From Know-It-Alls to Learn-It-Alls: Executive Development in the Era of Self-Refining Algorithms, Collaborative Filtering and Wearable Computing

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Abstract

We examine the future of executive education on a technological and cultural landscape that is imminent but different to the one we are accustomed to. We show how the contextualization, socialization and personalization of learning – avowed but distal goals of current executive education programs – are made real by the integration of a suite of currently available technologies and ways of using them that bring learners together in dense and intimate learning networks (socialization), powered by semantic and social search technologies that adapt content to individual learners' styles and preferences (personalization) and can be deployed in the setting of the learners' own organizations (contextualization) – all of which serve to optimize the learning production function for both skill acquisition and skill transfer – the two charges that the new skills economy has laid out for any educational enterprise.

Introduction: The Next Disruption in Executive Development   - and What it Means.

We have shown that the current state of the field of executive development is beset by both a skills gap and a skills transfer gap [Moldoveanu and Narayandas, 2018a] – and that that the current industry is set for massive disruption by a trio of forces induced by the widespread digitalization of both content and interactions: disaggregation of learning experiences, disintermediation of the value chain and decoupling of the sources of value to users. In [Narayandas and Moldoveanu, 2018] we showed that there is also a misalignment in the objectives and incentives of executives and the organizations that employ and support them with respect to the field of executive development yet another gap which encourages and facilitates the sort of fine-grained search and optimization of the units of learning that the Web 2.0 enables – and which is about to be exploited by a host of new entrants to the field [Moldoveanu and Narayandas, 2018b]. As real skill acquisition and transfer are likely to be the most important metrics by which executive development experiences are measured, we synthesized a strategic compass to help chief learning officers navigate the changing landscape [Moldoveanu and Narayandas, 2018b] and a vectoring map for incumbents who want to re-design their offerings to leverage the emerging personal learning cloud and the most important aspects of in-person interactions as they re-design the content, context and experience of their offerings.

In this paper, we loosen the constraints of current market and institutional structures - which have bounded and gridlocked human learning for centuries - and explore possible dynamics of executive learning in particular and adult learning more generally by asking: How can we leverage technology and culture to produce the optimal learner-centric learning experience for a developing

executive? Using examples whose relevance we justify through research findings we show that learning works best – it happens most efficiently and reliably - when it is *contextualized, personalized and socialized.* We explore the ways in which the technologies enabling sensing, interacting, computing, searching and storing can be leveraged by innovators and educational designers to produce learner-optimal experiences.

The science of learning may be mature, but learning technology is in its infancy. As the information technology revolution gains ground, the $5-trillion global education business is experiencing a series of changes that re-shape the processes, tools, techniques, and experiences of learning. The process is driven by the need to rein in the rising costs and enhance the currently uncertain benefits of the status quo as well as the disaggregation, decoupling, and disintermediation that is currently re-designing the learning landscape [Moldoveanu and Narayandas, 2018a].

That is not surprising. Industry-wide disruptions are not one-off events; they are akin to earthquakes in that they travel in groups, one tremor facilitating the next. In the case of digitalization, the vortex has spread from computing, telecommunications, and semiconductors to media, entertainment, publishing, travel, transportation, and, now, education. It is a well-documented habit of many organizations to focus on today's disruption, and not look ahead to the next day's.

But those seeking education and development are by their nature forward-looking. Educational 'products' – skills, abilities and mindsets - and the badges, diplomas, certificates and degrees that signal them to various degrees of verisimilitude - are expected by buyers to have useful lives of many years, even as descriptions of jobs deemed 'hot' by markets change over time scales of months. Executives and their organizations care about the 5- to 10-year value of their learning experiences. No conscientious prospectors of the executive development

industry can afford to turn their gazes from that which lies ahead of its current restructuration.

What we see when we do look ahead looks more like a *destruption* than a disruption: a 'destruptor' disrupts its industry by the destruction of incumbent value chains and associated activity sets or through the credible threat of imminent destruction thereof. What does this force look like in the case of executive development? Here is a scenario that looms imminent given the current ecosystem of learning tools and practices:

From Know-it-All to Learn-it-All: A Personalized Learning Assistant that Changes What We Mean by 'Education'

Suppose there existed a cloud-based platform that tapped into sensors to provide data, in real time, on all the physical, cognitive, and emotional activities that comprise an executive's everyday 'work': presentations, meetings, conversations – alongside the frantically evolving fabric of writing emails, texts, Slack messages and crafting memoranda, reports and slide decks.

Suppose the platform could "see" whatever the executive saw through a sensory augmentation device, duly miniaturized to decrease its footprint so it feats neatly as an ear piece or eyepiece or necklace. It could also see what the executive cannot when she interacts with other people and track her own gestures, emotional signs, and "tells," as well as the reactions of the executives around her, perhaps even those not in her field of vision.

Suppose the platform could understand what the executive were reading or writing. Its IBM Watson-like capabilities would allow it to parse, segment, and interpret the text. Based on its numerous "senses," the platform could estimate how tired or distracted the executive was, and after measuring the activity levels

in her pre-frontal cortex, could nudge her to read a paragraph more closely than she was doing.

Suppose the platform could also "comprehend" what the executive were saying, as well as what other people were saying, by using speech-to-text translation systems powered by learning algorithms that recover meaning from the past usage of words; the way people speak key words and phrases; and the signals generated by the executive's autonomic nervous system as she spoke those words.

Suppose the platform could also 'see inside' the executive's body and track physiological and neurophysiological variables such as pupil dilation, facial blood flow, and brain waves – as well as decode the executive's emotional landscape by measuring and making inferences from the tone, pitch, rhythm, and intonation of her voice and the facial action patterns of her face.

Suppose the platform could recognize the nature of the tasks in which the executive is engaged -- physical, cognitive, or emotional -- and the difficulties – the inferential, informational, translational, computational, motor, and visceral hurdles -- she experiences in carrying them out, and, on the basis of past experience with the executive herself and many others it could supply ideas, frameworks, data, and prompts -- including on-demand training modules in consultation with trusted learning partners -- to help her optimize her physiological and cognitive performance on the dimensions that matter most.

Suppose the platform could constantly adapt its functioning to help the executive do better at whatever it was that she was attempting. It would incorporate quantitative and qualitative feedback from one, or a sub-group, of the people with whom she interacts, weighting the feedback by its knowledge of each person's emotional state. That way, she would know if someone's positive

feedback was prompted by an unrelated visceral high in that person or by a considered response.

Suppose the platform operated under the assumption that no one can learn in a space devoid of human voices and feelings and would allow the executive to share data with learning partners, coaches, and mentors, helping her learn from each of them, enabling them to learn from her, and helping them help her learn from others – and herself.

Suppose we had a platform or a collection of platforms that could do all that right now. Because of its relentless adaptivity and dense coupling to the executive's own behavior and inner states, This cloud-based platform would allow her to learn anything about anything even if she started out knowing very little in a way that would be *personalized, contextualized, and socialized*.

Question 1: Would you, then, need 'Courses'? 'Classes'? 'Degrees'? "Development Modules"? "Case discussions"? Any of the 'batch mode' learning vehicles that are both poor approximations and obstacles to continuous learning?

Suppose you, as the executive client of this platform, could share your 'personal learning pathway' – including feedback from all others with whom you interact – with whomever you wanted, including prospective employers and business contacts.

Question 2: Would you then need 'Certificates of admission and completion' to signal that you underwent certain developmental or learning experiences that have allowed you to acquire net new abilities? That you, now, as a result, 'have what it takes' to do a job or perform a set of tasks?

That these questions seem rhetorical is not irrelevant: Personalized learning replicates – with the help of sensing, storage and computational technology – the products, processes and procedures of the ideally 'personalized'

executive development program. The technologies required to create the personalized learning assistant are at hand. They form the elements of a new wave of disruption, due to first arrive in the most ROI-sensitive sectors of the education sector are at hand an in play.

The Next Wave of Disruption: A Precis.

While the set of disruptors we are now experiencing speak largely to the *contextualization* of learning, the next set of disruptors speak to the *personalization* of learning. Institutionalized, certification-based education – the dominant mode in which humans have engaged in learning over the past 200 years is now being displaced by facilitated learning in the context of projects and jobs meant to address the 'skills gap' and the 'skill transfer problem' [Moldoveanu and Narayandas, 2018a] the field as whole faces. The next disruption will be facilitated by the ways in which technology based disaggregation and disintermediation allow for a more precise expression of end users' preferences in the marketplace. We - as developers of learning experiences and as inquirers into the ways humans learn - understand just enough about both the way in which the labor market values the complex and difficult-to-articulate skills associated with social, relational and emotional tasks and performances [Autor, 2014; Acemoglu and Autor, 2011; Deming, 2015] to realize they are core differentiators for individuals and sources of value for organizations. And we know just enough about their 'production function' in the context of human lifespans [eg., Heckman, 2006] to know it is complicated - and different from one individual to the next.

But while we recognize the urgent value of social and relational skills to executives, we are novices at training and developing them. While *nexi* of ability and skill such as empathic accuracy, dialogical connectedness, communicative

inclusiveness and authenticity, or the executive functions of self-monitoring and self-regulation – and the demand for these skills - plausibly account for 'why there are still so many jobs in the age of machine learning' [Autor, 2014], we need to come to grips with almost a century's worth of isolated, largely negative, sometimes optimistic, and widely disparate results produced by experimental attempts to modify or change behavior, ability, personality, and character [Seligman, 2007; Kegan, 2011].The personalization of learning is key to the next step in the evolution of the learning industry toward greater levels of adaptiveness to context and content changes. It refers to the tailoring of the learning experience to both the external and internal environment of the learner through the proficient use of mapping, measurement, prediction, feedback and feedforward strategies and will also include the specific abilities, moods and neuro-physiological states of the learner herself.

