From Learning to Knowing: A Psychological-Neurological Approach to Explain the Human Capital Formation Process

Tamilina, Larysa and Tamilina, Natalya

Independent Research, Greece

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Larysa Tamilina and Natalya Tamilina

Independent Research

Dikis 15 Zografou

15773 Greece

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Correspondence concerning this article should be addressed to Larysa Tamilina: Phone: +30 210 7777640; +49 152 37389799. E-mail: larysa.tamilina@gmail.com.

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Abstract

By drawing on neurological and psychological theories of learning, our study introduces a new conceptual framework to analyse the role learning plays in knowledge and skill acquisition. Learning is modelled through four mechanisms defined as individuals' participation in formal, non-formal, and informal learning, as well as learning-by-doing. Our analysis suggests heterogeneity in how various learning mechanisms affect individuals' overall stock of knowledge and skills. Additionally, the proposed analytical framework points to the existence of an optimal sequence in which different learning forms should be pursued in order to maximise overall stocks of human capital. These propositions are tested with the Adult Literacy and Life Skills Survey data (2003) utilising a variety of statistical techniques.

Keywords: lifelong learning, skill acquisition, neurology of learning, psychology of learning, economics of learning

JEL classification: I21, J01, J24, J28, J88

From Learning to Knowing: A Psychological-Neurological Approach to Explain the Human Capital Formation Process

Learning is incorporated into most public policies ranging from poverty alleviation to combating unemployment. Its impact remains questionable, however, with many arguing that education or training can only slightly change one's occupation-specific knowledge and skills and hence an individual's opportunities in the labour market. Despite strong evidence of a positive return to education, formal learning has often failed to explain the majority of cross-individual differences in wages, even within one country (Hanuschek & Woessmann, 2011). Similarly, training or non-formal learning often proves ineffective in increasing one's earnings or odds of employment (Fay, 1996; Heckman, LaLonde, & Smith, 1999; Sousounis, 2012). Consequently, governmental policies concerning equal access to education are being deprioritised, while a gradual expansion of private educational institutions can be observed in many developed and developing countries.

This study's main objective is to present a new comprehensive analytical framework explaining the relationship between participating in various learning activities and an individual's overall stock of knowledge and skills. The main idea we introduce is that learning has a continuous nature and effects thereof can only be maximised if various learning forms are combined throughout an individual's life. We explain this argument by supplementing economics with psychological and neurological approaches to modelling the initial formation and subsequent change of brain architecture within which the accumulation of knowledge and skills is embedded. The main rationale behind our idea is that synaptic connections storing knowledge need to: (1) be developed and (2) sustained throughout an individual's life in order to function effectively. Both stages are perceived as important. Initial learning helps to create the framework necessary for storing information. Later learning undertaken after formal education contributes to sustaining and further expanding this framework. Our argument promotes the idea that formal education should be combined with non-formal and informal learning as well as with learning at the workplace, as one can only observe strong educational effects on an individual's stock of human capital if they occur jointly. This article thus takes seriously the concept of lifelong learning.

Literature overview

While the term *lifelong learning* remains a popular one often associated with such research topics as poverty alleviation, social inclusion, unemployment reduction, and economic growth, there is no consensus in the literature regarding the extent to which each of the learning forms contributes to individual stocks of human capital. It is possible to distinguish between two major strands in economics that analyse learning. The first focuses on schooling undertaken within the framework of formal education and the second embraces post-school training.

The investments in schooling strand usually analyses returns to education. Denny, Harmon, and O'Sullivan (2004) suggest that formal education remains a dominant factor in predefining levels of earnings in the labour market even after controlling for the direct measures of skills. Hanushek, Woessmann, and Zhang (2011) demonstrate that there is a positive impact of years of schooling on individual earnings that varies depending on whether education is general or takes the form of vocational training. Not directly focusing on the return to education, Leuven, Oosterbeek, and Ophem (2004), Kahn (2007), and Freeman and Schettkat (2001) provide similar evidence for a positive return to education and skills that differ across countries. The cross-country variation in the reward to education is in turn attributed to differences in labour market institutions (Kahn, 2007) and demand-supply imbalances in the labour markets (Leuven et al., 2004).

The investments in post-schooling strand, in contrast, focuses on investments in training and their effects on earnings or employment patterns. Depending on the methodology and statistical methods used, the type of training programmes or the target groups subjected to the analysis, studies provide contrasting evidence on the effectiveness of training. Ashenfelter (1978), for instance, demonstrates that governmental post-school training programmes in the USA usually increase the earnings of trainees in the period immediately following the training. Similarly, Kluve, Lehmann, & Schmidt (1999, 2004), Lubyova and Van Ours (1999), and Puhani (1999) provide evidence that large-scale training programmes may have a positive effect on employment opportunities. In contrast to these studies, Sousounis (2012) reports that general training or employer-financed training has a statistically insignificant impact on the earnings of employees. In addition, Fay (1996) and Heckman et al. (1999) review relevant literature and offer a largely pessimistic assessment of publicly funded training programmes that actually succeed in raising employment opportunities for unemployed people.

Irrespective of the direction and the strength found for learning effects, one can derive three main drawbacks that are common for the existing studies. The first drawback is that analyses of cross-individual variations in labour market outcomes use a narrow definition of learning. Existing studies are largely limited to intentionally undertaken activities to acquire new knowledge or skills, generally resulting from participating in learning programmes organised by an employer or an educational establishment. This approach *a priori* denies the fact that learning may, on the one hand, occur unintentionally, such as learning-by-doing, or that knowledge and skills may, on the other hand, be formed outside of organised or institutionalised programmes, as in the case of informal learning.

The second drawback concerns a poor understanding of heterogeneity in regards to different forms of learning. Various learning forms have a different range of courses, varying degrees of their coverage, duration, teaching intensity, and attendance frequency, so they may lead to different levels of knowledge and skill accumulation. To the best of our knowledge, there is no juxtaposition of the learning impact on an individual's overall stock of human capital across different forms of learning, which may in turn hinder understanding which learning forms matter most to the formation of knowledge and skills and hence labour market outcomes.

The third drawback is a limited focus on the interplay between different learning forms in their impact on individual stocks of human capital. The studies usually solely focus on either formal or non-formal learning and rarely explore their joint effects. The only commonality is that highly educated people are more likely to participate in additional training (Hanushek &Woessmann, 2011) since their rewards from such investments tend to be greater than those for less educated people (Blundell, Dearden, & Sianesi, 1999). Nonetheless, there is no explanation whether similar interplays exist between other forms of learning and, if yes, whether such a combination of learning forms may accrue in more ways than just a simple sum of knowledge and skills resulting from the isolated participation in each form. Finally, if this is the case, it is unclear what causal mechanism is behind these joint effects.

