Intelligence Augmentation: Upskilling Humans to Complement AI

Applying Learning Sciences Research to Learning and Workforce Development for Next Level Learning Brief Series

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In the Star Trek series, Captain Picard's judgment, decision making, and deliberation skills are enhanced by the reckoning, computation, and calculation skills of Data, an android lacking human abilities. Together Captain Picard and Data complement one another. The synergistic combination of Picard's judgment and Data's reckoning provide better decision-making outcomes than the sum of their individual contributions. In this brief, we describe such a partnership as "intelligence augmentation."

Executive Summary

While many forecasts chart an evolution of artificial intelligence (AI) in taking human jobs, more likely is a future where AI changes the division of labor in most jobs, driving a need for workforce development to shift towards uniquely human skills.

Specifically, AI is becoming increasingly proficient at calculation, computation, and prediction ("reckoning") skills. As such, we will see increased demand for human judgment skills such as decision-making under conditions of uncertainty, deliberation, ethics, and practical knowing. Developing human judgment skills follows well from the broadened conception of learners presented in the earlier briefs in this series. This brief focuses on the important topic of how workforce development can help humans prepare to collaborate with artificial intelligence to do work that neither are capable of in isolation.

Framing Questions

- What does Intelligence Augmentation look like in action?
- Why can't AI now perform human-level judgment skills, and might this change in the future?
- What are the judgment skills that workforce development needs to prioritize?
- What learning models and experiences can help develop judgment skills?
- In what ways does prior research show promise for building judgment skills in a workforce development context?
- What next steps are recommended?

Introduction

To understand how to augment intelligence, we must first consider modern conceptions of what intelligence is. While there are significant bodies of literature on many aspects of intelligence, for this brief, we take a broad and general view and refer to intelligence as “the disposition to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience.”[1] Note that the conception of intelligence being used here is aligned with current research on intelligent behavior. It is performance-based—meaning that it depends upon what one can do with one's intelligence—instead of being only about what abilities one holds in one’s head.[2] Further, it is dispositional in that ability is only a part of what contributes to intelligent behavior; it also includes sensitivity to the occasion to deploy capacities and the inclination necessary to follow through.[3]

In a workplace context, our notion of intelligence can be divided into two complementary roles: *reckoning* and *judgment*.[4] Reckoning refers to calculative prediction and formulaic decision-making, at which computers and AI systems already excel.[5] For example, when an AI dashboard advises a food warehouse automated selector, it is asked to pick things considering the temperature at which the food item should be stored, its volume, and the order in which items will be dropped off by the delivery truck. Another illustration of this is when physicians consult programs that can estimate the life expectancy of a particular cancer patient, given their characteristics and available treatments.

In contrast, judgment is a form of deliberative thought that seeks to be unbiased, grounded in ethical commitment, and appropriate to the situation in which it is deployed.[6] Drawing on the example above, the warehouse foreperson considers the speed at which the automated selector should go based on the warehouse foot traffic and occupational health and safety. The physician exhibits judgment when helping a cancer patient choose treatment options, as they must weigh the quality of life and life expectancy.

These depictions suggest a complementary partnership in decision-making, with AI doing the reckoning at a level of speed, accuracy, and scale of data not attainable by humans, and humans basing their judgments in part on this reckoning, but also on other variables AI cannot factor. For example, without the AI dashboard, the warehouse foreperson spends most of their effort calculating a picking route and has limited time to focus on making sure it is done safely. The foreperson contributes knowledge of occupational health and safety, which the AI might struggle to incorporate. Equally, the cancer physician working without AI spends most of their effort in reckoning treatment options, with little time to realize the goal of helping the patient make complex decisions about the quality of life for which the AI is inadequate. Further, despite

spending considerable time on the reckoning task, both the foreperson and the physician cannot accomplish the massive and complex reckoning of which their AI peers are capable. On the other hand, the two of them bring judgment and decision-making skills to factor in the context-specific human experience and condition, which the AI cannot currently emulate to the same degree.

