Optimal Capacity Building:

Integrating Brain-based Learning and Educational Research

into Technology Supported Learning

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A Motivational Scenario

The following motivational scenario may happen during this century: A couple has their first newborn. Like many other families, inside their home reside thousands of microchips, tiny cameras, and sensors embedded in most tangible objects in the infant's room. This digital technology of infinitesimal size is part of the crib or the cradle, an integral part of animated toys in the form of simulated animals, peer companions, and/or educational robots, or even receiving blankets, clothes, doors, roof, walls, furniture, and so forth. These digital embedded objects communicate and exchange data with each other via wireless communications with linkage to online information as well. The minute-by-minute account of the infant's behavior is observed by the parents and recorded (see Rheingold, 2003). Through intelligent search of massive databanks of other infants' behavior and matching of relevant stored advices from experts such as neuroscientists, developmental psychologists, educational researchers, and parents are kept informed discreetly and unobtrusively with updated recommendations for how to best develop the potential capacity of the infant with respect to its behavioral, physical, and inheritance specificities, to avoid sudden crib death, and to fulfill other life-fostering goals.

Indeed, parenthood is an incessant endeavor for years. Parents are the first teachers of their

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newborn babies. It is likely that the best time to start instructing parents on how to nurture their babies or bring up their kids is even before the first day when their babies are born. An important aim of future technology-enhanced brain-based learning research will be to study how to help parents to be good observers, caretakers, and teachers of their babies from the day they are conceived. Individualized learning histories and performances of babies can be recorded and passed according to privacy agreements to the teachers of kindergartens and schools, with suitable abstractions of the complexities of these records – and with due cautions taken in categorizing learners as having problems – labels that can detract from a learner's opportunities in life. Ultimately, a teacher for every learner, whether the teacher is real or virtual, is possible, though the virtual may not need to be as competent and human as the real one to nonetheless serve important functions.

Continuous technology advancement, economy growth, and societal change have reached a stage that intensive and delicate nurture and education is financially feasible and desirable for every parent and teacher. Global researchers who are contributing to the G1:1 initiative (http://www.g1to1.org) advocate that in ten or more years to come, more and more experimental sites, test-beds with institutional support, or even large scale, such as school districts, deployment projects in which every learner is supported by at least one wireless, mobile, and personal device. The pace of changes in the uses of digital learning technologies will be accelerating in the forthcoming tens of years. The scenario above is not science fiction. It implies a common research goal for a community of scientists.

Grand Challenge Problem

A grand challenge problem (GCP) defines a common goal considered to be valuable and achievable within a predicted timescale by a scientific community working together. The best-known GCP example is in mathematics, with David Hilbert's address to International Congress of Mathematicians in 1900 that described 23 major mathematical problems to be studied for the century to come. Recently, researchers from different fields have proposed criteria for defining grand challenge problems (Gray, 2003). A GCP should be understandable so that the goal is *simple* to state and helps recruit researchers with international background to be involved. It should be *challenging* because the goal is not easy to achieve and some may even believe that it is impossible. It should be *useful* so that when the goal is achieved, the results can be useful to people and have long-term benefit to science, industry, and society. It should be *incremental* since it is desirable that the goal has intermediate milestones to keep researchers going. It should be progressively *measurable* so that one can tell if the intermediate or the final goal is achieved.

We define the problem of optimal capacity building (OCB) as the following: Based on brain-based learning and educational research, how to study and design learning activities to provide learning environments enriched by digital tools to help every individual live up to their full developmental potential? We argue that OCB is a GCP. First, OCB is *challenging* since there is no obvious approach to achieving the goal with the convergence of brain-based learning research and findings, educational research and practices, and the enhancement of digital technology supported environment and tools—even as they have been instrumental in shedding light on new possibilities. Second, OCB is clearly *useful* as it would have momentous impact on every individual, not to mention science, technology, education, and the society. Furthermore, OCB can be defined to reveal its *incremental* milestones and *measurable* progress.