We attribute the existence of these drawbacks to a more general economic problem regarding how the formation of knowledge and skills can be modelled and whether different learning forms can jointly be included in regressions. As such, a new comprehensive theoretical framework is needed to explain the process of human capital formation so that we can identify the way and the extent to which various learning activities contribute to human capital accumulation.

Theoretical model

In modelling the process of human capital formation, we refuse from the traditional economic approaches to analysing learning (Becker, 1975; Ben-Porath, 1967; Mincer, 1974). They are based on mathematical formalisations of the impact that education and employment experiences may have on different performance indicators and do not allow easily including other forms of learning in the models, such as informal or learning-by-doing. Instead, we resort to psychological and neurological theories of skill acquisition to construct our conceptual and empirical frameworks of analysis. Both disciplines focus on explaining the logic and biology of mental processes that constitute human capital formation. They can hence provide better methodological tools for linking various learning instances to an individual's overall stock of human capital and establishing interactions between them.

Neurology views learning as a biological process that is managed by neurological structures of the brain. Neurons, representing the basic unit of analysis, form synaptic connections that accrue into neural assemblies, enabling information to be stored in the brain. Certain types of information are believed to be stored in certain brain areas and using them jointly also requires the development of links, called fibres, between different, distant brain areas. The fibres are expected to lay the foundation for simultaneous or subsequent collaboration between different areas of the brain. The final brain architecture with the overall amount of neurons, synapses, and fibres reflects the overall stock of knowledge and skills that an individual possesses, whereas learning as such can largely be reduced to the formation of synaptic connections.

Neurology distinguishes between five determinants of synaptogenesis: Genetics, stimuli, motivation, emotions, and decay (Byrnes, 2001). Genetics predetermines the brain's overall quality, such as brain size, number of neurons of particular types in particular brain areas, and the number of synaptic connections each area's neurons can potentially form (Byrnes, 2001). It thereby predefines the brain's processing capacity and hence the individual's overall intelligence potential. The brain's processing capacity is believed to be dynamic and vary across a person's life span (Plomin & Spinath, 2002; Li et al., 2004). It proves particularly influential for learning during maturation and old age (Baltes, Lindenberger, & Staudinger, 1998).

While genetics predetermines the brain's ability to form synaptic connections, these synaptic connections do not generate themselves. They are usually developed through an individual's exposure to stimuli. When individuals are exposed to stimuli, their external sense organs perceive the information and transmit it to certain brain areas through a prewired circuitry, thereby stimulating neurons to form relatively permanent synaptic connections (Byrnes, 2001). The same person's exposure to the same set of stimuli may lead, however, to a different intensity of synaptogenesis, depending on two factors: attention and emotions. These act as mediators predetermining the brain's level of responsiveness to external stimuli (Byrnes, 2001). Attention is placed on a person's interest and hence on the motivation level that they exhibit when perceiving the existence of stimuli and exposing themselves to it (Atkinson & Shiffrin, 1968; Byrnes, 2001). The outcome of this attention can be quantitative and qualitative. The quantitative approach suggests that the level of attention may predetermine the number of stimuli an individual chooses to perceive and hence the number of synaptic connections that are formed. The qualitative approach suggests that attention may also predetermine which aspects of the situation or stimuli enter a person's mind and hence what kind of knowledge and skills are acquired (Atkinson & Shiffrin, 1968).

Emotions are believed to have a cognitive aspect that involves evaluating the relevance of events or information to one's goals, which helps to motivate individuals to perceive stimuli (Porges, 1992; Wigfield, 1994; Weiner, 1985). Additionally, emotions can influence the creation of synaptic connections by changing the brain's chemistry and directly facilitating or hindering synaptogenesis. Hormones released during stress (epinephrine and norepinephrine) are, for instance, believed to have a reverse U-shaped effect on memory (Cahill & McGaugh, 1998). Or, excessive negative emotions promote the death of neurons in key areas of the brain and hence negatively affect the overall process of synaptogenesis (Byrnes, 2001).

Genetics, stimuli, motivation, and emotions should be perceived as factors that predetermine the intensity and quality of synaptogenesis. These synaptic connections may however decay with time. Decay theory is based on the premise that a record's strength weakens over time if no further practice ensues (Byrnes, 2001). Activating certain synaptic connections may improve the accessibility of knowledge and skills stored in them. The theory, moreover, does not limit the decay process to synaptic connections but expands it to the ability of neurons to form synaptic connections over a lifetime. Recent neuroscientific findings suggest that brain areas' functional organisation is dynamic (Johnson, 2001), decreasing in specificity (Cabeza, 2002; Reuter-Lorenz, 2002; Logan, Sanders, Snyder, Morris, & Buckner, 2002) and the efficiency of mental operations during ageing (Baltes et al., 1998).

If we assume that synaptogenesis equals the process of knowledge and skills accumulation, combing the information on the determinants of synaptogenesis may allows us to introduce a new model of human capital formation. The formation of the stock of knowledge and skills can be presented as a two-stage process (see Figure 1): (1) The initial formation and (2) the subsequent preservation and change of synaptic connections. The initial stage refers to the initial creation of synaptic patterns through an individual's exposure to stimuli combined with a certain level of attention and emotions that the individual exhibits towards these stimuli. The stimuli selected and actually perceived will be filtered by genetics, resulting in the formation of a certain number of synaptic connections and hence knowledge and skills of a certain quality. Both the genetically pre-programmed ability of the brain to form synaptic patterns and the quality and quantity of stimuli can be considered key determinants at this stage of synaptogenesis.

The second stage involves two sub-processes: The preservation of synaptic connections that were previously formed and the additional formation of new synaptic patterns. The preservation process requires at least periodic activation of the existing synaptic connections which corresponds to the practical use of the existing stock of knowledge and skills. The new knowledge acquisition process includes either recombining the existing synaptic connections or adding new ones. This happens again through the individual's exposure to stimuli. The effectiveness of this stage depends on the volume and quality of synaptic connections previously formed and the frequency of their activation through usage. It will also depend on the quantity and quality of subsequent stimuli the person is exposed to.

Figure 1 near here

The functional form of this relationship can therefore be presented as:

$$\textit{Synaptic connections} = f(A, \textit{Stimuli}, \textit{Attention}, \textit{Emotions}, \textit{Decay}), \tag{1}$$

where A measures genetics, *Stimuli* represents the set of stimuli to which the person is exposed, *Attention* is the level of attention the person exhibits towards perceiving the existing stimuli, *Emotions* describes the set of emotions with which the person responds to the stimuli, and *Decay* captures the decay process of synaptic connections due to ageing or the insufficient activation of previously formed synaptic connections.

If we reduce learning to the creation of new synaptic connections, our model of human capital formation can be used to derive two propositions. *Proposition 1*: Since different forms of learning lean on each of our synaptogenesis factors to a different extent, they might result in different levels of success regarding the number and quality of synaptic connections. This implies that heterogeneity might exist in learning effects on the synaptogenesis process across various leaning forms. *Proposition 2*: The further formation of connections and hence knowledge or skills might be a function of the quantity and quality of existing connections. This suggests that the overall effect of learning might depend on which learning activities an individual ultimately undertakes and on the sequence in which these are pursued.