While some industry lists classify human judgment and decision-making skills as soft skills, we conceptualize these abilities as a unique category of their own. Soft skills are a host of social, emotional, attitudinal, and communication skills that influence people's interactions with one another. Judgment and decision-making leverage information or inputs gathered from an individual's soft skills, along with the interpretation of contextual factors and potentially non-human information, to determine a course of action. Thus, effective judgment needs strong soft skills, but the two concepts should not be considered equivalent.

Intelligence augmentation is when AI and humans engage in a complementary partnership in which a human-and-AI team's overall performance is greater than their individual capacity. As AI takes over a greater percentage of the reckoning tasks, the need for workers to engage in a complementary relationship with machines will become more important. Thus, workforce development must increasingly prepare people to thrive in this new division of labor by supporting the development of judgment skills rather than focusing primarily on reckoning skills.

What Does Intelligence Augmentation Look Like in Action?

One of the most challenging tensions facing workforce development is preparing people to attain a job tomorrow and thus maintain economic inclusion, versus preparing them to thrive in the future. One might say that this has been a long-time tension of the sector. Traditionally, people have been skilled for initial jobs on the assumption that they would then evolve with the job over time. However, the pace of AI-led changes to the division of labor between machines and humans (Figure 1) means that people need to leave workforce development programs with some judgment skills for the future as AI rapidly becomes more capable of reckoning.

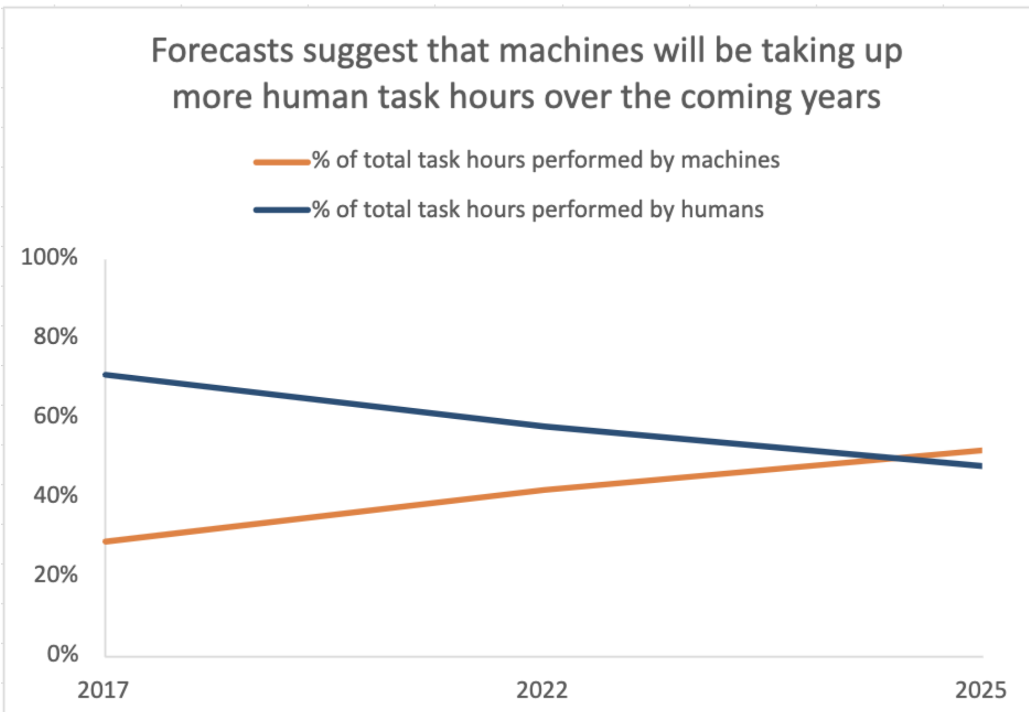


Figure 1. Division of Labor Between Humans and Machines[7]

To understand what these skills for the future are, it is helpful to highlight forecasts of likely shifts in occupations. In 2017, Pearson partnered with the British think tank NESTA to analyze the future of occupational skills.[8] As part of their findings, NESTA generated descriptions of six job roles in 2030, highlighting how current trends would reshape these occupations from what they were in 2017. Here, the brief builds on that foundational work to discuss how capacity building for two of these roles might alter because of the development of AI-based partnerships with humans' intelligence augmentation.

