessments in one domain appear to retain high degrees of certainty in distinct domains (Morony et al. 2013).

To be clear, self-confidence does not need to be respective of a positive outcome, *per se*, but rather to whichever outcome a person predicts, whether positive or negative. Although the theoretical, and often empirical, distinctions between self-efficacy and self-confidence are compelling, the constructs are difficult to disentangle in practice. Indeed, early scholars measured self-efficacy by asking people whether they believe they will succeed *and* their degree of confidence in their assessment (Gist and Mitchell 1992). Even recent self-efficacy measures contain items and/or prompts that explicitly reference self-confidence (Morony et al. 2013). Here, we focus our discussion on how self-efficacy may promote TF.

Several studies have demonstrated a positive relationship between self-efficacy and using technology. Due to the domain-specific nature of self-efficacy, there are a myriad of conceptualizations and measurement tools for measuring self-efficacy regarding technology; for example, scholars have studied technology self-efficacy, digital self-efficacy, computer self-efficacy, cybersecurity self-efficacy, and AI self-efficacy, to name a few. For instance, Wang et al. (2013) found that people's technology self-efficacy predicted higher performance when taking online courses, suggesting that their enhanced performance was partly due to their beliefs that they can succeed in virtual environments. Similarly, Popoola and Adedokun (2023) found that computer self-efficacy predicted students' use of electronic resources. In a separate study, Ulfert-Blank and Schmidt (2022) also found that people with higher levels of digital self-efficacy, specifically in the domains of content creation, digital safety, and problem solving, are more frequently engaged in programming and coding. Self-efficacy might predict performance across these technology domains because these beliefs motivate people to engage with the technology. Several studies corroborate the role of self-efficacy in motivating behaviors; for example, Chai et al.'s (2021) research revealed that students' AI self-efficacy predicted students' intention to learn AI. Research on AI self-efficacy is still very nascent; however, with the widespread adoption of AI in recent years, in conjunction with researchers' interest in developing AI self-efficacy measures (e.g., Wang and Chuang 2023), we expect researchers will soon yield more insights into the effects of self-efficacy on TF.

Analyzing the effects of self-efficacy on TF will be complicated by the fact that technological advances are designed to improve human performance, which may in turn increase self-efficacy. In fact, Wang et al. (2023) demonstrated that when higher education institutions embrace AI capabilities, students at those institutions experience increased self-efficacy. Other recent investigations corroborate the finding that exposure to AI-based tools enhances self-efficacy (Yilmaz and Yilmaz 2023), especially for low-ability workers (Noy and Zhang 2023). Future research ought to examine whether certain factors determine the extent to which people experience enhanced self-efficacy, and perhaps even increased TF, after exposure to AI.

<u>Motivation and (Vocational) Interest</u>: Motivation and interests constitute a general desire or willingness to engage in a behavior or pursue a particular type of work. We expect that appropriate motivation and interest are key to TF; after all, an individual would be hard pressed to develop skills in TF if they were not motivated or interested to do so.

Motivation and interests have been studied with respect to technology use, patterns of learning, and views of AI. According to Green (2005), motivation to use Internet technologies appears to initiate as a developmental path starting first with extrinsic motivational factors (e.g., duty, need), which then shifts into an intrinsic/extrinsic mixture of factors for usage (e.g., diversion, entertainment, membership into a technological culture); however, intrinsic motivational factors may be a more prominent predictor of TF. Intrinsic motivation originates with the individual and is typically driven by the following: need for exploration, curiosity, and even experimentation, and it has generally been shown to be a predicting factor for general student performance such as goal setting and goal attainment (Curry et al. 1990; Martin-Nunez et al. 2023). Intrinsically motivated individuals also tend to be more curious and engage in deeper level learning (Turner et al. 1998), as well as more exploratory behavior to discover alternative options in relation to acceptance of technology (Martens et al. 2004), and perhaps even the perception of the capabilities of more sophisticated technologies such as AI. For example, research shows that intrinsic motivation specifically mediates the relationship between perceived AI learning and computational thinking (Martin-Nunez et al. 2023). Computational thinking involves problem solving, system design, and understanding of human behavior, which are domains somewhat based in the concepts of computational sciences (Wing 2006) and are closely linked to how AI is defined (Ocana-Fernandez et al. 2019). Brennan and Resnick (2012), also argue that the strategies one uses for developing computational thinking patterns and behaviors are closely related to increased motivation. However, introducing computation style thinking in the classroom and teaching process as a learning strategy seems to be a promising method for increasing motivation, problem-solving skills, and learning performance (Parsazadeh et al. 2021). For example, research by Fidan and Gencel (2022) found that the introduction of, and interaction with, AI-based chatbots to a student's learning environment significantly increased their intrinsic motivation, compared to students who did not have the opportunity to interact with AI.

In addition, vocational interest plays a crucial role in performance, particularly in novel technology. Holland (1959) defines interest as the degree to which individuals prefer specific career choices or activities commonly associated with various positions. The Army Talent Attribute Framework (ATAF) expands on this definition, stating that interest relates to preferences for work environments and desired outcomes (Royston et al. 2022). Nye et al.'s (2012) meta-analysis supports the notion that interests are valid predictors of performance in work settings, emphasizing the significance of aligning an individual's interests with their environment for predicting performance outcomes. In addition, Smith (2002) highlights mastery experiences as the most influential predictor of vocational interest, particularly concerning technology. The study also identifies computer self-efficacy and outcome expectations as predictors of information technology interest.

Self-Directed Learning and Proactive Personality: Due to the rapid pace of technological developments, users of AI and advanced technologies will need to learn and adapt with little to no formal training if they wish to keep up. This means they will need to engage in self-regulated learning and self-directed learning (SDL). (Here, we use SDL to refer to both.) SDL is a behavioral tendency characterized by actively seeking out knowledge and guiding one's own learning and skill development. Self-directed learners do not need to wait for a teacher to give a lecture or for an instruction manual to be handed to them; they have a motivation—and ability—to learn on their own. Strategies for self-regulated learning and SDL involve metacognitive strategies as well as cognitive aspects, motivational elements, engagement, and resource management skills (Anthonysamy et al. 2020). SDL is conceptually related to lifelong learning behavior and has been found to correlate with it (Tekkol and Demirel 2018), so we consider these concepts together here. See Linkous (2020) for some distinctions.

SDL has been found to predict success in academic endeavors generally (e.g., Cazan and Schiopca 2014). SDL skills are also expected to be required when learning with technological systems (Azevedo et al. 2004), as users must search, vet, and integrate information from digital sources (Greene et al. 2014). We predict that SDL would similarly be related to performance with advanced technologies. Because AI and other advanced technologies update so rapidly, users of these technologies will have to learn technology-related information and techniques on the fly. They will not necessarily be able to wait for someone else to teach them. Therefore, we expect that people who have a strong tendency toward SDL are likely to be the ones who will most excel with AI and other advanced technologies.

In a recent study, Rini et al. 2022 found that SDL could be used to predict DL in a population of university students. Demir et al. (2022) found similar results for teachers responding to a "lifelong learning" scale. Conceptually supporting this, Green's (2006) qualitative interview study found that elements of lifelong learning behavior tended to characterize which of her (adult or elderly) participants were adopters of modern computer and Internet technology, and which were not. Karatas and Arpaci (2021) found that SDL predicted 21st century skills (including use of technology) and readiness for online learning; however, the readiness for online learning scale included a SDL subscale, so a correlation between the two measures should be interpreted with caution. Greene et al. (2014) found evidence that aspects of self-regulated learning helped predict learning gains from a web search task when aspects of self-regulated learning were separated, but not when they were lumped together. Similarly, Winters et al. (2008) also found that some aspects of self-regulated learning are predictive of success with computerized and online systems, but others are not. This may partly explain the mixed results in the literature (e.g., Chou 2012). This was further corroborated by Anthonysamy et al. (2020) who found that only some components of self-regulated learning were predictive of DL (specifically, the metacognitive, resource management, and motivational components). These studies suggest that SDL and its closely related concepts may not be ideal predictors of TF, because they may be insufficiently granular. It may be more valuable to look at metacognitive strategies or motivational elements directly. However, we found little research comparing SDL to performance with any technologies more advanced than Internet learning platforms and search engines. Findings with more advanced technologies may be different.

Although the granularity of SDL might make it too impractical for understanding TF, one possible cause of individual differences in SDL, proactive personality (Raemdonck et al. 2012), may also directly contribute to TF. Proactive personality refers to an individual's tendency to take initiative, change their environment, and influence situations in ways that benefit their goals or objectives (Bateman and Crant 1993). Proactivity also appears to be a "missing link" that explains connections between facets of extraversion, openness to experience, and honest-humility factors of the HEXACO model of personality (de Vries et al. 2016). There is some evidence that proactivity may facilitate TF; for instance, people with higher levels of proactive personality are protected from the negative impacts that communication overload can exert on productivity (Hung et al. 2015), and they appear to engage in more innovative work behavior (Ullah et al. 2023). In direct relation to working with technology, Zheng et al. (2020) found that proactive personality positively predicts the quality of online interactions, as well as Internet self-efficacy. In a separate study, Tiwari (2021) found that proactive personality moderated the effects of technostress on productivity, such that people with higher levels of proactive personality did not experience detriments in productivity due to technology-related stressors. The psychometric properties of proactive personality scales have also been studied across contexts and cultures, exhibiting high internal consistency and unidimensionality (Claes et al. 2005), thus making it a promising trait for measuring differences in TF.

Three commonly used questionnaires for measuring SDL are the Motivated Strategies for Learning Questionnaire ([MSLQ] Pintrich and De Groot 1990; Pintrich et al. 1993), the Self-Rating Scale of Self-Directed Learning ([SRSSDL] Williamson 2007), and the Self-Directed Learning Skills Scale (Tekkol and Demirel 2018). Refer to Prather et al. (2020) for lists and discussion of several other methods. SDL is related to other KSBs. SDL is related to the personality trait of Openness to Experience (Cazan and Schiopca 2014), and self-directed learners use metacognitive strategies to increase their knowledge and skills and are motivated to do so.

7. Category 2: Cognitive Abilities

Cognitive abilities refer to the mental processes that individuals use to acquire, process, and apply information. In the context of TF, cognitive abilities such as problem-solving, critical thinking, and creativity can be important for individuals to be technologically fluent. For example, individuals who are proficient in logical reasoning or pattern recognition can identify patterns and correlations in the data that AI systems generate and can use this information to make more informed decisions. The following KSBs fall within the *Cognitive Abilities* category.

General and (Logical) Reasoning: Reasoning involves the ability to think logically, analyze information, and draw conclusions based on evidence and principles. Higher levels of reasoning (e.g., inductive and deductive reasoning) have been found to correlate with better problem-solving skills (Bhat 2016; Süß and Kretzschmar 2018) and decision-making capabilities (Kushniruk 2001; Sinayey and Peters 2015), indicating that it may be predictive of performance in tasks involving novel AI technologies (e.g., adapting to new AI systems or troubleshooting AI-related issues). Furthermore, several researchers have developed frameworks that examine how reasoning interacts with AI technologies including the Joint Cognitive Systems (JCS) framework (Woods et al. 2006). The JCS framework posits that the collaboration between both the human and AI systems is integrated and complementary where humans contribute reasoning capabilities and AI contributes to processing vast amounts of data, pattern recognition, and computation speed.

The Group Assessment of Logical Thinking (GALT; Roadrangka et al. 1983) is an instrument that briefly measures logical thinking in tasks such as correlational reasoning, probabilistic reasoning, and combinatorial reasoning. The Test of Logical Thinking (TOLT; Tobin and Capie 1981) evaluates skills that include those based on understanding syllogisms (Hertzka and Guilford 1955) and on performing grammatical transformations (Baddeley 1968). Nunes et al. (2007) describe a series of tests of logical reasoning that can be performed without reading and can be used on children.

Probabilistic Thinking and Pattern Recognition: Probabilistic thinking involves the ability to estimate the likelihood of outcomes in situations of uncertainty. Often this type of thinking is accompanied by a good sense of numbers and high graph literacy (Peters et al. 2007; Galesic et al. 2010). Probabilistic thinking has emerged as a foundational cognitive skill in decision-making under uncertainty, more specifically in the context of leveraging novel future technologies. Some work has demonstrated the efficacy of probabilistic reasoning in optimizing resource allocation strategies in complex AI-driven environments (Silverman et al. 2019). Others have underscored the importance of accurate probabilistic interpretations in bolstering the reliability of AI systems, particularly in critical domains such as medical risk (Fagerlin et al. 2007) and financial forecasting (Chen and Zhu 2020). Some standardized tests to measure probabilistic thinking include Cognitive Reflection Test (CRT; Frederick 2005) and Probability Assessment Resource (PAR; Suurtamm and Koch 2013).

The CRT uses three seemingly straightforward math riddles to assess users' propensity to use Type 1 compared to Type 2 thinking. Individuals who primarily engage in Type 1 thinking are thought to be more prone to surface-level answers on the CRT without taking the time to carefully consider the questions and override their initial responses. This can lead to incorrect responses on CRT items that require deeper, reflective thinking to answer accurately. This feature of the CRT makes this assessment particularly interesting because it assesses the ability to switch from Type 1 to Type 2 thinking because items initially trigger more intuitive responses. Known correlates of CRT include cognitive engagement, reflective thinking, and resistance to impulsivity.

Another popular measure of probabilistic thinking is the PAR (Suurtamm and Koch 2013). The PAR is an online, web-based tool to assess probabilistic thinking, primarily in educational contexts. The PAR offers a range of assessment items and interactive learning resources to help individuals, including students, improve their grasp of probability concepts and their ability to make well-informed probabilistic judgments. This tool presents users with a variety of tasks that involve estimating probabilities, understanding conditional probabilities, and making predictions in situations with inherent uncertainty. Therefore, if probabilistic thinking indeed facilitates TF, then the PAR could be used to train probabilistic thinking and bolster TF competencies.

The importance of pattern recognition in AI has been emphasized by various researchers. A study by Johnson et al. (2018) showcased the efficacy of pattern recognition techniques in automating the identification of anomalous behavior in network security systems. This capability is also pivotal in enhancing the generalization capabilities of AI models. For instance, Liang et al. (2021) demonstrated that proficient pattern recognition aids in identifying novel patterns in medical image datasets, thereby improving the accuracy of disease detection and diagnosis. Probabilistic reasoning enhances decision making under uncertainty (Deutsch 2010; Kusumastuti et al. 2022).

An example of a frequently used metric to discern pattern recognition ability includes Raven's Progressive Matrices (Raven et al. 1998). Raven's Progressive Matrices is primarily a test of abstract reasoning and pattern recognition. It presents individuals with visual patterns consisting of matrices with missing elements. Test takers are required to choose the correct missing piece from a set of multiple options. Raven's Progressive Matrices taps into cognitive processes related to probabilistic reasoning. The test measures one's ability to recognize underlying patterns, make educated guesses, and infer missing information based on the available visual cues. Raven's Progressive Matrices is known for its capacity to assess cognitive abilities such as abstract reasoning, fluid intelligence, and problem-solving skills. Test takers who excel in this assessment demonstrate an aptitude for recognizing and applying patterns, in situations that may involve probabilistic elements (Myers et al. 2017; Gomez-Veiga et al. 2018). In summary, probabilistic reasoning enhances decision making under uncertainty and aids in assessing the reliability of AI systems, whereas pattern recognition techniques contribute to the efficiency, accuracy, and generalization capabilities of AI models.

Spatial Skills: Spatial skills refer to the cognitive and perceptual ability to understand, interpret, and mentally manipulate visuospatial information. More specifically, these skills involve visualizing and mentally representing objects, shapes, and spatial relationships, and thus they have a very strong visual as well as cognitive component. An individual with good spatial skills will be able to engage in mental rotation (i.e., mentally rotate 2D or 3D objects in the mind's eye), spatial visualization (i.e., visualizing and manipulating objects or shapes without physical stimuli), spatial orientation (i.e., understanding your position and orientation in space relative to your current environment), mental mapping (i.e., creating mental representation of physical environments and layouts), and finally spatial coordination (i.e., coordination of physical movements with spatial information, such as hand-eye coordination in sports or video games).

Further empirical testing is warranted and necessary to confirm this; however, we expect that having adequate spatial skills may help enhance TF due to the individual's ability to visualize and understand abstract concepts such as data structures, algorithms, or even complex system architecture. Here, mental manipulation may be easier and more effective because the technology-fluent individual may be able to mentally manipulate these concepts as well as visualize the connections between different components of a system. Furthermore, we speculate that technology-fluent individuals with strong spatial abilities might be able to (1) create, manipulate, and design 3D objects and environments more efficiently than non-technology-fluent individuals as well as (2) visualize code structures, algorithms, and programming logic, while also being able to understand complex data sets and patterns that will enable them to create effective data visualizations and graphs.

Moreover, Tolar et al. (2009) linked computational fluency to spatial ability and working memory (WM), with spatial and computational fluency mediating effects of WM on algebra and mathematical achievement. Ghani et al. (2021) also found that spatial imagination ability, calculation ability, and reasoning ability are positively linked with Science, Technology, Engineering, and Mathematics (STEM) multidisciplinary literacy, suggesting that spatial reasoning abilities may facilitate TF by improving mathematical reasoning and STEM literacy. Therefore, the results surrounding spatial ability in digital domains are quite vast. Spatial ability has consistently been shown to be predictive of computer programming performance (e.g., Jones and Burnett 2007, 2008; Parker et al. 2018) and computational thinking (Città et al. 2019). This may partly be because it improves people's ability to navigate computer code (as found by Jones and Burnett 2007) or because it helps people visualize the problem for which they are coding and the steps to complete it (Fincher et al. 2005).

Spatial ability has been widely researched and found to be a significant contributing factor for success in certain visual display domains (Stanney and Salvendy 1995), during multitasking of flight asset monitoring and management (Morgan et al. 2011), navigation (Rodes and Gugerty 2012), visual search tasks (Chen and Terrence 2009; Chen 2010; Fincannon et al. 2012), and human robot interaction tasks (Lathan and Tracey 2002; Cassenti et al. 2009). As outlined in the work by Chen and Barnes (2014), spatial ability was identified as a crucial factor for effective performance in piloting and sensor operations, with confirmation from interviews from relevant subject matter experts (Chappelle et al. 2010a,b).

Although much work has been done in terms of effective user interface design to compensate for low spatial ability, Rodes and Gugerty (2012) also point out that for optimal performance, both effective interfaces and high spatial ability are still crucial in some spatial tasks, namely, unmanned aerial vehicle (UAV) navigation. Because spatial skills contribute to people's abilities to understand and learn visual interfaces, we propose that spatial skills will play a crucial role in an individual's ability to efficiently navigate, adapt, and exploit new technologies. Although strong spatial abilities seem to relate to effective TF, it also appears that prolonged use of such systems can also impact the development of spatial abilities and other relevant skills (Preiss and Sternberg 2006).

At a basic level, technology should augment and amplify human skills and capabilities; however, the types of skills that can be impacted vary. For example, Nickerson (2005) argued that technology can amplify skills that are specific to motor, sensory, or cognitive abilities. In addition, Nickerson (2005) specifically claimed that this technology augmentation can thus transform not only the physical environment, but also the nature of human cognitive skills, an argument that has been advanced by others in the field (Scribner and Cole 1981; Tomasello 1999a, 1999b; Olson and Cole 2005; Preiss and Sternberg 2006).

Individuals may naturally possess varying degrees of spatial ability. Measuring spatial abilities in individuals requires specific assessment tools that target these skills in technologically relevant tasks. For example, spatial visualization tests can assess an individual's ability to mentally manipulate and rotate 2D and 3D objects (Shepard and Metzler 1971; Vandenberg and Kuse 1978), spatial reasoning tasks can assess an individual's ability to understand spatial relationships between objects (e.g., Krasnow et al. 2011), data visualization tasks can assess an individual's ability to work with complex data sets to create effective visualizations for conveying information accurately (e.g., Harsh and Schmitt-Harsh 2016), and finally game-based assessments could assess an individual's spatial thinking in technological contexts (e.g., Preiss and Sternberg 2006).

Mental rotation tests (Shepard and Metzler 1971; Vandenberg and Kuse 1978) are spatial visualization tests that require participants to match a figure to its rotated version among several distractor figures. Other tests such as Raven tests have withstood cultural influence and are capable of measuring fluid abilities such as general intelligence and spatial ability (Preiss and Sternberg 2006). Spatial abilities are also commonly measured by tests of human intelligence (Sternberg 1990; Mackintosh 1998) because several scholars in this area emphasize the innate aspects of these abilities over other determinants (e.g., Pinker and Bloom 1990; Herrnstein and Murray 1994).

Spatial abilities appear to be malleable (Uttal et al. 2013). Greenfield (1998) provided convergent evidence that supports the hypothesis that the diffusion of video games that have a strong visuospatial component (e.g., Tetris) over the last few decades have provided a context for individuals to foster the development of visual-spatial ability. In fact, Preiss and Sternberg (2006) point out that increased practice and use of video games such as Tetris resulted in greater performance in spatial and visual tasks as measured by Raven Matrices.

Further evidence has also been found that expertise in computer applications is related to improvements in attention, development of spatial representation, and enhanced performance on mental transformation tasks (Okagaki and Frensch 1994; Greenfield 1998; Maynard et al. 2005); however, the required exposure time to these types of technology to achieve proficiency or enhanced performance is still unknown. Finally, understanding whether deliberate practice or passive experience with such systems is required is still largely unknown and warrants more investigation.

Subsequently, individuals may naturally possess varying degrees of spatial ability; however, spatial skills are not fixed and can be trained and enhanced through practice and further exposure to various spatial tasks. Measuring spatial abilities in individuals requires specific assessment tools that target these skills in technologically relevant tasks. Spatial abilities are also commonly measured by tests of human intelligence (Sternber 1990; Mackintosh 1998) because several scholars in this area emphasize the innate aspects of these abilities over other determinants (e.g., Pinker and Bloom 1990; Herrnstein and Murray 1994). Mental rotation tests (Shepard and Metzler 1971; Vandenberg and Kuse 1978) are spatial visualization tests that require participants to match a figure to its rotated version among several distractor figures. Other tests, such as Raven tests, have withstood cultural influence and are capable of measuring fluid abilities such as general intelligence and spatial ability (Preiss and Sternberg 2006).

Furthermore, Greenfield (1998) provided convergent evidence that supports the hypothesis that the diffusion of video games that have a strong visuospatial component (e.g., games such a Tetris) over the last few decades have provided a context for individuals to foster the development of visual-spatial ability. In fact, Preiss and Sternberg (2006) point out that increased practice and use of video games such as Tetris resulted in greater performance in spatial and visual tasks as measured by Raven Matrices. Further evidence has also been found that expertise in computer applications is related to improvements in attention, development of spatial representation, and enhanced performance on mental transformation tasks (Okagaki and Frensch 1994; Greenfield 1998; Maynard et al. 2005); however, the required exposure time to these types of technology to achieve proficiency or enhanced performance is still unknown. Finally, understanding whether deliberate practice or passive experience with such systems is required is still largely unknown and warrants more investigation.

Graph Literacy: Graph literacy refers to the ability to understand, interpret, and communicate information using graphical representations such as graphs, charts, and diagrams (Galesic and Garcia-Retamero 2010). It involves extracting meaningful insights from data visualizations, making accurate inferences, and effectively communicating findings to others. Graph literacy is closely related to numeracy skills because both involve understanding and interpreting information presented graphically (Durand et al. 2020). This plays a crucial role in TF because it enables individuals to comprehend graphs and charts and helps them identify trends, patterns, and relationships within data. In this context, adapting technologies will be an iterative process: operators will need to examine how inputs affect a technology's performance, and technologies will often communicate their performance through graphical information. Therefore, operators will need to use graphical outputs to inform how they move forward with adapting the technologies. It is also possible that future technologies will take graphical information as input; therefore, operators will need to ensure that the information they provide is accurate and effective at producing desired outcomes.

Higher graph literacy also facilitates people making less biased decisions in difficult and impactful scenarios. For example, Okan et al. (2012) found that people with higher graph literacy had greater comprehension of health information data, and they benefited more from graphical aids than those with lower graph comprehension. Surprisingly, in a separate study, Okan et al. (2018) found that people with higher graph literacy were more susceptible to providing biased interpretations of misleading graphs. It would be important to know whether interventions designed to produce graph literacy (e.g., Jungiohann et al. 2022) attenuate or exacerbate bias susceptibility. Consequently, this understanding facilitates an individual's ability to creatively synthesize information and make informed decisions, which ultimately enhances their performance with novel technologies.

Furthermore, in previous measures of graph literacy, researchers used subjective and objective approaches. Subjective graph literacy assesses individuals' self-reported skills and perceptions of graph comprehension, including their beliefs, experiences, and comfort levels in graph-related tasks (Garcia-Retamero et al. 2016). However, objective measures of graph literacy, such as the scale developed by Galesic and Garcia-Retamero (2016), focus on individuals' actual performance in understanding and interpreting graphs. These measures evaluate abilities such as reading data, identifying relationships between data points, and making inferences beyond the presented data. Enhancing graph literacy can be achieved through training interventions, as demonstrated by Woller-Carter (2015) through the development of an online graph tutor. The tutor aims to train individuals in essential graph selection, design, and display skills, particularly in risk communications and decision education programs. By improving graph literacy, individuals can navigate and use graphical information effectively, likely leading to enhanced TF and improved decision making in various domains.

Numeracy: Numeracy encompasses individuals' proficiency in basic probability and mathematical concepts (Lipkus et al. 2001), including people's ability to comprehend and manipulate mathematical models, algorithms, and formulas. Numeracy is also closely associated with literacy in a digital environment. Xiao et al. 2019 found a positive correlation between participants' accuracy in problem-solving tasks and their numeracy and literacy competencies in a "technology enriched environment." The Lipkus Numeracy Scale (LNS) is commonly used to measure numeracy skills. This 11-item scale assesses individuals' understanding of risk, fractions, chance, proportions, and percentages (Lipkus et al. 2001).

Furthermore, numeracy is closely associated with DL in terms of problem-solving capabilities. Xiao et al. (2019) found a positive correlation between participants' accuracy in problem-solving tasks and their numeracy and literacy as observed in a technology-enriched environment (computer-based test), arguing that literacy displayed in such an environment stems from a combination of traditional and DL. This finding aligns with previous studies that emphasized the significance of numeracy and literacy skills in effective problem solving (Brand-Gruwel et al. 2009; Tett and Maclachlan 2007). The importance of numeracy for performance in technological domains can also be inferred from the relationship between grades in mathematics and subsequent performance in technology-heavy degree programs, such as engineering (De Winter and Dodou 2011).

Finally, numeracy is a skill that can be improved with interventions. For example, project-based learning has demonstrated promising outcomes in enhancing numeracy skills among students. This pedagogical approach fosters creative learning by allowing students to construct knowledge through firsthand experiences and project-based activities centered around problem solving (Jalinus et al. 2017). Project-based learning offers various advantages, including increased student motivation, improved problem-solving abilities, enhanced collaboration and teamwork, and refined resource management skills (Anazifa and Djukri 2017).

General Cognitive Ability: Understanding the relationship between general cognitive ability and TF is crucial for comprehending individuals' proficiency in technology-related tasks. As defined by the Army Talent Attribute Framework, general cognitive ability encompasses 1) the capacity to comprehend and interpret information, 2) problem-solving skills, and 3) the ability to learn new concepts rapidly and efficiently (Royston et al. 2022). Markauskaite (2007) discovered a significant correlation between general cognitive abilities and technological competencies, suggesting that an increase in confidence regarding one's general cognitive capabilities is associated with a positive change in technical capabilities.

In addition, basic ICT capabilities were directly linked to cognitive confidence, emphasizing the importance of core technological skills in effective problem solving. Furthermore, Daly et al. (2015) found that higher levels of cognitive ability in childhood were associated with an increased likelihood of holding leadership positions in adulthood, indicating that cognitive abilities, such as effective reasoning and problem solving, foster leadership potential throughout an individual's life, including the ability to supervise and manage subordinates. Considering the likely importance of leadership skills in TF (listed under Social and Teaming Skills), these findings highlight the potential role of general cognitive ability in TF.

Cognitive Biases: Human cognition is not perfect and is in some cases hampered by various cognitive biases. Cognitive biases are thinking patterns or heuristics that lead people to systematically bias their decision making toward conclusions that are not strictly, or mathematically, rational. Some cognitive biases are believed to have evolved to enable fast and efficient decision making in natural situations, albeit at the expense of occasionally making an erroneous conclusion (Haselton and Nettle 2006). Interacting with modern, advanced technologies puts humans in a position in which cognitive biases are likely to yield more frequent errors. People with reduced tendency toward cognitive biases—or perhaps with greater ability to recognize and override these biases—may therefore enjoy improved performance in human-technology domains.