Further analysis thus requires that a clear typology of learning forms is introduced. In classifying learning forms, we reject the typologies provided by economics or the policy-making literature. The distinct feature of the economics' approaches is that they mainly focus on intentional learning which individuals undertake rationally as a type of investment, while entirely neglecting learning that occurs without reward expectations. By distinguishing between three types of learning: formal, non-formal, and informal, the policy-making literature captures informal learning and thereby corrects for this drawback (CEDEFOP, 2000; European Commission, 2001; Eurostat, 2007; OECD, 1998). The main drawback here is that, unlike the previous strand, it overlooks the possibility of learning at a workplace. In addition, their classifications only look at learning from the perspective of the provider of learning opportunities and omits the view and, hence the role, of individuals in the learning process.

We combine the two approaches to introduce a new and more encompassing classification of learning forms that better suits the needs of our synaptogenesis model. In doing so, we define two broad dimensions of learning instances. The first dimension refers to the individual – the recipient of learning activities. The second dimension refers to the provider of learning activities and can include educational institutions, non-educational institutions, employers, etc. Two criteria are applied to describe both dimensions: intention and control. In this view, intention is a deliberate learning act on the part of the individual or organisation. For the recipient of learning, intention refers to a deliberate search for new knowledge or skills. With regard to the provider of learning, intention refers to the deliberate act of providing learning activities to the targeted group. The criterion of control refers to the control level possessed by each party of the learning process. For the recipient, control is linked to the possibility of influencing the content and depth of learning activities. For the provider of learning instances, the control criterion includes a range of control mechanisms that educators use to assess the learning process or to evaluate a recipient's performance or the quality of knowledge acquisition resulting from participation in learning activities. By applying the two criteria to the two dimensions, we can derive four types of learning, as shown in Figure 2: Formal, non-formal, informal, and learning-by-doing.

Figure 2 near here

Formal learning is defined as an individual's intentional acquisition of knowledge in a highly formalised environment that was intentionally constructed by the provider. The asymmetric concentration of control over learning processes resides with the provider. Studying at the university or undertaking vocational training are good examples of formal learning. Non-formal learning is defined as an individual's intentional acquisition of knowledge in learning environments that are still intentionally provided to him or her, but give the provider less control and hence offers the recipient more opportunities to influence elements of the learning process. Learning a foreign language with a private tutor or in a language school is a good example of non-formal learning.

Informal learning is an unintentional acquisition of knowledge resulting from activities undertaken for purposes other than learning. It does not involve any control on the provider's part. But the recipient has a certain level of control over the learning process since he or she may regulate when to enter and exit the learning process. Attending a museum or watching a documentary are illustrative examples of informal learning. Learning-by-doing can be defined as an unintentional acquisition of knowledge and skills from repetitive activities that are usually undertaken as part of a person's employment. These learning opportunities are not intentionally provided or pursued. The provider of this type of learning, the employer, has a certain level of control over the process since learning may only occur within areas related to work tasks, which are defined by the employer. In contrast, the recipient of learning has limited opportunities to influence the learning process.

Common sense suggests that any of these learning forms can contribute to the formation of synaptic connections. To understand the extent of their impact, we identify the degree to which each of the learning forms register on the four factors of synaptogenesis: Stimuli, attention, emotions, and decay. Accordingly, formal education exposes people to a diverse set of stimuli which may contribute to forming both general and occupation specific skills. However, since formal education often requires individuals to fully withdraw from the labour market, it usually occurs once in a life-time at an early age and remains relatively durable (several years). The one-time nature of participation means that the great stocks of human capital acquired through formal education are at a high risk of decay, especially those which are not demanded by later work tasks. Since learning providers use control mechanisms and because learning recipients have an interest in pursuing learning, attention levels may remain relatively high on a long-term basis within the period during which learning takes place. This type of learning may also be associated with intense emotions, both positive and negative.

Non-formal education is characterised by a narrow and brief focus on certain subjects either job-related or interest-related. Depending on the nature of interests or work tasks, a constant skills update might be necessary and require an individual to continuously participate in further learning. Depending on the interest level that the person exhibits in the topic, a high attention span can be maintained during the learning period. Since providing non-formal education involves few control mechanisms, we expect primarily positive emotions associated with great strength, but these may be limited to the duration and frequency of attending such learning activities. Knowledge and skills acquired through non-formal learning are believed to be at a lower risk of decay, especially if they are in the realm of the individual's interests or needed for current or future employment.

Informal learning tends to have a narrow focus along with a great depth. It is mostly related to an individual's hobbies, and it will likely remain on the non-scientific and non-professional level. Since the interest is likely to be ongoing over the course of a lifetime, the exposure to learning stimuli will be durable and largely continuous. This also suggests that a person's attention for this type of learning will be relatively high and continuously sustained. This may explain the low risk of acquired knowledge decaying. Emotions are expected to be positive and intensively experienced on a regular basis.

Learning-by-doing is perceived to be similar to formal learning in its features, with one difference being the exclusive focus on job-specific knowledge and skills. The exposure to stimuli created by this type of learning is highly likely to be employment-long and regular but also occupation and firm-specific. Attention might vary from low to high but it is usually limited by work periods over the employment duration. This type of learning is associated with both positive and negative emotions, relatively intensive in nature, depending on the company's management policies. Due to the continuous exposure to stimuli, the risk that knowledge and skills acquired through learning-by-doing will decay is low. Changing one's occupation or employer may however cause depreciation of such knowledge.

Overall, our model of synaptogenesis suggests that formal education might be the most effective in forming synaptic connections, but these are subject to a high degree of continuous decay over a lifetime. In comparison to formal education, non-formal learning is less effective in synaptogenesis since it covers a narrower range of subjects and is less durable, but it is highly likely to be more continuous in nature, reducing the impact of decay factors. Informal learning might be even less effective in building synaptic connections, but due to its strong link to an individual's interests, it might be undertaken on a regular basis, resulting in robust synaptic connections with a smaller risk of knowledge depreciation. Learning-by-doing is akin to formal learning, since it provides a broader range of learning opportunities which will, however, be linked to the nature of tasks at one's workplace (more complex tasks might be associated with more learning opportunities) and a slow decay process. We can now postulate the following hypotheses:

Hypothesis 1: A greater exposure of the individual to stimuli through participation in various types of learning is expected to lead to greater stocks of knowledge and skills.

Hypothesis 2: Formal learning and learning-by-doing will have a stronger positive impact on the individual's stock of knowledge and skills compared to participating in non-formal and informal learning.