The two examples of hypothetical cases detailed in Table 1 focus on small businesses in high-growth industries – food services and green energy – and represent the small business owners that account for two-thirds of net new jobs in the United States. These examples introducing the cases of Mel and Lisa are illustrative, and the described complementarity between AI-based reckoning and human judgment could generalize across various other economic sectors and organization sizes.

In both of these hypothetical cases, NESTA's 2030 future forecast has come about more quickly. For Mel, that has been due to the COVID-19 pandemic; for Lisa, it has occurred because of accelerated climate change. To maintain economic inclusion in 2030, both Mel and Lisa need to develop new skills.

Currently, each spends significant amounts of time and effort on reckoning skills. These include estimating sales and demand, ordering supplies and materials, keeping an inventory, developing advertising/marketing, scheduling, adjusting types and staffing levels to meet demand, and managing cash flow, accounting, payroll, and taxes.

Not only have AI-based systems already started to assume most of these tasks, but they also do these more effectively and accurately than the results humans could achieve. For example, AI tools can calculate demand for assorted items or services. Furthermore, they can adjust these calculations based on factors such as weather, customer demographics, food preferences, community health, and customer churn. This enables them to predict customer value figures or job marketing campaigns by systematically weighing a matrix of influential variables and data points. Offloading these parts of their roles will enable Mel and Lisa to invest in extended activities based on human judgment, where the computer's limited algorithmic structure breaks down. They can focus more on their embodied experiential knowledge (described in more detail below) about current customers, trends, regulations, and specifications.

Table 1: The Hypothetical Cases of Mel and Lisa Excerpted from NESTA 2017

Mel, an imagined 52-year-old restaurant owner in the year 2030

Mel, a restaurant owner from Manchester, has owned her own business and worked in catering for many years. While changing consumer needs have always impacted the industry, most recently shifts have shaped why and how people entertain. Consumers, predominantly millennials emerging as the dominant spenders, prioritize novel and engaging experiences in their spending preferences.

Further, the home is becoming the increasingly predominant venue to entertain, and a greater number of on-demand services are now available through doorstep delivery. While Mel has used some of these services to sell her products, she has had to innovate and diversify what she offers to attract new customers. She has experience in the management and service orientation aspects of her work, but she lacks proficiency in other skills such as designing original and new in-demand experiences.

Lisa, an imagined 39-year-old construction worker in the year 2030

Lisa, a construction worker, entered the workforce in 2007–09. At the time, she saw that green construction was one of the few segments that proved resilient to the market's global recession. After completing an apprenticeship program, demand for her green services grew in the residential and industrial markets. The promise of lower costs, new home energy efficiency policies, and the association of green homes with healthier living all acted as catalysts for growth.

A substantial part of Lisa's work has involved remodeling and refurbishment projects, from fitting water-efficient appliances such as dual-flush toilets, to installing systems that reuse greywater and roofs with solar photovoltaic panels. Gig work in construction, which puts a high premium on strong administration and management, has become even more prevalent in recent years. These skills and others, such as customer and personal service, are increasingly helpful for small businesses like Lisa’s. Due to robust demand for green construction, labor shortages have emerged. To encourage entry into the field, Lisa has expanded the number of apprenticeships and serves as an ambassador to local career fairs and schools.