Extension of two related grand challenge problems

Bloom (1984) found that one-to-one individual human tutoring was statistically 2-sigma superior to the learning performance in the conventional one-to-many classroom instructional practice. Searching novel classroom pedagogical models that can reach such a performance given that these models are costly by a normal school's standard is called the 2-sigma problem. This is a GCP. Bloom's approach to that problem is mastery learning (Block, 1971). Interestingly, tackling this 2-sigma problem has been a commonly cited quest of the *intelligent tutoring system* research endeavor, with the mission that every student will learn with an intelligent tutor simulated by the computer, since the first intelligent tutoring system prototype emerged in 1970. This mission is being pursued as strongly as ever for two reasons. First, G1:1 researchers expect that in 10 years there will be more classrooms in which every student is equipped with at least one handy, yet powerful, computing devices with wireless capability. This implies that the eventual vision of every student having a teacher—an intelligent tutor mimicked by the computer is possible. Second, we are beginning to have some successful stories of commercial intelligent tutoring systems in use by many tens of thousands if students (e.g., Carnegie Learning).

Vygotsky (1978) postulated that there is a difference in developmental level between what learning an individual can achieve alone and what learning with the aid of adults and more capable peers can achieve. The difference in this range is called the *zone of proximal development*, and extensive work in the learning sciences and educational research has been devoted to investigating how “scaffolding” of an individual’s developing performances by other people and tools can contribute to learning (e.g., Davis & Miyake, 2004; Pea, 2004; Stone, 1998). Pea claims that attaining this zone of proximal development is a GCP of educational research (2003; also see Pea, 1985), which, accordingly, is also a salient research goal in the field of *computer supported collaborative learning*.

Therefore, historically speaking, OCB evolves from two existing GCPs. From education and psychology perspectives, OCB is brought forth by two GCPs: Bloom’s 2-sigma problem and Vygotsky’s zone of proximal development. From a technological advancement perspective, OCB is the generalization of the implicit long-term goals of intelligent tutoring systems and the computer supported collaborative learning research endeavor. Thus, if the emergence of artificial intelligence and network-based collaborative learning frameworks propelled, respectively, research on intelligent tutoring systems and research on computer supported collaborative learning, then advancement of brain-based learning research and ubiquitous computing give rise to *technology supported capacity building research*.

The rest of this paper justifies OCB as incremental and measurable and outlines how this GCP can be scaled up to define an emerging research agenda.

Justification of Capacity Building Research

Before going further, we discuss in this session the segmentation of the OCB problem as well as some justifications for conducting this research, namely, relating innate versus environmental factors, why “optimal” and “individual,” and we discuss the social responsibility of researchers on this GCP.

Segmentation of the OCB problem

OCB is a feasible problem for research only if we can segment it into achievable sub-problems. Age is an obvious dimension for segmentation. For example, we can separate several age ranges from childhood to adulthood. Domains of capacity such as cognition, affect, and sociability are other dimensions of segmentation. Given an age range and a particular domain of development, some benchmarks for capacity assessment are needed for measuring the increase of capacity through comparing what technology enhanced environments and practices can yield as compared to existing ones. Note that childhood is perhaps the most important age range for building capacity such that substantial increase of capacity at a later age is possible if one is appropriately nurtured with individually tailored brain-compatible practices in a technology enhanced individual development-aware environment. Our discussion in this paper will target on childhood of 12 years and above.

Innate versus environmental

At the risk of oversimplification, we note that there are two broad camps on development for youth from 18 months to 5 years old. One camp regards human beings at such early ages as evolved such that nature has already provided the best environment for their development, without any artificial interference from cultural inventions. An opposing camp is that nurturing can always be improved by enriching the environment and with better interaction strategies if we come to know more about individual's developmental needs and how they interact with their environment. To justify this research, we take the latter position. However, being aware of these different views has led us to be prudent in our approach. For example, in the case of infants, we shall not design any artifacts that will be intrusive to the infant's daily activities nor the parents'. Development of intensive monitoring systems to detect and support infants' activities can be the first step.