Regarding Proposition 2, we suggest that the final stock of knowledge and skills will not only depend on the total number of learning instances that were undertaken by individuals throughout their lives, but also on the sequence in which these were pursued. The overview of existing research on psychology and neurology allows us to distinguish between two major areas of literature that support this idea. On the one hand, studies claim that the current stock of knowledge can predefine future knowledge. On the other hand, learning of any form can change the decay pattern of already acquired knowledge. We call the first argument *a knowledge accumulation enhancing effect* and the second a *knowledge decay delaying effect*.

Regarding the first effect, empirical studies have demonstrated that there is some positive association between past knowledge and subsequent knowledge even after controlling for the genetics of individuals (Ghisletta & Lindenberger, 2003). The main rationale behind this enhancing effect is the idea that new knowledge might be encoded through the establishment of similarities and differences between new and old information, making particular features or instances more or less memorable or influencing patterns of inductive generalisation (Keil, 1989; Wittenbrink, Hilton & Gist, 1998). Heit (1994, 1998) suggests that prior knowledge may represent the patterns of known knowledge which are retrieved and combined with observed examples while learning something new. Similarly, Johnson and Keil (2000) argue that prior knowledge can conceivably affect the way a person combines and uses concepts to communicate while solving problems (Markman & Makin, 1998). Kaplan and Murphy (2000) found that having prior knowledge about just one of six features present in individual exemplars facilitates category learning by adults. The overall idea implies that any subsequent learning will result in more knowledge or skills if the individual's prior stock of knowledge and skills is relatively great. The stock of knowledge coming from non-formal learning will, for instance, be higher when the same non-formal learning programme is undertaken after formal education.

The second, knowledge decay delay effect is derived from the assumption that knowledge and skills tend to decay with time. Psychology recognises that learning may postpone the existing stock of knowledge from depreciating as long as the knowledge maintenance and knowledge acquisition through leaning outweigh age-based losses in biological potential (Ghisletta & Lindenberger, 2003). In addition, several empirical studies found an age-associated influence of knowledge on changes in the brain's processing capacity (Ghisletta & Lindenberger, 2003). There is no explanation that would clarify the active effect of knowledge acquisition on the biological mechanics of the acquisition process, but it allows us to argue that more learning may to some, even if relatively limited, extent postpone the aging of genetic abilities to process information. We may hence expect that the negative effect of ageing on the neurons' ability to build new connections or to recombine old ones can be offset when the person is continuously exposed to any form of learning and keeps the relevant brain areas activated. This allows us to postulate the following hypotheses:

Hypothesis 3: There is a positive interaction between various learning forms in their effect on the overall stock of knowledge and skills.

Hypothesis 4: The individual's overall stock of knowledge and skills is maximised only when the individual participates in all four of the learning mechanisms.

Data and methods

To test our hypotheses, we use the Adult Literacy and Life Skills Survey (ALL) conducted in 2003. This database allows us to measure all the constructs that were introduced in the conceptual framework. The ALL dataset is unique because it provides direct measures of skills, such as prose and documentary literacy, numeracy, and problem solving (see OECD (2009) for a more detailed description of the ALL survey and its skill measures). Our sample includes four countries, the Bermudas, Italy, Norway, and Switzerland, and is restricted to respondents aged between 16 and 65, resulting in a total of 12,666 observations.

We utilise the following set of variables to empirically test our hypotheses:

Operationalisation of dependent variables

To assess the quality of synaptic connections reflecting the respondent's stock of knowledge and skills, we use a twofold approach. First, we utilise economics' conventional operationalisation of human capital through individual labour incomes. If we assume that labour markets pay for human capital, wages might approximate the respondent's job-specific skills. An individual's wage is operationalised by asking respondents to specify the pre-tax wage or salary received from their main job. Since wages are declared in different forms, we use a question about the respondent's preferred way to state their salary or wage. Monthly wages are used as a unit of analysis since the vast majority of respondents preferred declaring their labour income this way. If other forms of responses were chosen, the responses given were transferred as follows. For those stating an annual income, we divided the response values by twelve. For those who declared receiving an income twice a month, we multiplied the response values by two. For those declaring a weekly income, we multiplied the response values by four. And finally, for those declaring an hourly wage or salary, we first calculated a weekly wage by multiplying the response value to this question by the response value given to the question specifying the number of hours worked per week and afterwards multiplying that amount by four.

Second, we use problem solving scores as a measure of the volume of synaptic connections. Problem solving is defined as goal-directed thinking and action in situations for which no routine solution is available (OECD, 2009). It is widely established that this skill is a result of individual biographies rather than genetics (Fischer, Greiff, & Funke, 2012; Greiff, 2012) and hence it can be used to approximate human capital stocks needed to be effective at a workplace. The principle component analysis confirms that the problem solving skill constitutes a separate construct, with three other direct measures of skills forming a second construct. The correlation between the two constructs is relatively weak (about 0.3).

Operationalisation of independent variables

There are four main learning variables that capture the four specified learning mechanisms. Formal learning is operationalised by asking individuals how many years they spent in full-time education. Participation in non-formal learning is measured by a set of questions in which respondents specify whether they did any of the following learning activities within the last twelve months: (1) visited trade fairs, professional conferences, or congresses; (2) attended short lectures, seminars, workshops, or special talks that were not part of a course; (3) completed an educational training course at an organisation. Each item has two values with 1 "yes" and 0 "no". We sum up positive responses so that the values of the final construct ranges from 0 "no participation in non-formal learning" to 3 "active participation in non-formal learning".

The informal learning variable is constructed by summing up the responses to six items which ask whether respondents: (1) read manuals, reference books, journals, or other written materials but not as part of a course; (2) go on guided tours such as to museums, art galleries, or other locations; (3) use computers or the Internet to learn but not as part of a course; (4) use video, television, or tapes to learn, but not as part of a course; (5) learn by watching or getting help and advice from others, excluding any course instructors; (6) learn by themselves by trying things out, doing things for practice, or experimenting with different approaches to doing things. The factor has values ranging from 0 "no informal learning" to 6 "active informal learning".

Learning-by-doing is measured by the level of intellectual challenge at the workplace. We operationalise it through the questions that ask how often the respondent does 17 work tasks related to reading, writing, counting, or organising something. Each item is measured on a four-point scale ranging from 1"at least once a week" to 4 "never". Since all of the tasks require cognitive action, we combined the responses into one variable after recording their values. The final construct has values ranging from 17 "doing none of the tasks listed" to 68 "doing all of the tasks listed at least once a week". The four learning mechanisms are then rescaled to have values between 0 and 1. We also control for the length of experience at current employment by subtracting from 2003 (the year in which the survey was conducted) the responses to the question that asks individuals to specify what year they started working for their current employer.