Specifically, with developed judgment skills, Mel would draw more on her knowledge and background of sensory experiences with taste to understand and craft unique and enticing dishes and meals that meet customer demand. Mel would leverage her experience to forgo some initial profit to build a compelling reputation for social consciousness, fair dealing, and caring about her community. For Lisa, developed judgment skills would enable focusing on her knowledge about the physical and cognitive requirements of construction work and cultural knowledge about preferences and patterns related to the environment and style of living. She would apply her wisdom to socially champion increased investments in green technology and promote benefits to organizations that use sustainable practices.

Evolving workforce development initiatives to enhance judgment and, as a result, achieve intelligence augmentation is an under-recognized strategic priority. Over the next decade, as the cases of Mel and Lisa indicate, advances in AI will change the division of labor in most jobs, so workforce development must shift more towards capacity building for judgment and situationally applied wisdom.

Why Can't AI Now Perform Human-Level Judgment Skills, and Might This Change in the Future?

Although AI will take over many of the specific tasks humans perform, machines cannot achieve judgment skills in the creative, socially sensitive, and personally responsible way humans can.[9] Just because computers can perform something does not mean they can attain the level of competence humans provide.[10] People conduct these activities with the depth and sensitivities that computers lack.

Artificial intelligence fails to emulate judgment skills for several reasons.[11] AI-based systems cannot read social clues needed for accurate interpretation and are therefore confused when encountering the various indeterminacies and ambiguities confronted by people in everyday life. Further, nuances in language and social customs lack the stability and precision to be reliably captured by computers, particularly when processing information from many sources representing distinct customs.[12]

Specifically, any machine-based decision-making system, by its very nature, lacks several types of knowledge universal in human beings. The descriptions below draw closely on Gulick:[13]

- *Embodied Experiential Knowing (EEK).* This category includes bodily-based relational processes such as perceptions, interests, and drives. Intentional actions are based on embodied, experiential, and meaning-laden knowledge rather than simply observational and scientific knowledge. Because humans are embedded in and respond to our physical surroundings, their intelligence is different from the semantic and neural nets of AI. Extending beyond Gulick, humans bring the additional asset of emotion to the embodied knowing. As discussed in the first brief on agency, research in neuroscience underscores how emotion is key to using embodied experience in rational, efficient, and agile decision-making. It leverages what is referred to as "somatic markers" or memories stored in our bodies to facilitate our gut reactions.[14]
- *Collective Cultural Knowing (CCK).* This category reflects that other people's intentions are not obvious, nor is communication just a matter of rational discourse. It is difficult for AI to distinguish between sarcastic expression, irony, humor, or evoked expressions of the heart. A holistic understanding of context, attitude, tone of voice, body language, character, and much more is needed to interpret meaning. AI does not have the capacity in the near future to develop such sensitivity because it cannot experience culture in these ways. As discussed in the third brief on adaptive expertise, humans often hold a flexible notion of culture and can reflect upon different paradigms of cultural knowing, recognizing when an expression fits with the features of particular cultural assumptions.
- *Personal Performative Knowing (PPK).* This category celebrates the uniquely responsible character of human intelligence. Polanyi speaks of humans as centered beings who dwell under what he calls a firmament of values.[15] Certainly, human life must be responsive to the perceptions, interests, and drives of EEK and the social influences of CCK, but humans are not puppets without consciousness or identity. PPK involves a first person's conscious point of view having moral overtones and personal identity; AI will not demonstrate any of these characteristics soon.