Cognitive biases are myriad; we mention just a few examples here, which are primarily drawn from Chattopadhyay et al.'s (2020) analysis of cognitive biases that affect software development, a technological domain arguably closely tied to TF. Cognitive biases in memory, such as primacy and recency, occur when a person more readily recalls information they encountered first, or more recently, even though this information is not necessarily the most important. Similarly, fixation occurs when a person's attentional focus gets "stuck" on an existing idea or problem solution, even when this is not the most optimal solution. The bias of ownership describes when a person prefers their own idea or solution, rather than someone else's, even when the other person's solution is more effective. A convenience bias may lead a person to choose a seemingly easy solution to a problem, but this solution may not be the most effective and may not even save the most labor in the long run. Other well-known cognitive biases include confirmation bias, framing effects, fundamental attribution error, Dunning-Kruger (Kruger and Dunning 1999) effect, and groupthink (Azzopardi 2021; Edwards and Edwards 2022). We expect that these and other cognitive biases are likely to slow down problem solving in complex technological domains, interfere with learning new behaviors, and perhaps inhibit the detection of poorly performing AI or machine algorithms. For example, Edwards and Edwards (2022) found that people were likely to commit fundamental attribution errors towards robots by attributing their undesirable behaviors to their dispositions, even when the behaviors were clearly coerced. This has important implications for people's ability to trust in machine teammates. Kliegr et al. (2021) further discuss 20 different cognitive biases and how they may affect a user's interpretation of machine learning models.

Subjective questionnaires have been used to measure some types of biases (e.g., Scopelliti et al. 2018). Objectively scorable tests have also been devised for many biases of interest, which typically take the form of offering a logical or mathematical problem that the participant can answer either with the expected biased response or with the mathematically correct answer. Berthet (2021) provides a thorough review of objective measures of several cognitive biases, concluding that much work remains to be done to achieve psychometrically valid tests of many key biases.

In a recent study, Chattopadhyay et al. (2020) investigated the effects of several cognitive biases on performance, using a highly technological task: software design. Cognitive biases were measured using self-report, narrate-aloud, qualitative methods in which programmers described their thinking aloud while they worked. The researchers found that cognitive biases were associated with more coding errors that later needed to be reversed for the final program to operate as desired. We expect cognitive biases, and those individuals more prone to them, to generally yield worse performance when working in other advanced technological contexts, such as with AI (see also Kliegr et al. 2021).

Efforts in explainable AI aim to mitigate the effects of human cognitive biases (e.g., Miller et al. 2019; Wang et al. 2019a). Nonetheless, we expect that individual trait differences and state differences in cognitive bias are likely to remain important. Not all AI will include effective mitigations, especially as some systems learn and evolve in real time.

Metacognition: Metacognition may be succinctly defined as "thinking about thinking." It refers to the mental process of investigating one's thought processes and includes knowledge about and regulation of that thinking (Flavell 1979). In this report, we refer to facility in any of these aspects of metacognition as metacognitive skill. In practical contexts, strong skills in metacognition provide a person with an accurate understanding of what their knowledge and skill levels are—what they do and do not know. It also provides the person with an awareness of what they need to remedy their knowledge or skill gaps, along with awareness of proven strategies for making this happen.

Because advanced technology is constantly evolving, updating, and proliferating, it is unreasonable to assume that a user will come into any task scenario already knowing all they need to know to operate effectively with the technology (Yong et al. 2020; Pollard et al. 2022). We anticipate that a person who can rapidly identify what they do not know, what they need to know, and how to best learn it is a person who is going to excel at working with advanced, rapidly changing technologies. Education researchers have proposed that strong metacognition skills may be necessary for learning with technological systems, including web-based education (Azevedo et al. 2004; Cadamuro et al. 2019) and should be considered a core competency necessary for AI literacy (Yi 2021).

Metacognitive skills can be measured before, after, or during an activity and may involve self-report measures, instructor ratings, observations, interviews, think-aloud protocols, and some task-based assessments (Yong et al. 2020). Two commonly used assessments are the Metacognitive Awareness Listening Questionnaire ([MALQ] Vandergrift et al. 2006) and the Metacognitive Awareness Inventory (Schraw and Dennison 1994). Yong et al. (2020) provide detailed descriptions of these and several other methods. For an extensive review of 84 measures of metacognition that have been used with children (many of which can be used with adults), see Gascoine et al. (2017).

Canfield et al. (2019) conducted a study examining metacognitive skills and a direct, real-world example of TF: resistance to exploitation by deceptive and malicious technology. The researchers found that adult participants with stronger metacognitive skills were less likely to have malicious files on their home computers. In addition, Ramirez-Arellano et al. (2019) found that strong metacognitive strategies predicted performance in an online-applied computing course. Prather et al. (2019) similarly report that student participants who verbalized more metacognitive behaviors were more likely to arrive at correct solutions for computer programming problems. Karatas and Arpaci (2021) also found that metacognition predicted 21st century skills (including use of technology) and readiness for online learning. At the same time, there is considerable evidence that teaching with high-technology methods can improve students' metacognition (as reviewed by Cadamuro et al. 2019). Taken together, the evidence so far supports a bi-directional relationship between metacognition and performance with technology: strong metacognitive skills likely predict TF, and experience with technology can enhance metacognitive skills.

Metacognitive skills are related to SDL skills (Yong et al. 2020; Karatas and Arpaci 2021) and tend to be applied by persons who are self-directed learners (Cadamuro et al. 2019). Metacognitive skills also may be used when practicing Theory of Mind [ToM] see **Theory of Mind**section in this report); in that case, they are applied to thinking about *someone else's* thinking.

Systems Thinking and Strategic Thinking: As technologies become part of more complex systems and become more complex themselves, human operators may increasingly benefit from systems thinking, to better understand and predict the behaviors of these complex systems. Systems thinking examines how complex system behaviors emerge from lower-level patterns driven by basic physical, chemical, or human mindset (e.g., culture, attitudes, paradigms) properties and their relationships (Monat and Gannon 2015). Causal loops, self-organization, emergent properties, and other processes may be involved. A systems thinking perspective recognizes that the interrelationships between system components are at least as important as the components themselves (Monat and Gannon 2015).

Systems thinking approaches can be used to help understand any complex system, whether social, ecological, biological, economic, organizational, etc. (e.g., Carey et al. 2015; Dugan et al. 2022; Nguyen et al. 2023). Complex systems can of course cross multiple domains. More importantly, for our interests, many of these systems will have technological components, and they may also have technological outcomes and/or technological solutions (Davis et al. 2014). In addition, AIs can be complex systems and exhibit systems properties including feedback loops, emergent properties, and unintended consequences. Illustrative examples of unintended consequences in AI may include 1) tumor detection algorithms that learned to use the presence of a ruler (Okur and Turkan 2018) or use drawn purple surgical lines (Winkler et al. 2019) as cancer indicators or 2) face detection AI that can be foiled by patterned clothing (Lee 2020). Systemic social processes in humans can also have effects on AI behavior, as when Microsoft's chatbot Tay quickly became hateful (Alba 2016). We expect that a person skilled in systems thinking should be better able to predict or make sense of the behaviors that emerge from complex human-technology interactions or from complex technological systems like AI. Such a person should also be better equipped to find solutions to undesired effects.

Large organizations, including military organizations, are aware of the importance of systems thinking and seek personnel who can understand and engage with complex systems and effectively deal with complex systems problems (World Economic Forum 2016; Karam et al. 2020; Wisecarver et al. 2022). Systems thinking can be seen as a critical capacity for people who must design, analyze, monitor, or alter complex systems (Jaradat 2015). Jaradat and Keeting (2016) and

Karam et al. (2020) discuss seven dimensions of systems thinking. Among these are the key KSBs of flexibility, tolerance of change, and ability to handle uncertainty. Wisecarver et al. (2022) conceptualize systems thinking into five dimensions, including KSB elements related to responsiveness to change and ability to switch perspectives.

Building upon systems thinking, strategic thinking is the ability that promotes strategic decision making within organizations by considering the organization's historical context, current challenges, and how it will adapt to future demands (Steptoe-Warren et al. 2011). One critical element of strategic decision making is devising plans that are robust to the unknown (Dhir et al. 2018). Dhir et al. (2018) argue that strategic thinking is informed by one's organizational awareness, capacity for reflection, and competencies in recognizing patterns and analyzing trends. Srivastava and D'Souza (2021) offer a similar perspective, wherein they explicitly define strategic thinking in terms of systems thinking and reflection but deviate from Dhir et al. (2018) by introducing the dimension of divergent thought processing (Srivastava and D'Souza, 2021). Other strategic thinking scholars emphasize the importance of thinking about the future (e.g., Jelenc and Swiercz, 2011). In this section, we covered the importance of organizational awareness through systems thinking, and in other sections we argued that cognitive reflection, pattern recognition and analysis, as well as divergent thought processes (e.g., flexible thinking) constitute important KSBs for future research on TF. The strategic thinking framework reinforces each of these isolated components and provides an alternative perspective through which to view them. However, one of the challenges with applying strategic thinking approaches to analyzing TF is that strategic thinking is typically studied as an attribute of organizational leaders (Jalenc and Swiercz 2011) and is understood in terms of the organizational contexts that promote it and its organizational impacts (e.g., Moon 2013). Still, strategic thinking interventions can improve critical thinking at the individual level (Lou 2018), which suggests that strategic thinking skills can help to improve performance on diverse tasks.

From our investigations into how strategic thinking affects interactions with technology, we found that researchers seem to focus exclusively on how technologies can aid in strategic decision making (e.g., Jarrahi 2018; Du 2023; Wu et al. 2023). To make strides in this area, scholars need to appreciate the role that human input plays into the performance of learning-capable artificially intelligent technologies and how strategic thinking competencies promote TF.

Systems thinking can be measured with questionnaires such as the Individual Systems-Thinking Skills survey (Jaradat 2014) or Systems Thinking Scale

(Dolansky et al. 2020). Moreover, strategic thinking could be measured using self-report scales developed by Srivastava and D'Souza (2021) and Dhir et al. (2018).

Working Memory: Working memory is a cognitive ability that enables a person to hold information in an active state in the mind despite interference and/or during processing (Baddeley and Hitch 1974; Conway et al. 2005; Fellman et al. 2020). This ability may be conceptualized in multiple components, such as Baddeley's original (1986) three-component model that includes a domain-general *central executive* process that supervises and coordinates attention and processing, a domain-specific *phonological loop* for verbal information maintenance, and a domain-specific *visuospatial sketchpad* for maintenance of visual-spatial information. Other breakdowns have also been proposed (e.g., Oberauer et al. 2003).

Sufficient WM capacity is needed for connecting ideas, for understanding cause and effect, and indeed for any kind of mental synthesis. All these processes are important when interacting with AI systems and other complex technologies. This is especially the case for technologies that use large amounts of data, produce rapid or copious output, or operate in complex environments or as parts of complex, multi-agent systems (also see Systems Thinking). For example, Chen and Barnes (2014) suggest that WM may impact human-machine teaming performance and the ability to interact with groups of robotic agents.

Working memory has been found to predict general academic performance (Aronen et al. 2005; Alloway et al. 2010) and mathematics performance (as reviewed in Raghubar et al. 2010). Working memory is key for fundamental tasks like reading comprehension (Daneman and Merickle 1996; Palladino et al. 2001) and will contribute to an individual's ability to capitalize on many of their other skills and tendencies, such as SDL or spatial skills.

Working memory effects on TF have been found in some technological domains. Several research groups have found a positive relationship between WM (or aspects of WM) and university students' performance in computer-based online learning environments (e.g., Burin et al. 2018; Fellman et al. 2020; Harvey 2022). Ogata et al. (2012) found evidence that WM helps predict older adults' willingness to adopt computer technology. Garcia et al. (2011) found a similar correlation between WM and adolescents' use of personal computers and video games. However, it was not clear whether students with strong WM skills were more willing to use the technologies and/or whether use of the technologies may have helped to bolster their WM skills. In contrast, Wang et al. (2023) recently explored the relationship between visuospatial WM and coding ability (in children) but did not find a significant relationship.

One technological domain has been of particular research interest with respect to WM: facility with hypertext navigation (i.e., nonlinear information search and data interaction, accomplished via computer interfaces). Interacting with demanding hypertext interfaces is proposed to be particularly taxing to WM. Working with hypertext interfaces requires a user to store and process many elements in memory, including not just the material encountered but also the structure of data locations and history of or plans for navigational decisions—all coupled with near-constant opportunities for distraction and interference (DeStefano and LeFevre 2007). Individuals with poorer WM skills have been found to have more trouble navigating hypertext (e.g., Rouet et al. 2012), or they learn hypertext navigation more slowly, even if they start at similar skill levels (Rosman et al. 2016).

Hypertext navigation and data search may not be particularly advanced technology domains, but the challenges they pose are retained or even amplified in many modern advanced technologies—particularly those that sense, aggregate, manipulate, reason over, and display large amounts of complex data. Understanding machine learning models underlying AI and managing multi-robot teams are just two examples where we believe facilities with hypertext-like skills would be advantageous.

Working memory is frequently measured by span tasks (reviewed by Conway et al. 2005), which require a person to remember a series of items presented to them while being asked to simultaneously engage in other forms of cognitive processing and/or being subjected to distractions. A widely used set of WM measures is the Wechsler Memory Scale (Wechsler 2009). Other sets of measures have also been used, such as the Automated Working Memory Assessment (Alloway 2007).

Theory of Mind: Theory of Mind, and its related concepts *empathy* and *perspective taking*, generally refer to the ability to understand or imagine the inner workings of another individual's mind. Different fields define ToM differently (Apperly 2012; Schmetkamp 2020), some of which consider empathy and perspective taking to be subsets of ToM. Theory of Mind includes aspects such as knowing what others know, knowing that their state of knowledge may be different from yours and/or inaccurate, and being able to reliably predict how they may process and respond to a situation given their background and current emotional, physical, or knowledge state.

Theory of Mind ability is valuable because it allows a person to better understand the intents of, and predict the behavior of, other people, groups of people, or animals. This in turn enables appropriate responses (Brüne and Brüne-Cohrs 2006). By analogy, we predict that strong ToM skills would also enable humans to perform better when interacting with AI and other advanced technologies (Krach et al. 2008;

Schmetkamp 2020). If a human can understand or imagine an autonomous agent's state of knowledge, its sensory abilities, its processing tendencies, or relevant aspects of its current state, that human should be better able to predict the agent's behavior and needs, while also being better able to adapt themselves, or know what to adapt in the agent, to improve overall team performance (Krach et al. 2008; Schmetkamp 2020; Salm-Hoogstraeten and Musseler 2021).

Perspective taking is a strategy of ToM—one of particular importance in human-machine interaction, especially with embodied agents such as robots (Esterwood and Robert 2023). With perspective taking, the human can understand or imagine what a situation "looks like" from the perspective of their interaction partner. In the literature, perspective taking can refer to understanding another individual's perspective in the social, emotional, or life experience sense (e.g., Hollarek and Lee 2022). It can also refer to understanding another individual's literal visual-spatial perspective. This latter conception can be considered a form of spatial ability (Kozhevnikov and Hegarty 2001).

Empathy refers more to understanding another individual's feelings, that is, the emotional or sensory aspect of another individual's perspective. This may also evoke similar feelings in the observer. Although we do not expect computerized technology to have emotions in the same sense that its human teammate does, empathy may still be valuable if it helps a human more seamlessly estimate their autonomous teammate's functional state and predict its behavior. Empathetically perceiving an autonomous teammate as confused, uncertain, or overworked, for example, may enable faster or more accurate predictions of its future behavior and may help the human teammate modify or accommodate the system as appropriate to complete the task at hand (also see Schmetkamp 2020). Empathy may also be important because developers are designing AI agents to evoke empathic responses from human operators (e.g., Paiva et al. 2017), which suggests that future technologies may be capable of expressing important need-states by tapping into humans' empathic tendencies.

Most attention to ToM concepts in technology center on the following: 1) using information and communication technologies or virtual reality (VR) to train ToM improvements in human users (e.g., Drigas and Papoutsi 2015; Bamicha and Drigas 2022); 2) programming ToM-like capabilities into robots and virtual agents (e.g., Dissing and Bolander 2020); and 3) examining when and how humans use ToM when interacting with robots and agents (e.g., Salm-Hoogstraeten and Müsseler 2021; Esterwood and Robert 2023). However, notable exceptions have explored ToM skill and its relationship to performance with advanced technologies.

In a small study of seven aerospace engineers (Menchaca-Brandan et al. 2007), participants with better perspective-taking skills had lower angular error when teleoperating a robot arm in simulation using different camera perspectives. However, they were also slower at the task (Menchaca-Brandan et al. 2007). In contrast, Katifori et al. (2022) found that participants scoring higher in perspective-taking completed a VR object positioning task more quickly and with greater movement efficiency. Kleih and Kübler (2013) looked for a relationship between empathetic perspective-taking ability and performance with a brain-computer interface (BCI), but they found no significant difference between participants with high and low empathy in a BCI spelling task. Researchers have considered empathy as a digital competency and core to DL (Garcia-Perez et al. 2016); however, Tsortanidou et al. (2022) note a lack of research on empathy versus DL. Although it is not an individual differences study, Ono et al. (2000) found that people were better able to understand a robot's unclear speech when they used ToM to attribute agency (intention and shared attention) to the robot, which suggests that individuals with stronger ToM skills might perform better at tasks involving ambiguity with robots or other agents. Williams et al. (2019) implemented a clever robot interaction paradigm to examine children's understanding of robotics principles. They collected participants' ToM measures, but these were not regressed against the children's task performance. The opportunity remains for such a study to examine whether individual differences in ToM skills predict participants' performance on robotics or other advanced technology tasks.

Theory of Mind and its related concepts can be measured via tasks, tests, or self-report. Assessment of ToM can involve examining performance of specific ToM tasks, including White Lie detection and understanding (Happe 1994), Reading the Mind in the Eyes (inferring emotional state from partial facial images; Baron-Cohen 2001), The Awareness of Social Inference Test ([TASIT] inferring intent/sarcasm; McDonald et al. 2003, 2006), predicting Next Actions (Sarfati et al. 1997), and understanding others' False Beliefs (Baron-Cohen et al. 1985). Tasks for assessing children's ToM skills can be found in Wellman and Liu (2004). It is worth noting that although some of the aforementioned tests have been developed for clinical populations or children, they have also been used in nonclinical adult populations (e.g., Banks 2021). Tests of perspective taking include the Perspective-Taking Ability Test (Kozhevnikov and Hegarty 2001) and Purdue Spatial Visualizations Tests (Guay 1977). Commonly used self-report instruments include the Interpersonal Reactivity Index ([IRI] Davis 1983), Basic Empathy Scale ([BES] Jolliffe and Farrington 2006), and Empathy Quotient ([EQ] Baron-Cohen and Wheelwright 2004).

Theory of Mind is related to some other KSBs. Using ToM can involve metacognition, and it is impeded by anxiety (Todd et al. 2015) and by some stressful situations such as time pressure (Epley et al. 2004). ToM has been found to be related to WM (Wardlow 2013).

Learning Efficiency: If people differ in the rates at which they learn new information, then individuals with high learning efficiency may be more likely to be able to keep up with the constant changes and learning needs necessitated by AI or other rapidly changing advanced technologies. To the best of our knowledge, there are no foundational research products that identify individual characteristics that contribute to the efficient learning of technology per se. However, some research suggests that there is a marked difference in the rate at which people learn new information and that those who learn at a faster rate also tend to retain information for longer (McDermott and Zerr 2019). To test this, Zerr et al. (2018) examined how quickly people learned Lithuanian-English word pairs and found that recall was higher for more efficient learners, even 3 years after their initial exposure. In a subsequent study, Zerr et al. (2018) demonstrated that learning efficiency appeared to be consistent across content domains; however, both domains involved learning word pairs but used different modalities. In future studies, researchers would need to test whether these results hold true for learning novel technologies. Moreover, Zerr et al.'s (2018) conclusions that people learn at different rates were recently challenged by a large-scale study examining the rates at which students learn material in the classroom (Koedinger et al. 2023).

In their report, Koedinger et al. (2023) found remarkable consistency in the rate at which students learn new material; however, they also noted that their evidence supports the notion that practice is a strong predictor of students' mastery of new material. Therefore, it is likely that training to be more technologically fluent may be a more fruitful endeavor than attempting to identify individual differences in learning rates. Koedinger et al.'s (2023) findings suggest that individual differences in people's motivations to find and engage in opportunities to practice using novel technologies may be critical for identifying technologically fluent individuals. Even if people differ in how efficiently they learn new information, the effects of learning efficiency would be difficult to test with respect to learning novel technologies simply because everyone has different prior experiences with technology, so any effects of learning efficiency would likely be overshadowed by pre-existing knowledge and experience.

8. Category 3: Social and Teaming Skills

Social and teaming skills have been extensively researched in relation to functional task completion and social and cohesion dynamics within human autonomy teams (Lakhmani et al. 2022). As AI and advanced technologies continue to permeate industries and organizations, people will increasingly find themselves operating in mixed human-autonomy teams. Many social skills vital to effective functioning in human-human teams are likely to continue to be valuable in human-machine teams. Skills such as managing team projects, allocating tasks appropriately, aggregating input from various team members, and negotiating disagreements will be vital to human-team performance. Furthermore, AI and other advanced technologies are the products of human ingenuity and are intended to be used by and for humans, meaning that having a well-developed understanding of human social aspects (like cultural awareness) can be critical for proper and ethical usage or development of these technologies. The following KSBs fall within the *Social and Teaming Skills* category.

Cultural Awareness: Cultural awareness includes the capacity to learn and integrate knowledge about cultures and social backgrounds that are different from one's own into one's decision making. This awareness includes the ability to modify and adapt behaviors to synchronize to a different culture to mitigate conflict and build interpersonal relationships. Diverse cultural perspectives have been identified as potential sources of bias in AI algorithms. AI systems often encode cultural biases present in training data, leading to discriminatory outcomes (Buolamwini et al. 2018; Wang et al. 2019b). Some researchers have advocated for the incorporation of cultural awareness in AI development to promote fairness and equity (Denton et al. 2019; Garg et al. 2020). This aligns with the principles of inclusive design, as proposed by (Friedman and Nissenbaum 2022), which underscore the importance of recognizing and accommodating diverse cultural norms and values in AI systems.

Individuals with high cultural awareness exhibit the ability to effectively navigate and adapt to diverse cultural contexts (e.g., remaining respectful, open-minded, and flexible) in response to interactions with individuals from different cultural backgrounds. These individuals may be more likely to foster positive intercultural relationships and bridge cultural gaps, which is essential in the development of ethical and inclusive AI technologies. Key characteristics of cultural awareness include cultural sensitivity, effective cross-cultural communication, intercultural competence, empathy, and a willingness to learn and adapt (Jackson 2011). Being high in cultural awareness may also help individuals in multicultural or global settings. For example, cultural awareness tends to help individuals avoid cultural misunderstandings, promotes inclusive and respectful behavior, and enhances collaboration in diverse teams, ultimately contributing to the development of culturally sensitive AI technologies. Furthermore, cultural awareness relates to the ability to navigate complex and nuanced cultural norms, which allows individuals to adapt to different cultural expectations and engage in effective cross-cultural interactions.

Various combinations of assessments can be used to measure cultural awareness, including self-report measures, behavioral observations, and intercultural competence tests. Examples of self-report measures include the Cultural Intelligence Scale (CQS), which assesses an individual’s cultural sensitivity, awareness, and adaptability (Ang et al. 2007). Behavioral observations may involve assessing an individual’s behavior in multicultural or cross-cultural settings, observing their ability to adapt and communicate effectively with individuals from different cultural backgrounds. Intercultural competence tests, such as the Intercultural Development Inventory (IDI), measure an individual’s level of intercultural competence and their ability to bridge cultural differences (Hammer et al. 2003). Cultural awareness is not a fixed trait and can be developed or enhanced through training, education, and intercultural experiences. Cultural sensitivity training (e.g., Diversity, Equity, and Inclusion training), cross-cultural workshops, and immersive experiences in diverse cultural settings can all contribute to the development of cultural awareness.

Social Skills and Teamwork: Having social skills and being an effective team member are relatively well understood within the human autonomy team cohesion literature (Lakhmani et al. 2022); however, it is worth noting how these skills may relate to being technologically fluent. These types of skills generally facilitate effective collaboration (e.g., complementary team skills facilitate effective performance within technology-driven projects) and allow technology-fluent individuals to collaborate with others. Techataweewan and Prasertsin (2018) outlined four factors that relate to what they referred to as “digital literacy”: operation skills, thinking skills, collaboration skills (e.g., consisting of teamwork, networking, and sharing), and awareness skills (e.g., consisting consists of ethics, law, and safeguarding in digital domains). These authors further outlined that collaboration skills within DL domains consist of using digital technologies in collaboration with others, either as the leader or a member of a team, by working together to achieve team goals.

From a networking perspective, collaboration skills refer to the ability to create or subscribe to online network groups to build mutually beneficial relationships, whereas sharing refers to the ability to exchange technologically relevant information either through traditional routes or digital channels (Techataweewan and Prasertsin 2018). Teamwork and social skills also allow for effective communication, which is essential in technology-driven environments by allowing team members to articulate complex technical concepts both with their team members who are TF and non-TF. Teamwork may also facilitate problem solving within complex technological domains by fostering brainstorming, idea sharing, and seeking help from others when faced with setbacks during technological upset or unexpected events. Social skills are further related to other psychologically important constructs such as conflict resolution (Roseberry 1997), giving and receiving feedback, empathy (Spence 2003) (e.g., better at anticipating user needs to lead to more user-friendly technological solutions), openness and willingness to adapt to (technological) change (Kholin et al. 2016), creativity to foster brainstorming for innovative technological solutions and ideas (Paulus et al. 2006), and even cross-functional understanding to bridge the gap between technology and other domains.

Measuring social skills in TF individuals requires assessing interpersonal abilities within the context of performing a task. For example, one could observe an individual's social skills within a teaming setting to understand how TF and non-TF teammates communicate and work effectively, assess general emotional intelligence, gauge an individual's ability to understand and manage emotions in themselves and others, as well as utilizing several other subjective measures to assess cohesion in the individual and team. However, it should be noted that to effectively assess this skill, and other related teaming constructs such as team trust for example, it is recommended to use a combination of methods to gain a comprehensive understanding of not only the individual but also the team within which they find themselves (Krausman et al. 2022). In addition, social skills vary from context to context, and although this construct has been widely researched and assessed in the teaming literature (Griffith 1988; Griffith and Vaitkus 1999; Dion 2000; Salas et al. 2009, 2015a, 2015b), assessing social skills within technology domains may still be largely unknown and warrants further investigation to understand the direct impact that social skills have on being technologically savvy.

Leadership and Project Management: Future technologies will include dynamic, learning-capable agents who will require guidance from their operators. Following Smith and Green (2018), we suspect that individual differences in leadership and project management abilities will be predictive of TF. Pugliese et al.'s (2015) research, wherein a group of autonomous robots was incapable of coordinating without leadership, exemplifies the importance of understanding leadership competencies when working with autonomous systems. Many desirable leadership qualities are covered elsewhere in this manuscript (e.g., demonstrating an affinity for AI, self-efficacy, and trust), so we will not delve further into those attributes here. Instead, we focus on the unique challenges of applying leadership and project management understanding to TF, as well as the pertinent TF-promoting qualities that are unique to leadership. Because learning-capable technologies are still very new, there is a dearth of direct empirical evidence regarding the leadership characteristics that promote TF. In this study, we draw insights on the role of leadership in TF from two areas: first, we review recent research on the role of leadership in human-autonomy teams (HATs), which are teams involving one or more humans working together with one or more autonomous systems; and second, we review some general findings regarding leadership in human teams.

In recent studies, scholars have been anticipating how leadership roles will need to accommodate changing environments and technologies in HATs, especially with respect to how leaders might facilitate relationships between human and autonomous teammates (Larson and DeChurch 2020; Flathmann et al. 2021; He et al. 2023; Sengupta and McNeese 2023). In their theoretical review, Flathmann et al. (2021) argued that the attributes of human-autonomy team leaders could be distilled into two broad domains: resource management and information management. According to their model, resource management would require leaders to manage how resources are shared between teams, within teams, and to motivate humans by creating meaningful work using autonomous systems. In addition, information management would require leaders to create algorithmic feedback for agents, collect information for team use, monitor and assist information transfer between humans and agents, and determine information destinations. At the intersection of resource and information management, leaders would also need to create understandable performance feedback for humans. Although Flathmann et al.'s (2021) model of leadership in HATs is beyond the scope of understanding TF, it does provide some valuable insights for what leadership qualities to expect from a technologically fluent person. For instance, a person high in TF will be able to understand the computational limitations of the systems on which the novel technologies are built, thus enhancing their ability to dynamically allocate computational resources between systems when they are needed most, while understanding the trade-offs between sacrificing performance in one system to benefit another. Furthermore, managing these novel technologies' complex information inputs, processes, and outputs will be essential for people to excel in their ability to train future technologies.