Of course, adapting the learning experience to the user's own mind, brain and body is not enough. Ten years of experiments with open learning ecosystems have taught us that effective learning is *socially embedded* and that, to be successful, learning must also be *socialized.* The technologically mediated socialization of learning addresses both the feedback gap in higher education and its proficient use of mimesis to augment learning - and helps link the acquisition of algorithmic and functional skills to the development of social and relational skills. Harvard Business School's HBSOnline platform gives students incentives to answer questions from other students on the platform, helping them to hone their core skills and develop skills related to articulation, interpretation, explanation, legitimation and justification of solutions – important parts of the nexus of high-demand social and relational skills. Large scale platforms like EdX, Coursera and Udacity have found ways of increasing both

learning outcomes and participation by enhancing the interactivity of their learning platforms.

Established executive programs have always 'known' that social learning is one of the largest sources of value they bring to executive participants [Narayandas and Moldoveanu, 2018]: participants learn as much (or more) from one another as they do from their content, instructors and learning facilitators. But knowing-*that* is very different from knowing-*how*: Executive programs have barely scratched the surface of using available technology in both classroom and remote settings to enable to structure, broaden and deepen the ways in means by which such learning takes place.

To take an example: The case discussion has for a long time been the premier vehicle for 'social learning'. However, [Moldoveanu and Narayandas, 2019] the value of case discussions as skill development vehicles are greatly dependent on the expertise, charisma and presence of the case discussion facilitator. They often do not focus on the development of skill sets (such as dialogical openness, inclusiveness and coherence) that are the hallmarks of high-performing executive teams. But, propitiously, a new group of technologies that enable and promote the development of social and emotional skills [World Economic Forum, 2016] is about to be unleashed on the executive development space. They will contribute a significant 'third prong' (alongside personalization and contextualization) to the next wave of disruption. We will now unpack the key elements of this next wave of disruption.

Personalizing and Contextualizing Know-How via Algorithmic Intelligence: Wolfram Alpha, Watson, Tensor Flow and the "Working Knowledge" Landslide.

The first component is already in use. It is the personal learning cloud created by the set of linked informational and computational resources that have been in place for ten years and are congealing into a fabric of intelligent learning platforms that are ubiquitously available and ready to be deployed – the Personal LearningCloud. The 'Google matrix' (Web Search, Scholar, Patents, Applications, Code, Earth, etc…) places raw, real-time-accurate information and low-level inferences from it at multiple levels of resolution and analysis – in the hands of the connected and easily displaces the 'information transmission and imprinting' components of the learning experience and nullifies the informational advantage of all but a very small number of providers – those that are also creating or curating the data fields. Facts and data are updated in real time and available on demand on a distributed, shared basis.

However, in spite of being widely available, information is not always intelligible or useful. It is often encoded by the specialized language systems of scientists, physicians, engineers, patent agents, economists and jurists. This creates the need for special 'decoders' dedicated to making information not just accessible but intelligible to those who can use it. Enter computational platforms like Wolfram Alpha and those easily built from the IBM Watson matrix. True to their name ("computational knowledge engines"), they allow users to curate, decode and synthesize on an on-demand- on-spec basis – the information encoded in ways that make it unintelligible. They replicate – and thus eliminate, as replication by an algorithm often eliminates the need for the human task the algorithm reproduces - the function of informational *translation* that most providers of executive development programs supply and allow users to parse for themselves relevant original research findings, cases, video modules, simulations and data as it becomes available. Now we have algorithmic agents

that take over both the information dissemination and knowledge decoding functions of the traditional educator.

However, even very good algorithms for aggregating, decoding and translating specialized information and knowledge structures will not be able to answer *specific questions* whose syntactical and semantic architecture is more complicated and ambiguous than 'Define *enthalpy…*' or 'When was Vincent van Gogh born?' Defining - in Wikipedia-style - a 'collateralized debt obligation' (CDO), a 'credit default swap' (CDS) or a Gaussian copula using synonyms, formulas, and numerical examples is far more easily accomplished than answering specific questions about the causal roles these entities likely played in the decision processes by which assets were allocated within the Royal Bank of Scotland during the month of April, 2008. Developing *that* function may still benefit from human expert guidance even in the presence of computational knowledge engines.

Enter IBM's Watson engine for semantic query analysis, Microsoft Cognitive's suite, Narrative Science, Inc.'s *Quill* – or a customized reasoning platform based on Google Tensor Flow API's. These allow for natural language-based interactions between an uninformed user and an expert database and knowledge base, supported by associated query, question and challenge databases representing the stock of questions posed by other users, along with textured, multi-layer answers and multi-user ratings of the answers. Now we have a socially embedded and connected algorithmic agent and a distributed infrastructure for answering detailed questions in generalized domains that allow an executive to get up to the state of the art in a field on her own terms, by asking the questions she needs answered along with the questions others have found it useful to ask when in a situation like hers. The learning cloud has now

just grown to a capability that already exceeds the informational aggregation, dissemination, decoding, and interpretation functions of the executive development instructor of today.

One may argue there is still an irreducible role in executive programs for the stock of know-how of executive instructors and learning facilitators. It relates to the methods of thinking and reasoning about business problems they impart implicitly to participants or students, merely 'by the way they speak'. Enter, however, the learning platform and app ecosystem enabled by Google's Tensor Flow, Microsoft's Azure and Facebook's CaffeAI. They distinguish themselves from their non-adaptive algorithmic counterparts through their ability to improve their predictive performance with repeated uses on new data sets.They are easily deployable on cloud-based data repositories, some of which are provided by the mother companies themselves. The greatest impact they make to the executive development landscape is automating the stock of technical and functional skills that comprise its subject matter, and making this 'skill stock' available on demand or at the right time.

The impact of self-refining search and optimization algorithms to executive skill development seems difficult to grasp. But, it is intuitive and will likely have a dramatic effect on the field. Current functional and algorithmic skills are acquired and exercised through repeated demonstration using examples (eg: case studies; content-targeted questions; problem sets, etc.) and exercises. The 'see-it-done' - 'try-it-out' - 'do-it-now' ("see-try-do") model has been around for so long in the education business that we cannot easily see it as 'just one of several models' for skill formation. While the model seems to yield results in terms of skill acquisition (eg: graduates pass the final exams in their

courses because otherwise they would not be graduates) its skill transfer properties are dubious [Moldoveanu and Narayandas, 2018a].

By contrast, an adaptive algorithm embodies precisely the skill that adapts a problem-solving procedure to the context of its application - the essence of skill transfer. The machine learning-enabled executive deploys algorithmic intelligence directly to the problems, challenges and predicaments she faces – rather than needing to extrapolate from a stock of tried and true problems, case scenarios and test situations. The skill transfer problem is directly addressed and often solved, but the traditional 'exec ed' instructor is cut out of the value pie by the special combination of the executive, machine and algorithms that learn.

The constant or decreasing marginal returns to purely cognitive skills [Autor, 2014] that we have seen over the past 10 years, coupled with increased returns to social and emotional skills [Deming, 2015] suggests non-algorithmic, non-functional skill development is likely the most promising area for further investment in development. 'Non-algorithmic' skills are those skills that cannot (currently) be replicated by the operation of algorithms, regardless of their level of adaptiveness [Moldoveanu and Martin, 2008]. They are often emotional and relational in nature. They often have a strong epistemological and meta-cognitive component. Their development often requires detailed, in person feedback and interaction – just as coaching does. It may seem to follow that current executive programs that make specialized investments in non-algorithmic skill development modules making proficient use of face to face interactions with highly present learning facilitators are 'safe' from technological disruption. But that is not quite true.

Here is why:

Personalized and Socialized Learning via Wearable Technology, Affective Computing and the Mind-Brain-Body Optimization of Learning.

Alongside the 'algorithmic revolution' of the past twenty years, and buttressed by advances in computational power, informational storage, and sensor technology, a second silent wave has been rising. It rides the growth in wearable sensors, affective computing and associated platforms and applications that allow monitoring and real-time processing of brain-body signals of users and the inference and shaping of users' emotional and visceral states.

We sense and feel far more than we can say, and we 'emit' far more information than we willfully and consciously 'transmit'. This is the learning predicament that sensors, data rich platforms and machines that learn from them can be of great use in. From the adaptive sensor-enabled 'social physics' championed by Sandy Pentland at the MIT Media Lab – a mapping, intervention and learning paradigm that uses a distributed array of sensors and associated algorithms that make predictive inferences about social dynamics and interpersonal outcomes on the basis of a dense set of measurements of a sparse set of variables such as proximity and tone, pitch and rhythmic patterns of voice – to multi-sensor-powered affective computing platforms that allow users advance access to their own and others' emotional landscapes - the 'wearable affective computing' wave is changing the way in which 'relational' and 'affective' skill development is pursued.

How? There are three components to the impending change in modes of learning the skills that have for ages been deemed unteachable.

1. **Measurement**. Ineffable, subtle, complex states ('presence', 'connectedness') and abilities or skills ('empathic accuracy', 'emotional

attunement', 'self-regulatory response velocity') that are highly relevant to everyday activities and success of the executive become quantifiable and measurable using the combinations of brain-body signals they correlate with. User feedback, user feedforward and user experience sampling allows for the 'personalization' of predictive and mapping algorithms to each user, as a function of her context and state.

2. **Prediction** and **Inference**. Wearable affective computing allows for the use of direct, real time measurements to predict emotional states and behavioral responses, allowing users access to both higher levels of self-regulation (the essence of the X-factor skills [Moldoveanu and Narayandas, 2018a]) to finer-grained understanding of the effects of various situations and predicaments on their behavior. 'Classroom' and 'case-room' learning about the emotional landscape of executive work and the visceral and emotional 'labor' the functions it requires are replaced by a massively more efficacious learning platform focused on the self, guided by the self, aware of the self, and adaptive to the self of the executive and its context.

3. Intervention. The availability of affective remote sensing and inference platforms that measure, map, predict and guide their users enables a new approach to affective, relational and communicative skill development. Interventions and learning experiences happen continuously, on the job, in the right context, and in ways that are personalized to the state and aspirations of each individual participant.