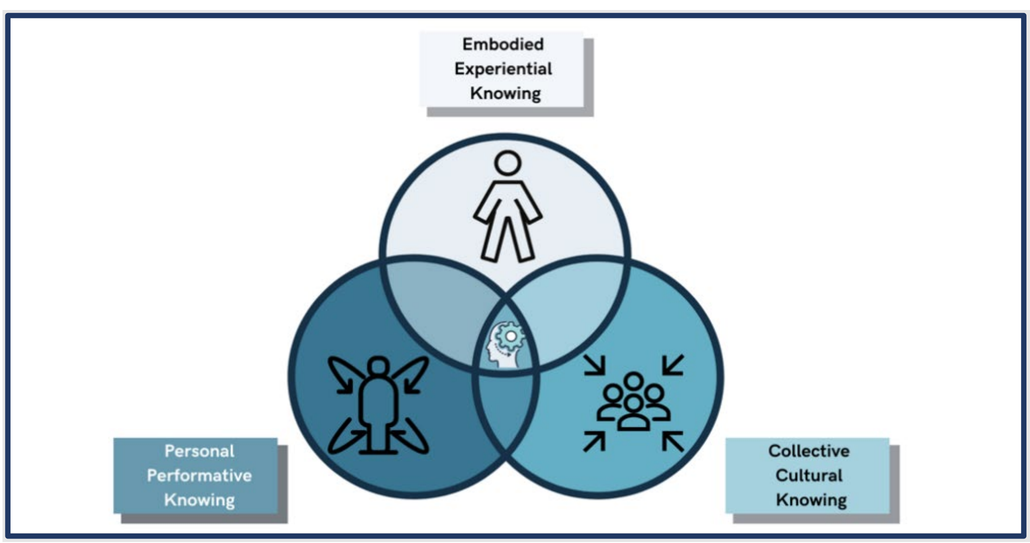


Figure 2. Fundamental Differences Between Persons and Machines[16]

What Are the Judgment Skills That Workforce Development Needs to Prioritize?

Workforce development needs to enable learners to develop EEK because it is practical and concerned with the actual doing of things within the embodied nature of lived experience. A computer will not know what it is like to have a body influenced by one's environment. Future workplaces will also require CCK because life involves social communication and cultural processes, norms, and values. A computer will not know what it is like to be inculcated in various cultures. Furthermore, to thrive in the workplace, people will need PPK because an ethical sensibility is part of all human beings—whether or not they choose to act on it—and computers lack consciousness, identity, and moral capacity.[17]

Levels of judgment can be classified as micro, meso, and macro (Figure 3).[18] For example, a workforce development practitioner might have micro-judgmental abilities to help a learner whose homelife faces an unexpected crisis. They could develop meso-judgmental abilities to aid learners experiencing socio-emotional difficulties, from abusive partners to bullying by peers, or even to food insecurity. While beyond what we will discuss in this brief, they could have the macro-judgmental capacity that draws upon their applied wisdom about helping people of any age experiencing socio-emotional trauma at work or in life.