Flathmann et al.'s (2021) review is perhaps the most direct attempt to model how leadership qualities could affect interactions with novel technologies; however, their report overlooked some major contributions to understanding how leadership attributes promote team success. First, they neglected to mention how resource and information management could be measured in HATs, limiting the direct applicability of their work to TF. Second, they overlooked many of the leadership attributes that scholars have been studying for decades. Although exemplary leadership qualities within human teams may not directly apply to TF, such as a leader's ability to motivate employees and attend to emotional needs, we argue that the future of technology is far beyond our current understanding; therefore, entertaining the relevance of these human-specific attributes may be worthwhile.

Over the past several decades, numerous leadership theories have contributed to understanding team performance outcomes in human teams. Theories of human team leadership may offer limited utility in understanding TF largely because these theories highlight leaders' abilities to find common ground through shared human experiences. For instance, transformational leadership theory underscores leaders' abilities to build rapport, connect emotionally, and motivate team members (Maqbool et al. 2017). Certainly, researchers are actively developing emotionally intelligent AI systems, which are already proving capable of influencing humans' trust (e.g., Fan et al. 2017); however, it is unclear whether emotional needs will emerge from future technological developments, thus making the need for emotional intelligence in TF tenuous.

Regardless of future AI's emotional capacities and responsiveness to emotionally intelligent humans, there are certain leadership and project management qualities that are certainly worth investigating with respect to TF. Specifically, a person's ability to understand the technology's unique requirements (e.g., version-specific issues, domains of higher vs. lower performance, etc.), an ability to communicate effectively with the technology, being attentive to the technologies' status, and managing conflicts within and between inputs, processes, and outputs. However, it remains to be seen whether the attentiveness required for TF (e.g., domain knowledge) may not stem from the same human capacities that promote attentiveness for humans (e.g., empathy). Indeed, a recent investigation found that people's trust in AI was not affected by their anthropomorphisms of AI (Chi and Hoang Vu 2022). Still, testing the applicability of human leadership qualities to TF will need to be an active area of research as technologies continue to develop.

One of the big unknowns relevant to understanding how leadership qualities will affect TF is task structure. Since the 1960s, scholars have understood that the efficacy of different leadership styles is situation-dependent (Shaw and Blum 1966). Because TF is concerned with how people transfer their abilities between radically different types of technologies (whether these technologies are deployed concurrently or sequentially through updates), it is likely that a person high in TF would need to adapt their leadership style flexibly. Indeed, Pizzolitto et al.'s (2023) meta-analytic evidence reinforces the importance of understanding the effects of hybrid leadership styles in human teams.

Effective Communication: Effective communication is a crucial aspect of TF and encompasses the ability to convey relevant information across different organizational levels and contribute to distributed processes. The ATAF identifies various components of effective communication, including active listening, oral communication, written communication, and general communication (Royston et al. 2022). It emphasizes the importance of communicating technical information to diverse audiences in a manner that they understand and appreciate, and thus foster rapport and promote a culture of innovation, adaptability, and continuous learning. In the context of TF, effective communication involves the following:

- Selecting the appropriate communication technology for specific purposes.
- Understanding how to communicate with autonomous agents (both in terms of providing them with information in a format they can understand and having facility with human-machine interfaces).
- Understanding how to communicate with humans about AI or other advanced technologies to complete a goal.
- Understanding the audience's impressions.

Effective communication can facilitate reflection and academic reasoning skills and encourage feedback and/or discussion (Sargeant et al. 2015). Simulation-Based Team Training (SBTT) has emerged as a promising method to improve effective communication among healthcare teams. The study conducted by Blum et al. (2005) used a realistic simulation-based Anesthesia Crisis Resource Management (ACRM) curriculum, replicating the actual patient care environment. The training focused on crisis resource management and effective communication among team members through debriefing sessions and innovative methods such as inserting and tracing probes. Although the probe transmission rates did not significantly change, trainees perceived improvements in information sharing, indicating construct validity. These findings highlight the potential of SBTT in enhancing effective communication within healthcare teams, ultimately leading to improved patient care outcomes.

9. Category 4: Adaptability and Response to Change

Technology is advancing at a rapid and accelerating pace. This pace can be extreme, with some advanced forms of AI even capable of updating their models and changing their behavior in real time. The AI that a person interacts with may be more advanced than it was just a few minutes previously. This rapid change and unpredictability put tremendous pressure on the human to be flexible in their thinking and strategies, to adapt to new conditions, and to have enough comfort with change and uncertainty to remain focused and effective in their tasks. A person's ability to adapt not just themselves but also to adapt elements of the situation, including the AI, will be vital. The following KSBs are ones we believe are key to adaptability.

Situational (General) Adaptability: Situational adaptability is an individual's capacity to adjust their behaviors and responses to a specific circumstance or context, which enables the individual to navigate and thrive in diverse circumstances and unpredictable situations. This also requires the individual to effectively monitor their own behaviors, communication style, and decision-making processes to adapt and cope to the changing or unexpected demands of the situation. Situational adaptability appears to be a key component to TF because it does not require a "one-size-fits-all" approach for digital solutions. Perhaps more importantly, individuals high in situational adaptability can adapt their decision-making and problem-solving processes to suit the situational complexities at hand, and they are also resilient and can bounce back from setbacks and challenging situations, the circumstances of which are often found in technological contexts.

Situational adaptability is also incredibly useful in technological domains because these individuals can adapt to dynamic and fast-paced situations in which individuals must continuously adapt to changing and emerging technologies. Here, technology-savvy individuals who are high in situational adaptability can quickly learn and assimilate new technologies by being open to learning new software, procedures, and tools as well as enabling them to stay ahead of technological change. In addition, individuals who are flexible in their ways of thinking (i.e., those with a propensity to adapt to new situations with less resistance; Barak and Levenberg 2016) may be able to adapt to, as well as drive technological adaptation, and can effectively use new technologies faster than those with more rigid thinking (Barak and Levenberg 2016; Barak et al. 2018; Jacobs et al. 2019). (Also see the Flexible Thinking section below.)

Some authors have outlined several key determinants of adaptation behavior, which include adaptation usefulness, ease of adaptation, and IT adaptability (Bhattacherjee and Harris 2009). These same authors further stress that the outcome of adaptation to technologies is enhanced IT usage, with effects that are moderated by the user's extent of work adaptation.

Situational adaptability may also be a predictor of TF because individuals high in situational adaptability tend to engage in flexible thinking, are open to change, which enables them to embrace new challenges and approaches, and are versatile and can demonstrate competence in a wide range of situations and roles. Schwartz et al. (2005) also discuss adaptive expertise as a function of two dimensions:

efficiency and innovation. Here, efficiency refers to an individual's ability to gather and execute with appropriate knowledge and skill (a quality typically expressed with routine expertise), whereas innovation is generally associated with creative and innovative responses (qualities typically associated with adaptive expertise). However, the following important distinction should be made here: the notion that although routine experts are high on the "efficiency" scale, adaptive experts are high on efficiency, but they can also engage in innovative solutions that may not be readily apparent to non-expert novices or routine experts (Schwartz et al. 2005). In other words, situationally adaptive experts can use their knowledge for efficiency, but they can also innovate with it, which is a key component to being technologically fluent.

Like other skills, situational adaptability is not fixed and can be developed through self-awareness, learning from experiences, and practicing adaptive behaviors. Measurement of situational adaptability must focus on assessing an individual's ability to adapt to scenarios that present challenges or changes, or those that occur in ambiguous situations that lack clear-cut solutions. For example, experimental assessments could focus on assessing an individual's ability to navigate uncertainty, make informed decisions, and adapt their strategies to address situational challenges within technological contexts. Here, assessing that an individual has recognized that a change has occurred and assess how they come up with problem-solving strategies to adapt to dynamic technological requirements will be crucial.

Finally, although used in a domain focusing on career aptitudes and abilities, Bhattacherjee and Harris (2009) developed a measure of what they refer to as "digital adaptability", which outlines five habits that help individuals learn technologies that are new to them. This may be a useful measure of adaptability in digital domains because these authors found that adaptability correlated with career aspirations in STEM-related fields; however, as previously stated within this section, this measure was designed and developed to assess career aptitude and digital inequality among students, not necessarily TF.

Employee Agility: Working with rapidly changing, learning-capable technologies will require operators to identify innovative approaches to working with these advanced systems. Scholars have sought to understand how employees adapt to changing task demands and organizational structures through the lens of employee agility. Employee agility is characterized by the ability to perform fast-learning processes within, as well as across, a variety of experiences inside and outside the organization, including flexible navigation between different ideas and their implementation in the organizational context (Salmen and Festing 2022). The employee agility construct is built upon learning agility and innovative work behaviors. Learning agility is the ability to quickly understand a situation and think flexibly to learn within and between scenarios. Innovative work behavior is intentional creation, introduction, and application of new ideas within a work role, group, or organization, to benefit performance.

Braun et al. (2017) studied the effects of employee agility on employees' individual performance and stress while a company was undergoing organizational change, and their results revealed that individual differences in agility can help employees cope with uncertainty and adapt to change quickly. In a recent analysis of employee agility, Petermann and Zacher (2022) developed a novel measure of workforce agility and evaluated the measure's ability to predict innovative performance and task performance; however, their measures of performance were based on self-report ratings, so further research would need to determine how well these effects hold up to observers' performance measures.

Although we are primarily concerned with individual differences in agility as predictors of TF, other research has considered alternative causal relationships between employee agility and technology interactions. For example, Wei et al. (2020) found that employees who engage with enterprise social media are more agile and that this effect is stronger among employees with higher levels of digital fluency (Bala et al. 2019; Rasheed et al. 2023; Sun et al. 2023). In addition, Syahchari et al. (2021) studied the effects of technology experience and agility on a port company's ability to organize shipments and provide logistics services. Considering that technologies are designed to solve problems in the workplace, it is understandable that applied researchers would be most interested in how technologies impact employee agility. Because future technology performance will depend on operators' individual characteristics, future research should focus on whether measures of employee agility influence TF.

Flexible Thinking/Cognitive Flexibility: Cognitive flexibility refers to the capacity to engage in critical thinking, deductive reasoning, and adaptive thinking, particularly in demanding and dynamic contexts (Martin and Rubin 1995). Within the framework of TF, cognitive flexibility involves the ability to adapt thinking strategies and adjust cognitive processes when confronted with changing situations or tasks, especially those involving novel and emerging technologies. The Flexible Thinking in Learning (FTL) questionnaire, developed and validated by Barak and Levenberg (2016), provides a means to assess cognitive flexibility. The FTL scale consists of three subscales: 1) acceptance of new or changing technologies, 2) open-mindedness to others' ideas, and 3) adapting to changes in learning situations.

In previous studies, researchers have revealed associations between cognitive flexibility and technology use. Bless et al. (2014) explored the effectiveness of self-administered cognitive training through a mobile application focused on auditory attention. The results indicated that task transfer to similar tasks was not observed, contrary to expectations. However, Rosen et al. (2013) found that young individuals accustomed to multitasking and continuous communication through their mobile phones use metacognitive strategies to multitask and perform well across different tasks successfully. Barak et al. (2018) discovered that technology-proficient students tend to exhibit greater flexibility in thought and are less resistant to change than those with lower technological proficiency levels. In addition, technology-proficient students who prefer collaborative learning reported a higher inclination toward cognitive flexibility.

Furthermore, research by Moore and Malinowski (2009) explored the relationship among meditation, self-reported mindfulness, cognitive flexibility, and other attentional functions. Their findings indicated that mindfulness practice and levels of mindfulness were positively correlated with attentional performance and cognitive flexibility. This suggests that mindfulness is closely associated with improved attentional functions and cognitive flexibility.

Measures such as the FTL questionnaire (Barak and Levenberg 2016) provide insights into the different aspects of cognitive flexibility. Moreover, research highlights the connection among cognitive flexibility, technology use, mindfulness practice, and attentional functions, all of which underscore the significance of cognitive flexibility in various domains.

Comfort with Uncertainty versus Need for Closure: Technological change forces people to confront uncertainty. How quickly will the state-of-the-art become obsolete? How drastic will the differences be moving from one technological change to the next? Compounding this uncertainty is the fact that the most powerful artificially intelligent technologies are the least transparent (Adadi and Berrada, 2018); therefore, future technology operators will need to navigate their uncertainty regarding which methods will produce desirable results and whether they can be confident in the realized technological outputs in complex, high-stress scenarios.

For decades, researchers have been investigating the detrimental effects that uncertainty can have on performance and how individual differences in people's ability to navigate uncertainty can attenuate these detrimental effects (Webster and Kruglanski 1994). Individual differences in how people navigate uncertainty has been studied through the lens of several tightly related constructs, such as need for cognitive closure (Webster and Kruglanski 1994), intolerance of ambiguity (also known as "intolerance of uncertainty") (Budner 1962; Berenbaum et al. 2008), and dispositional resistance to change (Oreg 2018). Need for cognitive closure represents a person's desire for an answer, any answer, on a topic to avoid being in a state of uncertainty (Webster and Kruglanski 1994), whereas intolerance of ambiguity represents a person's tendency to perceive ambiguous situations as threatening (Budner 1962).

Berenbaum et al. (2008) examined the relationship between measures for intolerance of ambiguity and need for cognitive closure due to the striking similarity in how scholars defined these two constructs. In their results, Berenbaum et al. (2008) found that there is indeed a great deal of overlap in these two constructs, although there are some subtle distinctions in some of the specific factors that define them; for instance, the need for cognitive closure scale (Webster and Kruglanski 1994) primarily assesses a person's preferences regarding uncertain situations, whereas intolerance of uncertainty scale (Buhr and Dugas 2002) primarily assess how much people experience distress in response to uncertainty. Although Oreg (2018) argues that dispositional resistance to change is distinct from intolerance of ambiguity, resistance to change is regarded as a direct consequence of need for cognitive closure (Livi et al. 2015), which is directly evident in the fact that "close-mindedness" is one factor used to define need for cognitive closure (Webster and Kruglanski 1994).

Several investigations have demonstrated that intolerance of ambiguity and its related constructs can impact how people engage with technologies. More importantly, people with higher levels of resistance to change (Nov and Ye 2008, 2009; Barak et al. 2018; Alanoglu et al. 2022) and need for cognitive closure (Knapová 2018) are less likely to use and gain expertise in new technologies. In addition to reducing the frequency of technology use, people with a high need for cognitive closure are less thorough when using technology to search for information (Choi et al. 2008; Mao et al. 2022). In addition, Leung and Chiu (2010) conducted a series of studies that demonstrated that people with high need for cognitive closure are less willing to accept ideas from foreign cultures. Because future technologies will generate ideas that human operators might not otherwise consider, the effects of a person's need for cognitive closure might also make them less open to accepting feedback from the technologies. In a related area, Oreg (2018) found that participants scoring low in resistance to change tended to perform worse at non-routine tasks (those requiring problem solving, greater complexity, and more uncertainty). Although the experimental tasks used by Oreg (2018) did not involve advanced technologies, these task properties are nonetheless likely to characterize interaction with advanced technological systems.

This KSB is frequently measured by the Need for Closure Scale ([NFCS] Webster et al. 1994; Roets and Van Hiel 2007) or the Resistance to Change (RTC) scale (Oreg 2003, 2006; Oreg et al. 2008), which includes subscales for routine seeking, emotional reactions, short-term focus, and cognitive rigidity. A scale developed by

Budner (1962) is commonly used to measure Tolerance for Ambiguity but see Furham and Marks (2013) for issues and thorough discussion of other methods.

10. Category 5: AI-Relevant Knowledge and Experience

In the context of AI, direct experience with AI or knowledge of it can be important in ensuring that individuals use AI technologies effectively and accurately. For example, individuals who have expertise in data analysis can ensure that the data input into the AI system is accurate and reliable. Similarly, individuals who have expertise in the field in which the AI system is being used can ensure that the output generated by the system is relevant and useful. The following KSBs fall within the *AI-Relevant Knowledge and Experience* category.

Knowledge, General Understanding of AI and Computational Thinking: The term computational thinking was coined by Seymour Papert (Papert 1980), described in depth by Wing (2006), and is generally understood as the ability to solve problems and communicate ideas while taking advantage of the power of computers. Here, learning is a central component to both AI (i.e., studying and understanding how machines learn and perform human actions) as well as computational thinking (i.e., how humans learn and how thought can be interpreted by a machine). However, with technological advances, the two concepts are closely related (Dohn et al. 2022, pp. 1−12). For example, research conducted by Martin-Nunez et al. (2023) found a significant and positive relationship and interaction ($p < .001$) between learning AI and computational thinking, suggesting a positive connection between knowledge accumulation within AI domains and student's computational thinking ability. Ultimately, findings such as these indicate that increased understanding of *how* AI works enables students to better conceptualize computational thinking notions because some of these elements (e.g., conceptualizing a problem, breaking it down into actionable steps, and solution potentials) are included in both constructs.

Here, AI knowledge refers to an individual's understanding of the basic functions of AI and their ability to use AI applications. In relation to TF, an individual's proficiency with AI and novel technologies plays a pivotal role in determining their AI-related behaviors. Having knowledge of AI can be seen as a component of TF, because it enables individuals to use AI correctly, as intended, and in appropriate situations. A lack of understanding can result in unintentional misuse, whereas high proficiency can lead to creative and beneficial unintended uses.

Pinski and Benlian (2023) developed an instrument to assess the general AI literacy of individuals and encompasses three categories: AI actor knowledge (explicit literacy), AI steps knowledge (explicit literacy), and AI experience (tacit literacy).

This instrument provides a means to measure individuals' level of AI knowledge and its potential relationship with technical savviness, highlighting the importance of AI literacy in navigating the complexities of AI-driven technologies.

Digital Literacy: Although DL can be thought of as one conceptualization of TF, here we also consider that it may be a KSB that helps predict our conceptualization of TF. Digital literacy refers to the multifaceted cognitive, motor, emotional, and social competencies that enable individuals to navigate digital environments effectively and intuitively for various purposes, including work, learning, and daily functioning (Porat et al. 2018). It encompasses the foundational knowledge and skills needed to critically evaluate information from digital resources, synthesize information, and adapt that knowledge to enhance performance with novel technologies. The assessment of DL competencies often involves self-report questionnaires, as seen in the work of Blau and Shamir-Inbal (2016) and Porat et al. (2018), in which participants evaluated their DL skills based on conceptual frameworks such as that developed by Eshet-Alkalai and Soffer (2012).

Digital literacy is closely related to self-efficacy, as evidenced by the positive and significant correlations between self-perceived competency in DL domains and performance in digital tasks found by Porat et al. (2018) and the high correlations between self-appraised DL competencies among elementary school students reported by Rozmarin et al. (2017).

Improving DL can be achieved through situation-based learning, as suggested by Detlor et al. (2022). This approach involves presenting students with realistic and relevant problems to solve, with instructors taking on the role of coaches or facilitators rather than lecturers. The learning environment should foster reflection, discussion, and evaluative thinking, engaging students actively. Furthermore, contextual and real-life learning activities should be incorporated into the course content to provide students with authentic learning experiences (Kurt 2021).

Digital literacy is interconnected with other KSBs, such as visual perception and perceptual acuity, as indicated by Martin and Grudziecki (2006) and Chetty et al. (2018), and encompasses various literacies, including digital, media, information, and visual, highlighting the interplay between technology, computer skills, information management, media literacy, communication, and visual literacy.

In summary, DL is crucial in technical savviness, enabling individuals to navigate digital environments effectively and leverage technology for various purposes. It is associated with self-efficacy and correlates with other KSBs. Improving DL can be achieved through situation-based learning approaches that prioritize problem-solving, active engagement, reflection, and real-life learning activities.

Beliefs About AI: Beliefs about AI encompass individuals' perceptions and assumptions regarding the intelligence and capabilities of AI systems (Von Walter et al. 2021). Implicit and explicit theories of intelligence influence these beliefs and can shape people's expectations of AI's potential across various domains (Sternberg, 1985; Furnham 2001). In the context of TF, beliefs about AI relate to how individuals perceive AI's competence and potential in handling technological tasks. These beliefs extend beyond technical capabilities to encompass AI's problem-solving abilities and socioemotional attributes (Von Walter et al. 2021). The connection between beliefs about AI and technological ability lies in how these perceptions influence individuals' interactions with technology. Individuals with positive beliefs about AI's capabilities are likely to exhibit a higher technological ability because they may feel more comfortable engaging with AI-driven solutions (Von Walter et al. 2021).

Moreover, beliefs about AI are linked to proficiency in technological tasks because individuals who believe in AI's superiority are more motivated to adopt and effectively use AI-driven tools and advice (Von Walter et al. 2021). The assessment of beliefs about AI typically involves measuring perceptions of AI's intelligence and problem-solving capabilities, which provide insights into individuals' attitudes toward AI and their readiness to embrace its functionalities. In summary, beliefs about AI are pivotal in shaping individuals' technological interactions, affecting their technological abilities, adoption of AI-driven solutions, and proficiency in complex technological tasks.

Algorithmic Thinking: Algorithmic thinking refers to the cognitive ability to approach problems in a manner similar to how computer algorithms work (Knuth 1985). It involves breaking down complex issues into smaller, manageable steps and designing efficient procedures to solve them. In the context of TF, algorithmic thinking encompasses the skill to apply computational thinking to real-world challenges, enabling individuals to convert these problems into computational models and leverage technology to create automated and effective solutions. We would expect that a person skilled in algorithmic thinking would also be better able to predict or guide the behavior of an AI or to be better able to repair if it is not functioning as intended.

Algorithmic thinking is closely intertwined with technological ability. It equips individuals with the mindset and skills to navigate digital environments and effectively use technology. By fostering logical reasoning, pattern recognition, and systematic problem-solving, algorithmic thinking enhances one's capacity to engage with and understand various technological tools and platforms. This relationship is highlighted by studies such as Çoban and Korkmaz (2021), who emphasize that algorithmic thinking plays a pivotal role in shaping DL and empowering individuals to participate actively in the digital landscape.

Moreover, the link between algorithmic thinking and proficiency in technological tasks is profound. Individuals who are adept in algorithmic thinking use digital tools and platforms efficiently. The ability to approach problems methodically and develop algorithms enhances competence in programming, data analysis, and other technological tasks. In previous studies, like the one by Sari et al. (2022), researchers have demonstrated how incorporating algorithmic thinking into educational activities can significantly improve participants' skills in this area. The quantitative findings revealed statistically significant improvements in algorithmic thinking skills among the participants during these activities. In addition, qualitative data supported these results, as teacher candidates expressed that the activities enhanced skills related to algorithmic thinking, such as problem-solving, decision making, analytical thinking, creative thinking, and collaborative work. Sari et al.'s (2022) findings demonstrated a positive causal effect of STEM-focused physical computing activities on enhancing algorithmic thinking skills in teacher candidates.

Assessment of algorithmic thinking can be achieved through various instruments and approaches. For instance, Korkmaz et al. (2017) developed a scale to measure students' computational thinking skills. This scale comprises items that assess different aspects of computational thinking, providing a quantifiable measure of individuals' algorithmic thinking abilities.

In conclusion, algorithmic thinking is a fundamental cognitive skill within technological savviness. It enables individuals to harness computational concepts, problem-solving strategies, and digital tools to devise efficient solutions. This capability plays a significant role in fostering DL and enhancing proficiency in technological tasks, aligning well with the demands of an increasingly technology-driven world.

AI Literacy: Artificial intelligence literacy, defined as the multifaceted ability to understand, apply, and critically evaluate AI technology within practical contexts, holds a pivotal role in the realm of TF (Ng et al. 2021). This proficiency shapes individuals' interactions with AI systems, enabling them to effectively navigate the intricacies of emerging technologies. It encompasses a comprehensive grasp of AI's functionalities, potential applications, and inherent limitations, fostering a deep understanding of its practical implications. As Wang et al. (2023) define it, AI literacy involves awareness, application, analysis, selection, and ethical considerations, thereby encapsulating a holistic approach to engaging with AI.

This concept of AI literacy intertwines with DL, users' attitudes toward robots, and their daily AI usage (Celik 2023). Moreover, AI literacy and computational thinking exhibit a positive association, wherein computational thinking facilitates the understanding, recognition, and evaluation of AI-based technologies (Celik 2023). This synergy between computational thinking and AI literacy underscores the interconnectedness of cognitive skills and AI proficiency.

The assessment of AI literacy is underpinned by the AILS, built upon the foundational ideas of DL models, adapting them to the unique context of AI literacy (Balfe et al. 2018; Calvani et al. 2008). The AILS framework comprises four core constructs: awareness, usage, evaluation, and ethics. Each construct contributes to individuals' comprehensive AI literacy, ensuring they are well-equipped to navigate AI technologies responsibly and effectively. Furthermore, AI literacy and its underlying constructs have been found to correlate negatively with negative attitudes toward robots, highlighting the role of positive AI literacy in shaping individuals' perceptions of and interactions with robotic systems (Celik 2023).

In summary, AI literacy is essential to TF, enabling individuals to engage proficiently with AI technologies. Its multidimensional nature—encompassing understanding, application, analysis, and ethical considerations—underscores the intricate relationship between AI proficiency and responsible AI usage. The AILS framework and its associated constructs provide a comprehensive tool for assessing and enhancing AI literacy, contributing to the broader discourse on fostering informed and responsible AI interactions.

<u>Propensity to Trust (in Autonomy) and Trust Calibration</u>: Interacting with new and rapidly evolving technology presents many uncertainties to individuals and requires them to be somewhat vulnerable by relying on said technology that may or may not be able to complete tasks. These types of scenarios may result in undesirable outcomes (Fukuyama 1995; Luhmann 1979), and thus they present a noteworthy domain in which to study and assess trust. In fact, Dutton and Shepherd (2006) argue that feelings of trust are closely connected to greater feelings of certainty and confidence, such as having a sense of "cyber trust" in regard to security and reliability of the Internet, for example.

However, some argue that feelings of certainty or even confidence in the Internet are closely related to usage and experience. For example, MacKenzie (1999) posited that a relationship between information gain on the Internet and certainty can be explained via a U-shaped "certainty trough". Like other models of this nature, at one end of the spectrum are individuals who are the most socially distant from the Internet (e.g., no knowledge of technology or its use, and very little certainty about its role) and are thus likely to feel alienated from it. On the other end of the spectrum are individuals who learn about the Internet by becoming users, which may lead to users obtaining a higher level of certainty and trust in the technology through knowledge gain (Dutton and Shepherd 2006).

Conversely, some also point out that increased usage and experience with the Internet may also increase uncertainty as individuals learn about the complexities surrounding reliability, security, and various privacy issues, which implies that the most informed users of the Internet are aware of the risks attached to such use. However, a strong caveat to this argument is that non-users of the Internet still tend to possess a *general distrust* of the technology because they are most distant from it, and thus they are uncertain and less confident of its value (Dutton and Shepherd 2006).

Here, a crucial differentiation is that the actual risks associated with the Internet are often much less than the risks imagined by non-users who have no conception or understanding of the benefits of this type of technology. Therefore, Internet users are more likely to gain greater expertise for accessing resources to combat potential problems, and although they are still aware of the risks previously mentioned, they are simply less concerned about them. All in all, it seems that time spent and actual usage as well as previous experiences (both good and bad) can either undermine or boost confidence in the technology and thus trust.

In these types of human-technology scenarios, trust propensity is a critical factor during early trust phases in which the absence of information or presence of uncertain situations is evident (Colquitt et al. 2007), and it is one of several critical determinants of whether someone or something can be trusted (McKnight et al. 1998; Borum 2010). Furthermore, propensity to trust in technology is a well-researched subject (see Krausman et al. 2022) and refers to an individual's general disposition toward trusting others; it is a trait that remains stable over time (Mayer et al. 1995; Burke et al. 2007); it is unique to the individual (Rotter 1967; Mayer et al. 1995; Jarvenpaa et al. 1998); and it impacts how individuals enact trusting behaviors (Borum 2010; Costa and Anderson 2011). In this domain, trust propensity is typically examined and defined in relation to trust in people, and some have focused on studying aspects of human trust (i.e., ability, benevolence, and integrity) in relation to trust in Web sites (Vance et al. 2008) and trust in online recommendation agents (Wang and Benbasat 2005) to determine how this influences individual decisions to use technology.

Furthermore, in recent studies, Krausman et al. 2022 focused on whether these findings can expand to trust in technology, and they attempt to assess how this type of trust impacts technology acceptance and usage. Specifically, an individual's propensity to trust in technology has been found to be based on prior experiences with automation and intelligent agents (Lee and See 2004), with further support finding that age and prior experience with video games also predicts an individual's tendency to trust robots (Desai et al. 2013). Others argued that general trust propensity relates to general trust in the Internet, for example (Katz and Rice 2002), where it was found that those individuals who are generally less trusting of people were also more likely to perceive the Internet as threatening (Uslaner 2000).