Why optimal and individual?

In general, it is practically impossible to reach an *optimal way* of building up one's capacity, yet it is always possible to develop better and more creative ways to improve. The word 'optimal' here emphasizes that, with the advancement in the understanding of learning, there is room to better develop a child that is adaptive to the child's individual specific characteristics. Such self-actualization through the lifespan is an ambitious perspective.

The activities of assessment and responsive support to guide improvements for the learner are at the heart of this issue of becoming optimal. Brain research might one day be able to quantify and prove that there exists an optimal brain development. In the meantime, we need to take advantage of the advent of ubiquitous computing that can accompany any individual and persistently record behavior in order to provide assistive support toward optimal learning, provided that privacy is safeguarded. Standardizing (or benchmarking) formative and summative assessments or tests of a variety of human capacities will emerge that can exploit these ubiquitous sensing technologies. *Brain-based learning technology*, by recording, assessing, and improving learning, is essentially trying to optimize individual capacity in the process of achieving the goal of OCB.

We should address here that OCB is *individual* in the sense that the attainment of learning optimality is relative to an individual's potential development, from the perspective of the individual. The word 'individual' here does not refer to individual learning or that individual learning is better than social learning. Individual and social learning should be complementary. Indeed, social cognition has already become a key component in learning sciences. However, from the view of an individual, the social learning environment, including other participating individuals, is a means of attaining OCB.

Social responsibility of researchers

It is not surprising that in the near future there will be many in the market that claim their books and toys for education are brain-research informed, when in fact they are unsubstantiated by research evidence. As findings of interdisciplinary research in the learning sciences continue to grow, we have to be cautious about how these findings are applied by parents or educators. While some argue that brain research findings are underutilized at this current level, others argue that it is too early to apply unsubstantiated claims from these neuroscience findings to education because educators and parents are not able to distinguish scientific facts from hype (e.g., Bruer, 1997). For example, there may be over-advertisement of some commercial products claiming that these products are derived from the findings of brain-based learning research. The history of science and technology tells us that we cannot cease advancement unless clear and serious controversies exist. Yet it is the social of researchers to be aware and to try to avoid these pitfalls. Another issue is the privacy problem posed by computing sensors installed everywhere. This is an inherent problem of the wireless and mobile technologies, especially when it penetrates into every aspect of our lives. Again, as a part of researchers' social responsibility, this issue must be taken seriously both as a research subject with socio-technical solutions and in terms of cautious policies and practices in handling user data (e.g., Ackerman, 2004; Robinson et al., 2005).

Brain-based Learning Research – Laying Down Fundamentals

Some profound problems such as the essence of matter, the origin of the universe, the nature of the human mind, have occupied the best minds for centuries. The human brain—an astoundingly intricate richly networked structure with approximately 100 billion neurons—represents a universe of infinite possibilities and mystery, and has drawn the curiosity of human beings for thousands of years. Many delve into the search on how the brain accomplishes its amazing feats. Neuroscience is a research field composed of anatomy, physiology, chemistry, and molecular biology studies of the nervous system. The 1990s was hailed as the decade of the brain because of the emergence of sophisticated and powerful instruments measuring the brain at work. Non-invasive imaging technologies such as computerized tomography (CT), positron-emission tomography (PET), magnetic resonance imaging (MRI), functional MRI (fMRI), and magnetoencephalograph (MEG) reveal brain activities by determining which parts of the brain are performing specific tasks and which are the parts that are dormant. With such advanced equipment, neuroscience researchers with particular interest in how brain activities relates to learning will be able to observe human learning process directly. See Begley (2000) for more on the predictions of future brain research development.