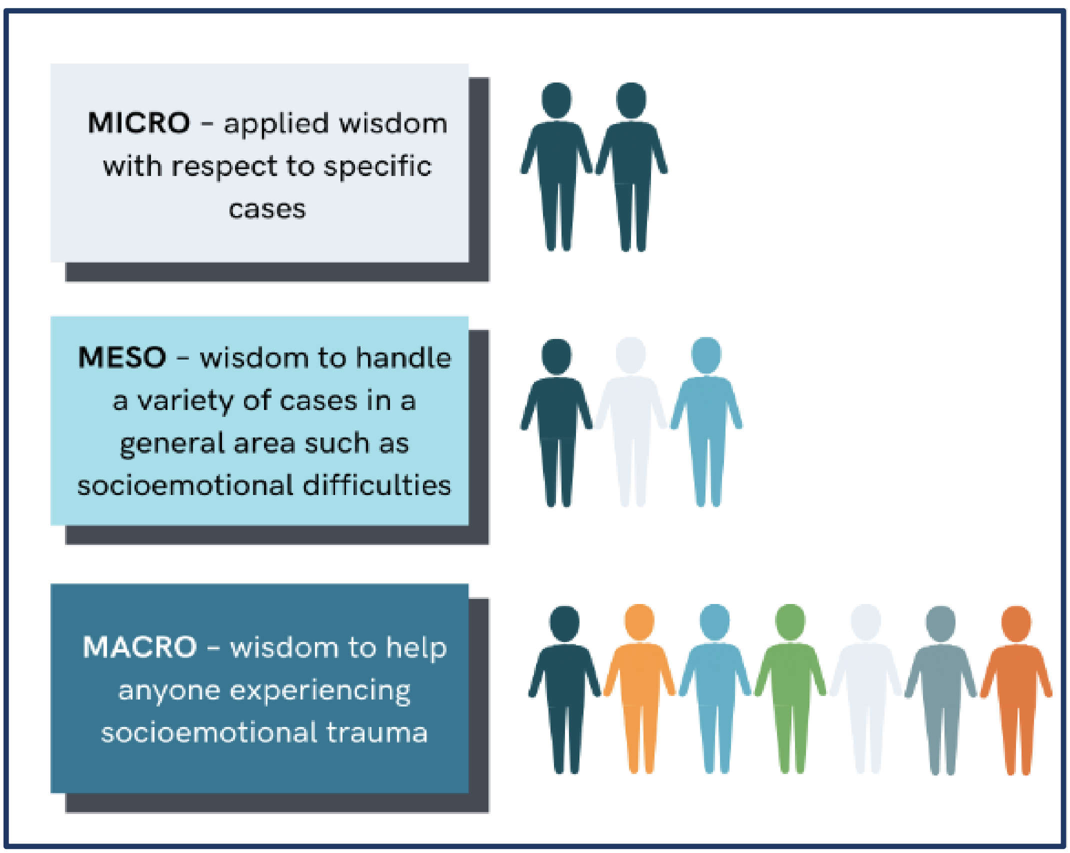


Figure 3. Micro, Meso, and Macro Levels of Judgment

In each of these three examples, the workforce development practitioner has shown judgment because they draw on types of knowledge (embodied, cultural, ethical) unattainable by AI. To complement workplace AI-based systems that perform reckoning, people need micro-level and meso-level capacity building in EEK, CCK, and PPK.

The Evolution of AI Towards Human Judgment Skills

How rapidly might AI develop towards the ability to emulate EEK, CCK, and PPK? No digital or biological technologies currently under development could experientially understand embodied, cultural, and ethical dimensions of judgment. However, some experts argue that, through machine learning and machine teaching (AI simulating situations, then using them as virtual venues for machine learning), AI could emulate human judgment even though it would have no conscious understanding of what it is doing.[19] Resolving the sophisticated technical and conceptual dimensions of this claim is beyond the scope of this brief, as this leads to complex philosophical issues, such as morality[20] and the definition of *understanding.*[21]

Fortunately, a simpler lens can shed light on whether AI will overtake human judgment in specific occupations over the next few decades. From an economic perspective, one substitutes a machine for a person only when it is more efficient or effective. AI systems that are more expensive or less efficient than what people will do for a reasonable wage won't be built. The cost of emulating EEK, CCK, and PPK in an occupational role depends on how dependent decision making is on contextual factors (the specific characteristics of the people affected and the setting in which the decisions are implemented). For example, tellers in a bank were largely replaced by ATMs in many locations because the service provided does not depend on the characteristics of the customer or the context in which the financial transaction occurs. In contrast, the services Mel and Lisa provided are very dependent on the attributes of their customers and the situated experiences those clients like to have.

So, in determining how long human judgment skills inculcated in workforce capacity building will resist the encroachment of AI, a good rule-of-thumb is the extent to which contextual factors shape the judgments involved. For many occupations, it will be a long time—if ever—before AI systems become capable of EEK, CCK, and PPK; and before their use outweighs the costs for their efficiency and effectiveness.

What Learning Models and Experiences Can Help Develop Judgment Skills?

