Approaching Lifelong Learning: An Integrated Framework for Explaining Decision-Making Processes in Personal and Professional Development

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Abstract

Background: Individual differences in commitment to lifelong learning, a process aimed at seizing opportunities for self-development, have not been extensively studied. *Objective*: Our aim is to provide a comprehensive understanding of the decision-making mechanisms involved in pursuing learning for self-development. *Method:* We conducted a literature review on the taxing nature of cognitive exertion and its impact on the inclination to engage in cognitively demanding tasks for learning, as well as individual differences in sensitivity to aversive or rewarding outcomes inherent in the learning process. *Results*: Our findings indicate that the Expected Value of Control (EVC) theory can elucidate the former, while research on approach-avoidance motivation can shed light on the latter. *Conclusion*: We propose and develop an integrated framework that incorporates both lines of research. This framework holds relevance for neuropsychology, experimental psychology, and education psychology, offering theoretical guidance for tailoring learning experiences to enhance engagement and commitment to self-development.

Key words: Lifelong learning; Decision-making; Expected Value of Control (EVC); Approach-avoidance motivation.

Introduction

Lifelong learning remains a concept suffering from imprecise definitions, yet it is commonly understood as hinging upon the ability to retain previous knowledge while continuously integrating new insights into one's cognitive framework [1,2]. In this article, we conceptualize lifelong learning as an ongoing, self-directed search for knowledge acquisition for personal growth. While individuals are constantly learning from their surroundings [3], lifelong learning is particularly characterized by: a) extending beyond the fundamental knowledge and skills necessary for functioning in society; b) being driven by individual volition and self-direction; and c) stemming from a pursuit of self-improvement. At its core, lifelong learning embodies a proactive stance towards skill development, necessitating a commitment to staying informed about advancements across diverse fields and adapting to evolving societal and technological landscapes.

Despite its appeal, not all individuals have a mindset geared towards lifelong learning. The process of updating existing skills or acquiring new ones often demands a significant investment of time and effort. Individuals may need to dedicate extensive periods—spanning hours, months, or even years—to cultivate and master their expertise. Moreover, pursuing lifelong learning may entail economic considerations, as individuals may invest in resources such as educational institutions, instructional materials, or professional mentors to facilitate their knowledge-acquisition journey. It might also entail foregoing other types of rewards, such as social or relaxing activities that cannot coincide with the learning process. Although various factors influence behavior towards lifelong learning, the enduring cost of cognitive effort, reflected by fatigue and boredom [4], stands out as one of the most significant considerations.

To elucidate the mechanisms behind the decision to engage and remain committed to cognitive control in service of lifelong learning goal we aim to integrate two lines of research: 1) experimental and theoretical contributions to the cost-benefit analysis for cognitive control allocation, and 2) approach-avoidance motivation contributions, which portraits individual differences in sensitivity towards rewarding and aversive outcomes. In the first line of research, we will place special emphasis on the Expected Value of Control (EVC) theory [5,6], its computational implementations, and further developments [7–14] to explain how individuals engage in a cost-benefit analysis for cognitive control allocation. We will discuss the value of learning in the predictions of these models and relate it to a specific type:

lifelong learning, aimed at professional and personal development. Furthermore, the second line of research will enable us to convey individual differences in behavioral approach-avoidance motivation in the presence of motivational conflicts. By framing lifelong learning as the presentation of different learning opportunities with mixed aversive and appealing motivations, we aim to explore how individual differences in the sensitivity towards aversive and rewarding incentives influence the value of control allocation for the decision to engage and remain committed to the learning goal.

Despite its increasing relevance, lifelong learning mechanisms have not received extensive scrutiny, highlighting the need for further investigation in this area. In a society marked by high demands and numerous tools for knowledge updating, lifelong learning emerges as a process that enables individuals to navigate the competitive world more efficiently. This framework can be significant in bridging the gap between cognitive neuroscience on human decision-making and educational psychology, contributing to a better understanding of the mechanisms behind personal and professional development. In the following sections, we will analyze how learning, as a voluntary process, has been related on one hand to the costs of control allocation and, on the other, to both intrinsic and extrinsic rewards. We will discuss its implications for personal and professional development.

Learning as a costly process

One of the major determinants in this trade-off process between deciding whether to engage or not in lifelong learning is the intensity or amount of cognitive control that needs to be allocated to achieve the learning goal. Cognitive control is a process involving the activation of mechanisms responsible for directing attention, updating, monitoring, or inhibiting responses, and flexibly adapting to established rules [15]. It overrides automatic responses to align with current goals [16], and it has been considered an effortful process [17–21], leading to avoidance.

The costs of cognitive control have been documented in experimental designs in which individuals would often choose the option demanding less cognitive effort [18,22] or devalue a reward if a large amount of cognitive effort was needed to achieve it [23,24]. It is important to note that deciding to approach a learning goal is not a one-moment decision, but rather multiple decisions over time where the situation is re-evaluated. Attrition is an important component in engagement, and even in game-designed learning tasks, it has proven to be high [25]. One possible explanation for learning disengagement might be the fact that errors or limited progress can deter individuals from persisting [26]. This underscores that committing to and engaging in the learning process carries the costly possibility of failure, or at the very least, the inherent likelihood of encountering challenges or setbacks along the way.