Trust also relates to being technologically fluent in several ways; however, first note that trust in people and trust in technology are different and thus result in different expectations of the user. For example, trusting a person reflects moral and volitional behaviors of the trustee, whereas trust in technology is dependent on human-created systems that have a limited range of capabilities and lack volition and moral agency (McKnight et al. 2011), although they might be perceived as having these properties (see the Theory of Mind section). Thus, trust in technology denotes a general expectation that the system will provide adequate, effective, and responsive help towards completing a task.

McKnight et al. (2011) offer additional insight in trust categorization, which is rooted in the definitions offered by Mayer et al. (1995) and McKnight et al. (1998) to operationalize trust in technology as a component of three different concepts: 1) propensity to trust general technology, 2) institution-based trust in technology, and 3) trust in a specific technology with which an individual has established a relationship. Here, the authors describe a causal ordering of these concepts in that trust propensity directly influences institution-based trust, which indirectly shapes trust towards a specific technology (McKnight and Chervany 2001). This further facilitates the development of knowledge-based trust towards a specific technology (i.e., technology-specific knowledge) (Pavlou 2003; Lippert 2007; Thatcher et al. 2011), which has also influenced postadoption technology use (McKnight et al. 2011). Conversely, other constructs based on technology usefulness (e.g., perceived usefulness and perceived ease of use) have been shown to have less predictive of postadoption technology use (Kim and Malhotra, 2005; McKnight et al. 2011).

Trust in technology may also relate to other relevant skills and abilities because individuals often work on collaborative projects in technology-heavy environments, which will require trust and effective teamwork. As previously mentioned in this section, those higher in trust propensity are more likely to trust their team members, share responsibilities, and engage in open communication. These are all abilities and skills that have been shown to predict good team cohesion and successful task outcomes (Lakhmani et al. 2022). Anecdotally, it appears that trust propensity may relate to openness and willingness to engage, explore, and use current and emerging technology, which can lead to a better understanding and integration of these technologies; however, this specific relationship needs empirical confirmation. Consequently, it cannot be stressed enough that when assessing and measuring a construct as complex as trust, one must also consider aspects relating to trust calibration. Trust levels that are too high may result in over trusting these systems and, thus, result in the individual missing or ignoring mistakes, anomalies, and or critical signals from the system. On the other hand, trust states that are too low may result in the individual not using the technology the way it is meant to be used and essentially renders the tools and system ineffective (Parasuraman and Manzey 2010).

Therefore, although trust propensity is important, we cannot overlook the crucial aspect relating to effective trust calibration. In this case, a technology-fluent person who engages in appropriate levels of trust should be willing to take calculated risks in pursuing innovative ideas in technology domains; they are more likely to share data securely and responsibly; and they are more likely to work seamlessly across departments to ensure smoother technology integration and implementation.

Finally, measuring trust in people has been widely researched; however, measuring trust in relation to technology has been a large focus in recent years. Although many typical assessment methods such as subjective reports exist and have been documented (e.g., trait measures of trust propensity and state measures of trust in response to technology interactions; see Yagoda and Gillan 2012; Krausman et al. 2022), other modalities have also been explored and focus on communication metrics, physiological signals, affective cues relating to changes in facial expression, and even communication measures. In fact, Krausman et al. (2022) highlighted the importance of trust measurement within human autonomy teaming as well as documenting a "toolkit" for various measures and modalities. Using subjective surveys is a terrific way to identify individuals with higher or lower trust propensity within the technological context, as well as understanding how trust changes over time as an individual works by themselves or in a team that uses technology; however, multimodal measurement approaches to trust may provide a more robust picture of this complex and dynamic state.

Video Gaming Experience: Video gaming experience generally refers to the amount of time a person has played video games, how often they play video games currently, and what types of games they play. Video gaming is an example of direct interaction with what, in some cases, is fairly advanced technology. This may even include AI or machine learning elements in the form of procedurally generated levels, interactive non-playable characters, or enemies and bosses with complex attack strategies. Some forms of video gaming additionally involve team processes. The player must interact with other players and with non-playable agents to achieve an in-game goal. Video gaming thus presents an opportunity for a person to develop or enhance a variety of skills that may transfer to proficiency with complex technologies or human-agent teams in the real world.

First, familiarity and comfort with video games should improve a person's facility with game-similar technologies. These would include components such as graphical interfaces, maneuver joysticks, VR or augmented reality systems, and autonomous agents of varying complexity—any of which are likely to be present in advanced, real-world technology systems. A seasoned gamer will likely know how to explore and begin to learn the limits and capabilities of a given piece of software or complex technological system. Literal physical dexterity with translating signals seen on a screen into appropriate button pushes may also be beneficial, particularly in time-sensitive human-technology domains. In addition to potential benefits from familiarity and dexterity, a gamer may also bring to the table improved attentional control (e.g., Dye et al. 2009), heightened visual perception (Green and Bavelier 2003), and honed spatial abilities (Spence and Feng 2010). In addition, Choi et al. (2020) provide an extensive review of six cognitive skills associated with gaming experience: attention, WM, visuomotor coordination, skills with probability and uncertainty, problem solving, and second language learning. This amalgam of skills and experiences is likely to improve a person's performance when working with advanced technologies.

Industry recruiters are beginning to note gaming experience as a valuable quality to consider in potential job applicants (Petter et al. 2018). As video gaming is becoming more and more widespread, and as games and multiplayer platforms become more complex, gaming may be a useful route through which job candidates build skills that can transfer to the workplace. Petter et al. (2018) provide anecdotal evidence of how such a recruiting philosophy can yield successful results for companies. They also provide a list of hypothetical examples of how in-game experiences can be discussed in hiring interviews and considered as evidence of various social and/or cognitive skills (such as conflict resolution, resource management, planning, adaptability, and problem solving).

In support of these points, researchers who performed interventional studies have found some effects of video gaming on soft skills. For instance, Badatala et al. (2016) found that participants who were made to play a cooperative video game scored better on a subsequent Prisoner's Dilemma exercise than participants who were not asked to play the game (although those who were made to play a competitive game scored worst of all). Barr's (2017) interventional study required undergraduates to play at least 1–1.5 h of each of the eight popular commercial video games, most of which were multiplayer, and found significant improvements in measures of adaptability, resourcefulness, and communication skills compared to a control group. We thus might expect experienced video gamers to bring improved social and adaptability skills into their human-technology interactions, which we expect could improve their technology performance.

In the research literature, gaming experience is generally measured with self-report questionnaires. Many studies appear to use one-shot bespoke questionnaires. These questionnaires are often not published with the study, and no attempts to validate the questionnaires are described in the study (but see Jadallah et al. 2022 who examined the reliability of their questionnaire when administered 2 months apart to teenaged participants). We are thus unaware of any widely used, standardized, validated questionnaire for measuring the amount of gaming experience a person has. However, we have observed some commonalities. Studies often ask how many years a person has been playing video games (or how old they were when they started), how many hours they play per week, and what sorts of games they play. This last question may be free response or a selection from pre-populated options of game genres and gaming platforms.

A related concept, gaming expertise–or the actual degree of skill and success a person has in the video games he or she plays–is also often measured with self-report questionnaires. However, there is evidence that this may not be reliable (Elliott et al. 2020). Objective measures can be used when scoring gaming expertise (e.g., Yao et al. 2020). These can include published leaderboards for online games, or they may include in-game scores, levels, or points-based measures of success in the game.

As expected, gaming experience has been linked to proficiency in advanced technology domains such as working with robots and multi-robot interaction. Lin et al. (2015) report that gaming expertise improved performance in a simulation of multi-UAV command and control. Chen and Barnes (2012a,b) found a similar relationship in their study of multi-robot control, with frequent gamers demonstrating improved task performance and improved situational awareness. McKinley et al. (2011) even found that video gamers could match or outperform experienced pilots on some UAV-related tasks. Leeper et al. (2012) found that video gamers, especially those with experience in 3D games, outperformed nongamers in a robot teleoperation task (robotically grasped more objects in the allotted time). Participants with video gaming experience also performed simulated fixed-wing craft flight tasks more quickly than nongamers, and they scored more highly on a test of spatial orientation bearings (Lu et al. 2022). Similarly, video gaming experience was associated with faster robot teleoperation skills in a remote-driving scenario, with more experienced gamers also reporting more enjoyment and less workload during the task (Takayama et al. 2011). Gaming experience has also been associated with improved performance on robot-assisted surgical tasks (Hvolbek et al. 2019).

11. Measuring the KSBs Relevant to Technological Fluency

Different KSBs contributing to TF will require specific measurement approaches, as listed in their respective sections. Within the broad categories of KSB that contribute to TF, however, specific measurement approaches are likely to yield better results. Any of these KSBs can be assessed for research using self-report measures, with varying degrees of accuracy, but once they are operationally deployed, self-report measures are likely to lose some correspondence to actual performance (Schmit and Ryan 1993).

For Category 1 KSBs, which focuses on dispositional and motivational attributes, the standard measures of personality use self-report instruments. Some use a Likert scale response (like the NEO; Costa and McCrae 2008), whereas others use a forced-choice paradigm (like the Tailored Adaptive Personality Assessment System [TAPAS]; Stark et al. 2014). Likert scales are easier to interpret, whereas forced-choice scales are more resistant to faking based on social desirability or job fit.

For Category 2 KSBs, which focuses on cognitive performance, measures should use performance-based outcomes requiring specific cognitive skills. For instance, measures of WM generally use complex span tasks, in which people are asked to maintain specific kinds of information in memory while performing unrelated tasks (Conway et al. 2005). Although these measures are not necessarily process-pure, in the sense that they may require cognitive skills that are not considered part of the competency (for instance, math ability in an operation span task), using multiple tests in different modalities may produce a more robust measure of performance.

For Category 3 KSBs, which focuses on social and teaming skills, the best measures will likely be situational judgment tests or small-scale role-playing activities. Although candidates may report a certain level of teamwork skill, unless they can demonstrate it, that skill remains largely theoretical.

For Category 4 KSBs, which focuses on adaptation and adaptability, performance and role-playing exercises that require those skills are most likely to elicit the desired kinds of behaviors for testing. Some kinds of adaptation may be amenable to assessment using self-report measures, but small-scale adaptive behaviors would need to be observed in a performance context.

For Category 5 KSBs, which relate to AI and technical skills, disentangling the assessment of those skills from TF itself will be the hardest challenge. For some information, such as AI knowledge, a simple knowledge assessment or prediction task probing AI outcomes would probably yield useful information, whereas for other KSBs, situational judgment, role playing, or performance would be more important.

Measuring KSBs in the context of TF may involve tailoring scenarios or other performance measures, including content or tasks relevant to TF performance, such as including synthetic teammates in teamwork measures or using domain-relevant knowledge as part of cognitive tests. Knowledge-based KSBs may be more malleable than other KSBs; it is easier to learn specific knowledge than it is to learn to lead. Therefore, certain KSBs may indicate an aptitude for TF, whereas others may reflect developed TF. A measurement model that relates these KSBs could help build assessments of TF and the KSBs that contribute to its development.

12. Conclusions

In this report, we introduced our definition of TF: the ability for individuals and teams to rapidly use and adapt to new technology without the need for formal training. We discussed the broad landscape of definitions and terms for similar concepts in the literature, and then we covered methods for measuring TF and its related concepts. Of great interest to our group is exploring which KSBs may be predictive of TF, especially in the context of operating with AI or other advanced technologies. We discussed 37 different KSBs, which were divided into five categories, and we covered what each KSB is, how it is measured, and why we believe it may be predictive of TF. A tremendous amount of work remains to be done in the study of these KSBs and in the realm of TF. Future work is needed to develop more refined models, improve measurement methods, and test KSBs against a greater variety of technological performance domains. Understanding these relationships will be critical for recruitment, team composition, and training efforts for ensuring a technologically fluent workforce of the future.

Furthermore, “technology” is a broad category, and different technologies may require different competencies. Thus, it may be a valuable exercise to develop a technology taxonomy wherein technologies are categorized based upon the characteristics required of the user. To undertake this task, descriptors that define the interaction between the technology and the user must be identified and defined. Developing a uniformed language to describe these interactions is necessary to clarify the relationship between specific KSBs and TF across the range of technologies. Characterizing the technologies that a specific assessment or KSB applies to may be a task that is as difficult as generating the list of KSBs or assessments in the first place. For example, specific aspects of a technology may require different sorts of problem solving or attention abilities, and specific behaviors of a technological system may require different social skills and personality attributes.

Nonetheless, in domains where technologies or task needs are unpredictable or change rapidly, it may be prudent to select personnel based on KSBs that are found to be the most broadly predictive across different forms of technological performance. Many KSBs discussed in this document have been associated with technological performance across multiple technologies or technology domains, such as spatial ability, video gaming experience, and general adaptability. These and other KSBs may be prime candidates to consider when selecting personnel for rapidly changing or highly unpredictable technological environments (Pollard et al. 2022).

In addition to the development of a taxonomy of technology, there is a need to develop a model of how the individual characteristics defined by the KSBs influence TF performance. A good model developed from a solid theoretical base or empirical evidence will provide the necessary framework for further empirical testing of TF. Although it is often impractical to explore the relationships of all KSBs with TF performance, a model will allow researchers to undertake smaller, more practical studies that explore individual paths or elements of the model, allowing the community to generate a body of evidence. As Lewin (1935) said, "there is nothing so practical as a good theory."

On a more fundamental level, there remains a need for better measurement in many cases. Some KSBs have no standard or validated measures, and neither do many types of technology performance. Examples include video gaming experience, some cognitive biases, and some social skills. Further development of assessments and scales to measure these individual differences is needed, along with efforts to validate the scales. For some measures, such as biographical data scales measuring gaming experience, it may be necessary to carefully construct a measure that is narrowly scoped to the measure of TF performance. However, perhaps a more fundamental challenge is that many of the KSBs are difficult to truly define. Different definitions and terminologies are used across disciplines and research groups, which makes it hard to compare across studies. This is also a challenge with overlapping definitions that encompass aspects of multiple KSBs.

Much experimental work remains to be done. Few KSBs have been compared against performance in the use of truly advanced technologies; although, admittedly, what counts as "advanced" changes with time. In addition to many studies comparing KSBs against performance with basic computer and Internet technologies, we did find studies that examined performance with more advanced technologies such as BCIs, multi-robot command and control systems, and computer programming tasks.

Although we expect that performance with virtually any digital technology (especially ones that were relatively cutting edge for their time) can be an informative proxy for TF, we acknowledge that we are on the cusp of another technological revolution. We also acknowledge that the ability to perform with future AI may require substantially different skill sets than those that were required by earlier Internet, home computer, or early robotics technologies. Empirical studies are needed to determine the extent to which the required KSBs are truly new or whether the KSBs that have always been associated with technological prowess will continue to be associated with TF in the future. In addition, few studies have examined KSBs in the context of multiple types of advanced technologies. This is the information that we need to determine the generalizability of any KSB's predictive power. Gathering these data will be a major thrust in our own future research.

13. References

Adadi A, Berrada M. Peeking inside the black-box: a survey on explainable artificial intelligence (XAI). IEEE Access. 2018;6:52138−52160.

Adomßent M, Hoffman T. The concept of competencies in the context of education for sustainable development (ESD). Engagement Global; 2013 [accessed 2016 Sep 22] http://esd-expert.net/assets/130314-ConceptPaper-ESD-Competencies.pdf.

Aesaert K, Van Braak J. Exploring factors related to primary school pupils' ICT self-efficacy: a multilevel approach. Computers in Human Behavior. 2014;41:327–341. https://doi.org/10.1016/j.chb.2014.10.006.

Ala-Mutka K. Mapping digital competence: towards a conceptual understanding. European Commission; 2011. Issue No.: 2011 Jan. https://doi.org/10.13140/RG.2.2.18046.00322

Alanoglu M, Aslan S, Karabatak S. Do teachers' educational philosophies affect their digital literacy? The mediating effect of resistance to change. Education and Information Technologies. 2022;27(3):3447–3466. https://doi.org/10.1007/s10639-021-10753-3.

Alba D. It's your fault Microsoft's teen AI turned into such a jerk. Wired. 2016. https://www.wired.com/2016/03/fault-microsofts-teen-ai-turned-jerk/.

Alloway TP. Automated working memory assessment [dataset]. Pearson Assessment; 2007.

Alloway TP, Banner GE, Smith P. Working memory and cognitive styles in adolescents' attainment. British Journal of Educational Psychology. 2010;80(4):567–581. https://doi.org/10.1348/000709910X494566.

Amabile TM. Creativity in context. Westview Press; 1996.

American Library Association. Digital literacy, libraries, and public policy: report of the Office for Information Technology Policy's Digital Literacy Task Force. American Library Association; 2013 [accessed 2023 Dec 6] https://alair.ala.org/handle/11213/16261?show=full.

Ananiadou K, Claro M. 21st century skills and competences for new millennium learners in OECD countries. OECD Publishing (NJ1); 2009. OECD Education Working Papers No.: 41. https://eric.ed.gov/?id=ED529649.

Anazifa RD, Djukri D. Project-based learning and problem-based learning: are they effective to improve student's thinking skills? Jurnal Pendidikan IPA Indonesia. 2017:6(2):346–355.

Anderson JR. Acquisition of cognitive skill. Psychological Review. 1982;89(4):369−406.

Ang S, Van Dyne L, Koh C, Ng KY, Templer KJ, Tay C, Chandrasekar NA. Cultural intelligence: its measurement and effects on cultural judgment and decision making, cultural adaptation and task performance. Management and Organization Review. 2007;3(3):335−371.

Anthonysamy L, Koo AC, Hew SH. Self-regulated learning strategies in higher education: fostering digital literacy for sustainable lifelong learning. Education and Information Technologies. 2020;25(4):2393–2414. https://doi.org/10.1007/s10639-020-10201-8.

Apperly IA. What is "theory of mind"? Concepts, cognitive processes and individual differences. Quarterly Journal of Experimental Psychology. 2012;65(5):825–839. https://doi.org/10.1080/17470218.2012.676055.

Aronen ET, Vuontela V, Steenari M-R, Salmi J, Carlson S. Working memory, psychiatric symptoms, and academic performance at school. Neurobiology of Learning and Memory. 2005;83(1):33–42. https://doi.org/10.1016/j.nlm.2004.06.010.

Australian Curriculum, Assessment, and Reporting Authority. NAP - ICT literacy years 6 and 10: assessment framework 2020. National Assessment Program, ACARA; 2020. https://www.nap.edu.au/nap-sample-assessments/assessment-frameworks.

Azevedo R, Cromley JG, Seibert D. Does adaptive scaffolding facilitate students' ability to regulate their learning with hypermedia? Contemporary Educational Psychology. 2004;29(3):344–370. https://doi.org/10.1016/j.cedpsych.2003.09.002.

Azzopardi L. Cognitive biases in search: a review and reflection of cognitive biases in information retrieval. Proceedings of the 2021 Conference on Human Information Interaction and Retrieval; 2021. p. 27–37. https://doi.org/10.1145/3406522.3446023.

Badatala A, Leddo J, Islam A, Patel K, Surapaneni P. The effects of playing cooperative and competitive video games on teamwork and team performance. International Journal of Humanities and Social Science Research. 2016;2(12):24–28.

Baddeley AD. A 3 min reasoning test based on grammatical transformation. Psychonomic Science. 1968;10:341–342.

Baddeley AD. Working memory. Clarendon Press/Oxford University Press; 1986.

Baddeley AD, Hitch G. Working memory. Psychology of Learning and Motivation. 1974;8:47–89. https://doi.org/10.1016/S0079-7421(08)60452-1.

Baker EL, O'Neil HF. Measuring problem solving in computer environments: current and future states. Computers in Human Behavior. 2002;18(6):609–622. https://doi.org/10.1016/s0747-5632(02)00019-5.

Bala H, Massey A, Seol S. Social media in the workplace: influence on employee agility and innovative behavior. Proceedings of the 52nd Hawaii International Conference on System Science; 2019.

Balfe N, Sharples S, Wilson JR. Understanding is key: an analysis of factors pertaining to trust in a real-world automation system. Human Factors. 2018;60(4):477–495. https://doi.org/10.1177/0018720818761256.

Ballantine J, Larres PM, Oyelere P Computer usage and the validity of self-assessed computer competence among first-year business students. Computers & Education. 2007;49(4):976–990. https://doi.org/10.1016/j.compedu.2005.12.001.

Bamicha V, Drigas A. The evolutionary course of theory of mind – factors that facilitate or inhibit its operation & the role of ICTs. Technium Social Sciences Journal. 2022;30:138–158. https://doi.org/10.47577/tssj.v30i1.6220.

Bandura A. Fearful expectations and avoidant actions as coeffects of perceived self-inefficacy. American Psychologist. 1986;41(12):1389–1391. https://doi.org/10.1037/0003-066x.41.12.1389.

Bandura A. Perceived self-efficacy in cognitive development and functioning. Educational Psychologist. 1993;28(2):117–148.

Banks J. Of like mind: the (mostly) similar mentalizing of robots and humans. Technology, Mind, and Behavior. 2021;1(2). https://doi.org/10.1037/tmb0000025.

Barak M. Are digital natives open to change? Examining flexible thinking and resistance to change. Computers & Education. 2018;121:115–123. https://doi.org/10.1016/j.compedu.2018.01.016.

Barak M, Levenberg A. Flexible thinking in learning: an individual differences measure for learning in technology-enhanced environments. Computers & Education. 2016;99:39–52. https://doi.org/10.1016/j.compedu.2016.04.003.

Baron-Cohen S. Theory of mind in normal development and autism. Prisme. 2001;34:174–183.

Baron-Cohen S, Leslie AM, Frith U. Does the autistic child have a "theory of mind"? Cognition. 1985;21(1):37–46. https://doi.org/10.1016/0010-0277(85)90022-8.

Baron-Cohen S, Wheelwright S. The empathy quotient: an investigation of adults with Asperger syndrome or high functioning autism, and normal sex differences. Journal of Autism and Developmental Disorders. 2004;34(2):163–175. doi.org/10.1023/B:JADD.0000022607.19833.00.

Barr M. Video games can develop graduate skills in higher education students: a randomised trial. Computers & Education. 2017;113:86–97. https://doi.org/10.1016/j.compedu.2017.05.016.

Barrett B. An artist used 99 phones to fake a Google Maps traffic jam. Wired. 2020 Feb 3. https://www.wired.com/story/99-phones-fake-google-maps-traffic-jam/.

Bateman TS, Crant JM. The proactive component of organizational behavior: a measure and correlates. Journal of Organizational Behavior. 1993;14(2):103–118.

Bawack RE, Wamba SF, Carillo KDA. Exploring the role of personality, trust, and privacy in customer experience performance during voice shopping: evidence from SEM and fuzzy set qualitative comparative analysis. International Journal of Information Management. 2021;58:102309.

Bawden D. Origins and concepts of digital literacy. In: Lankshear C, Knobe M, editors. Digital literacies: concepts, policies and practices. Peter Lang; 2008. p. 17e32.

Beaudoin MF, Kurtz G, Eden S. Experiences and opinions of e-learners: what works, what are the challenges, and what competencies ensure successful online learning. Interdisciplinary Journal of E-Learning and Learning Objects. 2009;5:275−289.

Benilian A. IT feature use over time and its impact on individual task performance. Journal of the Association for Information Systems. 2015;16(3):144−173.

Behrenbruch K, Söllner M, Leimeister JM, Schmidt L. Understanding diversity–the impact of personality on technology acceptance. Human-Computer Interaction–INTERACT 2013: 14th IFIP TC 13 International Conference. 2013 Sep 2−6; Cape Town, South Africa. Proceedings, Part IV 14; c2013. Springer Berlin Heidelberg. p. 306−313.

Beaudry A, Pinsonneault A. Understanding user responses to information technology: a coping model of user adaptation. Management Information Systems Quarterly. 2005;29(3):493. https://doi.org/10.2307/25148693.

Berenbaum H, Bredemeier K, Thompson RJ. Intolerance of uncertainty: exploring its dimensionality and associations with need for cognitive closure, psychopathology, and personality. Journal of Anxiety Disorders. 2008;22(1)117−125.

Bernstein DL. Developing technological fluency through creative robotics [dissertation]. University of Pittsburgh; 2010.

Berthet V. The measurement of individual differences in cognitive biases: a review and improvement. Frontiers in Psychology. 2021;12:630177. https://doi.org/10.3389/fpsyg.2021.630177.

Bhat MA. The predictive power of reasoning ability on academic achievement. International Journal of Learning, Teaching and Educational Research. 2016;15(1).

Bhattacherjee A, Harris M. Individual adaptation of information technology. Journal of Computer Information Systems. 2009;50(1):37–45.

Blau I, Shamir-Inbal T. Digital competences and long-term ICT integration in school culture: the perspective of elementary school leaders. Education and Information Technologies. 2016;22(3):769–787. https://doi.org/10.1007/s10639-015-9456-7.

Bless JJ, Westerhausen R, Kompus K, Gudmundsen M, Hugdahl K. Self-supervised, mobile-application based cognitive training of auditory attention: a behavioral and fMRI evaluation. Internet Interventions. 2014;1(3):102–110. https://doi.org/10.1016/j.invent.2014.06.001.

Blum RH, Raemer DB, Carroll JS, Dufresne RL, Cooper JB. A method for measuring the effectiveness of simulation-based team training for improving communication skills. Anesthesia & Analgesia. 2005;100(5):1375–1380.

Borum R. The science of interpersonal trust. Mental Health Law and Policy Faculty Publications; 2010. 574. http://scholarcommons.usf.edu/mhlp_facpub/574.

Brand-Gruwel S, Wopereis I, Walraven A. A descriptive model of information problem solving while using internet. Computers & Education. 2009;53(4):1207–1217. https://doi.org/10.1016/j.compedu.2009.06.004.

Brandtzaeg PB, Følstad A. Why people use chatbots. Proceedings of the 2017 Conference on Human Factors in Computing Systems; 2017. p. 3506–3517. ACM.

Braun TJ, Hayes BC, DeMuth RLF, Taran OA. The development, validation, and practical application of an employee agility and resilience measure to facilitate organizational change. Industrial and Organizational Psychology. 2017;10(4):703–723.

Brennan K, Resnick M. New frameworks for studying and assessing the development of computational thinking. Proceedings of the 2012 Annual Meeting of the American Educational Research Association; 2012; Vancouver, Canada. Vol. 1, p. 25.

Brüne M, Brüne-Cohrs U. Theory of mind—evolution, ontogeny, brain mechanisms and psychopathology. Neuroscience & Biobehavioral Reviews. 2006;30(4), 437–455. https://doi.org/10.1016/j.neubiorev.2005.08.001.

Budner S. Intolerance of ambiguity as a personality variable. Journal of Personality. 1962;30(1):29–50. https://doi.org/10.1111/j.1467-6494.1962.tb02303.x.

Buhr K, Dugas MJ. The intolerance of uncertainty scale: psychometric properties of the English version. Behaviour Research and Therapy. 2002;40(8):931–945.

Bunz U. The computer-email-web (CEW) fluency scale-development and validation. International Journal of Human-Computer Interaction. 2004;17(4):479–506. https://doi.org/10.1207/s15327590ijhc1704_3.

Bunz U, Curry C, Voon W. Perceived versus actual computer-email-web fluency. Computers in Human Behavior. 2007;23(5):2321–2344. https://doi.org/10.1016/j.chb.2006.03.008.

Buolamwini J, Gebru T. Gender shades: intersectional accuracy disparities in commercial gender classification. Conference on Fairness, Accountability and Transparency; 2018 Jan. Proceedings of Machine Learning Research; p. 77–91. http://proceedings.mlr.press/v81/buolamwini18a.html.

Burin DI, Irrazabal N, Ricle II, Saux G, Barreyro JP. Self-reported internet skills, previous knowledge and working memory in text comprehension in E-learning. International Journal of Educational Technology in Higher Education. 2018;15(1):18. https://doi.org/10.1186/s41239-018-0099-9.

Burke C, Sims DE, Lazzara EH, Salas E. Trust in leadership: a multi-level review and integration. Leadership Quarterly. 2007;18:606–632. doi:10.1016/j.leaqua.2007.09.006.

Cadamuro A, Bisagno E, Pecini C, Vezzali L. Reflecting a… “bit”. What relationship between metacognition and ICT? Journal of E-Learning and Knowledge Society. 2019;15(3):183–195.

Calvani A, Cartelli A, Fini A, Ranieri M. Models and instruments for assessing digital competence at school. Journal of E-learning and Knowledge Society. 2008;4(3):183–193. https://doi.org/10.20368/1971-8829/288.