Research in the learning sciences shows that judgment skills can be taught and that teaching and learning with particular features are instrumental to the endeavor. For instance, these instructional models view intelligence as learnable and teach the thinking dispositions that enable high-level judgment.[22] They recognize that emotion is a critical aspect of reasoned judgment,[23] and include attention to gut knowledge and intuition.[24] They purposefully seek to develop intellectual character, which includes attention to curiosity, open-mindedness, and skepticism.[25] They build upon the neuroscience and cognitive science of learning that offer insight into how the human mind learns best and how brains learn better than machines.[26] Currently, learning experiences related to EEK, CCK, and PPK tend to be restricted to those with access to expensive liberal arts degrees or informal learning environments where they are socially modeled. These spheres are highly privileged and not readily accessible to many – including Mel or Lisa. Instead, typical workers must rely on workforce development programs, eligible training providers, MOOCS, and alternative credentials to upskill. These forms of training currently focus on narrow, tangible reckoning skills (e.g., understanding formulaic processes involved in food safety or information-based politics like LEED regulations) rather than teaching a contractor, for example, how culture affects people's uptake of environmentally friendly construction materials.

At present, outside of an academic setting, learning opportunities for judgment skills are sparse and exclusive. For example, the Giving Voice to Values program, an innovative values-based judgment curriculum that focuses on ethical implementation, has been piloted in hundreds of schools, companies, and professional associations. But the program is delivered as a brief intervention, not as an ongoing option for interested individuals.[27] Work Wisdom Academy offers ongoing workshops to help Lisa and Mel in authentic communication, the science of influence, culture shaping, and meaningful work. However, it carries a prohibitive price tag between $3,000 and $5,000 for its programs.

More cost-effective options like edX's "Ethical Decision-Making: Cultural and Environmental Impact" or Class Central's "Cross-Cultural Competency," on the other hand, offer one-off experiences and lack engrained authentic practice of course concepts; these are not effective learning opportunities. Therefore, there presently is a shortage of accessible, valuable learning experiences related to judgment for workers. Furthermore, available programs lack sufficient levels of embedded practice of principles, which is central to developing judgment skills.[28]

In What Ways Does Prior Research Show Promise for Building Judgment Skills in a Workforce Development Context?

Prior research in immersive media shows promise for training practical wisdom and the EEK, CCK, and PPK inherent in judgment. The ability of immersive technology to simulate body ownership (the perceptual illusion that the virtual body is the person's own body) allows us to better comprehend the mechanisms governing experiential knowledge, cross-cultural understanding, and moral values development. Various experiments illustrate that taking the form of the virtual body can result in implicit changes in attitudes, perception, cognition, and behavior.[29]

Immersive media possess the potential to induce changes in people's bodily experiences, their viewpoints of the world and one another, and potentially their identities and conscious values.[30] Some strategies show promise regarding how we can effectively develop capacity-building experiences in judgment and applied situation-specific wisdom.

Table 2: Research and Studies on Teaching Gulick's Three Types of Knowing

- ***Embodied Experiential Knowing*** - An experiment in virtual reality (VR) demonstrated that people evaluate their own, virtually presented body differently, and sometimes more favorably when they view it from a third person- rather than first-person perspective.[31]
- ***Collective Cultural Knowing*** – Researchers found that perspective taking (i.e., perceiving a situation or understanding a concept from another's point of view) could be manifested in virtual worlds by having participants virtually experience another individual's perspective.[32]
- ***Personal Performative Knowing*** - A study of males placed in a VR scenario of sexual harassment showed that action conformity, possibly via moral judgment, could be influenced by experiencing an embodied perspective either as a woman or as a male in a group of virtual males.[33] In another study, when compared to traditional and less immersive perspective-taking activities, the immersive experience of becoming homeless resulted in a significantly higher proportion of participants exhibiting helpful behaviors toward the homeless.[34]