The impact of such an infrastructure is not limited to the development of relational, communicative and affective skill development : the ability of online learning platforms and learning management systems to access a set of variables that describe the central and autonomic nervous system responses of users

allows for the real time optimization of content (eg rhythm of presentation, tone, color schemes, cognitive load, informational complexity, etc.) to maximize traditional learning objectives even for functional and algorithmic skills. In a neurophysiologically optimized environment that adapts content to user state, functional and 'quasi-algorithmic' skills like 'financial statement analysis', 'operations management' or 'strategic industry analysis' will likely be teachable – and learnable – in a fraction of the time the process requires in the current, standard settings.

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Executives and their organizations come to development programs with multiple objectives [Narayandas and Moldoveanu, 2018] that include individual skill development and organizational capability formation alongside signaling, networking and certification. In spite of the foremost role in the learning value network that skill and capability formation have, one can take the view that strong, well-established, well-endowed, well-attended executive programs will continue for some time to be protected from innovators who will leverage algorithmic intelligence and wearables to produce massive shifts in the 'learning production function' along the lines we saw above. That is a poorly founded hope, on account of the effects the augmented learning cloud will have on precisely the signaling and selection effects of executive and leadership development programs. Here is why:

The Personal Know-How Network: Socialized Learning, Adaptive Algorithms and the Sharing Economy.

Every organization seeks to answer a simple-sounding but difficult-to-unpack question when it hires a human being: 'Will this person be the right or best one for this job, role, function, task and team?' The current informational

ecosystem supplies answers in the form of 'lumped-aggregated-averaged' signals of skill, effort and ability. They come in the form of degrees, certificates, recommendations, ratings and endorsements. The ability to track, measure, visualize and integrate across micro-behaviors (meetings, reports, presentations, etc.) represents a highly attractive proposition to most organizations. They know that the 'cost of getting it wrong' is amplified by the 'inability to predict on the basis of current measures' – the hallmarks of VUCA environments.

What happens when you bring computational intelligence to the ubiquitously distributed data sets produced by social platforms is a massive disambiguation of individuals' signals of skill, ability and character that are currently lumped into 'degrees', certificates' 'courses completed', 'programs attended' and undifferentiated 'five-star ratings'. The day to day performance and behavior of each participant becomes observable and measurable. Changes in either direction become trackable. The performance of each individual on work-relevant tasks is rendered visible.

'Microscopic, individualized performance tracking' makes it possible for organizations to see not only whether or not an executive has the right credentials, attended the right programs, and has registered the right endorsements, but also a detailed record of her performance on all the various components and sub-components of a program, along with and the views and opinions about her integrity, trustworthiness, credibility, openness, affability and competence of those that have worked with her on all of the projects and group assignments she has been part of. Given all of this individualized and textured data, the simple rule that has powered the information age, i.e.

USEFUL INFORMATION = RELEVANT DATA + PURPOSEFUL CALCULATION

we are within range of a set of 'learning agents' that can answer questions regarding functional and algorithmic tasks, relational and communicative tasks, and X-factor-relevant tasks. They do so by processing and learning from the tracks that an individual manager leaves in her wake of relevant tasks and assignments.

The network effects of this change are significant. Suppose that instead of having to hire individuals from certain cohorts of professional development organizations like business schools and consultancies, you can now hire from among different high-performing *teams* of individuals who trust implicitly in each other's competence and integrity. You no longer have to do the work of getting the groups to function like teams. Then the signaling value to individuals and organizations of degrees and certificates decreases relative to the signaling value of detailed, transparent maps of behavioral data that can be processed to derive measures of competence and integrity.

Not least among the impending dynamics of executive development is an educational version of the sharing economy. As the work of managers and executives is largely and increasingly done in groups that become teams through shared experiences and challenges and develop collaborative capital that is highly prized by organizations but resides in the team as a whole, the concept of a 'shared degree' and 'shared certificate' begins to make *more* sense than does that of an individual certificate: Organizations can then recruit 'pre-formed executive teams' and invest in developing 'teams' rather than individual executives. They can make their 'make or buy' decisions on the basis of the stock of skills and attributes these teams embody, and the specific challenges and problems they have successfully solved in the past.

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As the future of higher education is set to undergo massive changes over the next decade – and current pictures for the university of 2027 [Times HigherEd 2017] range from a fully personalized and remote learning environment with no classes, no teachers and no official students to a technologically more sophisticated variant of what we have in place today - it is useful to develop a vision of what *executive* education can aspire to in the age of machine learning, affective computing and the rapid automation of increasingly sophisticated tasks.

To do so, we focus on the most important limiting steps to learning in both in-person and remote environments: the scarcity of learning-enhancing feedback and the scarcity of learners' attention and motivation. In the ideal learning scenario, learning science tells is that feedback is immediate, accurate, personal, non-dispositional, incremental, contextualized and iterative; and that learners tune in to learning experiences at the right time, for the right reason, and with the right amount of purpose and coherence. In practice, the situation differs significantly from the ideal case: The scarcity and poverty of competent feedback and the vagaries and incoherence of learners' attention is what makes education such an arduous process: classes, lectures, lecturers, quizzes, graders, exams, and the entire scaffolding of human activity that together makes up a 'university' and a 'degree program'.

Feedback: Personalized Learning of the Unteachable by Turning Feedback Science into Feedback Practice.

The empirical science of learning offers abundant evidence of the critical link between feedback and learning outcomes and has recently come to focus on identifying the right *kinds* of feedback for different learners, skills and learning environments. Learning a foreign language, learning a computer language,

learning to communicate cogently, empathically and responsively, learning to suppress or sublimate behaviorally impulses that often destroy the cohesion of a team, learning to learn new skills in a specialized technical domain more rapidly – each requires specific kinds and sequences of feedback.

The neuroscience of learning has made significant advances in identifying the mind-brain mechanisms that safeguard the link between feedback and learning in many environments. Timeliness, precision, intelligibility, actionability, iteration - all represent features of learning-enhancing and enabling feedback across different domains of knowledge, skill and expertise. Finally, machine learning – the use of self-refining algorithms - has made rapid advances in the last ten years *precisely* because of its use of fast mechanisms that allow algorithms to learn from their own performance via feedback that tracks their successes and failures in replicating or predicting the data sets they are trained to compress and replicate (or, 'understand').

In spite of the momentous advances in understanding the role that feedback plays in learning, professional and higher education more generally are lagging dangerously behind what is now both possible. The lecture-homework-lecture-quiz routines in which feedback is given *en masse* lags student performance by a long time, and are not adaptive or personalized to the learner or her task currently pervade most professional education. Current educational practice and the learning environment it produces live in self-sufficient isolation from consilient findings from learning science, deep learning practice and the neuroscience of learning - together comprising 'feedback science' - regarding the impact of feedback on skill and competence development.

To see how feedback science can be turned into feedback practice, let us go back to a simple behavioral exchange model of learning: the learner produces

some behavior – anything from a written answer to a test problem or a live presentation and to a group. This is the output on which feedback is given. But not all feedback is equally useful or good. Some feedback is counterproductive. Some is uninformative. Some is harmful. Much of it is useless. What kind of feedback is most useful to learning? Learning-enabling feedback is:

Timely: it follows **promptly in the footsteps of the learner's behavior**. Feedback given in a week about performance on a test or problem set question is far inferior to feedback the next hour or the next day. In fact, neuroscientists have found that for cognitive tasks – like learning the grammar of a moderately complex language - **instantaneous** feedback trumps feedback that is given **even a few seconds later**;

Specific: feedback that enables learning is **not general or fuzzy**. It does not evince the cluelessness of currently common grading practices in which the grader is struggling for something meaningful to say to justify a letter or number grade arrived at on account of causes that have nothing to do with the reasons given for the grade. It is specific:

- To behavior or output - to the **details of the learner's written answer** or verbal and non-verbal behavior, and to the components of the output that can be usefully modified.
- To the **context** in which the written answer or verbal or non-verbal behavior is embedded. Good feedback points out, for instance, ways in which the learner misconstrued the situation or the question;
- To timing – to the **order or sequence** in which the learner's answer or verbal or nonverbal behavior occurs. Good feedback singles out the specific points in the learner's pattern of reasoning or behavior that make the **greatest** contribution to the quality of the work. If a learner cannot

differentiate continuous functions, for instance, and taking derivatives is an integral part of the chain of reasoning that leads to the right answer on an equilibrium calculation problem, then feedback that promotes learning should single out the learner's skill gap in differential calculus;

- To the learner herself – to **patterns of reasoning, calculation or behavior** that are specific to the learner's own way of thinking or being. Good feedback is **not generic** – it is highly tuned into the learner's patterns of thinking and behaving;

- To the **consequences of behavior or output and their interpretations**: good feedback on interpersonal, social or relational tasks points out the consequences of the learner's behavior on others' feelings, behavior and likely thoughts, allowing the learner to make textured inferences about the causal chain that links her behavior to their social consequences.

Actionable. Good feedback provides prompts for behavioral or conceptual changes that are **intelligible, clear and executable** by the learner. It does not merely provide an appraisal of how successful an answer or behavior was, but also a set of suggestions or injunctions for changing thought or behavior patterns which are likely to lead to a better result;

Credible. Good feedback is persuasive to the learner in virtue of being:

- **Legitimate:** it is connected to the learning objectives of the course or module or learning experience and to the learning objectives of the learner;

- **Justified**: it is buttressed by valid reasons, drawn from disciplinary research and/or research on optimal learning;

- **Objective or impartial**. Good feedback can be validated by others of comparable expertise to the feedback giver, and is not thus prone to personal biases that render it partial or unfairly slanted.

Developmental – its intent is to help the learner improve her performance on a task, or enhance her skill or competence in a domain – rather than merely to provide an ordinal or cardinal ranking of learners' effort and talent levels for the purpose of providing discriminant value to recruiters or other programs of training;

Iterative. Good feedback is not a one-shot deal. It proceeds in **iterative fashion**. Just as neural networks and automata learn from multiple rounds of feedback that build on each other, learners require **sequences of feedback sessions** that help them refine their skill or capability;

Responsive. Good feedback is responsive to the learner's **objections or interpretations of the feedback**. It is neither opaque nor definitive, even if and when it is legitimate and impartial.