Calvani A, Fini A, Ranieri M. Assessing digital competence in secondary education: issues, models and instruments. In: Leaning M, editor. Information and media literacy: education, practice and pedagogy. Informing Science; 2009. p. 153e172.

Campbell DT, Fiske DW. Convergent and discriminant validation by the multitrait-multimethod matrix. Psychological Bulletin. 1959;56(2):81–105. https://doi.org/10.1037/h0046016.

Canfield CI, Fischhoff B, Davis A. Better beware: comparing metacognition for phishing and legitimate emails. Metacognition and Learning. 2019;14(3): 343–362. https://doi.org/10.1007/s11409-019-09197-5.

Carey G, Malbon E, Carey N, Joyce A, Crammond B, Carey A. Systems science and systems thinking for public health: a systematic review of the field. BMJ Open. 2015;5(12):e009002. https://doi.org/10.1136/bmjopen-2015-009002.

Carlton M, Levy Y. Cybersecurity skills: foundational theory and the cornerstone of advanced persistent threats (APTs) mitigation. Online Journal of Applied Knowledge Management. 2017;5(2):16–28.

Carlton M, Levy Y, Ramim MM, Terrell SR. Development of the MyCyberSkills iPad app: a scenarios-based, hands-on measure of non-IT professionals’ cybersecurity skills. Proceedings of the Pre-International Conference of Information Systems (ICIS) SIGSEC - Workshop on Information Security and Privacy (WISP); 2015; Ft. Worth, TX.

Cassenti D, Kelley T. Swoboda J, Patton D. The effects of communication style on robot navigation performance. Proceedings of the Human Factors and Ergonomics Society Annual Meeting. 2009: p. 359–363.

Cazan A-M, Schiopca B-A. Self-directed learning, personality traits and academic achievement. Procedia - Social and Behavioral Sciences. 2014;127:640–644. https://doi.org/10.1016/j.sbspro.2014.03.327.

Celik I. Towards intelligent-TPACK: an empirical study on teachers' professional knowledge to ethically integrate artificial intelligence (AI)-based tools into education. Computers in Human Behavior. 2023;138:107468. https://doi.org/10.1016/j.chb.2022.107468.

Chai CS, Lin PY, Jong MSY, Dai Y, Chiu TK, Qin J. Perceptions of and behavioral intentions towards learning artificial intelligence in primary school students. Educational Technology & Society. 2021;24(3):89–101.

Chappelle W, McMillan K, Novy P, McDonald K. Psychological profile of USAF unmanned aerial systems predator & reaper pilots. Proceedings of the Aerospace Medical Association's Annual Scientific Meeting; 2010a. p. 339.

Chappelle W, Novy P, Randall B, McDonald K. Critical psychological attributes of U.S. Air Force (USAF) predator & reaper sensor operators according to subject matter experts. Proceedings of the Aerospace Medical Association's Annual Scientific Meeting; 2010b. p. 253.

Chattopadhyay S, Nelson N, Au A, Morales N, Sanchez C, Pandita R, Sarma A. A tale from the trenches: cognitive biases and software development. Proceedings of the ACM/IEEE 42nd International Conference on Software Engineering. 2020;654–665. https://doi.org/10.1145/3377811.3380330.

Chen JYC. UAV-guided navigation for ground robot teleoperation in a military reconnaissance environment. Ergonomics. 2010;53:940–950.

Chen JYC, Barnes MJ. Supervisory control of multiple robots: effects of imperfect automation and individual differences. Human Factors: The Journal of the Human Factors and Ergonomics Society. 2012a;54(2):157–174. https://doi.org/10.1177/0018720811435843.

Chen JYC, Barnes MJ. Supervisory control of multiple robots in dynamic tasking environments. Ergonomics. 2012b;55(9):1043–1058. https://doi.org/10.1080/00140139.2012.689013.

Chen JYC, Barnes MJ. Human–agent teaming for multirobot control: a review of human factors issues. IEEE Transactions on Human-Machine Systems. 2014;44(1):13–29. https://doi.org/10.1109/THMS.2013.2293535.

Chen JYC, Terrence P. Effects of imperfect automation on concurrent performance of military and robotics tasks in a simulated multitasking environment. Ergonomics. 2009;52:907–920.

Chen L, Zhu Z. Probabilistic neural networks: foundations and applications. IEEE Transactions on Neural Networks and Learning Systems. 2020;31(8):2827–2841.

Chetty K, Liu Q, Gcora N, Josie J, Li W, Chen F. Bridging the digital divide: measuring digital literacy. Economics: The Open-Access, Open-Assessment e-Journal. 2018;12(1). https://doi.org/10.5018/economics-ejournal.ja.2018-23.

Chi NTK, Hoang Vu N. Investigating the customer trust in artificial intelligence: the role of anthropomorphism, empathy response, and interaction. CAAI Transactions on Intelligence Technology. https://ietresearch.onlinelibrary.wiley.com/doi/full/10.1049/cit2.12133.

Choi E, Shin S-H, Ryu J-K, Jung K-I, Kim S-Y, Park M-H. Commercial video games and cognitive functions: video game genres and modulating factors of cognitive enhancement. Behavioral and Brain Functions. 2020;16(1):2. https://doi.org/10.1186/s12993-020-0165-z.

Choi JA, Koo M, Choi I, Auh S. Need for cognitive closure and information search strategy. Psychology & Marketing. 2008;25(11):1027–1042.

Chou P-N. Effect of students' self-directed learning abilities on online learning outcomes: two exploratory experiments in electronic engineering. International Journal of Humanities and Social Science. 2012;2(6):172–179.

Chou YC, Chiu C. The development and validation of a digital fluency scale for preadolescents. Asia-Pacific Education Researcher. 2020;29(6):541–551. https://doi.org/10.1007/s40299-020-00505-1.

Cihak D, Wright R, Smith C, McMahon D, Kraiss K. Incorporating functional digital literacy skills as part of the curriculum for high school students with intellectual disability. Education and Training in Autism and Developmental Disabilities. 2015;50(2):155–171. http://www.jstor.com/stable/24827532.

Città G, Gentile M, Allegra M, Arrigo M, Conti D, Ottaviano S, Reale F, Sciortino M. The effects of mental rotation on computational thinking. Computers & Education. 2019;141:103613. https://doi.org/10.1016/j.compedu.2019.103613.

Claes R, Beheydt C, Lemmens B. Unidimensionality of abbreviated proactive personality scales across cultures. Applied Psychology. 2005;54(4):476–489.

Clifford I, Kluzer S, Troia S, Jakobsone M, Zandbergs U. DigCompSat. European Union; 2020. https://publications.jrc.ec.europa.eu/repository/handle/JRC123226.

Çoban E, Korkmaz Ö. An alternative approach for measuring computational thinking: performance-based platform. Thinking Skills and Creativity. 2021;42:100929. https://doi.org/10.1016/j.tsc.2021.100929.

Colquitt J, Scott B, LePine J. Trust, trustworthiness, and trust propensity: a meta-analytic test of their unique relationships with risk taking and job performance. The Journal of Applied Psychology. 2007;92:909–27. doi.org/10.1037/0021-9010.92.4.909.

Conway ARA, Kane MJ, Bunting MF, Hambrick DZ, Wilhelm O, Engle RW. Working memory span tasks: a methodological review and user's guide. Psychonomic Bulletin & Review. 2005;12(5):769–786. https://doi.org/10.3758/BF03196772.

Cornell University. What is digital literacy? Cornell University; 2009. http://digitalliteracy.cornell.edu/welcome/dpl0000.html.

Costa AC, Anderson N. Measuring trust in teams: development and validation of a multifaceted measure of formative and reflective indicators of team trust. European Journal of Work and Organizational Psychology. 2011;20(1):119–154. doi:10.1080/13594320903272083.

Costa PT, McCrae RR. The SAGE handbook of personality theory and assessment. SAGE; 2008. Chapter 2, The revised neo personality inventory (NEO-PI-R). p. 179–198.

Cramer RJ, Neal T, Brodsky SL. Self-efficacy and confidence: theoretical distinctions and implications for trial consultation. Consulting Psychology Journal: Practice and Research. 2009;61(4):319.

Curry S, Wagner E, Grothaus L. Intrinsic and extrinsic motivation for smoking cessation. Journal of Consulting and Clinical Psychology. 1990;58(3):310–316.

Daly M, Egan M, O'Reilly F. Childhood general cognitive ability predicts leadership role occupancy across life: evidence from 17,000 cohort study participants. Leadership Quarterly. 2015;26(3):323–341. https://doi.org/10.1016/j.leaqua.2015.03.006.

Daneman M, Merikle PM. Working memory and language comprehension: a meta-analysis. Psychonomic Bulletin & Review. 1996;3(4):422–433. https://doi.org/10.3758/BF03214546.

Darling-Hammond L, Adamson F. (2010). Beyond basic skills: the role of performance assessment in achieving 21st century standards of learning. Stanford, CA: Stanford University, Stanford Center for Opportunity Policy in Education. https://globaled.gse.harvard.edu/sites/projects.iq.harvard.edu/files/geii/files/beyond-basic-skills-role-performance-assessment-achieving-21st-century-standards-learning-report_0.pdf.

Davis MC, Challenger R, Jayewardene DNW, Clegg CW. Advancing socio-technical systems thinking: a call for bravery. Applied Ergonomics. 2014;45(2):171–180. https://doi.org/10.1016/j.apergo.2013.02.009.

Davis MH. Measuring individual differences in empathy: evidence for a multidimensional approach. Journal of Personality and Social Psychology. 1983;44(1):113–126.

Demir O, Aslan SA, Demir M. Examining the relationship between teachers' lifelong learning tendencies and digital literacy levels. Journal of Educational Technology and Online Learning. 2022;5(2):379–392. https://doi.org/10.31681/jetol.1034697.

den Hartog DN, Van Muijen JJ, Koopman PL. Transactional versus transformational leadership: an analysis of the MLQ. Journal of Occupational and Organizational Psychology. 1997;70(1):19–34.

Denton E, Hutchinson B, Mitchell M, Gebru T, Zaldivar A. Image counterfactual sensitivity analysis for detecting unintended bias. arXiv:1906.06439. 2019. https://doi.org/10.48550/arXiv.1906.06439.

Desai M, Kaniarasu P, Medvedev M, Steinfeld A, Yanco H. Impact of robot failures and feedback on real-time trust. ACM/IEEE International Conference on Human-Robot Interaction; 2013. p. 251–258.

DeStefano D, LeFevre J-A. Cognitive load in hypertext reading: a review. Computers in Human Behavior. 2007;23(3):1616–1641. https://doi.org/10.1016/j.chb.2005.08.012.

Detlor B, Julien H, La Rose T, Serenko A. Community-led digital literacy training: toward a conceptual framework. Journal of the Association for Information Science and Technology. 2022;73(10):1387–1400. https://doi.org/10.1002/asi.24639.

Deutsch S. Bayesian brain: probabilistic approaches to neural coding. In: Doya K, Ishii S, Pouget A, Rao RPN, editors. IEEE Pulse. 2010;1(3):64–65.

de Vries RE, Wawoe KW, Holtrop D. What is engagement? Proactivity as the missing link in the HEXACO model of personality. Journal of Personality. 2016;842:178–193.

De Winter JDF, Dodou D. Predicting academic performance in engineering using high school exam scores. International Journal of Engineering Education. 2011;7(6):1343–1351.

Dhir S, Dhir S, Samanta P. Defining and developing a scale to measure strategic thinking. Foresight. 2018;20(3):271–288.

DiCerbo KE, Behrens JT. Impacts of the digital ocean on education. Pearson; 2014 [accessed 2015 Sep 1] https://research.pearson.com/content/plc/prkc /uk/open-ideas/en/articles/a-tidal-wave-of-data/_jcr_content/par /articledownloadcompo/file.res/3897.digital_ocean_web.pdf.

Dion KL. Group cohesion: from “field of forces” to multidimensional construct. Group dynamics: theory, research, and practice. 2000:4(1):7–26.

Dissing L, Bolander T. Implementing theory of mind on a robot using dynamic epistemic logic. Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence. 2020;1615–1621. https://doi.org/10.24963/ijcai.2020/224.

Dohn NB, Kafai Y, Mørch A, Ragni, M. Survey: artificial intelligence, computational thinking and learning. Künstliche Intelligenz. 2022;36:5–16. https://doi-org.spot.lib.auburn.edu/10.1007/s13218-021-00751-5.

Dolansky MA, Moore SM, Palmieri PA, Singh MK. Development and validation of the systems thinking scale. Journal of General Internal Medicine. 2020;35(8):2314–2320. https://doi.org/10.1007/s11606-020-05830-1.

Downey JP, Smith LA. The role of computer attitudes in enhancing computer competence in training. Journal of Organizational and End User Computing. 2011;23(3):81–100.

DQ Institute. (n.d.). [DQ (Digital Intelligence) 24 Framework of the 8 Critical Areas of Digital Life and Their Digital Competencies]. [Info-graphic]. DQInstitute. https://www.dqinstitute.org/global-standards/#contentblock1. ©2023 DQ Institute. All Rights Reserved.

DQ Institute. (n.d.). [The DQ Index’s Thematic Pillars & Questions that are Being Measured]. [Info-graphic]. DQInstitute.

https://www.dqinstitute.org/collaborative-rd/. ©2023 DQ Institute. All Rights Reserved.

Drigas A, Papoutsi C. ICTs for assessment and intervention on cultivation of empathy. International Journal of Emerging Technologies in Learning (iJET). 2015;10(5):10. https://doi.org/10.3991/ijet.v10i5.4731.

Du M. Strategic thinking in artificial intelligence and expert: problem solving and creativity. PsyArXiv. 2023 July 11.

Dugan KE, Mosyjowski EA, Daly SR, Lattuca LR. Systems thinking assessments in engineering: a systematic literature review. Systems Research and Behavioral Science. 2022;39(4):840–866. https://doi.org/10.1002/sres.2808.

Durand M, Yen R, O'Malley J, Elwyn G, Mancini J. Graph literacy matters: Examining the association between graph literacy, health literacy, and numeracy in a Medicaid eligible population. PLOS ONE. 2020;15(11):e0241844. https://doi.org/10.1371/journal.pone.0241844.

Dutton WH, Shepherd A. Trust in the Internet as an experience technology. Information, Communication & Society. 2006;9(4):433–451.

Dwivedi YK, Hughes L, Ismagilova E, Aarts G, Coombs C, Crick T, Duan Y, Dwivedi R, Edwards J, Eirug A, et al. Artificial intelligence (AI): multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International Journal of Information Management. 2021;57:101994.

Dye MWG, Green CS, Bavelier D. The development of attention skills in action video game players. Neuropsychologia. 2009;47(8–9):1780–1789. https://doi.org/10.1016/j.neuropsychologia. 2009.02.002.

Edwards A, Edwards C. Does the correspondence bias apply to social robots?: Dispositional and situational attributions of human versus robot behavior. Frontiers in Robotics and AI. 2022;8:788242. https://doi.org/10.3389/frobt.2021.788242.

Elliott LJ, Hampton T, McCoy J, Kriebs K, Rowlison M, Waite A, Blackwell A. Quantifying video gaming expertise. In: Nazir S, Ahram T, Karwowski W, editors. Advances in Human Factors in Training, Education, and Learning Sciences; 2020. vol. 1211. p. 198–203. Springer International Publishing. https://doi.org/10.1007/978-3-030-50896-8_30.

Epley N, Keysar B, Van Boven L, Gilovich T. Perspective taking as egocentric anchoring and adjustment. Journal of Personality and Social Psychology. 2004;87(3):327–339. https://doi.org/10.1037/0022-3514.87.3.327.

Eschenbrenner B, Nah FF-H. Information systems user competency: a conceptual foundation. Communications of the Association for Information Systems. 2014;34:1363–1378.

Eshet-Alkalai Y. Digital literacy: a conceptual framework for survival skills in the digital era. Journal of Educational Multimedia and Hypermedia. 2004;13(1):93–106. https://www.openu.ac.il/personal_sites/download/digital-literacy2004-jemh.pdf.

Eshet-Alakali Y, Amichai-Hamburger Y. Experiments in digital literacy. Cyber Psychology and Behavior. 2004;7:421e429.

Eshet-Alkalai Y, Chajut E. Changes over time in digital literacy. Cyberpsychology & Behavior. 2009;12(6):713–715. https://doi.org/10.1089/cpb.2008.0264.

Eshet-Alkalai Y, Soffer O. Guest editorial--navigating in the digital era: digital literacy: socio-cultural and educational aspects. Educational Technology & Society. 2012;15(2):1–2.

Esterwood C, Robert LP. The theory of mind and human–robot trust repair. Scientific Reports. 2023;13(1):9877. https://doi.org/10.1038/s41598-023-37032-00.

European Commission. Implementation of 'Education and Training 2010' work programme. Directorate for Education and Culture; 2003. http://hdl.voced.edu.au/10707/105163.

European Commission. A new Europass: making skills and qualifications more visible across the EU. Directorate-General for Employment, Social Affairs and Inclusion; 2019a. https://data.europa.eu/doi/10.2767/494093.

European Commission. SELFIE forum - teaching and learning in the digital age. Publications Office of the European Union; 2019b; doi:10.2760/799301, JRC117482.

Evans AM, Revelle W. Survey and behavioral measurements of interpersonal trust. Journal of Research in Personality. 2008;42(6):1585–1593. doi:https://doi.org/10.1016/j.jrp.2008.07.011.

Fagerlin A, Zikmund-Fisher BJ, Ubel PA, Jankovic A, Derry HA, Smith DM. Measuring numeracy without a math test: development of the subjective numeracy scale. Medical Decision Making. 2007;27(5):672–680.

Fan L, Scheutz M, Lohani M, McCoy M, Stokes, C. Do we need emotionally intelligent artificial agents? First results of human perceptions of emotional intelligence in humans compared to robots. Intelligent Virtual Agents: 17th International Conference, IVA 2017; 2017 Aug 27–30; Stockholm, Sweden. Proceedings 17, p. 129–141. Springer International Publishing.

Fellman D, Lincke A, Berge E, Jonsson B. Predicting visuospatial and verbal working memory by individual differences in E-learning activities. Frontiers in Education. 2020;5(22). https://doi.org/10.3389/feduc.2020.00022.

Feltz DL. Gender differences in the causal elements of self-efficacy on a high avoidance motor task. Journal of Sport and Exercise Psychology. 1988;10(2):151–166.

Ferrari, A. (2013). DIGCOMP: a framework for developing and understanding digital competence in Europe. eLearning Papers. Joint Research Centre of the European Commission. http://omk-obrazovanje.gov.rs/wp-content/uploads/2015/02/A-Framework-for-Digital-Competence-in-Europe.pdf.

Fidan M, Gencel N. Supporting the instructional videos with chatbot and peer feedback mechanisms. Journal of Educational Computing Research. 2022;60(7):1716–1741.

Fincannon T, Jentsch F, Sellers B, Keebler J. Beyond "spatial ability": examining the impact of multiple individual differences in a perception by proxy framework. HRI '12: Proceedings of the Seventh Annual ACM/IEEE International Conference on Human–Robot Interaction; 2012. p. 127–128. https://doi.org/10.1145/2157689.2157718.

Fincher S, Baker B, Box I, Cutts Q, de Raadt M, Hamer J, Hamilton M, Lister R, Petre M, Robins A, et al. Programmed to succeed?: A multi-national, multi-institutional study of introductory programming courses (1–05). University of Kent; 2005.

Fitts PM. Perceptual-motor skill learning. In: Melton AW (editor). Categories of human learning. Academic Press; 1964. p. 243–292.

Flathmann C, Schelble BG, McNeese NJ. Fostering human-agent team leadership by leveraging human teaming principles. 2021 IEEE 2nd International Conference on Human-Machine Systems (ICHMS); 2021 Sep. p. 1–6. IEEE.

Flavell JH. Metacognition and cognitive monitoring: a new area of cognitive-developmental inquiry. American Psychologist. 1979;30(10):906–911.

Ford N, Miller D. Gender differences in Internet perception and use. Third ELVIRA Conference; 1996 Apr 30. London. Electronic Library and Visual Information Research. ASLIB; p. 87–202.

Frederick S. Cognitive reflection and decision making. Journal of Economic Perspectives. 2005;19(4):25–42.

Friedman B, Nissenbaum H. Excerpt from bias in computer systems. In: Ethics of Data and Analytics. Auerbach Publications; 2022. p. 20–26.

Fukuyama F. Trust: the social virtues and the creation of prosperity. The Free Press; 1995.

Furnham A. Self-estimates of intelligence: culture and gender difference in self and other estimates of both general (g) and multiple intelligences. Personality and Individual Differences. 2001;31(8):1381–1405. https://doi.org/10.1016/s0191-8869(00)00232-4.

Furnham A, Marks J. Tolerance of ambiguity: a review of the recent literature. Psychology. 2013;04(09):717–728. https://doi.org/10.4236/psych.2013.49102.

Gaillard AW. Concentration, stress and performance under stress. CRC Press; 2017. p. 75–92.

Galesic M, Garcia-Retamero R. Graph literacy. Medical Decision Making. 2010;31(3):444–457. https://doi.org/10.1177/0272989x10373805.

Garcia L, Nussbaum M, Preiss DD. Is the use of information and communication technology related to performance in working memory tasks? Evidence from seventh-grade students. Computers & Education. 2011;57(3):2068–2076. doi.org/10.1016/j.compedu.2011.05.009.

García-Pérez R, Santos-Delgado J-M, Buzón-García O. Virtual empathy as digital competence in education 3.0. International Journal of Educational Technology in Higher Education. 2016;13(1):30. https://doi.org/10.1186/s41239-016-0029-7.

Garcia-Retamero R, Cokely ET, Ghazal S, Joeris A. Measuring graph literacy without a test: a brief subjective assessment. Medical Decision Making. 2016;36(7):854–867.

Garg N, Mathews A, Agarwal A. Reducing gender bias in Indian advertisements. Proceedings of the ACM Conference on Fairness, Accountability, and Transparency; 2020. p. 188–197.

Gascoine L, Higgins S, Wall K. The assessment of metacognition in children aged 4-16 years: a systematic review. Review of Education. 2017;5(1):3–57. https://doi.org/10.1002/rev3.3077.

Gati I, Tal S. Decision-making models and career guidance. In: Athanasou JA, van Esbroeck R, editors. International handbook of career guidance. Springer Science & Business Media; 2008. p. 157–185.

Gefen D, Karahanna E, Straub DW. Trust and TAM in online shopping: an integrated model. MIS Quarterly. 2003;27(1):51–90. doi:10.2307/30036519.

Ghani U, Zhai X, Ahmad R. Mathematics skills and STEM multidisciplinary literacy: role of learning capacity. STEM Education. 2021;1(2):104–113. doi: 10.3934/steme.2021008.

Ghobakhloo M. Industry 4.0, digitization, and opportunities for sustainability. Journal of Cleaner Production. 2020;252:119869.

Gilster P. Digital literacy. Wiley Computer Publications; 1997.

Gist ME, Mitchell TR. Self-efficacy: a theoretical analysis of its determinants and malleability. Academy of Management Review. 1992;17(2):183–211.

Gockley R, Bruce A, Forlizzi J, Michalowski M, Mundell A, Rosenthal S, Sellner B, Simmons R, Snipes K, Schultz AC, et al. Designing robots for long-term social interaction. Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS); 2005. p. 1338–1343. IEEE.

Goldhammer F, Naumann J, Keßel Y. Assessing individual differences in basic computer skills. European Journal of Psychological Assessment. 2013;29(4):263–275. https://doi.org/10.1027/1015-5759/a000153.

Gómez-Veiga I, Vila Chaves JO, Duque G, García Madruga JA. A new look to a classic issue: reasoning and academic achievement at secondary school. Frontiers in Psychology. 2018;9:400.

Gosling SD, Rentfrow PJ, Swann WB Jr. A very brief measure of the Big-Five personality domains. Journal of Research in Personality. 2003;37(6):504–528.

Gravill JI, Compeau DR, Marcolin BI. Experience effects on the accuracy of self-assessed user competence. Information & Management. 2006;43(3):378–394.

Green CS, Bavelier D. Action video game modifies visual selective attention. Nature. 2003;423(6939):534–537. https://doi.org/10.1038/nature01647.

Green RM. Predictors of digital fluency. Dissertation Abstracts International Section A: Humanities and Social Sciences. 2005.

Green RM. Unpacking “I don’t want it”—Why novices and non–users don’t use the Internet. First Monday. 2006;11(9):1–13.

Greene JA, Yu SB, Copeland DZ. Measuring critical components of digital literacy and their relationships with learning. Computers & Education. 2014;76:55–69. https://doi.org/10.1016/j.compedu.2014.03.008.

Greenfield PM. The cultural evolution of IQ. In: Neisser U, editor. The rising curve: long-term gains in IQ and related measures. American Psychological Association; 1998. p. 81–125.

Griffith J. Measurement of group cohesion in US Army units. Basic and Applied Social Psychology. 1988;9(2):149–171.

Griffith J, Vaitkus M. Relating cohesion to stress, strain, disintegration, and performance: an organizing framework. Military Psychology. 1999;11(1):27–55.

Guay R. Purdue spatial visualization test—visualization of views. Purdue Research Foundation; 1977.

Hammer MR, Bennett MJ, Wiseman R. Measuring intercultural sensitivity: the intercultural development inventory. International Journal of Intercultural Relations. 2003;27(4):421–443.

Hakkarainen K, Ilomäki L, Lipponen L, Muukkonen H, Rahikainen M, Tuominen T, Lakkala M, Lehtinen E. Students’ skills and practices of using ICT: results of a national assessment in Finland. Computers & Education. 2000;34(2):103–117. https://doi.org/10.1016/s0360-1315(00)00007-5.

Halic O, Lee D, Paulus TM, Spence M. To blog or not to blog: student perceptions of blog effectiveness for learning in a college-level course. Internet and Higher Education. 2010; 13(4):206–213. https://doi.org/10.1016/j.iheduc.2010.04.001.

Happé FGE. An advanced test of theory of mind: understanding of story characters’ thoughts and feelings by able autistic, mentally handicapped, and normal children and adults. Journal of Autism and Developmental Disorders. 1994;24(2):129–154. https://doi.org/10.1007/BF02172093.

Harsh JA, Schmitt-Harsh M. Instructional strategies to develop graphing skills in the college science classroom. The American Biology Teacher. 2016;78(1):49–56.

Harvey JC. Exploring the relationships between working memory capacity, academic reading, and academic achievement in online distance e-learning first-year students. University of South Africa; 2022.

Haselton MG, Nettle D. The paranoid optimist: an integrative evolutionary model of cognitive biases. Personality and Social Psychology Review. 2006;10(1):47–66. https://doi.org/10.1207/s15327957pspr1001_3.

Hatano G, Inagaki K. Two courses of expertise. In: Stevenson H, Azuma H, Hakuta K, editors. Child development and education in Japan. W.H. Freeman and Company; 1986. p. 262−272.

Havelka D, Merhout JW. Toward a theory of information technology professional competence. The Journal of Computer Information Systems. 2009;50:2106−2116.

He G, Liu P, Zheng X, Zheng L, Hewlin PF, Yuan L. Being proactive in the age of AI: exploring the effectiveness of leaders' AI symbolization in stimulating employee job crafting. Management Decision. 2023;61(10):2896−2919.

Herrnstein RJ, Murray CA. The bell curve: intelligence and class structure in American life. Free Press; 1994.

Hertzka AF, Guilford JP. Logical reasoning. Sheridan Supply Company; 1955.

Holland JL. A theory of vocational choice. Journal of Counseling Psychology. 1959;6(1):35–45. https://doi.org/10.1037/h0040767.

Hollarek M, Lee NC. Current understanding of developmental changes in adolescent perspective taking. Current Opinion in Psychology. 2022;45:101308. https://doi.org/10.1016/j.copsyc.2022.101308.

Huang MH, Rust RT. Artificial intelligence in service. Journal of Service Research. 2018;21(2):155–172.

Huggins AC, Ritzhaupt AD, Dawson K. Measuring information and communication technology literacy using a performance assessment: validation of the student tool for technology literacy (ST2L). Computers & Education. 2014;77:1–12. https://doi.org/10.1016/j.compedu.2014.04.005.

Hung WH, Chen K, Lin CP. Does the proactive personality mitigate the adverse effect of technostress on productivity in the mobile environment? Telematics and Informatics. 2015;32(1):143–157.

Hvolbek AP, Nilsson PM, Sanguedolce F, Lund L. A prospective study of the effect of video games on robotic surgery skills using the high-fidelity virtual reality

RobotiX simulator. Advances in Medical Education and Practice. 2019;10:627–634. https://doi.org/10.2147/AMEP.S199323.

INTEF. Common digital competence framework for teachers. 2017. https://aprende.intef.es/sites/default/files/2018-05/2017_1024-Common-Digital-Competence-Framework-For-Teachers.pdf.