Human brain at birth is equipped with all the neurons in their appropriate positions, and yet, this does not mean that brain development is complete. Research has indicated obvious increase in size and complexity of the dendrite tree of neurons. And this process of brain development is closely related to the degree of richness in the environment. Piaget proposed the assimilation and accommodation mechanism for learning that is evidenced in neuroscience study. In addition, brain research reveals that learning brings about localized changes in areas of the brain associated with the task, thus organizing and reorganizing the physical structure of the brain. Different parts of the brain responsible for different functions may be ready to learn at different times. Learning continues throughout our life and may be exceptionally important for children from the perspective of brain development.

Cognitive psychologists and neuroscientists thus collaboratively studied the neural basis of cognition and learning (Gazzaniga, 2004; Posner & Raichle, 1994). Emerging connectionist modeling approaches to investigating the mind and new technologies of brain-imaging provide convenient tools to understand the brain and its functions and have promoted cognitive neuroscience to an unprecedented state. Studies have revealed new evidence of the neural basis of cognition. For example, the frontal lobes have been found to be associated with word generation, verbal working memory, memory strategies, attention vigilance, semantic association of emotions, and higher-order reasoning.

Developing brain-based learning theories

Theories of learning seek to offer a holistic view of how learning occurs. A learning model gives us a conceptual foundation for designing and evaluating the effectiveness of learning activities, materials with different media, artifacts, and thus enriched learning environments as well as to develop learning objectives to be promoted for the needed qualities of citizens of our next-generation society. For OCB, we need a model to describe how the brain functions in the process of learning and how it gives meaning and purpose into our learning activities so that it reveals components of perception, attention, self-awareness, reflection and so forth. There has been inexorable movement towards specialization through the claims for separate mechanisms for processing visual objects versus locations (Ungerleider & Miskin, 1982), procedural versus declarative knowledge (Squire, 1987), language (Fodor, 1983), arithmetic (Dehaene, Spelke, Stanescu, Rinel, & Tsivkin, 1999), and categorical knowledge (Warrington & Shallice, 1984).

Never has there been a time of greater challenge for learning per se, and never has there been such an opportunity to rethink the whole process of learning. Theories of learning were typically based on behaviorism and cognitive psychology, and more recently on socio-cognitive theories. With experiments and observations, they make informed hypotheses about the human learning process. Some of the theories will continue to stand the test of time while some others may have to be revised due to new discoveries in neuroscience.

Education Research - Forming and Changing of Mental Representations

As mentioned above, brain research has been contributing valuable information related to learning. Educators are attracted to the idea and ask what they can do accordingly. Yet psychologist Byrnes (2001) after reviewing brain related literatures offered a way to take brain study into educational consideration. He said: “ brain research cannot be used to support particular instructional practices, it can, however, be used to support particular psychological theories of learning, which in turn can be used to design more effective forms of instruction” (p.185).

We take memory studies as an example. Psychological studies have indicated that human memory is a multifaceted process. Studies of brain-injured patients indicate that there are different types of memory. The distinctions between implicit vs. explicit memory, declarative vs. procedural memory are theoretically accepted. Based on psychological theories, brained-based memory research studies were carried out. It has been shown that memory systems are widely distributed across the brain (Table 1, Johnson, 1997; Squire & Knowlton, 1995).

Memory types	Different kinds of memory	Brain structures
Declarative (explicit)	Facts, events	Medial temporal lobe, diencephalons
Non-declarative (implicit)	Skills and habits	Striatum
	Priming	Neocortex
	Classical conditioning	Amygdale, cerebellum
	Non-associative learning	Reflex pathways
Working memory		Frontal lobe, parietal lobe

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Table 1: Memory structures (Goldman-Rakic, 1992; Squire & Knowlton, 1995).

Obviously our brain is specialized to carry different types of knowledge. In addition, brain matures area by area. For example, around age 5and 6 the visual and auditory areas of the brain resembles those of the adult. Yet, the areas of higher cognitive functions approach adult's level of efficiency around mid to late adolescence. It is not all kinds of knowledge can be learned in the same way at different period of age.