Opportunity exists to explore better ways of designing immersive learning experiences to maximize the development and transfer of meso-level judgment abilities from the domain they were acquired to different situations. Immersive technology can potentially unlock ways to make judgment training more tangible and sustainable by transforming what is abstract (e.g., ethics, cultural values) into concrete instances. It can support "doing" rather than mere observation, arming participants with agency to initiate actions that have novel consequences and encouraging social interactions between coexisting participants where each participant can interact with others and influence what occurs in the simulation via their actions.[31]

While this section has focused on high-end technologies, such as immersive media, some training can be done with "Wizard of Oz" approaches in which learners interact with technology controlled surreptitiously by humans who emulate AI-system behavior that is not currently possible but is expected within a few years. For example, as a research experiment, some restaurant owners could be provided with various types of reckoning not now available from machines but simulated via a machine controlled by a human being. They could then be asked to spend the additional time they gained from their typical work refining judgment-related activities. This would be an initially, low-tech way of assessing how improved reckoning might lead to intelligence augmentation.

What Next Steps Are Recommended?

Tactical investment in understanding how to enhance various forms of judgment is an important priority. Insights and evidence about developing these capabilities are needed, and design-based research is a useful approach. Focusing on roles for which machine-based reckoning is now emerging is an excellent place to start. Our team has conceptualized a few research questions that, if addressed, would be the next steps down this line of inquiry:

1. To what extent, if any, is immersive learning of micro-level and meso-level judgment more effective or efficient than non-immersive learning? And what "dosage" is needed in the length and timing of learning experiences?

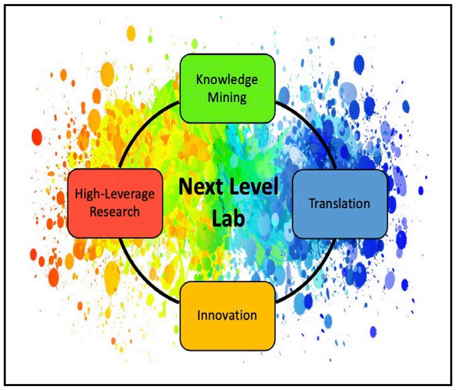
2. How much is situational variation in learning experiences for meso-level judgment necessary to develop transfer of judgment skills from one context to another?

3. To what extent can reckoning skills be deemphasized in human capacity building as these tasks shift to AI-based systems?

4. Given the potential for algorithmic bias in AI-based reckoning, what types of judgment-based training should people receive to recognize and mitigate this?

These and other issues will require substantial research to enable their successful resolution. We believe that this type of tactical investment will have considerable pay-off in the future of work.

About the Next Level Lab:



This work was developed through the Next Level Lab: Applying Cognitive Science for Access, Innovation, and Mastery (AIM) at the Harvard Graduate School of Education (HGSE) with funding from Accenture Corporate Giving (ACC). Any opinions, findings and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the funder. The Next Level Lab is pursuing this work as we articulate the findings from research in cognitive science, neuroscience, and learning sciences that inform approaches to education and workforce development. Our work sits at the intersection of mining extant research of promise; conducting research questions with the potential for high-leverage impact; translating research on learning and the mind for public use; and innovating in the space of technology and learning to develop new visions for what is possible in developing human potential.

We are a small research lab. We view our mission as one of providing purpose and guidance to the field. Buckminster Fuller talked about the power of small influences in his description of a trimtab in this quote.

"Something hit me very hard once, thinking about what one little [person] could do. Think of the Queen Elizabeth again: The whole ship goes by and then comes the rudder. And there's a tiny thing on the edge of the rudder called a trim tab. It's a miniature rudder. Just moving that little trim tab builds a low pressure that pulls the rudder around. It takes almost no effort at all. So I said that the individual can be a trim tab. Society thinks it's going right by you, that it's left you altogether. But if you're doing dynamic things mentally, the fact is that you can just put your foot out like that and the whole ship of state is going to turn around…." -Buckminster Fuller.

It is our hope that our small lab can function as a trimtab to create better outcomes for humankind.

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