Operationalisation of control variables

The set of control variables includes genetics, attention, emotions, and decay. The *genetics variable* reflects an individual's cognitive abilities and is measured by averaging the results for the cognitive tests in the areas of numeracy, prose, and document literacy, as in Blau and Kahn (2005). Factor analysis previously showed that the items of the three measures load on the same construct and provide high reliability (Cronbach's alpha = 0.985). In addition to this measure, we employ a conventional psychological approach to operationalising the respondent's genetics through the mother's level of education (Cunha and Heckman, 2008). Two dummies are derived from the question about the mother's highest education attained, with the first including all of those who attained an upper secondary or post secondary education and the second combining those who attained the first or second stage of tertiary education. The values "*no primary*," "*primary*," and "*lower secondary*" are combined together and used as a reference category.

We limit attention to the respondent's motivation level operationalised through two questions. First, we measure his or her motivation to improve job-related knowledge and skills. For this, we use the question that asks respondents to specify whether, during the last twelve months, there were any training or educational opportunities that they wanted to pursue for career or job-related reasons but did not. Second, we capture each respondent's motivation to improve their interest-related knowledge and skills by using a similar question that focuses on non-job related reasons for learning, such as hobby, recreational, or personal interest courses. For both variables, the value of one is assigned if the response to this question is positive, and the value of zero if the response is negative. The individual is considered more motivated if their responses take the value of one.

The person's emotions are operationalised in a two-fold manner. The positive emotions variable is constructed by summing up the responses to the following three questions: How much of the time during the past 4 weeks (1) have you felt calm and peaceful? (2) did you have a lot of energy? (3) have you felt downhearted and blue? Each item has values ranging from 1 "all the time" to 6 "none of the time". We record the responses and sum them up so that the final construct has higher values when respondents feel more positive. The presence of negative emotions is operationalised through questions that ask whether the respondents had any problems with (1) their work or (2) other regular daily activities recently as a result of any emotional problems (such as feeling depressed or anxious). The variable takes the value of one if a positive response is given to at least one of the questions and zero if no such problems were experienced.

The decay process is captured by two variables. The respondent's age measures the decay of abilities due to an individual's aging. Age is operationalised through a question that asks the respondents to specify their actual age at the moment the survey was conducted. The out of work variable captures the decay of knowledge and skills due to unemployment or inactivity for various reasons. We construct a dummy based on a question in which the respondent is required to specify whether he or she is working, not working, retired, a student, doing unpaid household work or other. The dummy takes the value of zero if the respondent is employed; otherwise it takes the value one.

In addition, we control for the number of hours worked, employment type, gender, and whether the respondent is a student. These are all operationalised through the corresponding questions. Table 1 presents the descriptive statistics for the key variables.

Table 1 near here

Our analytical strategy includes four steps. ***Step 1*****:** We replicate the conventional Mincer model. To do so, we run OLS regression for each country's earning's functions independently, since wages are measured in different currencies and are not comparable across countries. The Mincer model takes the conventional form:

$$lnwages = \alpha_0 + \alpha_1 Form\_edu + \alpha_2 Work\_Exp + \alpha_3 Work\_Exp^2 + \varepsilon, \qquad (2)$$

where *lnwages* is a natural log of wages received by the respondents, *Form_edu* is formal education measured by years in formal education completed, *Work_Exp* is total work experience calculated as the difference between the year the survey was conducted (2003) and the year in which the highest level of education was completed.

Step 2: We incorporate data on wages into our new conceptual framework by augmenting the Mincer model with factors of synaptogenesis. The model can be presented in its general form as:

$$lnwages = \alpha_0 + \alpha_1 Form\_edu + \alpha_2 Work\_Exp + \alpha_3 Work\_Exp^2 + \alpha_4 Genetics + \alpha_5 Stimuli + \alpha_6 Emotions + \alpha_7 Motivation + \alpha_8 Decay + \alpha_9 X + \varepsilon, \qquad (3)$$

where *Genetics* is a measure of genetics. *Stimuli* is a set of stimuli created by learning other than formal education or work experience, *Emotions* includes a set of emotions operationalised through positive and negative emotions, *Motivation* encompasses two measures of how motivated an individual is to undertake job-related or interest-related learning. *Decay* is a set of measures of decay, *X* is a set of control variables.

Step 3: We apply the model of synaptogenesis to the direct measures of the individual' stock of knowledge and skills as follows:

$$Skills = \alpha_0 + \alpha_1 Genetics + \alpha_2 Stimuli + \alpha_3 Emotions + \alpha_4 Motivation + \alpha_5 Decay + \varepsilon, \qquad (4)$$

where *Skills* is a measure of problem solving ability, while *Genetics, Stimuli*, *Emotions*, *Motivation,* and *Decay* are as described in step 3.

Step 4: We demonstrate that the integrity of learning forms is necessary to maximise the synaptogenesis process. For this purpose, we carry out a prediction exercise that simulates skills given the current characteristics of the individuals and assuming that their learning is maximised in all of the four forms. STATA gllasim option (for more details see Rabe-Hesketh & Skrondal, 2008) is used for this purpose. The procedure presupposes first conducting a multilevel analysis of skills and then calculating predictions. One should note that when used repeatedly, gllasim always produces a different answer, suggesting that the latter may be sampling from a distribution of the parameter estimates. To minimise this effect, we generate predictions that are repeated 100 times and then averaged out, which makes the process akin to a Monte Carlo simulation. We calculate a mean value of such predictions for each country and report it as comparable to the actual value of skills.

Empirical results

Our empirical analysis supports the new framework. Table 2 (Model 1) contains results from the replication of the Mincer model based on the ALL data. In line with the previous findings, they suggest that more exposure to traditional learning stimuli, such as formal education and employment, is associated with higher wages, with an increase in the reward from work experiences slowing down with time. The Mincer model, however, has a very poor fit, varying between ten and sixteen percent. It somewhat improves if all of the learning mechanisms are included in the regression (Model 2).

Table 2 near here

Further augmenting the Mincer model with the factors of synaptogenesis enables us to explain cross-individual variations in wages to a considerable extent, although this provides relatively poor support for our conceptual framework (Table 3). Many of the additional factors related to non-formal or informal learning, emotions, or motivation appear statistically insignificant, with a wrong sign or are inconsistent across countries. This might be due to the insufficient number of observations on wages resulting from low response rates to relevant questions or due to miscalculations resulting from transformations used to approximate respondents' monthly labour income.

Table 3 near here

When using problem solving scores as an alternative measure of the extent to which synaptic connections are developed, we receive strong support for our conceptual framework of synaptogenesis (Table 4). Each of the factors develops a certain relationship to the problem solving ability. Jointly, they explain about 74 percent of cross-individual variations in the skill measure. The preselected set of stimuli relate to problem solving skills in an expected way, which supports Hypothesis 1. Even after using a mother's level of education as a conventional measure for an individual's genetics, the results still remain in line with the previous findings, suggesting their robustness.