Current approaches to executive education are far from embodying the insights of feedback science. Given the foundational importance of feedback to learning and the gap between current and optimal feedback practices, we are faced with an opportunity to make the $10Bn executive development industry – and even the global higher education industry - massively more effective by changing its feedback practices. Specifically: What if the learning outcomes that the current lecture-quiz-test-exam course achieves in 25 hours of lectures and 50 hours of homework and testing can be replicated in a feedback intensive environment with just 4-6 hours of learner-teacher time?

There are two routes to realizing this opportunity. Each has the potential to radically change the way teaching and learning are done. One makes use of the semantic, dialogical and conversational capabilities of AI agents and enhanced formal and natural language processing technologies. The other relies on a new generation of teachers, educators and instructors that make feedback the centerpiece of their curricular designs and teaching plans.

I.   **Semantic Engines and Learning Machines: Feedback on Technical Skill Development Becomes Algorithmic**. Walking in the footsteps of IBM's Watson and Bluemix, and making use of deep learning ecologies of algorithms and platforms like Microsoft's Cognitive Services, adaptive feedback agents (AFA's) will take the learner's 'stream of thought' attempt to solve a problem and give targeted, immediate, iterative, specific, objective, accurate feedback on each step of the learner's process of reasoning or calculation, along with suggestions for remedial exercises and drills that develop each sub-skill or competency required for the successful execution of a task. Powered by the database of questions, problems, answers and solutions from some 60MM learners (2018 figures) currently taking some 13,000 massively open (MOOC) and small private online courses (SPOC) offered by 700 universities around the clock, AFA's will be trained to address patterns of errors, idiosyncrasies and reasoning styles that learners exhibit. New results from feedback science can be embedded into feedback practice *via* updates to algorithmic platforms without the need to train up armies of teaching assistants and graders. Feedback is liberated from the fluctuations of quality, mood, resources and acumen of human graders, for those skills that are sufficiently explicit and cognitive in nature to be tracked by algorithmic agents.

The basic building block of learning in most business schools is a technical *problem* – requiring the learner to (re)-produce a problem solving method (or, algorithm) – a sequence of operations that takes the evaluator from the problem statement to the solution in small and self-evident steps. An adaptive feedback agent (AFA) takes each step in the problem solving process (from turning a 'word problem' into numbers and symbols and performing operations on these to get to the solution) and gives instantaneous feedback to the learner at each step, using intuitive prompts ('need to take derivatives here', 'forgot to invert the matrix', 'this is a *European* call option, use formula….') that also contain prompts to targeted tutorials ('differentiating polynomials', 'inverting matrices'). A script rolling in the background films the entire sequence of operations and tutorials, so that this learning session remains available in mp4 form for the learner to look back on.

II. **The Feedback-Centric Learning Facilitator**: **High Precision Feedback for Relational and Social Skill Development**. The Fourth Industrial Revolution is not only one in which many tasks previously performed by humans can be performed by algorithmic agents hooked up to server farms, but also one in which the nature of the highest value tasks performed by humans have changed. They have become predominantly social, relational and interactive. 80% of the work managers now do in organizations is performed in groups and teams. The skills most prized by business and non-business organizations alike are communicative and relational in nature. They comprise as many and even more **affective skills (**empathic accuracy**,**

expressiveness**)** and **executive skills** (like problem structuration and quick task switching) as they do **cognitive** skills. With affective computing still in a turbulent – though promising – infancy, there is a need to rapidly develop the language and base of expertise for giving feedback on **interpersonal, relational and communicative 'genres' of work,** such as board presentations, sales pitches, negotiations, deliberations, processes of collaborative inquiry and debate, that will enable and foster real learning of skills that are (still) quintessentially human and currently very 'hot' in the labor market. 'Communication skill' is now used as a 'catch-all', low-resolution label, which makes the development of all of the skills that go into 'communicating' very far from the elaborate evaluation rubrics that have been developed over a century of practice in teaching and grading calculus, microeconomics, structured language programming or thermal system design quizzes. But progress on creating the practices that will promote the rapid acquisition and transfer of hot skills requires that we think carefully about the semantic and syntactic (eg: coherence and completeness) and dialogical and interactive (eg: responsiveness, attentiveness, informativeness, attunement, presence) of the learner's behavior in a social context – and that our feedback practices reflect a much higher level of precision.

Once turned into practice, the science of human feedback transforms the way we think about the skills that we value most but feel most pessimistic about being able to learn or teach: the social, emotional and relational skills that most businesses prize most: You say 'charisma', 'collaborativeness' and 'relationality' cannot be taught? You may be right. But if by that you mean it cannot be learned,

you are wrong. Much of what is unteachable can be leaned through feedback that is precise, adaptive, targeted, iterative, actionable and developmental.

The coach trained in feedback science focuses on the basic unit of social work of the learner – 2D footage, or VR or 360 degree footage of a *real* presentation, meeting, gathering or work session in which the learner interacts *for real* with others. Each communicative act (in increments of 10-15 seconds) of the learner is mapped into all of the ways in which it conveys information (like: her *message*: use of imagery and image, coherence, completeness, responsiveness; her *voice*: tone, pitch, dynamic range – and the emotions they convey, as well as their fit with her message; her *body movements*: amplitude, periodicity, expressiveness, dominance, submissiveness – and their fit with her message; her *facial actions and micro-expressions*: basic emotions, expressiveness, congruence, positivity, negativity, attention) – and the effect of each 'micro-behavior' of the learner on each of the members of her focal group is fed back to her, along with actionable suggestions for incremental, adaptive changes.

Using Wearable Learning and Affective Computing to Improve the Economics of Learners' Attention and Optimize the Online Acquisition of Skills.

10 years of intense practice and research on online learning have clearly shown that e-learning is not just 'regular learning, electronically delivered'. It is often less. But, it can also be more. Here is how:

Online Courses versus Off-line Classrooms: The Differences that Make a Difference. The classroom environment is not electronically replicable to a degree of fidelity that makes the learning experience of the classroom and the e-learning

program substitutes for one another. The immediate, in-the-moment 'feel' of the learning experience in the two environments is very different.

Assume the 'content' – what is being said and the specific visual and auditory form in which it is said – is identical in the two settings. The classroom environment constrains the learner's attention and shapes her micro-behavioral responses *via* several factors:

- the immediate presence of the instructor - with whom the learner feels connected in a "quasi-dialogue";
- the immediate presence of other learners, whose mutual expectations and joint attention focused on the instructor or blackboard or screen further constrain the degree to which the learner can produce behavior that disrupts the experience of the class;
- the shared and mutually reinforced norms and normatively grounded expectations of 'classroom behavior' by participant and instructor; and -
- the inconspicuous *absence* of stimuli that induce behavioral or cognitive wandering, which may be found in abundance in other environments (like, at home).

Consider now an online environment. The behavioral and perceptual constraints and inducers supplied by the classroom experience are missing. Moreover, they are supplemented by an environment seemingly designed to produce maximum distraction and dilution of focus – the learner's home. The 'learning stimulus' that comes off the platform must compensate for the absence of the constraints of the physical classroom. Current e-learning experiences are clearly not able to fully compensate for these constraints. Informal reports of the

average participant's average 'attention span reductions' of the orders of *5x* to *10x* in a remote learning environment are unsurprising.

If online learning vehicles are to be at least as successful as in person environments at producing or facilitating learning, then what we call 'teaching' needs to be re-designed. 'Chunking' online content into shorter activity units is only a small part of the re-design. The body-brain-and-mind context of the learning experience supplies the critical set of differences between in-person and remote learning environments, then designing and engineering the e-learning experience for skill development requires we first re-conceptualize the entire psycho-physiological variable space in which learning happens. What does this variable space look like?

The neurophysiological correlates of the participant's cognitive, sensory, visceral and behavioral activities can be used to generate adaptive, and personalized estimates of the degree to which the learner participates in a learning experience. The emergence of sensing and measurement technologies for inference of emotional states via physiological measurements [Cacioppo et al, 2000; Healey et al, 2010; Setz, 2012] offers an unprecedented opportunity for the optimization of 'learning experiences'. Physiological and neurophysiological sensing afford an expanded state space of intra-personal variables relevant to learning through their impact on attention span and focus, perceptual acuity, working memory, etc. They can be used to design both the content and the form of an online experience in ways that maximize skill development. Key to using neurophysiological measurements to optimize the design of pedagogical vehicles is a set of models of the effects of learners' emotional and visceral states on her learning process and outcomes, and of the correlation and of the learning stimuli of the e-learning platform with the salient set of emotional states.

Emotional states and landscapes (sets of related emotional states) are not easy to map and classify. But, difficulty does not entail impossibility. Even a naïve and coarse grained approach   goes a long way to helping us organize the variable space. More than 300 emotions can be classified in terms of their valence (positive like joy?, Or – negative - like rage?) and the level of arousal they are associated with (active like disgust? - Or passive - like sadness?) by pooling together large numbers of responses of human subjects asked to rate and rank their own emotions in s structured fashion [Seitz, Lord and Taylor, 2007]. Within this more structured state space of emotions, we can ask: to what extent are emotions in the four quadrants of this classification system (active-positive; active-negative; passive-positive; passive-negative) conducive to different learning outcomes? Even a set of weakly informed priors (learning is maximized when the learner's emotional states are in the 'north-east-east' quadrant (mildly active and positive) can help provide useful heuristics for content design.

Deeper distinctions yield new insight. We can model the emotional landscapes of feedback and evaluation processes with respect to their immediacy (how soon after the work is produced?), accuracy (how specific to errors and mishaps?), materiality (is the feedback used developmentally or as a selection tool?) and opacity (how easy to link the feedback to the material taught?) - and ask:

- To what extent are more/less precise/immediate/opaque forms of user feedback related to heightened fear, stress and anxiety?
- To what extent do these emotional states impede/enhance learning?