It implies that teaching practices either of reading, writing, or arithmetic should be reformulated. And most of all, assessment of what students know needs to go beyond discrete bits of knowledge and skills. Learning evaluation should include how students know, how they use knowledge to solve problems and to reveal crucial features of different knowledge representation and proficiency. At the present time, assessing a learner's individual knowledge schemas and how the brain represents learned information in terms of neural connections are challenges to all researchers.

Designing longitudinal assessment attributes

For individual capacity building, it is also desirable to have capacity-aware learning tools and environments for continuous detecting and monitoring for an extended period. This means that we need to design longitudinal assessment attributes. These assessment attributes will be crucial in setting some milestones for the GCP to be achieved. However, before deciding on these attributes, we have to *rethink our educational objectives* so that the learning activities and pedagogical strategies can be designed to meet the needs of the rapidly changing future.

In general, capacity development at early ages will include assessment of five senses: sight, sound, touch, taste, and smell. However, assessment research is more related to the first three senses, we in particular, shall stress on three domains of assessment—cognitive, affective, and social. For the cognitive domain, we divide that into two dimensions, *thinking* types and *knowledge* types. For thinking types, there are three attributes, *acquiring* (remember, understand, and apply), *creative* (analyze and synthesize), and *reflective* (evaluate). For knowledge types, there are *declarative* (factual and conceptual) and *non-declarative* (procedural and meta-cognitive) attributes. In all, we assess knowledge representations and strategies. For affective domain, the tentative attributes are *attention*, *interest*, *challenge*, *achievement*, *perseverance*, and *confidence*. For the social domain, attributes to be assessed include *negotiation*, *coordination*, and *responsiveness*. For all three domains, we will need to assess both individual and group attainment in order to explore the interaction among members of the learning community.

Learning Technology – Realizing Capacity Building by Crafting Ubiquitous Educational Computing Environment

What distinguishes humankind from other species is the ability to create and use tools and symbolic systems such languages for communication. The role of learning technology is to assist developing appropriate educational environments, constructing computational scaffolding and assessment tools, and building experimental sites. Thus far, most digital technology for supporting learning and teaching were mainly desktop computers. Today, there are various mobile devices with wireless communication capabilities such as notebooks, tablet PCs, palm or pocket PCs, and cellular phones. As envisioned by G1:1 initiative (www.g1to1.org), in ten years or less, we shall see a growing number of students using portable computing devices equipped with wireless communication capabilities both inside and outside classrooms.

Looking a bit further in the future, the mega-pace of digital technology evolution continues to be governed by Moore's Law as the number of elements on a microchip doubles every 18 months, and Metcalfe's and Reed's Law have validated that the number of potential connections among nodes (and thus the power of networks) grows more quickly than the number of nodes. Together with the reducing costs of computers and the emergence of wireless sensor networks, we will witness the arrival of ubiquitous computing era (Weiser, 1991). Almost every tangible object (Ishii & Ullmer, 1997; Norman, 1998), in our daily lives, and people in the physical world will be attached and linked to tiny computers. When connected online, these computers will create a communication world associated with place-specific information and nurture generations of wearable computing communities. Nonetheless, technology is a medium for learning, not the aim itself. These technologies will bring forth a unique opportunity for us to capitalize past research findings to construct a seamless integrated learning environment. In such an environment, we are able to consider the entirety of children's experiences when they immerse in a sensor and microchip embedded environment where most tangible objects, places, and individual children are interlinked to form a pervasive web of information, communication, interaction and knowledge (Rheingold, 2003).