Table 4 near here

Out of the preselected learning mechanisms, formal learning and learning-by-doing prove to be the strongest determinants of problem solving skills, which is in line with Hypothesis 2. More years spent in formal education leads to improvements in an individual's ability to solve problems. Similarly, more intellectually challenging tasks, or a greater diversity of them, augment an individual's problem solving scores. Non-formal and informal learning also have a positive impact on the ability to solve problems, but this is weaker than the impact of formal education or challenging workplace tasks.

By considering interactions between various learning forms, we can study complementarities between different learning activities. The models with interaction terms reveal that non-formal learning has a rather compensatory nature in forming skills and is often used as a substitute to formal education or learning-by-doing and not as a framework for continuous learning (Werquin, 2010). Informal learning, however, develops a strong complementary relationship to formal learning and learning-by-doing. It is better facilitated in use when prior knowledge, acquired through the two major learning mechanisms, exists. Thus, we only receive partial support for Hypothesis 3.

Table 5 near here

The results of our analysis suggest that learning in any form enhances the volume of synaptogenesis. To clarify the role that each of them might play in this process, we conduct a prediction exercise (Table 5). In doing so, we predict the problem solving score while assuming maximum participation by individuals in all of the learning forms simultaneously or assuming maximum participation in only one of the learning instances with the participation in other learning forms remaining unchanged. By juxtaposing the predictions with actual scores, we reveal that skill scores are only maximised when all four of the learning stimuli take the highest value in the sample. Having more individuals participate in formal education may increase their skills substantially, but the maximum potential will never be reached if formal education is not combined with post-school learning or learning at one's workplace. Learning at the workplace is a second important factor but it never leads to the highest possible scores on its own. Non-formal and informal learning are the least important to the development of skills; they can never guarantee a substantial enhancement of skills formation if there was not already a foundation laid by formal learning that was further enhanced by workplace learning. Overall, individuals can expose themselves to enough stimuli to form a great stock of human capital, but only when they maximise their participation in all the four learning forms, which is commensurate with Hypothesis 4.

Conclusions

This study introduces a new conceptual framework for analysing human capital formation derived from neurological theories of synaptogenesis and supplemented by psychological theories of skill acquisition. If regarded in terms of synaptic connections, knowledge and skills can be presented as a function of genetics, stimuli, attention, emotions, and decay factors. Stimuli prove particularly important for synaptogenesis and an individual is perceived to experience them through four types of learning: formal, non-formal, informal, and learning-by-doing. Our analysis provides evidence for positive effects that the four learning mechanisms may have on the process of synaptogenesis. We suggest that these four learning mechanisms must be perceived as complementarities, and they can only maximise synaptogenesis when combined. In addition, our theoretical discussion and empirical results indicate that non-formal and informal learning are not equal substitutes for formal education and workplace learning in the process of human capital formation.

The results suggest that the conventional earnings or learning functions should be revisited to include opportunities for intentional and unintentional learning that occurs both at the workplace and outside of it. Non-formal and informal learning should be incorporated into the existing models as important sources of human capital and are hence factors of individual outcomes in the labour market. Similarly, learning at the workplace can no longer be limited to the length of work experiences. One should account for the nature of tasks that an individual deals with on the job and the extent to which these tasks intellectually challenge him or her on a daily basis. Finally, the existence of a certain optimal sequence in undertaking various learning forms should be recognised. As such, learning outcomes are highly likely to vary depending on whether or not this sequence is maintained by individuals.

Further research is needed to confirm the validity of our results by eliminating two major drawbacks in our study. An additional analysis based on longitudinal data is required to confirm the dynamic nature of synaptogenesis processes. Better operationalisations of stimuli mechanisms, such as non-formal and informal learning, would also permit more precise estimations of effects of each of them in generating synaptic connections while direct measures of people's genetics, such as IQ levels, would help rule out the self-selection problem in the analysis.

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Table 1

Descriptive Statistics for Main Variables Used in the Analysis

Variables	Mean	Std. Dev.	Min	Max
ln_wages	8.134	2.838	-6.908	12.463
Problem solving ability	52.707	11.123	12	90
Stimuli				
Formal learning	12.790	3.757	0	24
Non-formal learning	0.931	1.018	0	3
Informal learning	3.508	1.858	0	6
Learning-by-doing	45.484	13.485	17	68
Current experience	10.005	9.681	0	38
Genetics				
Mother's education (middle)	0.303	0.459	0	1
Mother's education (high)	0.143	0.350	0	1
IQ measure	268.030	51.836	79	420
Emotions				
Negative emotions	0.160	0.367	0	1
Positive emotions	7.171	2.726	3	18
Motivation				
Job-related	0.320	0.467	0	1
Interests-related	0.373	0.484	0	1
Decay				
Age-related	41.168	13.611	16	65
Inactivity-related	0.329	0.469	0	1
Control variables				
Full time (dummy)	0.777	0.416	0	1
Gender (Female)	1.525	0.499	1	2
Student (dummy)	0.090	0.287	0	1
Hours worked	37.752	13.764	0	95
Born in the country	1.147	0.354	1	2

Note. For the analysis, we rescale the four learning mechanisms to have values between 0 and 1 in order to ensure the comparability of their effects.

Table 2

The Mincer Model of Wages with the ALL Data

	Model 1				Model 2			
Variables	Switzerland	Italy	Norway	Bermuda	Switzerland	Italy	Norway	Bermuda
Stimuli								
Formal learning	2.152***	1.089***	7.405***	1.851***	1.379***	0.587***	4.787***	1.339***
	(19.10)	(11.62)	(13.91)	(13.39)	(12.41)	(5.25)	(9.13)	(8.52)
Non-formal learning					0.195***	0.071	-0.011	0.189***
					(4.15)	(1.27)	(-0.06)	(3.52)
Informal learning					-0.283***	-0.013	-1.517***	-0.286***
					(-3.90)	(-0.23)	(-5.23)	(-3.87)
Work experience	0.031***	0.026***	0.236***	0.031***	0.028***	0.024***	0.166***	0.026***
	(6.87)	(6.80)	(13.35)	(7.15)	(6.16)	(5.70)	(10.14)	(6.31)
Work experience2	-0.000***	-0.000***	-0.004***	-0.001***	-0.000***	-0.000***	-0.003***	-0.000***
	(-4.30)	(-4.68)	(-9.66)	(-6.03)	(-3.84)	(-3.71)	(-6.71)	(-4.94)
Learning-by-doing					1.336***	0.443***	4.012***	0.806***
					(15.16)	(6.33)	(9.95)	(12.05)
R sq	0.143	0.097	0.127	0.159	0.297	0.128	0.166	0.253
Number of observations	2508	1745	4228	1714	2187	1392	3725	1591

Note. Controlling for the selection problem by utilizing Heckman's sample selection model does not change the logic of our results in Tables 2 and 3 suggesting their robustness. Due to space limits, we do not report the results here but can make them available on request.
* p < .10. ** p < .05. *** p < .01.