We can use the emerging causal map to design feedback instruments that optimize the average learner's response by tuning his/er levels of precision and timeliness, and by adjusting the forms of feedback used.

Recent development of 'affective-visceral remote sensing' techniques for mapping physiological measurements to emotional states [Setz, 2012] allows us to ask these questions at the level of individual learners. The relationship between individual stress level and learning outcome will vary between individuals. So will the of 'optimal stress level' the learner needs to feel to do well on a test. The 'affective style' of an individual learner [Davidson, 2003] - her propensity to feel certain emotions when exposed to certain stimuli and to behave in particular ways when feeling a certain emotion - can also function as a reliable moderator of optimal learning outcomes of different learners in different contexts (more/less personal; more/less formal; more/less intense; more/less evaluative) and afford an additional degree of freedom in the adaptive design of learning vehicles.

We are at a stage of simultaneous technological development in multiple disciplines that, once integrated, allows for the development of affective-visceral sensing enabling discrimination among different groups of emotions and in some cases of different emotional states. To wit:

- Cardiac function sensor measurements (heart rate, cardiac output, stroke volume) [Cacioppo et al, 2000] allow us to distinguish between emotional pairs such as (fear, anger), as well as between emotional pairs such as (anger, disgust), (fear, anger), (fear, disgust), (happiness, surprise), (happiness, disgust), and (sadness, disgust).

- Heart rate variability measurements, moreover, allow us to distinguish between emotions that involve the different components of the autonomous nervous system (sympathetic, parasympathetic), and therefore to distinguish between strong (stress-related responses) and weak (depressive-withdrawing responses) emotional states [Seitz, 2012];

- Facial muscle movement sensors [Cacioppo et al 2000] allow us to track the relative positivity (as a function of the activation of the *zygomaticus major* and the *orbicularis oculi* muscles) or negativity (via the activation of the *corrugator supercili* muscle). Measurements of facial muscle activation can be carried out by non-invasive means, using Facial Action Coding System-enabled video camera recorders [Sejnowski and Ekman, 1999; Ekman, 2007];

- Vascular blood flow measures such as finger pulse volume, total peripheral resistance and face temperature) can be used to distinguish between emotion pairs that differ in both intensity and valence (anger, sadness, sadness, happiness) [Setz, 2012];

- Electro-dermal activity measures such as skin conductance level and the number of nonspecific skin conductance responses can be used to distinguish between different levels of psycho-physiological stress, and between emotional response pairs like (disgust, happiness);

- Speech parameter measures [Setz, 2012] can be used to discern levels of intensity of the emotional state of the speaker by focusing on the speed (relative to baseline), pitch and prosody of the voiced signal in order to distinguish, for instance between 'anger complex'

emotions (irritation, sarcasm, rage) and 'joy-complex' emotions (happiness, glee);

- Non-invasive, unconfined, low spatial resolution measures of brain activity – like electroencephalographic (EEG) signals of cortical and hemispheric activation levels in the superficially accessible parts of the brain – provide reliable estimates of both levels of intensity (alpha/beta wave amplitude ratios) and emotional negativity (hemispherical inactivation, translating in higher alpha wave amplitude);

- Non-invasive, confined, high spatial resolution measures of brain activity – like brain-oxygen-level-dependent (BOLD) signal levels from different parts of the brain – can provide measurements of activity levels in brain areas (pre-frontal cortex and sub-components, limbic system, motor cortex) whose activity has been reliably implicated in different perceptual, sensory-visceral, motor and cognitive activities that comprise what we refer to as *learning* (Logothetis, 2011);

- Eye-movement measures can be used to discern both between different emotional states of the user (as blinking rate is correlated with the valence of the experience) and as identifiers of the stimuli that produce micro-level variations in physiological responses (via eye tracking movement monitors).
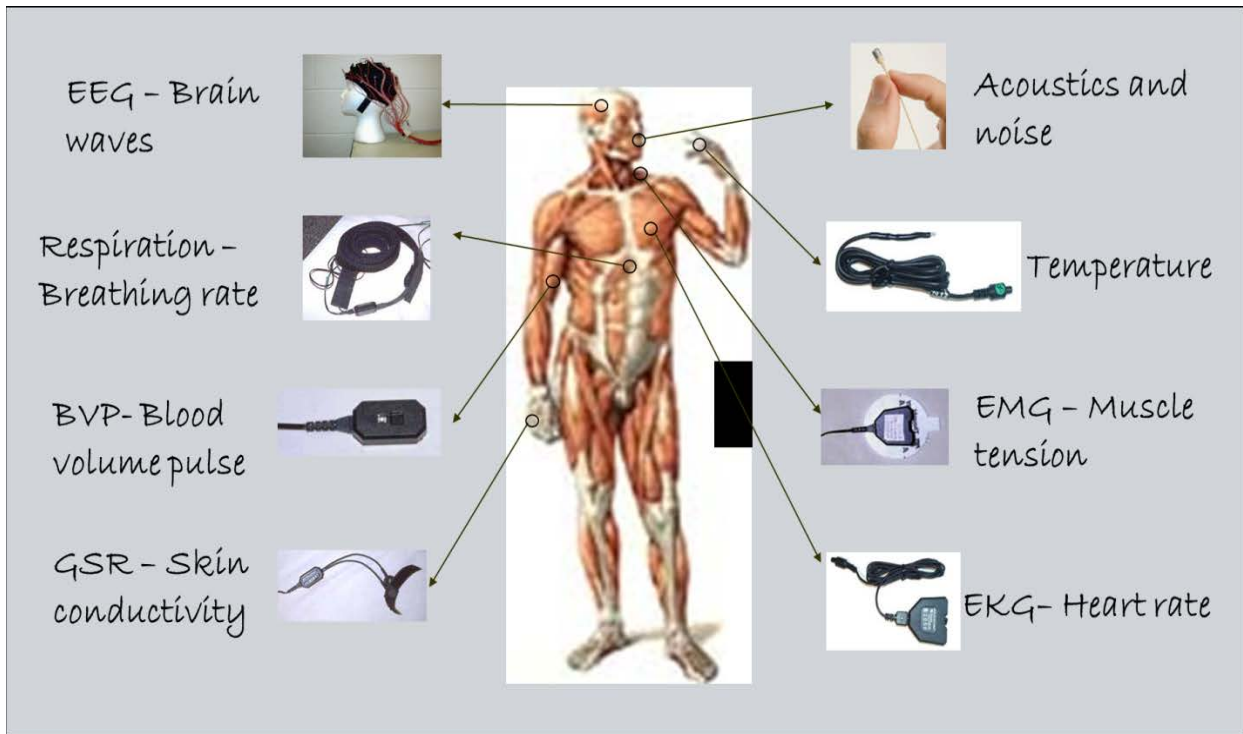
Figure 5.1. The Brain-Body State Sensing Suit(e). Physiological and Neurophysiological Measures of Brain-Body Activity that can be Used by a Decision-Tree-Based Classifier to Distinguish Among Emotional States .

Because *in vivo* deployment of affective remote sensing technologies leads to measurement noise and 'missing data', the key to the use of neuro-physiological remote sensing to reliably identify and map emotional states of e-learners is the concatenation of measurements taken by a suite of measurement devices (Figure 5.1) that produces multiple outputs for every user state. Sensor 'fusion' algorithms [eg. Setz, 2012] can distinguish between different groups of emotions at various valences and degrees of arousal. This enables the construction of simple classifiers for learners' emotional states based on multidimensional aggregates of emotional state data (Fig. 5.2).
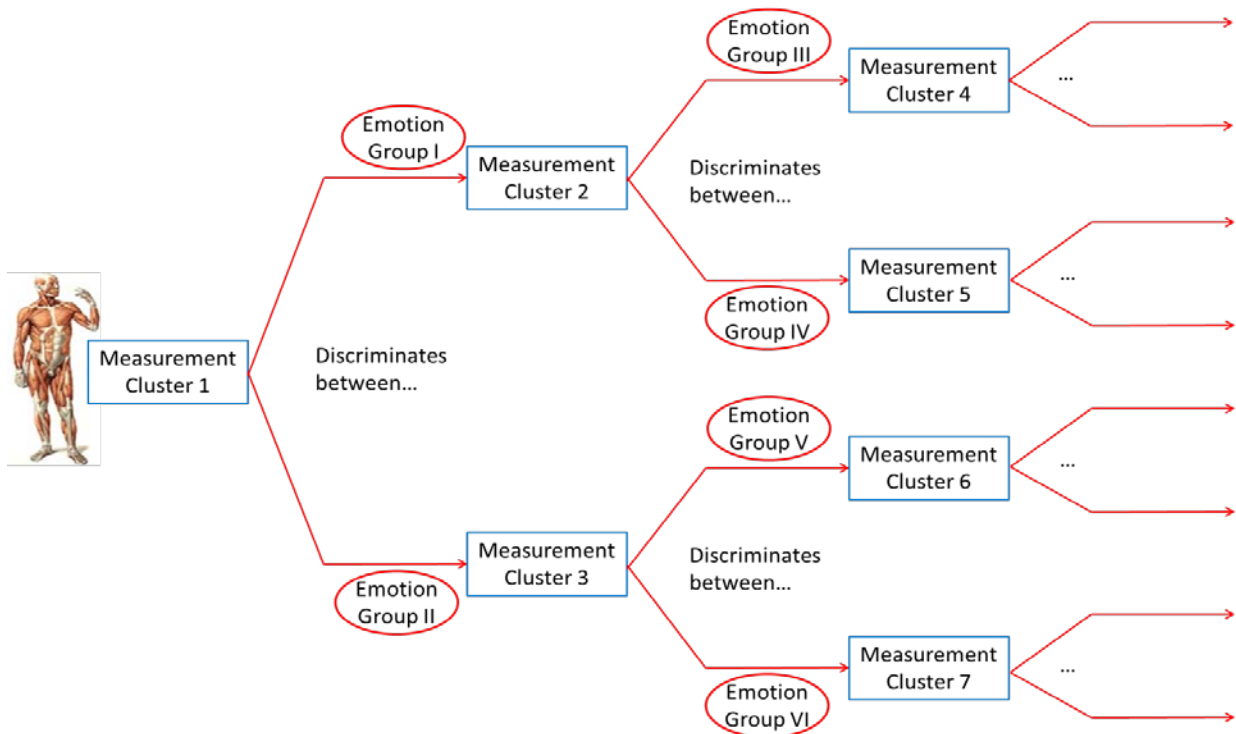
Figure 5.2. Binary Decision-Tree Based Classifier for Discerning Among Different Emotional States on the Basis of Measurements or Clusters of Measurements of Brain-Body States. Every Stage of the Tree produces a Factor of 2 Decrease in the Uncertainty Around the Instantaneous Emotional State of the Participant.