International ICT Literacy Panel. Digital transformation: a framework for ICT literacy. Educational Testing Service. 2002;1(2):1–53. https://www.ets.org/Media/Research/pdf/ICTREPORT.pdf.

International Society for Technology in Education. ISTE standards for students. ISTE; 2007. https://www.iste.org/ standards/standards/for-students.

Jacobs RJ, Caballero J, Parmar J, Kane N, MN. The role of self-efficacy, flexibility, and gender in pharmacy students' health information technology readiness. Currents in Pharmacy Teaching and Learning. 2019;11(11):1103–1110.

Jackson A. The cultural awareness journal: for those new to cultural awareness and those already on the journey. Authorhouse. 2011.

Jadallah M, Green CS, Zhang J. Video game play: any association with preteens' cognitive ability test performance? Journal of Media Psychology. 2022;35(4): 213–220. https://doi.org/10.1027/1864-1105/a000364.

Jalinus N, Nabawi RA, Mardin A. The seven steps of project based learning model to enhance productive competences of vocational students. International Conference on Technology and Vocational Teachers (ICTVT 2017). 2017;102:251–256. https://doi.org/10.2991/ictvt-17.2017.43; 2017 Sep 28; Yogyakarta, Indonesia.

Jaradat RM. An instrument to assess individual capacity for system thinking. Old Dominion University Libraries; 2014. https://doi.org/10.25777/WZH1-2563.

Jaradat RM. Complex system governance requires systems thinking—how to find systems thinkers. International Journal of System of Systems Engineering. 2015;6(1/2):53. https://doi.org/10.1504/IJSSE.2015.068813.

Jaradat RM, Keating CB. Systems thinking capacity: implications and challenges for complex system governance development. International Journal of System of Systems Engineering. 2016;7(1/2/3):75. https://doi.org/10.1504/IJSSE.2016.076130.

Jaramillo F, Locander WB, Spector PE, Harris EG. Getting the job done: the moderating role of initiative on the relationship between intrinsic motivation and adaptive selling. Journal of Personal Selling and Sales Management. 2007;27(1):59–74. https://doi.org/10.2753/pss0885-3134270104.

Jarrahi MH. Artificial intelligence and the future of work: human-AI symbiosis in organizational decision making. Business Horizons. 2018;61(4):577–586.

Jarvenpaa S, Knoll K, Leidner D. Is anybody out there? Antecedents of trust in global teams. Journal of Management Information Systems. 1998;14:29–64. 10.1080/07421222.1998.11518185.

Jelenc L, Swiercz PM. Strategic thinking capability: conceptualization and measurement. SSRN 2011. SSRN 2747927. http://dx.doi.org/10.2139/ssrn.2747927.

John OP, Srivastava S. The big five personality traits. In: Pervin LA, John OP, editors. Handbook of personality: theory and research. 2nd ed. Guilford Press; 1999. p. 102–138.

Johnson BM, He Z, Kanich C, Levchenko K. Identifying and characterizing VPN-probing malware: implications for accurate traffic classification. IEEE Transactions on Network and Service Management. 2018;15(3):1090–1103.

Jolliffe D, Farrington DP. Development and validation of the Basic Empathy Scale. Journal of Adolescence. 2006;29(4):589–611. https://doi.org/10.1016/j.adolescence.2005.08.010.

Jones S, Burnett G. Spatial skills and navigation of source code. ITiCSE'07. Annual Conference on Innovation and Technology in Computer Science Education; 2007 June 23; Dundee, UK.

Jones S, Burnett G. Spatial ability and learning to program. Human Technology: An Interdisciplinary Journal on Humans in ICT Environments. 2008;4(1):47–61. doi.org/10.17011/ht/urn.200804151352.

Joyce M, Kirakowski J. Measuring confidence in internet use: the development of an Internet self-efficacy scale. Lecture Notes in Computer Science; 2014. p. 250–260. https://doi.org/10.1007/978-3-319-07668-3_25.

Jung JH, Byun MS, Sohn BK, Yi D, Lee JH, Jeon SY; KBASE Research Group. Neuroticism, conscientiousness, and in vivo Alzheimer pathologies measured by amyloid PET and MRI. Psychiatry and Clinical Neurosciences. 2020;74(5):303–310.

Jungjohann J, Gebhardt M, Scheer D. Understanding and improving teachers' graph literacy for data-based decision-making via video intervention. Frontiers in Education. 2022 Sep;7:919152.

Kaasbøll J. Developing digital competence - learning, teaching and supporting use of information technology. Department of Informatics, University of Oslo; 2012. https://www.uio.no/studier/emner/matnat/ifi/INF3280/v12/undervisningsmateriale/Book4.pdf.

Karam S, Nagahi M, Dayarathna VL, Ma J, Jaradat R, Hamilton M. Integrating systems thinking skills with multi-criteria decision-making technology to recruit employee candidates. Expert Systems with Applications. 2020;160:113585. https://doi.org/10.1016/j.eswa.2020.113585.

Karatas K, Arpaci I. The role of self-directed learning, metacognition, and 21st century skills predicting the readiness for online learning. Contemporary Educational Technology. 2021;13(3):ep300. https://doi.org/10.30935/cedtech/10786.

Karpati A. Digital literacy in education, UNESCO: United Nations Educational, Scientific and Cultural Organisation. Russian Federation; [accessed 2023 Dec 6] https://policycommons.net/artifacts/8228563/digital-literacy-in-education/9144016/.

Katifori A, Lougiakis C, Roussou M. Exploring the effect of personality traits in VR interaction: the emergent role of perspective-taking in task performance. Frontiers in Virtual Reality. 2022;3:860916. https://doi.org/10.3389/frvir.2022.860916.

Katz IR. Testing information literacy in digital environments: the ETS's iSkills™ assessment. Information Technology and Libraries. 2007;26(3):3–12. https://doi.org/10.6017/ital.v26i3.3271.

Katz IR, Williamson DM, Nadelman HL, Kirsch I. Assessing information and communications technology literacy for higher education. The Annual Meeting of the International Association for Educational Assessment; Philadelphia, PA. 1 June 2004.

Katz J, Rice RE. Social consequences of Internet use: access, involvement, and interaction. MIT Press; 2002.

Khan M, Iahad NA, Mikson S. Exploring the influence of big five personality traits towards computer based learning (CBL) adoption. Journal of Information Systems Research and Innovation. 2014;8:1–8.

Kholin M, Meurs JA, Blickle G, Wihler A, Ewen C, Momm TD. Refining the openness–performance relationship: construct specificity, contextualization, social skill, and the combination of trait self and other-ratings. Journal of

Personality Assessment. 2016;98:277–288. doi: 10.1080/00223891.2015.1076430.

Kim SS, Malhotra NK. A longitudinal model of continued IS use: an integrative view of four mechanisms underlying postadoption phenomena. Management Science. 2005;51(5):741–755.

Kleih SC, Kübler A. Empathy, motivation, and P300 BCI performance. Frontiers in Human Neuroscience. 2013;7. https://doi.org/10.3389/fnhum.2013.00642.

Kliegr T, Bahník Š, Fürnkranz J. A review of possible effects of cognitive biases on interpretation of rule-based machine learning models. Artificial Intelligence. 2021;295:103458. https://doi.org/10.1016/j.artint.2021.103458.

Knapová L. Need for cognitive closure and the use of information and communication technology by older adults [dissertation]. Masarykova Univerzita; 2018.

Knuth DE. Algorithmic thinking and mathematical thinking. American Mathematical Monthly. 1985;92(3):170–181. https://doi.org/10.1080/00029890.1985.11971572.

Kochanski J. Competency-based management. Training and Development. 1997;51:41–44.

Koedinger KR, Carvalho PF, Liu R, McLaughlin EA. An astonishing regularity in student learning rate. Proceedings of the National Academy of Sciences. 2023;120(13):e2221311120.

Korkmaz Ö, Akir R, Zden MY. A validity and reliability study of the computational thinking scales (CTS). Computers in Human Behavior. 2017;72:558–569. https://doi.org/10.1016/j.chb.2017.01.005.

Kozhevnikov M, Hegarty M. A dissociation between object manipulation spatial ability and spatial orientation ability. Memory & Cognition. 2001; 29(5):745–756. https://doi.org/10.3758/BF03200477.

Krach S, Hegel F, Wrede B, Sagerer G, Binkofski F, Kircher T. Can machines think? Interaction and perspective taking with robots investigated via fMRI. PLoS ONE. 2008;3(7):e2597. https://doi.org/10.1371/journal.pone.0002597.

Krasnow MM, Truxaw D, Gaulin SJ, New J, Ozono H, Uono S, Ueno T, Minemoto K. Cognitive adaptations for gathering-related navigation in humans. Evolution and Human Behavior. 2011;32(1):1–12. https://doi.org/10.1016/j.evolhumbehav.2010.07.003.

Kraus J, Scholz D, Baumann M. What's driving me? Exploration and validation of a hierarchical personality model for trust in automated driving. Human Factors. 2020;63(6):1076–1105. https://doi.org/10.1177/0018720820922653.

Krausman A, Neubauer C, Lakhmani S, Wright J, Baker A, Fitzhugh S, Forster DE, Metcalfe JS, Gremillion G, Schaefer KE. Team trust measurement in human-autonomy teams. Transactions on Human Robot Interaction. 2022;11(3):1–58.

Kruger J, Dunning D. Unskilled and unaware of it: how difficulties in recognizing one's own incompetence lead to inflated self-assessments. Journal of Personality and Social Psychology. 1999;77(6):1121–1134.

Kuhlemeier H, Hemker BT. The impact of computer use at home on students' Internet skills. Computers & Education. 2007;49(2):460–480. https://doi.org/10.1016/j.compedu.2005.10.004.

Kurt Y, Öztürk H. The effect of mobile augmented reality application developed for injections on the knowledge and skill levels of nursing students: an experimental controlled study. Nurse Education Today. 2021;103:104955. https://doi.org/10.1016/j.nedt.2021.104955.

Kushniruk AW. Analysis of complex decision-making processes in health care: cognitive approaches to health informatics. Journal of Biomedical Informatics. 2001;34(5):365–376.

Kusumastuti SA, Pollard KA, Oiknine AH, Dalangin B, Raber TR, Files BT. Practice improves performance of a 2D uncertainty integration task within and across visualizations. IEEE Transactions on Visualization and Computer Graphics. 2022.

Lakhmani S, Neubauer C, Forster DE, Wright J, Krausman A, Berg S, Schaefer KE. Cohesion in human-autonomy teams: an approach for future research. Theoretical Issues in Ergonomic Science. 2022. https://doi.org/10.1080/1463922X.2022.2033876.

Larres PM, Ballantine J, Whittington M. Evaluating the validity of self-assessment: measuring computer literacy among entry-level undergraduates within accounting degree programmes at two UK universities. Accounting Education. 2003;12(2):97–112. https://doi.org/10.1080/0963928032000091729.

Larson L, DeChurch LA. Leading teams in the digital age: four perspectives on technology and what they mean for leading teams. The Leadership Quarterly. 2020;31(1):101377.

Lathan CE, Tracey M. The effects of operator spatial perception and sensory feedback on human–robot teleoperation performance. Presence: Teleoperators Virtual Environments. 2002;11:368–377.

Law N, Woo D, De La Torre J, Wong K. A global framework of reference on digital literacy skills for indicator 4.4.2. Centre for Information Technology in Education (CITE); 2018. https://hub.hku.hk/bitstream/10722/262055/1/Content.pdf.

Lazarus RS, Folkman S. Stress, appraisal, and coping. Springer Publishing Company; 1984.

Leahy D, Dolan D. Digital literacy: a vital competence for 2010? In: Reynolds N, Turcsanyi-Szabo M, editors. Key competencies in the knowledge society. Springer; 2010. p. 210e221.

Lee A. This ugly t-shirt makes you invisible to facial recognition tech. Wired UK. 2020. https://www.wired.co.uk/article/facial-recognition-t-shirt-block.

Lee JD, See KA. Trust in automation: designing for appropriate reliance. Human Factors. 2004;46(1):50–80.

Leeper AE, Hsiao K, Ciocarlie M, Takayama L, Gossow D. Strategies for human-in-the-loop robotic grasping. Proceedings of the Seventh Annual ACM/IEEE International Conference on Human-Robot Interaction. 2012;1–8. https://doi.org/10.1145/2157689.2157691.

Leimeister JM, Schmidt L. Understanding diversity–the impact of personality on technology acceptance. Human-Computer Interaction–INTERACT 2013: 14th IFIP TC 13 International Conference; 2013 Sep 2–6; Cape Town, South Africa; Proceedings, Part IV 14. Springer Berlin Heidelberg; p. 306–313.

Leung AKY, Chiu CY. Multicultural experience, idea receptiveness, and creativity. Journal of Cross-Cultural Psychology. 2010;41(5–6):723–741.

Levy Y, Ramim MM. An assessment of competency-based simulations on e-learners' management skills enhancements. Interdisciplinary Journal of E-Learning and Lifelong Learning. 2015;11:179–190. www.ijello.org/Volume11/IJELLv11p179- 190Levy1958.pdf.

Lewin K. A Dynamic theory of personality. McGraw-Hill; 1935.

Liang M, Ma S, Li Y. Deep generative models for medical image synthesis and analysis: a review. IEEE Reviews in Biomedical Engineering. 2021;14:130–153.

Lin T. CA computer literacy scale for newly enrolled nursing college students: development and validation. Journal of Nursing Research. 2000;19(4):305–317.

Lin J, Wohleber R, Matthews G, Chiu P, Calhoun G, Ruff H, Funke G. Video game experience and gender as predictors of performance and stress during supervisory control of multiple unmanned aerial vehicles. Proceedings of the Human Factors and Ergonomics Society Annual Meeting. 2015;59(1):746–750. https://doi.org/10.1177/1541931215591175.

Linkous HM. Self-directed learning and self-regulated learning: what's the difference? A literature analysis. American Association for Adult and Continuing Education Inaugural 2020 Conference Proceedings. 2020:118–122.

Lipkus IM, Samsa G, Rimer BK. General performance on a numeracy scale among highly educated samples. Medical Decision Making. 2001;21(1):37–44. https://doi.org/10.1177/0272989x0102100105.

Lippert SK. Assessing post-adoption utilisation of information technology within a supply chain management context. International Journal of Technology Management. 2007;7(1):36–59.

Livi S, Kruglanski AW, Pierro A, Mannetti L, Kenny DA. Epistemic motivation and perpetuation of group culture: effects of need for cognitive closure on trans-generational norm transmission. Organizational Behavior and Human Decision Processes. 2015;129:105–112.

Lou J. Improvement in university students' critical thinking following a strategic thinking training program. NeuroQuantology. 2018;16(5).

Lu T, Tang M, Guo Y, Zhou C, Zhao Q, You X. Effect of video game experience on the simulated flight task: the role of attention and spatial orientation. Australian Journal of Psychology. 2022;74(1):1–18. https://doi.org/10.1080/00049530.2021.2007736.

Lucia A, Lepsinger R. The art and science of competency models: pinpointing critical success factors in organizations. San Francisco, CA: Jossey-Bass/Pfeiffer; 1999.

Luhmann N. Trust and power. John Wiley; 1979.

MacKenzie D. 'The certainty trough', in Society on the Line. In: Dutton WH, editor. Oxford University Press; 1999. p. 43–46.

Mackintosh NJ. IQ and human intelligence. Oxford University Press; 1998.

Mansfield RS. Building competency models: approaches for HR professionals. Human Resource Management. 1996;35:7–18.

Mao S, Wang D, Tang C, Dong P. Students' online information searching strategies and their creative question generation: the moderating effect of their need for cognitive closure. Frontiers in Psychology. 2022;13:877061.

Maqbool R, Sudong Y, Manzoor N, Rashid Y. The impact of emotional intelligence, project managers' competencies, and transformational leadership on project success: an empirical perspective. Project Management Journal. 2017;48(3):58–75.

Marcolin BL, Compeau DR, Munro MC, Huff SL. Assessing user competence: conceptualization and measurement. Information Systems Research. 2000;11(1):37–60.

Markauskaite L. Exploring the structure of trainee teachers' ICT literacy: the main components of, and relationships between, general cognitive and technical capabilities. Educational Technology Research and Development. 2007;55(6):547–572. https://doi.org/10.1007/s11423-007-9043-8.

Martens R, Gulikers J, Bastiaens T. The impact of intrinsic motivation on elearning in authentic computer tasks. Journal of Computer Assisted Learning. 2004;20(5):368–376.

Martin A, Grudziecki J. DIGEULIT: concepts and tools for digital literacy development. Innovation in Teaching and Learning in Information and Computer Sciences. 2006;5(4):249–267. https://doi.org/10.11120/ital.2006.05040249.

Martin MM, Rubin RB. A new measure of cognitive flexibility. Psychological Reports. 1995;76(2):623–626. https://doi.org/10.2466/pr0.1995.76.2.623.

Martín-Núñez JL, Ar AY, Pérez Fernández R, Abbas A, Radovanovićf D. Does intrinsic motivation mediate perceived artificial intelligence (AI) learning and computational thinking of students during the COVID-19 pandemic? Computers and Education: Artificial Intelligence. 2023;4(100128):100128. doi.org10.1016/j.caeai.2023.100128.

Matthews G, Campbell SE. Task-induced stress and individual differences in coping. Proceedings of the Human Factors and Ergonomics Society Annual Meeting. 1998;42(11):821–825.

Matthews G, Joyner L, Gilliland K, Campbell S, Falconer S, Huggins J. Validation of a comprehensive stress state questionnaire: towards a state big three. Personality Psychology in Europe. 1999;7:335–350.

Matthews G, Joyner LA, Newman R. Stress, age and hazard perception in simulated driving. Paper presented at: The International Conference on Applied Psychology. 1998 Aug; San Francisco, CA.

Mayer RC, Davis JH, Schoorman FD. An integrative model of organizational trust. The Academy of Management Review. 1995;20(3):709–734.

Maynard AE, Subrahmanyam K, Greenfield PM. Technology and the development of intelligence: from the loom to the computer. In: Preiss D, editor. Intelligence and Technology: The Impact of Tools on the Nature and Development of Intelligence. Lawrence Erlbaum Associates; 2005. p. 29–54.

McDermott KB, Zerr CL. Individual differences in learning efficiency. Current Directions in Psychological Science. 2019;28(6):607–613.

McDonald S, Bornhofen C, Shum D, Long E, Saunders C, Neulinger K. Reliability and validity of The Awareness of Social Inference Test (TASIT): a clinical test of social perception. Disability and Rehabilitation. 2006;28(24):1529–1542. https://doi.org/10.1080/09638280600646185.

McDonald S, Flanagan S, Rollins J, Kinch J. TASIT: a new clinical tool for assessing social perception after traumatic brain injury. Journal of Head Trauma Rehabilitation. 2003;18(3):219–238. https://doi.org/10.1097/00001199-200305000-00001.

McKinley RA, McIntire LK, Funke MA. Operator selection for unmanned aerial systems: comparing video game players and pilots. Aviation, Space, and Environmental Medicine. 2011;82(6):635–642. https://doi.org/10.3357/ASEM.2958.2011.

McKnight DH, Carter M, Thatcher JB, Clay PF. Trust in a specific technology: an investigation of its components and measures. ACM Transactions on Management Information Systems. 2011 June;2(2) Article 12;1–25.

McKnight DH, Chervany NL. The meanings of trust. University of Minnesota MIS Research Center; 1996. Working Paper series No.: WP 96-04. http://misrc.umn.edu/wpaper/WorkingPapers/9604.pdf.

McKnight DH, Chervany NL. What trust means in E-commerce customer relationships: an interdisciplinary conceptual typology. International Journal of Electronic Commerce. 2001;6(2):35–59.

McKnight DH, Cummings LL, Chervany NL. Initial trust formation in new organizational relationships. Academy of Management Review. 1998;23(3):473–490.

Menchaca-Brandan MA, Liu AM, Oman CM, Natapoff A. Influence of perspective-taking and mental rotation abilities in space teleoperation. Proceedings of the ACM/IEEE International Conference on Human-Robot Interaction; 2007. p. 271–278. https://doi.org/10.1145/1228716.1228753.

Messick S. Meaning and values in test validation: the science and ethics of assessment. Educational Researcher. 1989;18(2):5–11. https://doi.org/10.3102/0013189x018002005.

Mirabile RJ. Everything you wanted to know about competency modeling. Training and Development. 1997;51:73–77.

Miller T. Explanation in artificial intelligence: insights from the social sciences. Artificial Intelligence. 2019;267:1–38. https://doi.org/10.1016/j.artint.2018.07.007.

Monat JP, Gannon TF. Systems thinking. American Journal of Systems Science. 2015;4(1):11–26.

Moon BJ. Antecedents and outcomes of strategic thinking. Journal of Business Research. 2013;66(10):1698–1708.

Moore A, Malinowski P. Meditation, mindfulness and cognitive flexibility. Consciousness and Cognition. 2009;18(1):176–186. https://doi.org/10.1016/j.concog.2008.12.008.

Morgan B, D'Mello S, Abbott R, Radvansky G, Haass M, Tamplin A. Individual differences in multitasking ability and adaptability. Proceedings of the Human Factors Ergonomics Society Annual Meeting; 2011. p. 919–923.

Morony S, Kleitman S, Lee YP, Stankov L. Predicting achievement: confidence vs self-efficacy, anxiety, and self-concept in Confucian and European countries. International Journal of Educational Research. 2013;58:79–96.

Musharraf S, Bauman S, Anis-Ul-Haque M, Malik JA. General and ICT self-efficacy in different participants roles in cyberbullying/victimization among Pakistani university students. Frontiers in Psychology. 2019;10. https://doi.org/10.3389/fpsyg.2019.01098.

Myers T, Carey E, Szűcs D. Cognitive and neural correlates of mathematical giftedness in adults and children: a review. Frontiers in Psychology. 2017;8:1646.

National Research Council. Improving student learning: a strategic plan for education research and its utilization. National Academies Press; 1999.

National Research Council. Education for life and work: Developing transferable knowledge and skills in the 21st century. In: Pellegrino JW, Hilton ML, editors. The National Academies Press; 2012.

Ng DTK, Leung JKL, Chu KWS, Qiao MS. AI literacy: definition, teaching, evaluation and ethical issues. Proceedings of the Association for Information Science and Technology. 2021;58(1):504–509. https://doi.org/10.1002/pra2.487.

Nguyen L-K-N, Kumar C, Jiang B, Zimmermann N. Implementation of systems thinking in public policy: a systematic review. Systems. 2023;11(2):64. https://doi.org/10.3390/systems11020064.

Nickerson RS. Technology and cognition amplification. In: Sternberg RJ, Preiss DD, editors. Intelligence and technology. The impact of tools on the nature and development of human abilities. Lawrence Erlbaum Associates; 2005. p. 3–27.

Nomura T, Kanda T, Suzuki T, Kato K. Prediction of human behavior in human–robot interaction using psychological scales for anxiety and negative attitudes toward robots. IEEE Transactions on Robotics. 2008;24(2):442–451. doi:10.1109/TRO.2008.915453.

Norman DA. Worsening the knowledge gap: the mystique of computation builds unnecessary barriers. Annals of the New York Academy of Sciences. 1984;426:220–233.

Nov O, Ye C. Personality and technology acceptance: personal innovativeness in IT, openness and resistance to change. Proceedings of the 41st Hawaii International Conference on System Sciences; 2008. p. 1–9.

Nov O, Ye C. Resistance to change and the adoption of digital libraries: an integrative model. Journal of the American Society for Information Science and Technology. 2009;60(8):1702–1708. https://doi.org/10.1002/asi.21068.

Noy S, Zhang W. Experimental evidence on the productivity effects of generative artificial intelligence. SSRN; 2023. SSRN 4375283.

Nunes T, Bryant P, Evans D, Bell D, Gardner S, Gardner A, Carraher J. The contribution of logical reasoning to the learning of mathematics in primary school. British Journal of Developmental Psychology. 2007;25(1):147–166. https://doi.org/10.1348/026151006X153127.

Nye C, Su R, Rounds J, Drasgow F. Vocational interests and performance: a quantitative summary of over 60 years of research. Perspectives on Psychological Science. 2012;7(4):384–403. https://doi.org/10.1177/1745691612449021.

Nye CD, Su R, Rounds J, Drasgow F. Interest congruence and performance: Revisiting recent meta-analytic findings. Journal of Vocational Behavior. 2017;98:138–151. https://doi.org/10.1016/j.jvb.2016.11.002.

Oberauer K, Suß H-M, Wilhelm O, Wittman WW. The multiple faces of working memory: storage, processing, supervision, and coordination. Intelligence. 2003;31:167–193.

Ocana-Fernandez Y, Valenzuela-Fernandez LA, Garro-Aburto LL. Inteligencia artificial y sus implicaciones en la educacion superior. Propositos y Representaciones. 2019;7(2):536–568.

Ogata K, Ueda K, Suto S, Kumada T, Ifukube T. Relationship between age-related decline of cognitive functions and willingness to work using a computer. Procedia Computer Science. 2012;8:255–260. https://doi.org/10.1016/j.procs.2012.01.054.

Okagaki L, Frensch PA. Effects of video game playing on measures of spatial performance: gender effects in late adolescence. Journal of Applied Developmental Psychology. 1994;15(1):33–58.

Okan Y, Garcia-Retamero R, Cokely ET, Maldonado A. Individual differences in graph literacy: overcoming denominator neglect in risk comprehension. Journal of Behavioral Decision Making. 2012;25(4):390–401.

Okan Y, Garcia-Retamero R, Cokely ET, Maldonado A. Biasing and debiasing health decisions with bar graphs: costs and benefits of graph literacy. Quarterly Journal of Experimental Psychology. 2018;71(12):2506–2519.

Oksanen A, Savela N, Latikka R, Koivula A. Trust toward robots and artificial intelligence: an experimental approach to human–technology interactions online. Frontiers in Psychology. 2020;11:568256.

Okur E, Turkan M. A survey on automated melanoma detection. Engineering Applications of Artificial Intelligence. 2018;73:50–67. https://doi.org/10.1016/j.engappai.2018.04.028.

Olson DR, Cole M. Technology, literacy and the evolution of society: implications of the work of Jack Goody. Lawrence Erlbaum; 2005.

O'Neill T, McNeese N, Barron A, Schelble B. Human–autonomy teaming: a review and analysis of the empirical literature. Human Factors. 2022;64(5):904–938.

Ono T, Imai M, Nakatsu R. Reading a robot's mind: a model of utterance understanding based on the theory of mind mechanism. Advanced Robotics. 2000;14(4):311–326. https://doi.org/10.1163/156855300741609.

Oreg S. Resistance to change: Developing an individual differences measure. Journal of Applied Psychology. 2003;88(4):680–693. https://doi.org/10.1037/0021-9010.88.4.680.

Oreg S. Personality, context, and resistance to organizational change. European Journal of Work and Organizational Psychology. 2006;15(1):73–101. https://doi.org/10.1080/13594320500451247.

Oreg S. Resistance to change and performance: toward a more even-handed view of dispositional resistance. The Journal of Applied Behavioral Science. 2018;54(1):88–107. https://doi.org/10.1177/0021886317741867.

Oreg S, Bayazit M, Vakola M, Arciniega L, Armenakis A, Barkauskiene R, Bozionelos N, Fujimoto Y, González L, Han J, et al. Dispositional resistance to change: measurement equivalence and the link to personal values across 17 nations. Journal of Applied Psychology. 2008;93(4):935–944. https://doi.org/10.1037/0021-9010.93.4.935.

Organization for Economic Cooperation and Development. 21st century skills and competences for new millennium learners in OECD countries. OECD Publishing; 2009. OECD Education Working Papers 41. https://doi.org/10.1787/218525261154.

Paiva A, Leite I, Boukricha H, Wachsmuth I. Empathy in virtual agents and robots: a survey. ACM Transactions on Interactive Intelligent Systems. 2017;7(3):1–40. https://doi.org/10.1145/2912150.

Paletz SBF, Kim KH, Schunn CD, Tollinger I, Vera A. Reuse and recycle: the development of adaptive expertise, routine expertise, and novelty in a large research team: team adaptive expertise. Applied Cognitive Psychology. 2013 July;27(4):415–28. https://doi.org/10.1002/acp.2928.

Palladino P, Cornoldi C, De Beni R, Pazzaglia F. Working memory and updating processes in reading comprehension. Memory & Cognition. 2001;29(2):344–354. https://doi.org/10.3758/BF03194929.

Papert S. Mindstorms: children, computers, and powerful ideas. Basic Books, Inc.; 1980.

Parasuraman R, Manzey DH. Complacency and bias in human use of automation: an attentional integration. Human Factors. 2010;52:381–410.