Table 3

Application of the Synaptogenesis Model to Wages

Variables	Switzerland	Italy	Norway	Bermuda
Genetics				
IQ measure	0.003***	0.001***	0.006**	0.004***
	(5.02)	(2.69)	(2.28)	(8.86)
Stimuli				
Formal learning	0.802***	0.479***	1.781***	0.607***
	(6.55)	(3.82)	(3.13)	(3.76)
Non-formal learning	-0.035	0.047	-0.231	0.178***
	(-0.76)	(0.82)	(-1.08)	(3.59)
Informal learning	0.032	0.014	-0.601**	-0.210***
	(0.46)	(0.25)	(-1.97)	(-3.10)
Work experience	0.014***	0.011**	0.046***	0.006*
	(3.11)	(2.22)	(2.70)	(1.76)
Work experience2	-0.000***	-0.000**	-0.001***	-0.000***
	(-4.56)	(-2.25)	(-3.17)	(-3.23)
Learning-by-doing	0.465***	0.251***	1.659***	0.291***
	(5.88)	(3.45)	(3.73)	(4.42)
Emotions				
Negative	-0.046	-0.046	-0.196	-0.021
	(-1.09)	(-1.37)	(-0.78)	(-0.53)
Positive	0.010	-0.011**	-0.013	0.001
	(1.64)	(-2.11)	(-0.42)	(0.22)
Motivation				
Job-related	0.026	-0.003	0.158	-0.028
	(1.02)	(-0.07)	(1.27)	(-0.88)
Interest-related	-0.060**	0.108**	-0.183	-0.040
	(-2.12)	(2.53)	(-1.46)	(-1.28)
Decay				
Age-related	0.021***	0.010***	0.046***	0.013***
	(6.51)	(3.00)	(6.18)	(6.27)
Inactivity-related	-0.176**	-0.121	-1.031***	0.061
	(-2.49)	(-1.53)	(-2.89)	(1.10)
Control variables				
Student	-0.399***	0.358	-2.257***	-0.548***
	(-2.72)	(1.31)	(-4.44)	(-5.15)
Gender (Female)	-0.139***	-0.148***	-0.294**	-0.131***
	(-4.70)	(-4.96)	(-2.10)	(-4.75)
Hours worked	0.026***	0.007***	0.006	0.014***
	(10.07)	(4.10)	(0.61)	(8.08)
Born in the country	0.071**	0.084	-0.182	0.021
	(2.24)	(0.63)	(-0.63)	(0.74)
Full time	0.252***	0.244***	0.367	0.385***
	(4.22)	(4.47)	(1.78)*	(5.76)
R sq	0.655	0.253	0.265	0.432
Number of observations	1469	1230	2973	1561

Note. * p < .10. ** p < .05. *** p < .01.

Table 4

Application of the Synaptogenesis Model to the Problem Solving Skill

Variables	Model 1	Model 2	Model 3	Model 4
Genetics				
IQ measure	0.166***			
	(131.32)			
Mother's education (middle)		2.188***	2.150***	2.164***
		(12.31)	(12.04)	(12.09)
Mother's education (high)		4.236***	4.070***	4.131***
		(15.72)	(14.98)	(15.19)
Stimuli				
Formal learning	0.685*	16.694***	13.694***	16.499***
	(1.74)	(28.19)	(17.80)	(27.58)
Non-formal learning	0.233**	1.334***	1.870***	1.678***
	(2.03)	(7.27)	(7.59)	(7.24)
Informal learning	0.673***	3.771***	2.443***	3.140***
	(3.78)	(12.62)	(7.61)	(10.18)
Current experience	0.014**	0.046***	0.045***	0.044***
	(2.40)	(5.00)	(4.80)	(4.77)
Learning-by-doing	1.813***	9.328***	8.829***	7.044***
	(7.34)	(24.35)	(22.43)	(12.34)
Interactions				
Formal * Non-formal			-2.941***	
			(-5.10)	
Formal * Informal			6.198***	
			(9.69)	
Learning-by-doing * Non-formal				-1.979***
				(-4.12)
Learning-by-doing *Informal				4.454***
				(7.62)
Emotions				
Negative	-0.856***	-2.108***	-2.108***	-2.106***
	(-5.14)	(-8.33)	(-8.31)	(-8.29)
Positive	0.208***	0.340***	0.333***	0.338***
	(10.05)	(10.27)	(10.02)	(10.15)
Motivation				
Job-related	0.435***	0.188	0.088	0.113
	(3.75)	(1.06)	(0.50)	(0.64)
Interest-related	0.272**	0.572***	0.441***	0.480***
	(2.45)	(3.37)	(2.59)	(2.81)
Decay				
Age-related	-0.032***	-0.061***	-0.062***	-0.062***
	(-6.27)	(-7.39)	(-7.43)	(-7.41)
Inactivity-related	-0.786***	-0.287	-0.339	-0.321
	(-3.00)	(-0.77)	(-0.90)	(-0.85)
Control variables				
Student	1.854***	4.164***	3.801***	4.022***
	(5.45)	(8.27)	(7.46)	(7.89)
Gender (Female)	1.199***	1.058***	1.008***	1.037***
	(12.45)	(6.94)	(6.57)	(6.75)
R sq	0.739	0.378	0.385	0.383
Number of observations	12666	12093	11915	11915

Note. * p < .10. ** p < .05. *** p < .01.

Table 5

Predictions of Problem Solving Skill Scores Given Increases in Various Learning

	Switzerland	Italy	Norway	Bermuda
Original scores:				
Respondents' participation in				
Formal learning	13.4	10.8	13.2	14.2
Non-formal learning	1.2	0.4	1.1	1.1
Informal learning	4.1	1.9	4.0	4.0
Learning-by-doing	48.5	36.9	46.9	48.7
Problem Solving Skill	54.0	45.1	54.0	54.6
Predictions of Problem Solving Skill if:				
Formal learning maximized	61.4	58.2	60.8	61.5
Non-formal learning maximized	54.5	50.3	54.4	55.6
Informal learning maximized	54.1	49.7	54.4	55.1
Learning-by-doing maximized	56.1	52.9	56.9	57.6
All learning forms maximized	64.4	63.8	64.8	64.5
Number of observations	3887	3287	4621	2696

Note. The predictions are calculated based on the following model: *Skills= 38.670 + 1.615Mother's education (middle) +2.698Mother's education (high) + 17.140Formal learning + 0.865Non-formal learning + 1.229Informal learning + 0.010Current experience + 7.145Learning-by-doing - 1.799Negative_Emotions + 0.253Positive_Emotions + 0.282Job-related_Motivation + 0.530Interest-related_Motivation - 0.109Age-related_Decay - 1.035Inactivity-related_Decay + 2.461Student + 0.885Gender.*