To turn the affective remote sensing capability into a genuine 'learning experience design instrument', we need to also be able to map the space of stimuli that comprise the 'learning vehicle'– a video lecture, an interactive presentation, or a quiz, test or exam. The range of possible 'moves' that its designer can make can be described in terms of a set of variables that intuitively and comprehensively capture the degrees of freedom at our disposal. To wit:

- *Visual complexity* relates to the informational content of teaching vehicles – such as slide decks and mock-ups – that are used to convey information. It can be measured at the pixel/voxel level (how many color schemes? How many combinations?), or at the level of different visual objects the user is likely to use in order to parse or make sense of the visual stimulus;

- *Semantic complexity* of the content- of both visual and auditory stimuli - relates to the degree to which the vocabulary used by the teacher is transparently accessible to the learner (without the need for a translational device, like a dictionary or *Wikipedia*);

- *Syntactic complexity* relates to the logical depth of the informational representation used by the instructor in various forms. It can be, for instance, a measure of the inferential depth of arguments, of the computational complexity of formal proofs, or of the Kolmogorov complexity of certain visual objects used to illustrate a procedure (such as proof construction on a graph);

- *Rhythm* relates both to the speed at which visual cues change (as in flipping through slides and frames) and the *syncopation* patterns of alternating visual cues (i.e. the variance of changes in *tempo*);

- *Speech-expressiveness measures* (like prosody ('tone'), speed, pitch and variances thereof) relate to the space-time-frequency characteristics of voiced and unvoiced speech of the presenter in the medium;

- *Color schemes and color combination patterns* relate to the patterns of colors used to encode visual stimuli used for teaching purposes;

- *Modality* relates to the ways in which information of different kinds (symbolic, narrative, schematic, graphical) is presented to the user, and includes both the specific mode in which the information is presented, and the sequence and combination of modes in which its is presented (i.e. multi-modality);

- *Interactivity level* relates to the frequency, relevance, informativeness, auditability and material implications (high-stakes versus low-stakes) of the user's own participation in the learning experience, whether through

answering or asking questions or inputting answers to a quiz, or making remote presentations to co-users.

These represent a set of *design or policy variables* for the online learning experience, whose specific values may be optimized to produce *learning-optimal* emotional landscapes, and adaptively changed as a function of user emotional states – as reconstructed from a brain-body sensing suite. To fully specify the problem of using neurophysiological measures to optimize learning experiences, we have to also specify a set of *outcome or performance measures* for personalized, electronic skill development. These include:

- *Performance on tests, quizzes and assignments* that are directly related to the content of the learning experience, and which directly measure skill transfer in the specific domain of the course being taught;
- *Performance on cognitive function tests* – many of which have already been automated and are available for dissemination in an online environment (eg., Lumosity's gamified battery of pre-frontal function tests - www.lumosity.com) – which include working memory tests, multi-modal recall tests (can you recall the name associated with a visual stimulus), tests of the logical depth of inferential chains to which the participant can function, and tests of the computational complexity of inferential procedures the participant can engage in;
- *Performance on perceptual function tests* - which relate to the set of higher (object recognition) and lower (stimulus registration) level perceptual skills that the participant may be expected to acquire in virtue of achieving a certain level of performance in the skill transfer exercise.

Automating the testing process, together with the inclusion of new measures for the evaluation of skill transfer outside of the 'training set' enables us to use the e-learning environment to design experiences that optimize not only the transfer of a specific skill to a participant with respect to a particular domain (eg. finance theory), but also the transfer of a higher-level cognitive skills (convex optimization, iterative dominance reasoning, proof construction using deductive operators) to domains that are far (software design, user experience design, strategic reasoning) from that in which the skill was originally developed. The expanded set of performance measures for the learning vehicle design allows online learning designers to make progress on the *skill transfer problem* that is central to the executive development field [Moldoveanu and Narayandas, 2018a].

The combination of a state space model (instantaneous measurements of brain-body states that correlate with emotional and visceral state), a design variable model (the set of moves and manoeuvres that online designers can make to change the learning experience) and a set of performance measures in a single platform for the optimization of skill transfer via e-learning allows us to:

- Design learning-optimal sequences of voice – video- data presentation sequences for maximizing presence and participation, as evidenced by the physiological and neuro-physiological portrait of the learner;
- Design optimal uses of graphics and optimal topology of graphical interfaces for the maximization of participation and presence;

- Design optimal sequences of participatory and individual tasks and exercises for the maximization of learner presence and participation and the maximization of skill transfer;

- Design new tools and technologies for immersion of the e-learner into the know-how and know-what of the domain of skill transfer sought via the design and engineering of stimuli that trigger high-intensity affective responses;

- Design optimal acoustic backgrounds for the maximization of learner participation and presence and the maximization of skill transfer to the learner on the basis of feedback from physiological remote sensing of the learner;

- Design optimal visualization and visuo-auditory content superposition techniques and interfaces for the increase of learner traits and states associated with learning – such as working memory size and accessing speed and working , visuo-spatial reasoning, deductive, inductive and abductive reasoning abilities, specific methods of inquiry and modes and specific methods and blueprints for argumentation.

Consider how the optimization of an e-learning skill acquisition for facilitating the learning of competitive game theory (CGT) might proceed within the variable-space and measurement-space we have introduced (Figure 5.3). Suppose we'd like to teach participants to solve generalized games (inter-dependent, multi-agent decision problems featuring a set of players, strategies, and mutually dependent payoffs). 'Solving' a game entails finding – and playing, in an interactive situation – one of a set of un-dominated strategies, or strategies that maximize the payoff for the user given other users' strategies.

A brain-body-state-based optimization procedure for a game-theory-learning module might look as follows:

- We design and optimize an audio-visual interface for introducing basic concepts (game trees, payoffs and beliefs, iterative dominance reasoning and the calculation of reaction and best response functions) for maximal retention and on-demand recall;

- We use the set of brain body measurements (eg. eye movements to different parts of the screen; skin conductivity as a function of prompt and locus of attention, facial expression, facial temperature distribution and heart rate, indicating annoyance and anxiety levels; cortical activation levels) of a test participant to adapt and optimize the syntactic complexity (how logically complex?), the semantic complexity (how many new words and novel phrases per frame?) visual complexity (how difficult to encode the image in terms of familiar sub-images?), the tempo and syncopation (how often and how predictably do visual stimuli change?) and the color scheme (which colors, what sequences, what dispositions on the screen, how predictably are certain colors associated with certain semantically distinct pieces of information (payoffs, strategies, agents)?) to minimize a composite set of emotional states that are aversive to learning and skill transfer (anxiety, boredom, ennui, anger);

- We measure the degree of in-domain skill transfer (whether or not the participant can parse an everyday situation into a strategic form game, how reliably the participant can define the different, logically independent components of a competitive game; how reliably and how quickly a participant can reproduce definitions of

terms of art like *rationality of players*, *common knowledge*, *Nash or correlated equilibrium*) as a function of different emotional states and different audio-visual stimulus combinations.
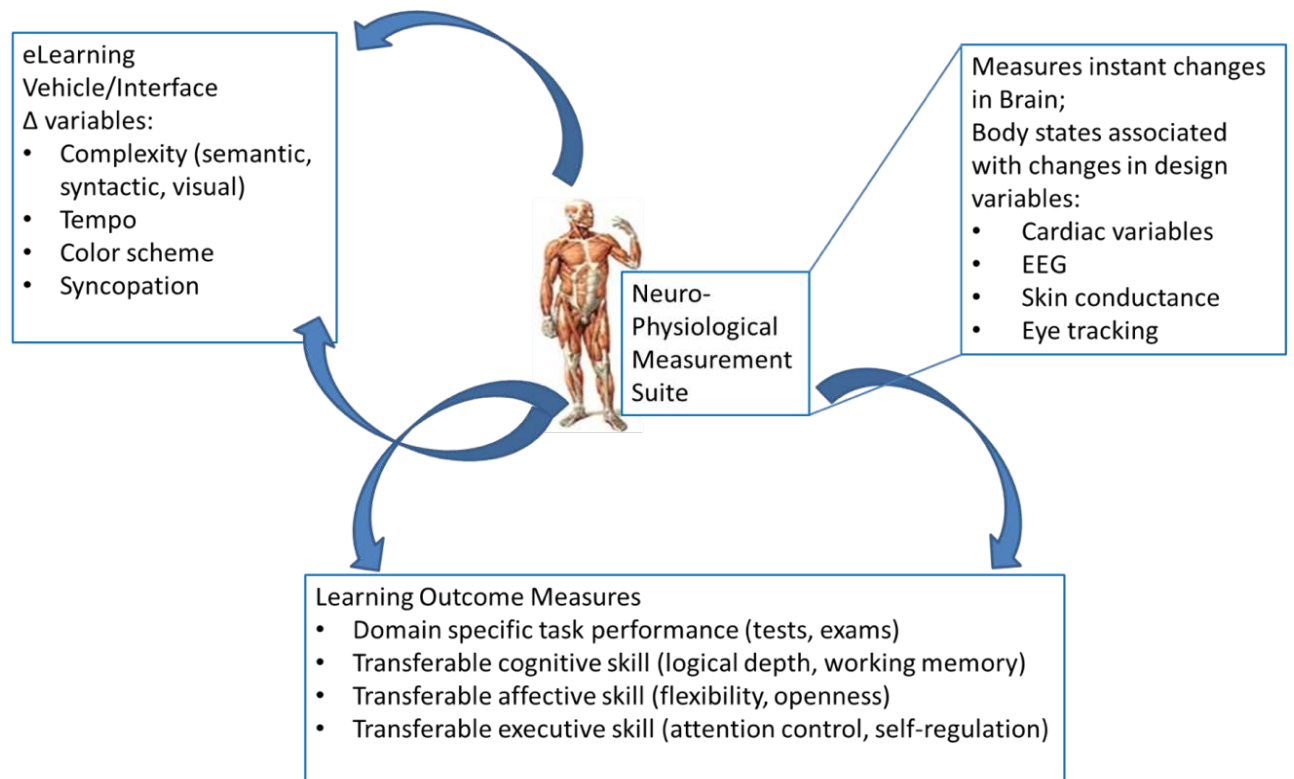