In the past, most learning technology research has assumed that computers are used as tools for or mediators of communication or interaction. A shift in the research paradigm, however, may emerge, as reported in the special issue Journal of Computers Assisted Learning 2003 (JCAL, 2003) on research and development of various toy technologies. Also, in a panel discussion in CSCL2005 (www.cscl2005.org), new possibilities were explored on “how the 'person-to-daily-physical-objects' communication affordance may extend the current 'person-to-person via computers' communication so that one can interact simultaneously and unobtrusively with multiple micro-sensor embedded objects reacting to external stimuli.”

Some definitions and guided design principles

Every child is surrounded by tangible objects everyday, for example, crib, go-cart, desk, wall, floor, clothes, socks, etc. Most of these tangible objects are not meant for learning. In principle, we can embed microchips and sensors in every such tangible object. The question is, with such additional computing power to these objects, can we enhance children’s learning? The following definitions and principles provide some guidelines for future research in this perspective.

Definition: *Learning enhanced object* is a tangible object with embedded chip(s) or sensor(s) for the purpose of observing and enhancing learning.

Definition: *Embedded* ubiquitous *educational computing environment* is an environment composed of massive learning enhanced objects. These learning enhanced objects can communicate and share data with each other and/or computing systems in the environment.

Below is a set of guiding design principles:

1. ***Non-intrusive, privacy protection, and safety:*** Learning-enhanced tangible objects should be non-intrusive to the daily activities of children. That is why they are embedded and to a large extent, invisible. Data collected through these sensors should be protected for privacy reasons. The design of learning enhanced objects and hence the environment should not negatively affect the health of children.
2. ***Data sustainability and persistency:*** Data collected should be maintained for a long period of time.

This is lifelong data used for individual capacity building.

3. ***Research and design feedback loop:*** We have to consider different people to be involved in this endeavor, including researchers, parents, teachers, and learners and how tasks are distributed among them.
   (a) Technically, wireless sensors can be embedded in every location and every object in the environment and thus extensive data can be collected from the environment. For researchers, including neuroscientists, psychologists, education researchers, digital technology experts, designers, many issues need to be concerned and the results will be valuable feedbacks for the research, such as what kinds of sensors are developed, where the sensors are embedded, and how the data be interpreted.
   (b) For parents and teachers, the interpretation of the research data by neuro-cognitive psychologists and education researchers will be helpful for them to monitor, understand, and help learners. This process will also educate parents and train teachers on how to observe learners and build individual capacity.
   (c) For learners, research data will bring about collaboration among researchers to develop technology enhanced brain-based learning tools and environment.

Relating Three Research Areas

This paper attempts to relate the three different disciplines in the hope that it can shed light in paving a research roadmap in the future. We define relationships among the three areas as follows:

Research area 1: Basic research - neural pathway of learning

(3) ↓ ↑ (2a)

Research area 2: Psychological theories and education practice - development of knowledge representations

(1) ↓ ↑ 2b)

Research area 3: Learning technology – building environment and tools to realize capacity building

Figure 1

*(number) indicates communication pathway of 3 research areas.

Since brain-based learning theory is still under construction, psychological theories will be considered first in developing learning technology to enhance learning (pathway 1). In return, the learning outcomes provide feedback to psychological theories (2b) and brain studies (2a) to further the explanation and exploration of the relationship between brain and learning.

For example, attention involves orientation, filtering, and enhancing. Correspondingly, three brain-based networks were identified: orientation network, executive network, and alerting network (2a) (Posner, 1995). Moreover, attention can be both automatic and controlled and it changes with age. Technology can help teachers create learning environment to maximize young learners' attention (3 & 1). We postulate that:

1. Engaging learning activities with multimedia content material attract learners and engage them as active participants;
2. Computers can keep track of learners' progress and establish routines to allow efficient progress toward goals.

Besides, there are links between attention, motivation, and emotion. Emotional feelings serve as contextual cues that can be used to help retrieve memories. Further, attribution theories reported how students have different emotions when they attribute outcomes to different kinds of antecedent causes. It may prove to be more effective instructionally if we enlighten learners' emotions by designing game like practices equipped with modeling, encouragement, and mentoring and rewire their perceiving antecedent causes (1 & 3).