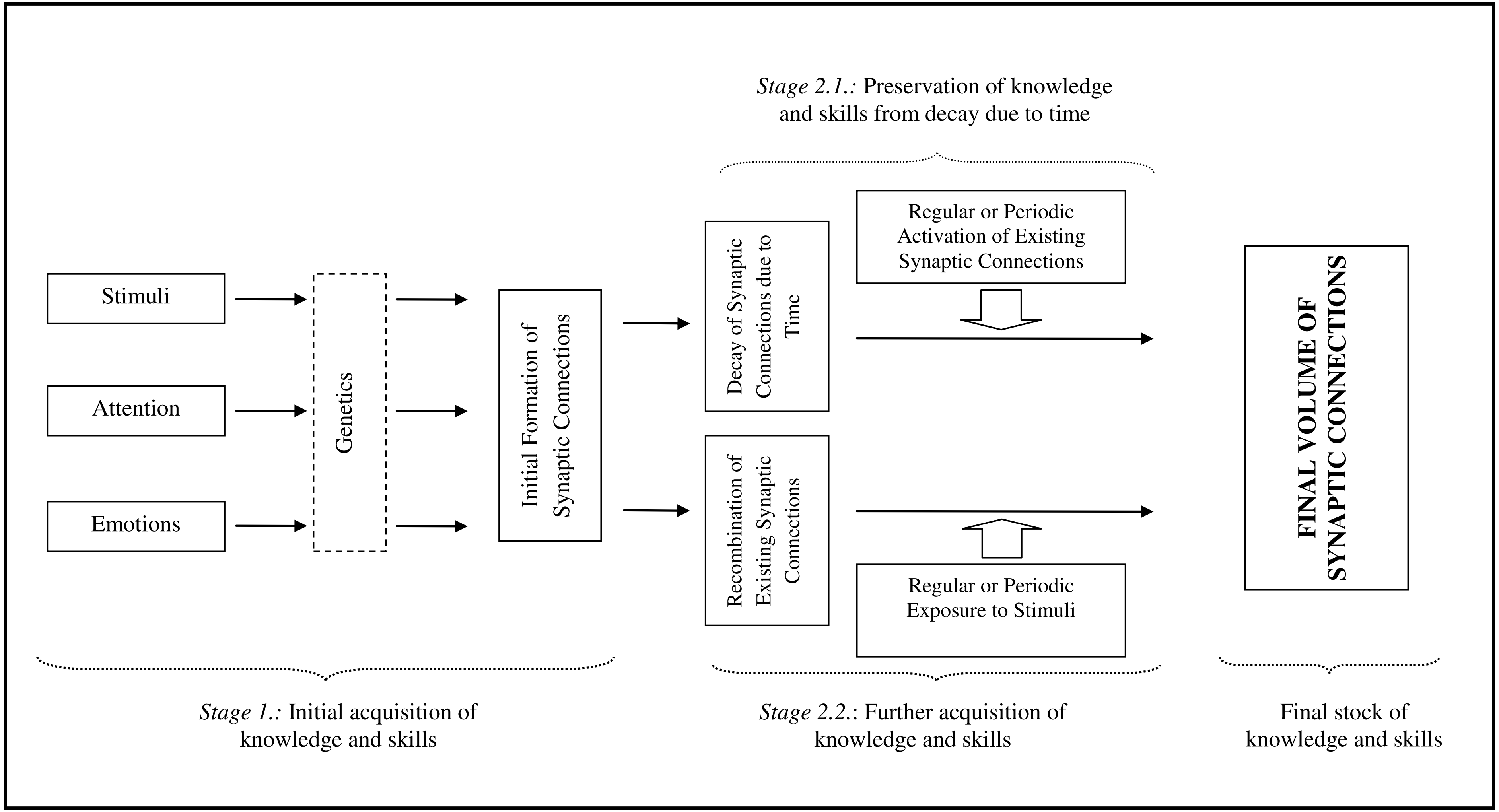

Figure 1. Model of human capital formation: A lifelong approach

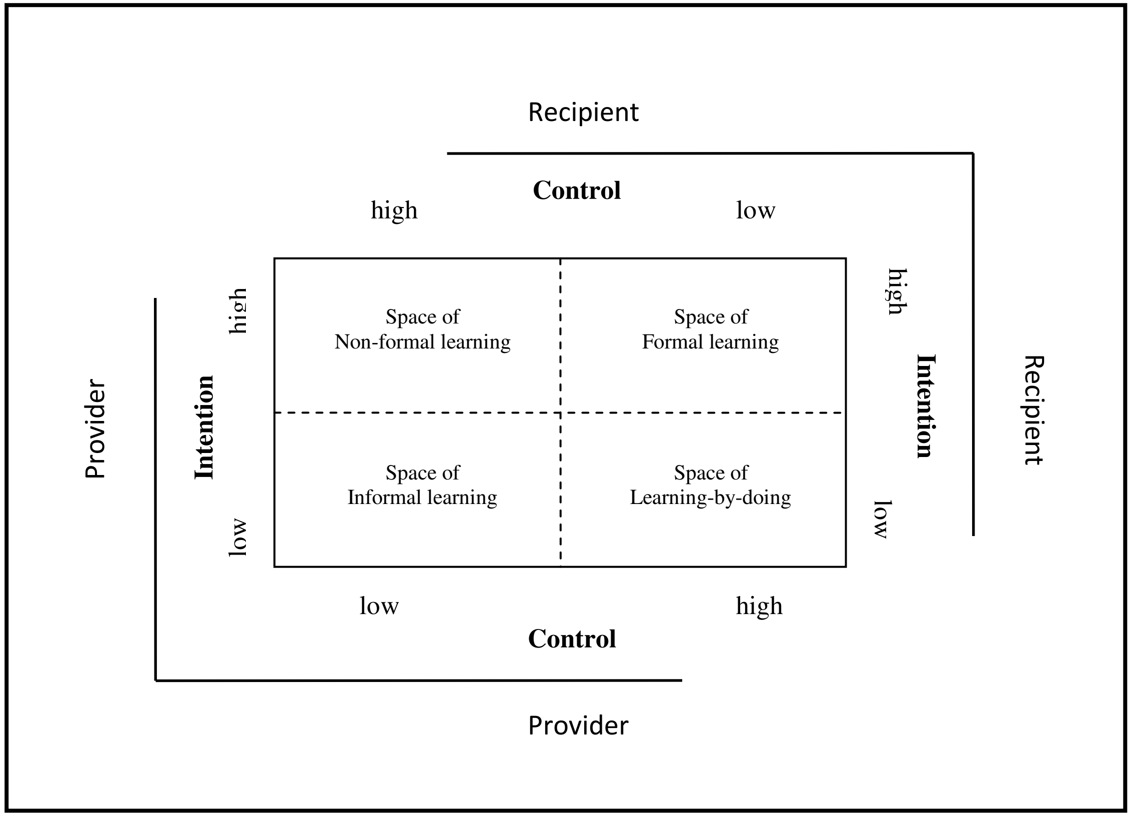

Figure 2. Classification of learning instances