Figure 5.3. Design-Measurement-Outcome Space for the Brain=Based Optimization of the eLearning Experience. Changes in the Values of the Set of Design Variables (parametrizing the qualia of the eLearning stimuli) are correlated with changes in the user brain-body states that are remotely sensed by a brain-body suit, allowing for inferences about changes in instantaneous emotional states triggered by the e-learning stimuli. The effects of these changes on learner outcome measures (both domain-specific and cross-domain, higher level skills) is then inferred from performance measure changes.

We can also focus on measuring the specific transfer of procedural knowledge of game theoretic reasoning - including belief formation, interactive reasoning and strategy selection - that we can achieve using an online learning vehicle, by varying:

- The type of games that participants are induced to play (familiar (tic tac toe, end-games in chess, Go, Prisoner's Dilemma, WolfPack) versus unfamiliar (matching pennies, stag-hare hunt, Rubinstein Bargaining) games; competitive versus cooperative games; mixed strategy equilibrium versus pure strategy equilibrium games; games of perfect information versus games of imperfect information);
- The informational and computational complexity (2-player, 2-strategy, versus 5-player, 4-strategy games) of the games that participants play;
- The frequency of the test-games (every few minutes versus every session; one game at a time versus several games at a time);
- The incentive-intensity of the test game (whether or not performance on the test counts for the final grade; whether or not the participant can gain or lose – face or money – as a result of poor performance as a player in a competitive game).

Access to both the set of design variables (screen layout and GUI dynamics), a set of *thought probes* (quick-fire, pop-up questions about the current beliefs of the participant about the structure of the game and about the beliefs other participants have about the structure of the game and about the beliefs about the structure of the game each of them has) – as well as to measurements that correlate with instantaneous perceptual-cognitive-affective states (via brain-body measurements) allow us to infer the degree and the depth to which participants think about the incentive and belief structure of the game (for instance, the number of moves they think *ahead* in the game, or the number of moves they think ahead, conditional upon the number of moves they think other

players think ahead) – as a function of both the design of the interface (visual, semantic, syntactic complexity, rhythm, color, audio-visual integration) and the instantaneous emotional state (anger, irritation, boredom) of the participant.

We can then:

- optimize the interface for the optimal transfer of the proximal skill (mastery in playing strategies based on equilibrium considerations) in *these* particular games, or in games of *these* particular types;
- identify sources of error and sub-optimal reasoning related to the emotional states of the participant that are independent of the design of the interface (eg: anger arising from moral indignation leading to sub-optimal strategy selection in an ultimatum game); and –
- measure the degree to which the transfer of a higher-level, interactive social reasoning skill that is applicable outside of the domain of the course has been achieved (in some cases, using fMRI BOLD signal measurements generated by the brains of participants engaged in a strategic game (played for real, monetary payoffs) before and after the completion of the course.

'Side-Benefits': Multitasking, Supertasking, and the Enhancement of Executive Function in eLearners**.**

So far, our discussion has focused – implicitly – on the problem of re-designing electronic learning vehicles to correct for the lacunae in learning environment in the electronic medium – vis a vis the classroom experience. However, the possibilities for disambiguating the measurement of skill and

quantifying componential enhancement in skill development via affective and perceptual remote sensing of the user experience opens up the possibility of using e learning skill vehicles to produce improvements in specific skills that are not adequately addressed in the classroom environment.

These are often the skills a new generation of problem solvers and decision makers most need in a hyper-textual and hyper-connected work environment. We want to focus in particular on the nexus of skills associated with media multitasking (Ophir, Nass and Wagner, 2009), which is (usually) associated with impairment of executive function such as suppression of unwanted interference and goal-dependent resource allocation to various sub-tasks. The finding that media multitasking decreases task performance levels at the individual level should concern designers of online learning environments - which are likely to provide precisely the kind of learner experiences that simulate multitasking.

However, recent findings suggest that there are very significant inter-personal differences in multi-tasking ability (Watson and Strayer, 2010): some individuals seem to do *better* on individual tasks in the presence of the cognitive-perceptual-affective interference provided by a multitasking environment. (Jaeggi et al. 2007) corroborate the prevalence of significant inter-subject differences in ability to perform at a high level in a multi-tasking environment, and adduce evidence of significant differences at the level of brain activation patterns in successful versus unsuccessful multitasking. Thus, performance in online courses that make significant use of multitasking skills can function as a *selection filter* for super-taskers. Can they also function as engines for the development of super-tasking skills?

Consider the X-skills decomposition we introduced [Moldoveanu and Narayandas, 2018a] and focus on the *executive functions* of the brain – currently thought to be correlated with heightened activity levels in various parts of the frontal lobes (Smith and Jonides, 1999; Stuss, 2011). The literature offers up various taxonomies for these functions, but those emerging from clinicians having to solve practical problems of addressing neuropsychological deficit are by far the most helpful to engineers of learning vehicles trying to solve practical problems and include: (Stuss, 2011):

- Task energization (speeding up and slowing down the performance of various tasks),
- Monitoring of states of self, task and environment (keeping track of stimulus and response content as well as one's visceral feelings in real time),
- Task setting (adjustment of scheduling one's mental activities and setting of appropriate subtasks),
- Behavioral emotional self-regulation (suppression of propensity to act on aversive preferences or counterproductive temptations),
- Emotional self-regulation (suppression of the propensity to evince or even experience a certain feeling in response to a stimulus or recollection) and –
- The meta-cognitive and meta-perceptual integration of multi-modal stimuli (visual-auditory, olfactory-visual, for instance).

They can also be categorized in a more cognitively-oriented approach (Smith and Jonides, 1999) as:

- **focusing** on specific parts of a stimulus, to the exclusion of noise or irrelevant detail,
- **scheduling** cognitive, perceptual and behavioral processes with regard to their value contribution to the performance of different tasks,
- **planning** or **designing a sequence** of sub-tasks aimed at attaining some goal,

- **updating and adjusting** the contents of working memory to adapt to environmental changes, and –
- en**coding/re-coding** various representations of stimuli in working memory for maximum efficiency in task performance.

The digital learning environment is well suited to the design of interventions and experiences that help participants develop executive functions through targeted practice. This turns the *problem* that media multitasking poses for individual task performance into an *opportunity* for (a) selecting media *super*-taskers on the basis of performance on specially designed testing instruments that stress executive control functions, and (b) *developing* multi-tasking abilities through the design and deployment of interventions aimed at improving executive functions in participants. The key to doing so stems from realizing that all executive functions have to do with the production of action sequences *in time* and under time or speed constraints. Incorporating 'speed-sensitive' versions of quizzes, problems, and other learning tasks will likely serve instructional designers that want to turn the 'short attention span' problem into the 'executive function enhancement' opportunity.

The "Disruption Matrix": An Entrepreneur's Compass for Innovating in the Learning Industry

We have [Moldoveanu and Narayandas, 2019] provided design compasses for chief learning officers and executive program providers in the current landscape. Radical disruption, however, generates new landscapes and calls for a different sort of compass - aimed at the *entrepreneurs* of the EdTech space affixing their attention on the executive development market. The compass

is a nested sequence of questions that innovators and entrepreneurs should ask themselves, and which follow from our analysis of the social and technical landscape that lies just over the visible horizon of executive education. Each question induces a filter on opportunities and feature sets.