Subject matter wise, both math and language/reading have extensive and reputable brain and psychological studies. For example, in arithmetic area, researchers proposed different neuroscience models of calculation (McCloskey, Caramazza, & Basili, 1985; Dehaene & Cohen, 1997). Dehaene and Cohen (1997) argue that exact arithmetic and approximate arithmetic require different processes in the brain. The former is language dependent and the latter is visual-spatial dependent. Instructional activities equipped with technology can be designed (Research areas 2 & 3) to promote the acquisition of number concepts (approximate arithmetic) and to enhance schemata for word problems (language and exact arithmetic). In addition, design can also promote meta-cognitive understanding of the sensibility of the answer (combination of exact arithmetic and approximate arithmetic). Since arithmetic skill also involves spatial domain of the brain, besides math and language/reading, we will also need to study spatial abilities.

Researchers from area 1 will observe the brain activities with brain imaging technology or sensory technology (tangible object) developed by area 3. Researchers of area 2 will measure learning outcomes especially on the changes of mathematical knowledge representations. The (1), (2a), (2b), and (3) will go in cycles to fulfill the objectives of GCP.

Moreover, as mentioned previously, age is a benchmark for capacity building, and Table 2 lists some key learning goals for different domains at different ages.

Learning goal/ Age	0-3	3-5	5-12
Language: phonology	Categorical perception	Phonological awareness	Zu Yin Fu How and characters
Language: semantic	Vocabulary	Semantic network	Comprehension
Language: syntactic	Word order	Story grammar	Syntax
Reading	Story	Learn to read	Learn to read / read to learn
Arithmetic	Part-whole concept	Counting	Number sense, word problem
Spatial	Shape, position, location	Orientation	Math, science patterns

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Table 2: Learning goals for different ages.

To monitor learning progress, observations will need to be conducted longitudinally. The learner's vocabulary growth (age 0-5), reading skills (age 3-12), representational change - physical object concept (age 0-5), number concept (age 0-5), knowledge of syntax (age 3-5), knowledge of nature (age

3-12), sense of self (age 0-12), and peer relationship (age 3-12) will be recorded by innovative learning technology. We will also observe parent-child (target learner) interaction. All learning data collected by monitoring systems will be analyzed by experts or by designed artificial intelligent mechanisms and then the results may serve as feedback to learners. Parents will also receive advice with the feedback data if it is necessary.

All learning will be embedded in a social and affective environment that is designed by the above-mentioned principles.

1. ***The social environment**:* Learning objects are presented with interactive modes. For example, language learning will be situated in story and conversation style, with practice and feedback provided by learning mates. Learning mates can be peers in a group or simulated peers (learning enhanced object).
2. ***The affective environment**:* When someone gets interested in learning something, he has affection for it. Thus an environment can be designed (a) to attract learner's attention; (b) to sustain the attention; (c) to provide challenges to motivate in-depth learning; and (d) to provide achievement as feedback.

Summary and Discussion

This paper proposes a Grand Challenge Problem: OCB. To attain the goal of OCB, we have to orchestrate the integration of three different disciplines. Brain-based learning research, the first research area, is the fundamental research of learning that studies the essence, process and theory of learning from the perspective of brain. Education research, the second area, intends to inquire and translate brain study and digital technology research into better ways in assessing and understanding how learners learn and how teachers teach, through participatory design and field study. Learning technology, the third area, aims at designing tools and environment to record, assess, and enhance learning, making learning more fun and effective.

As we have accumulated more research evidence and significant progress in this avenue of research, it may be worthwhile to consider postulating some quantified statement of OCB, for example, “doubling individual capacity in 50 years!”

In summary, given the advancement of the three related areas, it is time to revise some long term goals so that researchers of learning sciences can set up some milestones to achieve this goal through the concerted effort of different disciplines. OCB is just one possibility towards such a goal.

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