Parker MC, Solomon A, Pritchett B, Illingworth DA, Marguilieux LE, Guzdial M. Socioeconomic status and computer science achievement: spatial ability as a mediating variable in a novel model of understanding. Proceedings of the 2018 ACM Conference on International Computing Education Research; 2018. p. 97–105. https://doi.org/10.1145/3230977.3230987.

Parry SB. The quest for competencies. Training. 1996;33:48–54.

Parsazadeh N, Cheng P, Wu T, Huang Y. Integrating computational thinking concept into digital storytelling to improve learners' motivation and performance. Journal of Educational Computing Research. 2021;59(3):470–495.

Paulus PB, Nakui T, Putman VL. Group brainstorming and teamwork: some rules for the road to innovation. In: Thompson LL, Choi H, editors. Creativity and innovation in organizational teams. Lawrence Erlbaum Associates; 2006. p. 69–86.

Pavlou PA. Consumer acceptance of electronic commerce: integrating trust and risk with the technology acceptance model. International Journal of Electronic Commerce. 2003;7(3):101–134.

Pernia EE. Strategy framework for promoting ICT literacy in the Asia-Pacific region. UNESCO Bangkok Communication and Information Unit; 2008. http://119.82.251.165:8080/xmlui/handle/123456789/34.

Petermann MK, Zacher H. Workforce agility: development and validation of a multidimensional measure. Frontiers in Psychology. 2022;13:908.

Peters E, Dieckmann N, Dixon A, Hibbard JH, Mertz CK. Less is more in presenting quality information to consumers. Medical Care Research and Review. 2007;64(2):169–190.

Petter S, Barber CS, Barber D, Berkley RA. Using online gaming experience to expand the digital workforce talent pool. MIS Quarterly Executive. 2018;17(4). https://doi.org/10.17705/2msqe.00004.

Pinker S, Bloom P. Natural language and natural selection. Behavioral and Brain Sciences. 1990;13(4):707–784.

Pinski M, Benlian A. (2023). AI literacy - towards measuring human competency in artificial intelligence. Darmstadt Technical University, Department of Business Administration, Economics and Law, Institute for Business Studies

(BWL).
https://scholarspace.manoa.hawaii.edu/server/api/core/bitstreams/06fa6203-9d34-4c05-89c5-d00eebaca1e8/content.

Pintrich PR, De Groot EVD. Motivational and self-regulated learning components of classroom academic performance. Journal of Educational Psychology. 1990;82(1):33.40.

Pintrich PR, Smith DAF, Garcia T, Mckeachie WJ. Reliability and predictive validity of the motivated strategies for learning questionnaire (MSLQ). Educational and Psychological Measurement. 1993;53(3):801–813. https://doi.org/10.1177/0013164493053003024.

Pizzolitto E, Verna I, Venditti M. Authoritarian leadership styles and performance: a systematic literature review and research agenda. Management Review Quarterly. 2023;73(2):841–871.

Pollard KA, Files BT, Oiknine AH, Dalangin B. How to prepare for rapidly evolving technology: focus on adaptability. DEVCOM Army Research Laboratory (US); 2022. Report No.: ARL-TR-9432.

Popoola SO, Adedokun OO. Computer self-efficacy, computer anxiety, cognitive skills, and use of electronic library resources by social science undergraduates in a tertiary university in Nigeria. Journal of Librarianship and Information Science. 2023;55(1):111–122.

Porat E, Blau I, Barak A. Measuring digital literacies: junior high-school students' perceived competencies versus actual performance. Computers & Education. 2018;126:23–36. https://doi.org/10.1016/j.compedu.2018.06.030.

Prather J, Becker BA, Craig M, Denny P, Loksa D, Margulieux L. What do we think we think we are doing? Metacognition and self-regulation in programming. Proceedings of the 2020 ACM Conference on International Computing Education Research; 2020. p. 2–13. https://doi.org/10.1145/3372782.3406263.

Prather J, Pettit R, Becker BA, Denny P, Loksa D, Peters A, Albrecht Z, Masci K. First things first: providing metacognitive scaffolding for interpreting problem prompts. Proceedings of the 50th ACM Technical Symposium on Computer Science Education. 2019;531–537. https://doi.org/10.1145/3287324.3287374.

Preiss DD, Sternberg RJ. Effects of technology on verbal and visual-spatial abilities. Cognitive Technology. 2006;1(1)1:1–9.

Pugliese F, Acerbi A, Marocco D. Emergence of leadership in a group of autonomous robots. PLoS One. 2015;10(9):e0137234.

Punie Y. European Framework for the Digital Competence of Educators: DigCompEdu. European Union; 2017. https://publications.jrc.ec.europa.eu/repository/handle/JRC107466.

Purington A, Taft JG, Sannon S, Bazarova NN, Taylor SH. "Alexa is my new BFF": social roles, user satisfaction, and personification of the Amazon Echo. Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems; 2017. p. 3259–3267. ACM.

Raemdonck I, van der Leeden R, Valcke M, Segers M, Thijssen J. Predictors of self-directed learning for low-qualified employees: a multi-level analysis. European Journal of Training and Development. 2012;36(6):572–591.

Raghubar KP, Barnes MA, Hecht SA. Working memory and mathematics: a review of developmental, individual difference, and cognitive approaches. Learning and Individual Differences. 2010;20(2):110–122. https://doi.org/10.1016/j.lindif.2009.10.005.

Ramirez-Arellano A, Bory-Reyes J, Hernández-Simón LM. Emotions, motivation, cognitive–metacognitive strategies, and behavior as predictors of learning performance in blended learning. Journal of Educational Computing Research. 2019;57(2):491–512. https://doi.org/10.1177/0735633117753935.

Rasheed MI, Pitafi AH, Mishra S, Chotia V. When and how ESM affects creativity: the role of communication visibility and employee agility in a cross-cultural setting. Technological Forecasting and Social Change. 2023;194:122717.

Raven J, Raven JC, Court JH. Raven's progressive matrices and vocabulary scales. Oxford Psychologists Press; 1998.

Riedl R. Is trust in artificial intelligence systems related to user personality? Review of empirical evidence and future research directions. Electronic Markets. 2022;32(4):2021–2051.

Rini R, Mujiyati, Sukamto I, Hariri H. The effect of self-directed learning on students' digital literacy levels in online learning. International Journal of Instruction. 2022;15(3):329–344. https://doi.org/10.29333/iji.2022.15318a.

Roadrangka V, Yeany RH, Padilla MJ. The construction and validation of Group Assessment of Logical Thinking (GALT). Paper presented at: The Annual Meeting of the National Association of Research in Science Teaching; 1983; Dallas, TX.

Rodes W, Gugerty L. Effects of electronic map displays and individual differences in ability on navigation performance. Human Factors. 2012;43:589–599.

Rodriguez D, Patel R, Bright A, Gregory D, Gowing MK. Developing competency models to promote integrated human resource practices. Human Resource Management. 2002;41:309–324.

Roets A, Van Hiel A. Separating ability from need: clarifying the dimensional structure of the need for closure scale. Personality and Social Psychology Bulletin. 2007;33(2):266–280. https://doi.org/10.1177/0146167206294744.

Rogers M, Smoak ND, Liu J. Self-reported deviant computer behavior: a big-5, moral choice, and manipulative exploitive behavior analysis. Deviant Behavior. 2006;27(3):245–268.

Roseberry L. An applied experimental evaluation of conflict resolution curriculum and social skills development. Dissertation Abstracts International: Section A. Humanities and Social Sciences. 1997;58(03):724.

Rosen LD, Carrier LM, Cheever NA. Facebook and texting made me do it: media-induced task-switching while studying. Computers in Human Behavior. 2013;29(3):948–958. https://doi.org/10.1016/j.chb.2012.12.001.

Rosman T, Mayer A-K, Krampen G. A longitudinal study on information-seeking knowledge in psychology undergraduates: exploring the role of information literacy instruction and working memory capacity. Computers & Education. 2016;96:94–108. https://doi.org/10.1016/j.compedu.2016.02.011.

Ross JA. The reliability, validity, and utility of self-assessment. practical assessment, research and evaluation. 2006;11(10):10. https://doi.org/10.7275/9wph-vv65.

Rotter JB. A new scale for the measurement of interpersonal trust. Journal of Personality. 1967;35:651–665.

Rouet J-F, Vörös Z, Pléh C. Incidental learning of links during navigation: the role of visuo-spatial capacity. Behaviour & Information Technology. 2012;31(1):71–81. https://doi.org/10.1080/0144929X.2011.604103.

Royston R, Goodwin G, Ness A, Keil C, Lockhart P, Jones M. Army talent attribute framework: a unified framework for defining personnel characteristics. Army Research Institute for the Behavioral and Social Sciences (US); 2022 Aug. Report No.: 1421.

Rozmarin T, Shamir-Inbal T, Blau I. What are the implication of integration one-to-one computing with network laptops (Chromebooks) on students' digital literacy skills. Learning in the Technological Era. 2017;201–210.

Salas E, Grossman R, Hughes AM, Coultas CW. Measuring team cohesion: observations from the science. Human Factors. 2015a;57(3):365–374.

Salas E, Rosen MA, CS Burke, Goodwin GF. The wisdom of collectives in organizations: an update of the teamwork competencies. Cambridge Hand-Book of Expertise and Expert Performance. In: Ericsson KA, Charness N, Feltovich PJ, Hoffman RR, editors. Cambridge University Press; 2009. p. 439–453.

Salas E, Shuffler ML, Thayer AL, Bedwell WL, Lazzara EH. Understanding and improving teamwork in organizations: a scientifically based practical guide. Human Resource Management. 2015b;54(4):599–622.

Salm-Hoogstraeten SV, Müsseler J. Human cognition in interaction with robots: taking the robot's perspective into account. Human Factors: The Journal of the Human Factors and Ergonomics Society. 2021;63(8):1396–1407. https://doi.org/10.1177/0018720820933764.

Salmen K, Festing M. Paving the way for progress in employee agility research: a systematic literature review and framework. The International Journal of Human Resource Management. 2022;33(22):4386–4439.

Samuel Y, George J, Samuel J. Beyond stem, how can women engage big data, analytics, robotics and artificial intelligence? An exploratory analysis of confidence and educational factors in the emerging technology waves influencing the role of, and impact upon, women. arXiv preprint; 2020. arXiv:2003.11746.

Sardone N. Developing information technology fluency in college students: an investigation of learning environments and learner characteristics. Journal of Information Technology Education. 2011;10:101–122. https://doi.org/10.28945/1381.

Sarfati Y, Hardybayle M, Besche C, Widlocher D. Attribution of intentions to others in people with schizophrenia: a non-verbal exploration with comic strips. Schizophrenia Research. 1997;25(3):199–209. https://doi.org/10.1016/S0920-9964(97)00025-X.

Sargeant J, Lockyer J, Mann K, Holmboe E, Silver I, Armson H, Driessen E, MacLeod T, Yen W, Ross K, et al. Facilitated reflective performance feedback: developing an evidence- and theory-based model that builds relationship, explores reactions and content, and coaches for performance change (R2C2). Academic Medicine. 2015;90(12):1698–706.

Sari U, Pektaş HM, Şen ÖF, Çelik H. Algorithmic thinking development through physical computing activities with Arduino in STEM education. Education and Information Technologies. 2022;27(5):6669–6689. https://doi.org/10.1007/s10639-022-10893-0.

Savickas ML. New questions for vocational psychology: premises, paradigms, and practices. Journal of Career Assessment. 2014;19:251–258.

Schmetkamp S. Understanding A.I.—can and should we empathize with robots? Review of Philosophy and Psychology. 2020;11(4):881–897. https://doi.org/10.1007/s13164-020-00473-x.

Schmit MJ, Ryan AM. The big five in personnel selection: factor structure in applicant and nonapplicant populations. Journal of Applied Psychology. 1993;78(6):966–974. https://doi.org/10.1037/0021-9010.78.6.966.

Schneider TR, Jessup SA, Stokes C, Rivers S, Lohani M, McCoy M. The influence of trust propensity on behavioral trust. The Meeting of Association for Psychological Society; 2017 May; Boston, MA.

Schraw G, Dennison RS. Assessing metacognitive awareness. Contemporary Educational Psychology. 1994;19(4):460–475. https://doi.org/10.1006/ceps.1994.1033.

Schwartz DL, Bransford JD, Sears D. Innovation and efficiency in learning and transfer. In: Mestre J, editor. Transfer. Erlbaum; 2005.

Scopelliti I, Min HL, McCormick E, Kassam KS, Morewedge CK. Individual differences in correspondence bias: measurement, consequences, and correction of biased interpersonal attributions. Management Science. 2018;64(4):1879–1910. https://doi.org/10.1287/mnsc.2016.2668.

Scribner S, Cole M. The psychology of literacy. Harvard University Press; 1981.

Sengupta S, McNeese N. Synthetic authority: speculating the future of leadership in the age of human-autonomy teams. AutomationXP23: Intervening, Teaming, Delegating - Creating Engaging Automation Experiences (at CHI2023); 23 Apr 23; Hamburg, Germany.

Senkbeil M, Ihme JM, Wittwer J. The Test of Technological and Information Literacy (TILT) in the National Educational Panel Study: development, empirical testing, and evidence for validity. Journal for Educational Research Online. 2013;5(2):139–161. https://doi.org/10.25656/01:8428.

Shamir-Inbal T, Blau I. How the implementation of tablet computers impacts learning and pedagogy and promotes "Digital wisdom" of students and teachers in the elementary school? INTED2014 Proceedings; 2014. p. 3438. https://library.iated.org/view/SHAMIRINBAL2014HOW.

Sharan NN, Romano DM. The effects of personality and locus of control on trust in humans versus artificial intelligence. Heliyon. 2020;6(8).

Shaw ME, Blum JM. Effects of leadership style upon group performance as a function of task structure. Journal of Personality and Social Psychology. 1966;3(2)L:238.

Shepard RN, Metzler J. Mental rotation of three-dimensional objects. Science. 1971;171(3972):701–703. https://doi.org/10.1126/science.171.3972.701.

Schippmann JS, Ash RA, Battista M, Carr L, Eyde LD, Hesketh B, Kehoe J, Pearlman K, Prien EP, Sanchez JI. The practice of competency modeling. Personnel Psychology. 2000;53:703–740.

Siddiq F, Gochyyev P, Wilson M. Learning in digital networks – ICT literacy: a novel assessment of students' 21st century skills. Computers & Education. 2017;109:11–37. https://doi.org/10.1016/j.compedu.2017.01.014.

Silverman J, Purshouse RC, Fleming PJ. Probabilistic model predictive control: theory and applications. IEEE Transactions on Automatic Control. 2019;64(10):4129–4151.

Sinay E, Graikinis D. (2018). Global competencies in deeper learning environments enabled by pervasive digital technologies: evolving framework for theoretical foundation and developmental evaluation. Toronto District School Board. https://www.researchgate.net/publication/323883706.

Sinayev A, Peters E. Cognitive reflection vs. calculation in decision making. Frontiers in Psychology. 2015;6:532.

Singh IL, Molloy R, Parasuraman R. Automation-induced "complacency": development of the complacency-potential rating scale. International Journal of Aerospace Psychology. 1993;3:111–122.

Sinkkonen H-M, Puhakka H, Meriläinen M. Adolescents' internet use in relation to self-esteem and adaptability in career decision-making. British Journal of Guidance & Counselling. 2018;46(6):738–751.

Smith AM, Green M. Artificial intelligence and the role of leadership. Journal of Leadership Studies. 2018;12(3):85–87.

Smith SM. Using the social cognitive model to explain vocational interest in information technology. Information Technology, Learning, and Performance Journal. 2002;20(1):1–9. https://eric.ed.gov/?id=EJ654965.

Spence I, Feng J. Video games and spatial cognition. Review of General Psychology. 2010;14(2):92–104. https://doi.org/10.1037/a0019491.

Spence SH. Social skills training with children and young people: theory, evidence and practice. Child and Adolescent Mental Health. 2003;8(2):84–96.

Spielberger CD. State-trait anxiety inventory: bibliography. 2nd ed. Consulting Psychologists Press; 1989.

Srivastava S, D'Souza D. Measuring strategic thinking in organizations. Editorial Policy. 2021;33(1):90–11.

Stanney K, Salvendy G. Information visualization: assisting low spatial individuals with information access tasks through the use of visual mediators. Ergonomics. 1995;38:1184–1198.

Stark S, Chernyshenko OS, Drasgow F, Nye CD, White LA, Heffner T, Farmer WL. From ABLE to TAPAS: a new generation of personality tests to support military selection and classification decisions. Military Psychology. 2014;26(3):153–164. https://doi.org/10.1037/mil0000044.

Steptoe-Warren G, Howat D, Hume I. Strategic thinking and decision making: literature review. Journal of Strategy and Management. 2011;4(3):238–250.

Sternberg RJ. Implicit theories of intelligence, creativity, and wisdom. Journal of Personality and Social Psychology. 1985;49(3):607–627. https://doi.org/10.1037/0022-3514.49.3.607.

Sternberg RJ. Metaphors of mind: conceptions of the nature of intelligence. Cambridge University Press; 1990.

Süß HM, Kretzschmar A. Impact of cognitive abilities and prior knowledge on complex problem solving performance–empirical results and a plea for ecologically valid microworlds. Frontiers in Psychology. 2018;9:626.

Sun Y, Mengyi Z, Jeyaraj A. How enterprise social media affordances affect employee agility: a self-determination theory perspective. Information Technology & People. 2023.

Suurtamm C, Koch I. The probability assessment resource: a web-based tool for teaching probability. Behavior Research Methods. 2013;45(1):139–145.

Syahchari DH, Herlina MG, Saroso H, Sudrajat D, Jordaan HK. The influence of digital employee experience and employee agility: do they boost firm's effectiveness? 2021 International Conference on Information Management and Technology (ICIMTech), 2021 Aug. Vol. 1, p. 67–71. IEEE.

Takayama L, Marder-Eppstein E, Harris H, Beer JM. Assisted driving of a mobile remote presence system: system design and controlled user evaluation. 2011 IEEE International Conference on Robotics and Automation; 2011. p. 1883–1889. doi.org/10.1109/ICRA.2011.5979637.

Techataweewan W, Prasertsin U. Documentary research to identify the components of digital literacy for Thai undergraduate students. Proceedings the Universal Academic Cluster International Summer Conference; 2016. Hokkaido. p. 23e30.

Techataweewan W, Prasertsin U. Development of digital literacy indicators for Thai undergraduate students using mixed method research, Kasetsart Journal of Social Sciences. 2018;39(2):215–221.

Tekkol İA, Demirel M. An Investigation of self-directed learning skills of undergraduate students. Frontiers in Psychology. 2018;9:2324. https://doi.org/10.3389/fpsyg.2018.02324.

Teodorescu T. Competence versus competency: what is the difference? Performance Improvement. 2006;45(10):27e30. https://doi.org/10.1002/pfi.027.

Tett L, Maclachlan K. Adult literacy and numeracy, social capital, learner identities and self-confidence. Studies in the Education of Adults. 2007;39(2):150–167. https://doi.org/10.1080/02660830.2007.11661546.

Thatcher JB, Mcknight DH, Baker EW, Arsal R, Roberts N. The role of trust in postadoption exploration: an empirical investigation of knowledge management systems. IEEE Transactions on Engineering Management. 2011;58(1):56–70.

Tiwari V. Countering effects of technostress on productivity: moderating role of proactive personality. Benchmarking: An International Journal. 2021;28(2):636–651.

Tobin KG, Capie W. The development and validation of a group test of logical thinking. Educational and Psychological Measurement. 1981;41:413–423.

Todd AR, Forstmann M, Burgmer P, Brooks AW, Galinsky AD. Anxious and egocentric: how specific emotions influence perspective taking. Journal of

Experimental Psychology: General. 2015;144(2):374–391. https://doi.org/10.1037/xge0000048.

Tolar TD, Lederberg AR, Fletcher JM. A structural model of algebra achievement: computational fluency and spatial visualisation as mediators of the effect of working memory on algebra achievement. Educational Psychology. 2009;29(2);239–266.

Tomasello M. The cultural origins of human cognition. Cambridge, Mass: Harvard University Press; 1999a.

Tomasello M. The human adaptation for culture. Annual Review of Anthropology. 1999b;28:509–529.

Tost LP, Gino F, Larrick RP. When power makes others speechless: the negative impact of leader power on team performance. Academy of Management Journal. 2013;56(5):1465–1486. doi:10.5465/amj.2011.0075.

Toth P, Klein P. A role-based model for federal information technology/cyber security training. [accessed 22 Sep 2016] http://csrc.nist.gov/publications/drafts/800-16-rev1/sp800_16_rev1_3rd-draft.pdf.

Trochim WMK, Donnelly JH, Donnelly JP. The research methods knowledge base. 2001. https://openlibrary.org/books/OL8803205M/The_Research_Methods_Knowledge_Base?v=5.

Tsortanidou X, Daradoumis T, Barberá-Gregori E. Convergence among imagination, social-emotional learning and media literacy: an integrative literature review. Early Child Development and Care. 2022;192(2):173–186. doi.org/10.1080/03004430.2020.1753720.

Turner JC, Meyer DK, Cox KE, Logan CM, DiCintio M, Thomas CT. Creating contexts for involvement in mathematics. Journal of Educational Psychology. 1998;90(4):730–745.

Ulfert-Blank AS, Schmidt I. Assessing digital self-efficacy: review and scale development. Computers & Education. 2022;104626.

Ullah I, Hameed RM, Mahmood A. The impact of proactive personality and psychological capital on innovative work behavior: evidence from software houses of Pakistan. European Journal of Innovation Management; 2023.

UNESCO. The plurality of literacy and its implications for policies and programmes: position paper. 2004. United Nations Educational, Scientific and Cultural Organization. https://unesdoc.unesco.org/ark:/48223/pf0000136246.

UNESCO. ICT competency framework for teachers version 3. 2018. http://unesdoc.unesco.org/images/0021/002134/213475E.pdf.

UNESCO. Digital competence frameworks for teachers, learners and citizens. UNESCO-UNEVOC International Centre for Technical and Vocational Education and Training, UNESCO; c2023 [accessed 2023 Aug]. https://unevoc.unesco.org/home/Digital+Competence+Frameworks.

Ushashree R, Swaminathan V, Vivian B, Madhuri R. Psychological predictors of multitasking performance of private sector employees. Indian Journal of Community Psychology. 2016;12(2):220–226.

Uslaner E. Trust, civic engagement and the Internet. Joint Sessions of the European Consortium for Political Research; 2000 Apr; University of Grenoble.

Uttal DH, Meadow NG, Tipton E, Hand LL, Alden AR, Warren C, Newcombe NS. The malleability of spatial skills: a meta-analysis of training studies. Psychological Bulletin. 2013;139(2):352–402. https://doi.org/10.1037/a0028446.

Vance A, Elie-Dit-Cosaque C, Straub D. Examining trust in information technology artifacts: the effects of system quality and culture. Journal of Management Information Systems. 2008;24(4):73–100.

Vandenberg SG, Kuse AR. Mental rotations, a group test of three-dimensional spatial visualization. Perceptual and Motor Skills. 1978;47(2):599–604. https://doi.org/10.2466/pms.1978.47.2.599.

VandenBos GR, editor. APA dictionary of psychology: adaptability. APA Dictionary of Psychology. American Psychological Association; 2007. p. 17. https://psycnet.apa.org/record/2006-11044-000.

Vandergrift L, Goh CCM, Mareschal CJ, Tafaghodtari MH. The metacognitive awareness listening questionnaire: development and validation: language learning. Language Learning. 2006;56(3):431–462. https://doi.org/10.1111/j.1467-9922.2006.00373.x.

Von Walter B, Kremmel D, Jäger B. The impact of lay beliefs about AI on adoption of algorithmic advice. Marketing Letters. 2021;33(1):143–155. https://doi.org/10.1007/s11002-021-09589-1.

Vuorikari R, Kluzer S, Punie Y. DigComp 2.2. The digital competence framework for citizens - with new examples of knowledge, skills and attitudes. Publications Office of the European Union; 2022. https://doi.org/10.2760/115376.

Wang B, Rau PP, Yuan T. Measuring user competence in using artificial intelligence: validity and reliability of artificial intelligence literacy scale. Behaviour & Information Technology. 2022;42(9):1324–1337. https://doi.org/10.1080/0144929x.2022.2072768.

Wang D, Yang Q, Abdul A, Lim BY. Designing theory-driven user-centric explainable AI. Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems; 2019a. p. 1–15. https://doi.org/10.1145/3290605.3300831.

Wang L, Geng F, Hao X, Shi D, Wang T, Li Y. Measuring coding ability in young children: relations to computational thinking, creative thinking, and working memory. Current Psychology. 2023;42(10):8039–8050. https://doi.org/10.1007/s12144-021-02085-9.

Wang S, Sun Z, Chen Y. Effects of higher education institutes' artificial intelligence capability on students' self-efficacy, creativity and learning performance. Education and Information Technologies. 2023;28(5):4919–4939.

Wang W, Benbasat I. Trust in and adoption of online recommendation agents. Journal of the Association for Information Systems. 2005;6(3):72–101.

Wang Y, Veale M, Das A, Gao J, Wachter-Boettcher S. Algorithmic bias in advertising: theory and evidence. Proceedings of the Conference on Fairness, Accountability, and Transparency; 2019b. p. 199–208.

Wang YY, Chuang YW. Artificial intelligence self-efficacy: scale development and validation. Education and Information Technologies. 2023:1–24.

Wardlow L. Individual differences in speakers' perspective taking: the roles of executive control and working memory. Psychonomic Bulletin & Review. 2013;20(4):766–772. https://doi.org/10.3758/s13423-013-0396-1.

Webb M. The impact of artificial intelligence on the labor market. SSRN; 2019. SSRN 3482150.

Webster DM, Kruglanski AW. Individual differences in need for cognitive closure. Journal of Personality and Social Psychology. 1994;67(6):1049–1062.

Wechsler D. Wechsler Memory Scale—(WMS-IV). 4th Ed. APA PsycTests; American Psychological Association; 2009. https://doi.org/10.1037/t15175-000.

Wei C, Pitafi AH, Kanwal S, Ali A, Ren M. Improving employee agility using enterprise social media and digital fluency: moderated mediation model. IEEE Access. 2020;8:68799–68810.

Wellman HM, Liu D. Scaling of theory-of-mind tasks. Child Development. 2004;75(2):523–541. https://doi.org/10.1111/j.1467-8624.2004.00691.x.

Williams R, Park HW, Breazeal C. A is for artificial intelligence: the impact of artificial intelligence activities on young children's perceptions of robots. Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems; 2019 May 4–9; Glasgow Scotland UK. p. 1–11. https://doi.org/10.1145/3290605.3300677.

Williamson SN. Development of a self-rating scale of self-directed learning. Nurse Researcher. 2007;14(2):66–83. https://doi.org/10.7748/nr2007.01.14.2.66.c6022.

Wing JM. Computational thinking. Communications of the ACM. 2006;49(3):33–35. https://doi.org/10.1145/1118178.1118215.

Winkler JK, Fink C, Toberer F, Enk A, Deinlein T, Hofmann-Wellenhof R, Thomas L, Lallas A, Blum A, Stolz W, et al. Association between surgical skin markings in dermoscopic images and diagnostic performance of a deep learning convolutional neural network for melanoma recognition. JAMA Dermatology. 2019;155(10):1135. https://doi.org/10.1001/jamadermatol.2019.1735.

Winters FI, Greene JA, Costich CM. Self-regulation of learning within computer-based learning environments: a critical analysis. Educational Psychology Review. 2008;20(4):429–444. https://doi.org/10.1007/s10648-008-9080-9.

Wisecarver M, Byrd C, Loer A, Engelsted L, Adis C, Kaplan M, Weyhrauch WS. A conceptual model of army leader systems thinking. Army Research Institute (US); 2022 Dec. Report No: Technical Report 1420.

Woller-Carter M. Development of the intelligent graphs for everyday risky decisions tutor [dissertation]. Michigan Technological University; 2015.

Woods DD, Hollnagel E. Joint cognitive systems: patterns in cognitive systems engineering. CRC Press; 2006.

Woods DD, Roth EM, Potter SS, Fowlkes J, Hoffman RR. Evaluating the effectiveness of a joint cognitive system: metrics, techniques, and frameworks. Proceedings of the Human Factors and Ergonomics Society Annual Meeting. Sage Publications; 2006;50(3) p. 314–318.

World Economic Forum. The future of jobs: employment, skills and workforce strategy for the fourth industrial revolution. World Economic Forum; 2016. https://www.weforum.org/reports/the-future-of-jobs.

Wu C, Zhang R, Kotagiri R, Bouvry P. Strategic decisions: survey, taxonomy, and future directions from artificial intelligence perspective. ACM Computing Surveys. 2023;55(12):1–30.