The filters do not relate to 'table stakes questions' any start-up or incumbent business should attempt to answer (eg.: competitive and regulatory forces, to the market power of suppliers, customers and employees, and to technological lock-ins and trajectories that can shift competitive ground). They relate to the ways in which the new product, service and associated business is attuned to the dynamics of the executive development industry and can withstand the industry wide changes it itself creates:
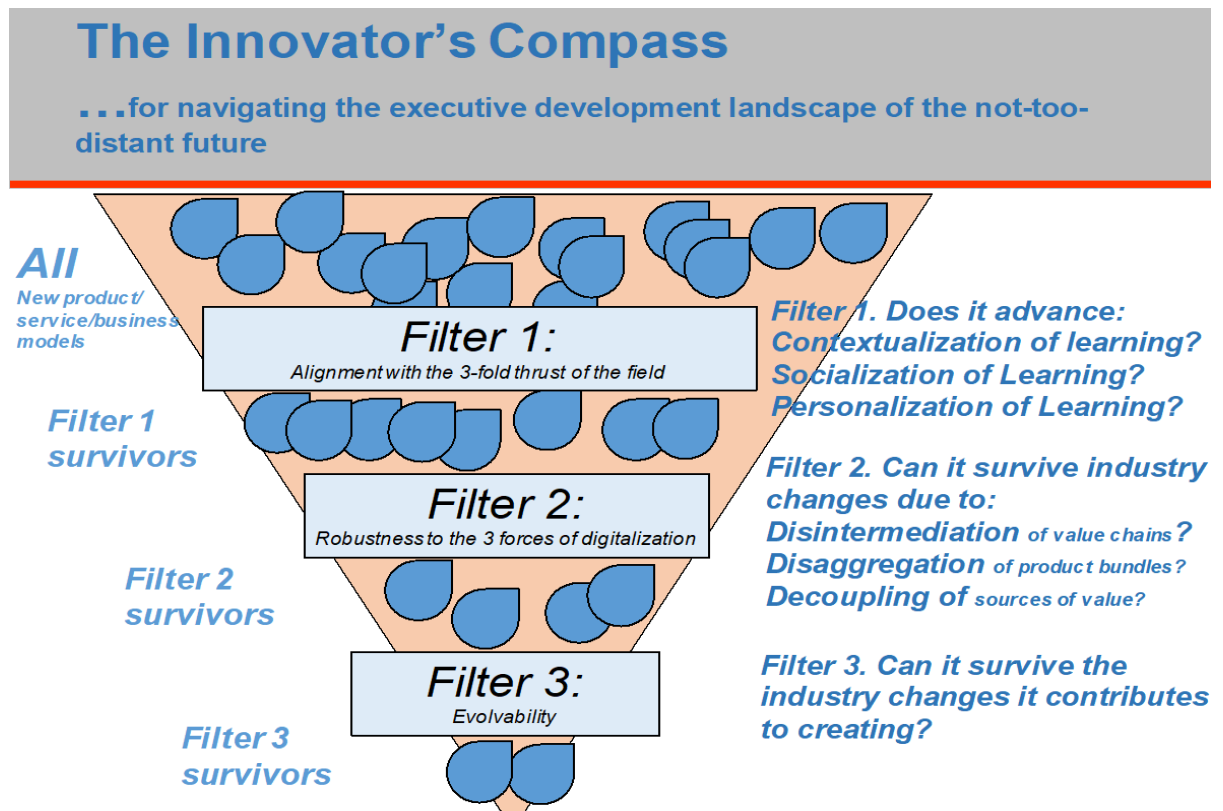

Figure 5.4. An innovator's compass for the executive development market, in the form of a 3-fold filter.

Filter 1. Does the newborn deliver greater personalization and/or socialization and/or contextualization of the learning experience? If only one or two, then at what cost to the other(s)?

For instance: *E-to-Me, Inc.* provides an algorithm-based tutor for any senior manager or board member who needs to learn a business discipline currently considered to be 'quantitative' (accounting, finance, operations research) very quickly (on time scales of hours to weeks - on account of having to use this knowledge in a time-sensitive situation). It uses the executive's current predicament and unstructured materials (documents, spreadsheets and slide decks she needs to parse and understand) as starting points for the 'learning experience'. Learners can ask questions about definitions and uses of words, phrases, formulas and data formats, in 'everyday' language, or in a language system that is most convenient to them. They do not need to speak a word of jargon, nor do they need to phrase their questions in grammatical, connected, cohesive, complete sentences and paragraphs. They can inquire about best practices of activities to which various words and phrases refer. The algorithmic intelligence unit gives answers tailored to the sophistication of the user's queries and questions. It matches the answers to the user's time constraint (and perhaps even her working memory constraint, which the system can, over time, measure).

It gets high grades on contextualization (it starts from the learner's predicament, not some academic's rubric's and PowerPoint slides); and personalization (it matches answers and prompts to its estimates of the user's abilities and states and remembers the user's state-dependent actions). Its founders need to think carefully about the ways in which the social network of learners is created and maintained – specifically, on the ways in which learners

communicate, coordinate and collaborate with other users, whose knowledge of and expertise in the same subject may be similar or different amongst them. This may require the designers to introduce a different set of 'social operations' (conflict/disagreement resolution; disambiguation) than those required by a machine that coaches individuals working in isolation.

Filter 2. Can the newborn survive the dynamic of disintermediation, disaggregation and decoupling that is currently re-shaping the industry?

For instance: Eliza Jones, Inc. is a fledgling virtual business school 'for executives whose motto is 'don't waste my time'' '. It is built on the premise that all business expertise is dialogical and communicative in nature. There is no such thing as a concept or method without the conversation it is part of. This attitude has profound implications to its product design. Its founders believe that teaching people 'finance theory', 'economics', 'accounting', 'marketing' and such - is a big mistake, because it obfuscates the details of practice and context and gets them to perpetuate the mistakes of the past. It also makes them immune to change and mal-adaptive to subtle changes in the social nuances and technical details of context.

Rather, Eliza Jones' products teach them 'the grammar and semantics of finance' in short courses with names like 'How to talk to your commercial loan officer'; 'How to get your analyst to give you the information you need about tech deals' and 'How to persuade your local hedge fund to have a look at your mid-size cash-positive business.' Because it believes all business disciplines (and others too) are simply 'ways of talking', it treats business education like a set of language courses, complete with vocabulary, grammar, pronunciation ('how to punctuate your sentence like an investment banker') and listening/comprehension exercises, using levels, 'lingots' and Blockchain-

verifiable digital badges to allow users to signal their degree of expertise in a discipline to others on social networking platforms. It uses AI-powered 'conversational agents' that can stretch a user's ability to speak a 'new business language' under the pressure of time (and of other people watching the unfolding 'game'). To source the kernels for its learning algorithms, Eliza Jones uses advisors and consultants drawn from what are currently the most highly regarded business schools, economics, philosophy, semiotics, and psychology, computer science and neuroscience departments in the world, and rewards them with equity-like claims on its product lines in the form of royalties-on-net-margins that extend 17 years out (mimicking the lifetime of a patent in the US).

Eliza Jones does well against the 'disruptive trio' of disintermediation, disaggregation and decoupling: It is difficult to disintermediate its product, as it only uses faculty members as designers and developers for products that are ultimately its own. It is also difficult to disaggregate its product, as any realistic unbundling of language learning is bound to feel unnatural: reading, writing, oral expression and aural comprehension – along with dialogicality and discursivity – come 'as a package' in the teaching and learning of a language.

Finally, there is no obvious way to decouple the different sources of value that it brings to its users (networking, different aspects of linguistic – and therefore functional – skill) and preserve the value associated with each component: people on the platform get together ('networking value') in order to learn a discipline *as a language*; the written, aural and oral components of this competence are part of an inseparable nexus or whole ('skill acquisition value'); and the signaling value of the platform is based ONLY on the fact that it is successful at producing the kind of skills it is designed to produce (and not because 'it is Columbia' - for instance).

Filter 3. Can the newborn survive the dynamics it is itself creating in the industry?

For instance: McKharvard, a new B-Form Corp. is a new elite training and development enterprise that is seeking to consolidate the $8-10Bn MBA/EMBA/Executive Education market 'under one roof', using the distributed real estate infrastructure of the world's leading strategy consulting firm and the brand name and teaching prowess of the world's best-known business school. Its goal is no less than to provide 'defining experiences' – at different levels of selection, certification, and development – for all 200,000+ current takers of GMAT tests and 100,000 executives around the world seeking specialized, dedicated training that helps them develop the 'hot skills' leading organizations behave as if they think their executives should have. Its business model is to target test takers and talented undergraduates directly, with programs custom-designed to their specific career interests and individual abilities, and at prices that undercut (sometimes by a lot) the prices of competing MBA, EMBA and executive education programs.

There is some reason to believe that the McKharvard could and should consolidate the market quickly, as there are very few combinations of universities and corporations (IMD-BCG? Stanford-Accenture? Wharton-Deloitte?) that can replicate its status, reach and prowess; and none that can move as quickly as the HBS-McKinsey duo. Does the breakthrough enterprise change the industry in a way that challenges its own business model?

Well, the demand for selection and training into the market for organizational leadership and corporate control remains the same as before; except that instead of being serviced by 300 business schools and the odd consultancy acting separately and providing natural segmentation and

stratification in terms of price and quality, it is now serviced by a single large organization, potentially at many different levels of intensity (10-day to 360-day programs and everything in between, at various price, selectivity and certification levels). It is true that most *business schools* will be left with massive unfunded liabilities (the salaries and benefits of faculty members they can no longer cover) and that many universities that depend on *their* business schools to subsidize their otherwise non-net-income generating activity sets will end up either bankrupt or wards of their states or countries. But, McKharvard Ltd (B-form) does not produce changes at the level of the industry that challenge *its own* ability to survive.

By contrast, consider Filtronics, Inc. - which provides individual-level predictive analytics for organizations seeking executives at all levels. Using combinations of genetic, neurophysiological (fMRI), cognitive and behavioral tests and measures, it provides individuals and corporations with 'much better than chance' estimates on any individuals' potential to lead, manage, execute, create, ideate, and deliver. Its founders believe that education, understood as a developmental activity, is a hoax, and that the only real function of an educational system is to select for individuals that have the skills their future employers value.

Buoyed by recent findings of the predictive power of fMRI scans [Gabrieli et al, 2016] and using the latest affective and cognitive 'remote sensing' technology, Filtronics offers large organizations a proven battery of tests that reliably filter out 'B-players'. In spite of the obvious appeal of Filtronics' approach to would-be employers (and perhaps the early-stage success of the company, provided the technology works and its founders do not squabble) there is something self-undermining about its approach. *Giltronics*, Inc. for

instance, can take the same approach to the market for recent college graduates, and provide filters for 'fresh off the bench' graduates. Their tests will be different from those of Filtronics in some respects and similar in others. But since recent graduates will within 3 or 4 years turn into aspiring executives whose tests are the inputs to the Filtronics filter, the outputs of the latter will be dependent on those of the Giltronics pre-filter. And soon, Kidtronics, Inc. will successfully speculate research that shows early stages of child development are critical to the formation of precisely the high-value skills that employers of individual contributors, managers and executives alike value most [Heckman, 2006] and will create its own search and filtering engine that takes as inputs tests performed on 12 year-olds. Or, 8 year olds. Now, there is something self-undermining about the ubiquitous filtering approach to education, in that Filtronics' success fuels a cycle of testing-based filtering that undermines the reliability and predictive validity of its own measures.

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