Xiao F, Barnard-Brak L, Lan WY, Burley H. Examining problem-solving skills in technology-rich environments as related to numeracy and literacy. International Journal of Lifelong Education. 2019;38(3):327–338. https://doi.org/10.1080/02601370.2019.1598507.

Yagoda R, Gillian D. WHAT! You want me to trust a ROBOT? The development of a human robot interaction (HRI) trust scale. International Journal of Social Robotics. 2012;4:235–248.

Yao Y, Cui R, Li Y, Zeng L, Jiang J, Qiu N, Dong L, Gong D, Yan G, Ma W, et al. Action real-time strategy gaming experience related to enhanced capacity of visual working memory. Frontiers in Human Neuroscience. 2020;14:333. https://doi.org/10.3389/fnhum.2020.00333.

Yi Y. Establishing the concept of AI literacy: focusing on competence and purpose. JAHR - European Journal of Bioethics. 2021;12(2):353–368. https://doi.org/10.21860/j.12.2.8.

Yilmaz R, Yilmaz FGK. The effect of generative artificial intelligence (AI)-based tool use on students' computational thinking skills, programming self-efficacy and motivation. Computers and Education: Artificial Intelligence. 2003;4:100147.

Yong TL, Kew CS, Fen HC, Begum AT. A review of metacognition: implications for teaching and learning. National Institute of Education (NIE) Working Paper Series. 2020;17:3–59.

Yoon S, Yen PY, Bakken S. Psychometric properties of the self-assessment of nursing informatics competencies scale. Studies in Health Technology and Informatics. 2009;146:546–550.

Zerr CL, Berg JJ, Nelson SM, Fishell AK, Savalia NK, McDermott KB. Learning efficiency: identifying individual differences in learning rate and retention in healthy adults. Psychological Science. 2018;29(9):1436–1450.

Zhang H, Zhu C. A study of digital media literacy of the 5th and 6th grade primary students in Beijing. Asia-Pacific Education Researcher. 2016;25(4):579–592. doi.org/10.1007/s40299-016-0285-2.

Zhang Z, Yao X, Yuan S, Deng Y, Guo C. Big five personality influences trajectories of information seeking behavior. Personality and Individual Differences. 2021;173:110631.

Zheng F, Khan NA, Hussain S. The COVID 19 pandemic and digital higher education: Exploring the impact of proactive personality on social capital through internet self-efficacy and online interaction quality. Children and Youth Services Review. 2020;119:105694.

Zywica J, Danowski J. The faces of Facebookers: Investigating social enhancement and social compensation hypotheses; predicting Facebook and offline popularity from sociability and self-esteem, and mapping the meanings of popularity with semantic networks. Journal of Computer-Mediated Communication. 2007;14(1):1–34. doi:10.1111/j.1083-6101.2008.01429.x.

Appendix. Complete List of Relevant Knowledge, Skills, and Behaviors for Technological Fluency

Category 1: Disposition and Motivation				
Extraversion	An individual's inclination toward sociability, assertiveness, and comfort in group settings.	Extraversion plays a significant role in facilitating effective communication and collaboration, because extroverts tend to excel in social interactions, aiding in understanding and integrating emerging technologies. Extraverts are often early adopters and influencers in adopting social technologies and are more inclined to embrace innovation and risk taking. Their enthusiasm and positive energy contribute to team cohesion, which may translate to mixed human-agent teams.	Ten-Item Personality Inventory (Gosling et al. 2003) (a short form of Big Five) Flexible Thinking in Learning (Barak and Levenberg 2016) (includes open-mindedness subscale) Resistance to Change (Oreg 2003) (includes routine-seeking subscale)	N/A
Agreeableness	The tendency to be cooperative, empathetic, and willing to compromise.	Agreeable individuals tend to be cooperative, empathetic, and good team players. In the context of working with artificial intelligence (AI), these traits can facilitate and foster effective collaboration and positive relationships between humans, machines, and technologies.	Ten-Item Personality Inventory (Gosling et al. 2003) (a short form of Big Five) Flexible Thinking in Learning (Barak and Levenberg 2016) (includes open-mindedness subscale) Resistance to Change (Oreg 2003) (includes routine-seeking subscale)	Not applicable (N/A)
Conscientiousness	The extent to which an individual is organized, responsible, and goal oriented.	Conscientious individuals have a willingness to embrace new ideas and approaches encouraging innovation, exploration, and integration of diverse perspectives. This construct reflects the degree of organization, reliability, and responsibility in collaborating effectively, ensuring consistent and accurate human technology interactions.	Ten-Item Personality Inventory (Gosling et al. 2003) (a short form of Big Five) Flexible Thinking in Learning (Barak and Levenberg 2016) (includes open-mindedness subscale) Resistance to Change (Oreg 2003) (includes routine-seeking subscale)	N/A
Neuroticism	Neuroticism refers to an individual's relatively stable tendency to experience negative emotions, such as anxiety and depression.	Neuroticism may impact an individual's ability to accept, trust, and effectively use digital technologies.	Ten-Item Personality Inventory (Gosling et al. 2003) (a short form of Big Five) Flexible Thinking in Learning (Barak and Levenberg 2016) (includes open-mindedness subscale) Resistance to Change (Oreg 2003) (includes routine-seeking subscale)	N/A
Openness to Experience	Having an inclination toward curiosity, creativity, and trying new things, etc.	Openness to experience influences adaptability and willingness to explore new methods and ideas, aiding in the incorporation of AI and future technologies by fostering innovative approaches and embracing change. This may enable effective communication, collaboration, and engagement with others when working on novel technologies or interacting with users.	Ten-Item Personality Inventory (Gosling et al. 2003) (a short form of Big Five) Flexible Thinking in Learning (Barak and Levenberg 2016) (includes open-mindedness subscale) Resistance to Change (Oreg 2003) (includes routine-seeking subscale)	N/A
Stress Tolerance	The ability to recognize and manage one's emotions in stressful situations as well as the capacity to endure pressure or uncertainty without becoming negative (e.g., hopeless, bitter, or hostile) toward oneself or others. People strong in stress tolerance can withstand and may even thrive in high-pressure situations by remaining calm, resilient, and composed in the face of challenges or setbacks.	Interactions with technology may be new and thus inherently activating and stressful. Individuals must be tolerant to these situations to perform well in technology-relevant environments.	Coping Inventory for Task Stress (CITS) measures 3 types of post-task coping strategies: 1) task- or problem-focused coping; 2) emotion-focused coping; and (3) avoidance. Ten items relevant to task performance are assessed for each dimension. State, Trait Anxiety Inventory (Spielberger et al. 1989) is a commonly used measure of trait and state anxiety (Spielberger et al. 1989). State anxiety items include the following: "I am tense; I am worried" and "I feel calm; I feel secure." Trait anxiety items include the following: "I worry too much over something that really doesn't matter" and "I am content; I am a steady person." All items are rated on a four-point scale (e.g., from "Almost Never" to "Almost Always"). Higher scores indicate greater anxiety.	The success of this KSB is not overly concerned about avoiding stressful situations, but rather engaging in effective coping strategies, such as task-focused coping, when stress does arise.

Table A-1 Complete list of relevant knowledge, skills, and behaviors (KSBs) for technological fluency (continued)

KSB	Scope and definition	Scope for technological fluency	Tools/metrics to measure	Notes and possible caveats
Self-Efficacy and Self-Confidence	The belief (and certainty) that one can achieve goals. Individuals high in self-efficacy maintain confidence in technical ability when faced with inherent dangers and potential collateral impacts during operations.	People who believe they will do well tend to do better than those who believe they will fail. Therefore, technology self-efficacy should predict technological fluency.	Self-efficacy is domain-specific; therefore, there is a scale for every conceptualization of self-efficacy, including a recently developed AI self-efficacy scale (Wang and Chuang 2023). There are also scales designed to measure information self-efficacy, computer self-efficacy, digital self-efficacy, robotics learning self-efficacy, human-robot-interaction self-efficacy, and technology self-efficacy. Miller's (1996) 12-item questionnaire; Computer Self-Efficacy (CSE) (Thatcher et al. 2011).	N/A
Motivation and (Vocational) Interest	The general desire or willingness to engage in an action/behavior or perform a certain way. (Vocational) interests are relatively stable individual preferences for certain types of work, work environments, and outcomes.	General willingness to work with, perform, use, or drive change in technological usage and adaptation. Previous work shows self-efficacy can predict vocational interest in technology. Interest types reflect individuals' preferences for different work environments and activities that allow them to creatively use, synthesize, and adapt to novel technologies.	The Self-Directed Search (SDS); Intrinsic Motivation (Jaramilio et al. 2007).	There may be a connection between interest and performance and is based on other factors (e.g., congruence, self-efficacy); previous work shows that self-efficacy can predict vocational interest in technology.
Self-Directed Learning and Proactive Personality	Self-directed learning and self-regulated learning allow a person to guide their own learning and does not require formal training or external motivation. A proactive personality is likely to	Technology changes so quickly that a tech fluent person will need to learn technology and AI-related information and behaviors on the fly. There may not be time to wait for someone	See description in Section 6 for specific tools.	N/A
		Category 2: Cognitive Abilities		
General and (Logical) Reasoning	Ability to analyze complex problems, identify logical connections, and generate informed conclusions. Includes the capability to apply formal rules and logical principles to reach valid conclusions.	Supporting the effective interpretation of data, algorithm design, and decision making within the context of AI technologies. Reasoning, particularly logical reasoning, is crucial for assessing the capabilities and limitations of AI, making informed decisions about technology integration, and troubleshooting complex scenarios, all of which enhance the quality and efficiency of human-AI collaborations.	Watson-Glaser Critical Thinking Appraisal Halpern Critical Thinking Assessment Cornell Conditional Reasoning Test	N/A
Probabilistic Thinking and Pattern Recognition	Aptitude for reasoning under uncertainty, estimating probabilities, and interpreting probabilistic outputs, as well as the ability to identify meaningful patterns in data, extract relevant features, and apply appropriate machine learning techniques.	Enables individuals to navigate uncertainty by assessing and using probabilities, allows the identification of trends and regularities in complex data, aiding in the interpretation and interaction with AI-generated insights.	Cognitive Reflection Test (CRT) Probability Assessment Resource	N/A
Spatial Skills	Capacity to understand, reason, and remember the visual and spatial relations among objects or space.	Able to solve problems and make decisions based on perceiving and prioritizing relevant cues and patterns in info coming from multiple sources of a visual display that is embedded or embodies some type of technological or digital component.	Raven Tests The Mental Rotations Test (Vandenberg and Kuse 1978) is a test of spatial visualization using the stimuli from Shepard and Metzler (1971). This test consists of 20 items that prompt participants to indicate which figure is a rotated version of the criterion figure among distractor figures. The reported internal consistency and test-retest reliability were substantial (Kuder-Richardson 20 = .88 and α = .83, respectively).	N/A
Graph Literacy	Refers to the ability to understand, interpret, and communicate information using graphical representations, such as graphs, charts, and diagrams. It involves the ability to extract meaningful insights from data visualizations, make accurate inferences, and communicate findings to others.	One's ability to understand graphs and charts can help individuals identify trends, patterns, and relationships within the data, facilitating their ability to creatively use and synthesize information for enhanced performance with novel/new technology.	Graph Literacy Scale Galesic and Garcia-Retamero (2010)	N/A

Table A-1 Complete list of relevant knowledge, skills, and behaviors (KSBs) for technological fluency (continued)

KSB	Scope and definition	Scope for technological fluency	Tools/metrics to measure	Notes and possible caveats
Numeracy	How at ease people are with basic probability and mathematical concepts.	The ability to understand and work with mathematical models, algorithms, and formulas, enabling individuals to creatively use technology to enhance performance.	Lipkus Numeracy Scale (LNS) (Lipkus et al. 2001)	N/A
General Cognitive Ability (e.g., Inductive and Deductive Reasoning)	General cognitive capabilities of problem solving, and information processing refer to the capacity to understand and interpret information that is being presented, the ability to identify and solve problems, and the capability to learn new things quickly and efficiently.	The ability to facilitate problem solving, learning, adaptation, analytical thinking, troubleshooting, innovation, and creativity within a technological context may be crucial skills related to technological fluency.	Markauskaite (2007): see description in Section 7 for specific tools	N/A
Cognitive Biases	Common cognitive heuristics that may lead to inappropriate conclusions, such as fixation, convenience, ownership, and memory (like recency), etc.	Cognitive biases can interfere with problem solving, learning new behaviors, detection of poor performing AI, and implementing solutions.	Self-report, narrate-aloud qualitative methods: see section description for further specific tools	It might be helpful to look at or understand what underlies these traits, states, etc. What are likely to be impactful to these types of errors?
Metacognition	Thinking about thinking. This includes awareness of what is needed to learn or solve a knowledge or ability gap and strategies for doing so.	Understanding what one knows and does not know, and how to address any such gaps, will facilitate rapid learning and problem solving required for interacting with advanced technologies.	See description in Section 7 for specific tools	N/A
Systems Thinking and Strategic Thinking	Systems thinking is nonlinear thinking that examines not just the component parts of a system but also their interrelationships, allowing the consideration of emergent patterns, feedback cycles, unintended consequences, etc. Built upon systems thinking, reflection, divergent thought processing, and planning for an unknown future.	AI, and other advanced technologies, can be complex systems in themselves and are also parts of complex systems involving humans, machines, sensors, copious data, etc. Systems thinking should enable a person to better understand, predict, and improve outcomes from such complex systems. strategic thinking enables people to appreciate relevant complexities and plan for uncertain futures. Research in this area is primarily concerned with how technologies can facilitate strategic thinking; however, future research needs to examine reciprocal causal effects.	14-item self-report measure of strategic thinking (Srivastava and D'Souza 2021)	N/A
Working Memory	Working memory maintains information in an active state while simultaneously processing information or during distractions.	Working memory is needed for connecting ideas, understanding cause and effect, and any kind of mental synthesis—all of which are important when interacting with AI or systems.	See description in Section 7 for specific tools	N/A
Theory of Mind (ToM)	Ability to know what others (including machines) know, think, are aware of, and can do, etc. This also includes empathy and perspective-taking.	Working with AI or other machine agents will require understanding what the agent knows and does not know, what it can perceive, what it can do, and how it is thinking.	Assessing the degree of shared mental models can be an outcome measure for ToM	It might be worth noting whether technology can have a shared mental model with a human and whether that contributes to ToM. Explainable AI approaches may impact the development of shared mental models.
Learning Efficiency	Individual differences in learning rate and retention.	As technologies develop at a faster rate, operators who can learn the technologies faster will likely be at an advantage. It will be important to identify who is likely to pick up these new technologies more quickly. If technologies change rapidly, people who can learn rapidly will be at an advantage; however, to date, there is no direct evidence of this claim. Finding that people learn at different rates has been challenged using large-scale data.	Lithuanian-English word pairs (Zerr et al. 2018)	N/A

Table A-1 Complete list of relevant knowledge, skills, and behaviors (KSBs) for technological fluency (continued)

KSB	Scope and definition	Scope for technological fluency	Tools/metrics to measure	Notes and possible caveats
		Category 3: Social and Teaming Skills		
Cultural Awareness (Army Talent Attribute Framework [ATAF])	An individual's understanding and recognition of diverse cultural perspectives, fostering awareness, tolerance, and appreciation of cultural differences within the context of AI technologies.	Promoting fairness, inclusivity, and ethical considerations in AI development and deployment of novel technologies. Ensures sensitivity to diverse perspectives, enabling collaboration across global boundaries and preventing biased algorithmic outcomes. By understanding various cultural contexts, individuals can navigate ethical and social considerations inherent to AI and emerging technologies, fostering inclusive and responsible innovation.	Cultural Intelligence Scale (Ang et al. 2007). Intercultural Development Inventory (IDI) (Hammer et al. 2003). Cultural sensitivity training (e.g., Diversity, Equity, and Inclusion training)	N/A
Social Skills and Teamwork	Developing relationships, empathy, inspiring trust, humility, and sociability. Fostering inclusiveness, motivating different personalities, resolving conflicts, collaboration, coaching, and empowering others.	These types of skills generally facilitate effective collaboration (e.g., complementary team skills facilitate effective performance within technology-driven projects) and allow technology-fluent individuals to collaborate with others. Allows individuals working in teams to communicate via technological means, as well as using technology to augment team member skills and abilities.	Team Cohesion Measures and Performance Outcomes in Technology-Relevant Tasks. Communication Metrics to Assess Team Cohesion (Krausman et al. 2022)	N/A
Leadership and Project Management	Ability to gain consensus, place constraints on work processes, and prioritize and delegate efforts with a team to minimize duplication of effort. Includes general leadership, task/project management, performance management, and morale, and trains and develops others. Ability to plan, schedule, and manage complex work processes within domain of specialization, at times working with an interdisciplinary project team.	Future technologies will be able to learn; a good leader should be better equipped with the skills to guide learning-capable technology toward desirable outcomes. Autonomous agents have difficulty coordinating without a leader (Pugliese et al. 2015)	Multifactor Leadership Questionnaire ([MLQ] den Hartog et al. 1997)	N/A
Effective Communication	Able to communicate relevant information, written and spoken, across levels within the organization to contribute to distributed processes (e.g., supporting command and control processes during operations). Includes active listening, oral communication, written communication, and general communication. Ability to communicate technical information to diverse audiences in ways that the audience understands and are receptive to the message; develops rapport.	Common grounding outcome of good communication includes being able to select the appropriate communication technology to fit the purpose. Increased understanding of the range of personal, and public broadcast methods and awareness of the impressions of the audience. It can encourage reflection and academic reasoning skills through feedback and discussion.	Situational judgment tests	N/A

Table A-1 Complete list of relevant knowledge, skills, and behaviors (KSBs) for technological fluency (continued)

KSB	Scope and definition	Scope for technological fluency	Tools/metrics to measure	Notes and possible caveats
Category 4: Adaptability and Response to Change				
Situational (General) Adaptability	Those skilled at situational adaptability recognize the need to be flexible and act differently because no two situations are exactly alike. They know that using the same approach, tone, and style in different settings may be consistent but not necessarily effective.	Working with technology may be new and provide an environment that is inherently uncertain OR ambiguous OR does not have a clear-cut answer or path. This type of person must be comfortable in these scenarios and not allow the ambiguity of the environment to hinder their interactions with technology or performance. This KSB may allow individuals to adapt, restrategize, or restructure their plan of action to complete a task goal when faced with novel or unexpected situations, both of which may be readily apparent when working with new or evolving technology.	I-ADAPT: https://www.emerald.com/insight/content/doi/10.1016/S1479-3601(05)06001-7/full/html. Measure of "digital adaptability" (Bhattacherjee and Harris 2009). Measures relating to adaptation speed, facilitation, adaptation accuracy, recognizing change in AI, anomaly detection, rule set shifting, and procedural flexibility may be relevant for this construct.	N/A
Employee Agility	Ability to perform fast-learning processes by flexibly navigating between ideas and situations	Future tech will create turbulent work performance expectations. Future operators will need to quickly learn novel interfaces and functionalities (e.g., agile learning) and will need to think creatively about different approaches that could be implemented efficiently (e.g., innovative work behaviors).	Salmen and Festing (2022) recommend developing measures based on learning flexibility and Innovative Work Behaviors. Major criticisms of existing learning agility and other employee agility measures. Measure of employee agility Alavi et al (2014): measures the quick response of an individual to unexpected environmental changes and to adopt those changes appropriately.	N/A
Flexible Thinking/ Cognitive Flexibility	Able to exercise critical thinking, deductive reasoning, and adaptive thinking in high-intensity contexts. Considers new problem-solving approaches, creates new plans and ideas, and initiates and accepts change and innovation.	The ability to adapt thinking strategies and adjust cognitive processes when faced with changing situations or tasks, particularly those with novel and newer technologies.	Flexible Thinking in Learning (Barak and Levenberg 2016)	N/A
Comfort with Uncertainty vs. Need for Cognitive Closure	Intolerance of uncertainty, resistance to change, and need for closure are included in this category. These concepts refer to the ability to deal with changing technology, changing situations, changing battlefield conditions, changing teams, etc., and not always having full predictive ability or information. The ability to perform well even with the occurrence of unplanned events, interrupting the regular flow of work, prompting changes to a work schedule or planned action and making it difficult to predict the future of the work or necessary tasks.	Technology advances quickly, bringing change and unpredictability. A technology-fluent person should have sufficient tolerance for this change and unpredictability to effectively handle challenges that emerge. In addition, working with technology may be new and provide an environment that is inherently uncertain or does not have a clear-cut answer or path; thus, individual's high in this KSB will be comfortable with this and not allow the uncertainty to hinder their interactions with technology or performance. Finally, the technology fluent individual may face immense time pressure and other stressors; thus, a greater need for cognitive closure could interfere with making timely and effective decisions.	Resistance to Change Scale (Oreg 2003) (with subscales related to emotional stability) Budner (1962) Tolerance of Ambiguity Scale Personal Innovativeness in Information Technology (PIIT) (Agarwal and Prasad 1998) Measured by need for cognitive closure (NFCC) as a negative indicator, NFCC is a desire for an answer, any answer, on a topic, compared to being in a state of uncertainty. Time pressure and other perceived costs (e.g., effort, labor) could elevate this desire.	N/A
Category 5: AI-Relevant Knowledge and Experience				
Knowledge, General Understanding of AI, and Computational Thinking	Refers to several actions and behaviors including using AI in the correct situations, correctly, and as intended. This also refers to debugging, classifying AI errors, general understanding of AI, and computational thinking. Knowing the basic functions of AI and how to use AI applications. Knowing that artificial general intelligence (AGI) is the representation of generalized human cognitive abilities in software so that, faced with an unfamiliar task, the AGI system could find a solution. The intention of an AGI system is to perform any task that a human being can.	Someone with this KSB would have a general knowledge of how AI works, what the processes are, and how to best use those capabilities. An individual's ability with novel technology plays a crucial role in determining their AI-related behaviors. Proficiency enables them to use AI correctly, as intended, and in the right situations. Conversely, a lack of understanding can result in unintentional misuse, whereas high proficiency may lead to creative and beneficial unintended uses and ensuring that users are able to identify where novel technologies break down.	Pinski and Benlian (2023); perceived AI-learning (Halic et al. 2010)	N/A

Table A-1 Complete list of relevant knowledge, skills, and behaviors (KSBs) for technological fluency (continued)

KSB	Scope and definition	Scope for technological fluency	Tools/metrics to measure	Notes and possible caveats
Digital Literacy	Digital literacy is described as complex thinking competencies involving cognitive, motor, emotional, and social skills that enable users to operate intuitively and effectively in digital environments for work, learning, and daily functioning.	The foundational knowledge and skills necessary to creatively and proficiently discern reliable sources, synthesize information from various digital resources, and adapt that knowledge to enhance their performance using novel technologies.	The five digital competences assessment tool: https://fiction.pixel-online.org/TK_ICTLO.php Review of other measures: https://fiction.pixel-online.org/TK_CAT.php Digital Competence Test (European): https://digital-skills-jobs.europa.eu/en/inspiration/resources/digital-competence-test	N/A
Beliefs About AI	Beliefs about AI can be defined empirically using a scale that includes two items designed to gauge public perceptions of AI's superiority and problem-solving abilities compared to human intelligence.	Individuals' attitudes and willingness to embrace AI as a tool for enhancing performance. Individuals who believe that AI is higher than human intelligence are more likely to adopt algorithmic advice.	See description in Section 10 for specific tools	N/A
Algorithmic Thinking	Knowledge of potential AI models: Algorithmic thinking is a system of thinking methods that is necessary to build a sequence of obtaining intermediate results, planning the structure of actions and its implementation, leading to the achievements of the goal.	The ability to use computational thinking to translate real-world problems into computational models, allowing them to apply algorithmic thinking and leverage technology to develop efficient and automated solutions. Algorithmic thinking plays a significant role in shaping digital literacy. It enables individuals to comprehend and engage with digital technologies more effectively, fosters critical thinking and problem-solving skills, and empowers them to actively participate in the digital world.	Çoban and Korkmaz (2021; see description in Section 10 for specific tools)	N/A
AI Literacy	The ability to be aware of and comprehend AI technology in practical applications; to be able to apply and exploit AI technology for accomplishing tasks proficiently; and to be able to analyze, select, and critically evaluate the data and information provided by AI, while fostering awareness of one's own personal responsibilities and respect for reciprocal rights and obligations.	In the context of tech fluency, AI literacy complements the broader concept of tech-savviness. Although technology savviness focuses on individuals' ability to use and adapt to novel technologies creatively, AI literacy is a specific subset of technology savviness that relates to AI technology. Technology savviness encompasses a wider range of technological skills and adaptability, whereas AI literacy is more specialized, concentrating on AI-related competencies.	Artificial intelligence literacy scale (Wang et al. 2022)	N/A
Propensity to Trust in Technology and Trust Calibration	Propensity to trust, also referred to as a general disposition toward trusting others, is a trait that remains stable over time, is unique to the individual, and influences the decision to enact trusting behaviors. This includes the ability to self-monitor interactions with autonomous or smart systems to maintain awareness of potential states of over trust.	This may relate to detecting deficiencies in the system. Calibrating trust in this context may relate to individuals being able to effectively use technology because they trust it and can see that it is working as it should. In contrast, if the system is not working as it should, the individual must be able to perceive and comprehend this (thus avoid over-trust state), change course, or communicate this to their team or lead for example. However, propensity is a trait and something someone comes in with. Trust calibration is an outcome variable and may relate to a person's ability to detect that the system is not working as it should.	Interpersonal Trust Scale (Rotter 1967); Propensity to Trust Scale (Mayer et al. 1995); Propensity to Trust Survey (Evans and Revelle 2008); Complacency Potential Rating Scale (Singh et al. 1993); Propensity to Trust Technology Scale (Schneider et al. 2017); Internet perceptions Ford and Miller's (1996) 12-item questionnaire.	Trust propensity and trust calibration are different things. Trust propensity does not necessarily mean you will have proper trust calibration; however, if your trust propensity is too high or too low to begin with, it will be very hard to develop appropriate levels of trust and thus be able to effectively calibrate trust.
Video Gaming Experience	The amount and/or frequency of experience a person has with playing video games, often considered along with the types of games they play. It may also involve consideration of video gaming expertise.	Familiarity and comfort with video games should improve facility with game-similar technology elements that are present in many AI and advanced-technology systems. Video game experience is also associated with a suite of diverse skills, including spatial, attentional, and social soft skills, and these are beneficial for interaction with advanced technology and human-technology systems.	See description in Section 10 for specific tools.	N/A

List of Symbols, Abbreviations, and Acronyms

2D/3D	2-dimensional/3-dimensional
ACRM	Anesthesia Crisis Resource Management
AGI	artificial general intelligence
AI	artificial intelligence
AILS	AI Literacy Scale
ATAF	Army Talent Attribute Framework
BCI	brain-computer interface
BES	Basic Empathy Scale
CDCFT	Common Digital Competence Framework for Teachers
CEW	computer-email-web
CITS	Coping Inventory for Task Stress
CQS	Cultural Intelligence Scale
CRT	Cognitive Reflection Test
CV	Curriculum Vitae
DEVCOM	US Army Combat Capabilities Development Command
DIGCOMP	Digital Competence
DL	digital literacy
DQ	digital intelligence
EQ	Empathy Quotient
ETS	Educational Testing Service
FTL	Flexible Thinking in Learning
GALT	Group Assessment of Logical Thinking
HAT	human-autonomy team
ICT	Information and Communication Technology
ICT-CFT	ICT Competency Framework for Teachers

IDI	Intercultural Development Inventory
IRI	Interpersonal Reactivity Index
ISTE	International Society for Technology in Education
IT	information technology
JCS	Joint Cognitive Systems
KSB	knowledge, skills, and behavior
LNS	Lipkus Numeracy Scale
MALQ	Metacognitive Awareness Listening Questionnaire
MLQ	Multifactor Leadership Questionnaire
MSLQ	Motivated Strategies for Learning Questionnaire
N/A	not applicable
NAP	National Assessment Program
NFCC	need for cognitive closure
NFCS	Need for Closure Scale
OECD	Organization for Economic Cooperation and Development
PAR	Probability Assessment Resource
PIIT	Personal Innovativeness in Information Technology
RTC	Resistance to Change
SBTT	Simulation-Based Team Training
SDL	self-directed learning
SDS	Self-Directed Search
SMS	Short Message Service
STEM	Science, Technology, Engineering, and Mathematics
SRSSDL	Self-Rating Scale of Self-Directed Learning
TAPAS	Tailored Adaptive Personality Assessment System
TASIT	The Awareness of Social Inference Test
TF	technological fluency

TOLT	Test of Logical Thinking
ToM	Theory of Mind
UAV	unmanned aerial vehicle
UNESCO	United Nations Educational, Scientific, and Cultural Organization
VR	virtual reality
WM	working memory

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