Despite its associated costs, individuals choose to engage and commit to learning across various situations. Several existing models aim to elucidate the mechanisms behind this decision-making process [14]. One of the most prominent models is the Expected Value of Control [5,6], which elucidates the mechanisms involved in selecting, executing, and maintaining cognitive control according to the situation. This theory has significant implications for motivation, as individuals weigh the expected costs against the expected rewards of cognitive control allocation to establish short-term or long-term goals. It delineates the components working together to determine the expected value of control allocation. The *specification* component evaluates the current situation to determine the identity (i.e., which task to allocate control to, if any) and the intensity (i.e., how much control to allocate) of the control signal. The *regulation* component is responsible for executing the control signal chosen by the specification component. Meanwhile, the *monitoring* component continuously evaluates the ongoing execution of the control signal to determine its appropriateness and whether adjustments are necessary in relation to the current situation.

Learning and cognitive control are intricately intertwined, as evidenced by advancements in the EVC theory. The Learning Value of Control (LVOC) extends the EVC theory to include the effect of learning [8]. It posits that if a given situation repeats itself over time, the pattern of action is likely to change, as choices are influenced by previous decisions. In essence, the cost-benefit analysis is not fixed; rather, it adapts as the brain continually learns from experience, showcasing its plasticity. Consequently, one could argue that the inclination towards lifelong learning hinges on the cumulative impact of both positive and negative outcomes in similar contexts. It is important to note that the LVOC model specifically addresses how learning influences the allocation of cognitive control, rather than how the costs of cognitive control influence the decision to engage in learning.

However, cognitive control allocation also impacts learning. The Learning Expected Value of Control model (LEVC) delineates how experience can shape task automaticity, necessitating less cognitive control allocation over repeated exposure [9]. It elucidates why the decision to engage in an experimental task that allows for learning is a better choice than engaging in an experimental task that does not facilitate learning. Task learnability can be inferred by how predictable the individual finds the environment or by the improvement observed in repeated exposures to the task. By comparing the optimal learning rates of both types of tasks, the model incorporates the discounted value of learning, advocating that optimal decision-making should aim at tasks that allow for improvement to further benefit from these enhancements. Unlike the LVOC model, the LEVC model does not only considers past choices but also anticipates potential future decisions. This is of relevance regarding the continuation of the learning process; if an individual does not intend to continue developing the learning goal, its expected value will decrease. From this perspective, engaging in lifelong learning is advisable as it enhances task learnability by continually exposing individuals to new information and experiences. Thus, lifelong learning emerges not only as a pragmatic choice but also as a rewarding process that fosters personal growth and development.

Learning as a rewarding process

The motivation for learning has been extensively studied, encompassing both its intrinsic and extrinsic rewards. Intrinsic motivation, as elucidated by Self-Determination Theory (Deci and Ryan, 1985), stems from the fulfillment of fundamental psychological needs: competence, relatedness, and autonomy, all of which are central tenets addressed by lifelong learning endeavors. The concept of learning as an intrinsically rewarding process has been explored across three lines of investigation: 1) curiosity, which draws parallels between information-seeking behavior and extrinsic rewards at the neuronal level; 2) interest, which examines prolonged engagement with tasks over time; and 3) trait curiosity/interest, which explores individual differences in the propensity for knowledge acquisition [27].

Research has shown that curiosity is a desired state when engaging in knowledge acquisition, as information is better remembered when curiosity is higher [28]. Although there are different perspectives on the environmental triggers of curiosity [29–32], a recent analysis proposed that curiosity is stimulated by both the current knowledge about the situation and the probability of the acquired knowledge being useful in the future, which can be used to determine the value of knowledge [33]. This value is considered for both its intrinsic and rewarding properties. On one side, curiosity has been portrayed as the psychological mechanism by which people mobilize resources to fill a knowledge gap, indicating that individuals inherently value the procurement of information [34]. On the other, it has been demonstrated that curiosity activates the same reward network in the brain as extrinsic rewards do, indicating that these mechanisms share some properties [35]. Going beyond this concept, other investigations support the idea that the value of learning resides in its potential to yield future extrinsic rewards [36], positioning learning as a secondary or conditioned reinforcer.

Extrinsic rewards are of great importance in learning. It has been shown that expectations of extrinsic rewards can guide the value of cognitive control allocation [37]. This expectation is relevant to lifelong learning, as there are various extrinsic incentives one might receive. Particularly, lifelong learning yields rewards in the form of *opportunities*. Marketing oneself and promoting one's skills and attributes are essential in various aspects of life where competition and personal advancement play a key role, such as securing scholarships, landing desirable jobs, or becoming attractive to potential partners. Moreover, it provides rewards in terms of *adaptability*. Our society's tools for interaction are in constant evolution, and staying up to date with the latest trends allows one to adapt to the environment and maintain success. This adaptability also enhances *efficiency*, as learning to use novel tools can minimize the time and effort required to achieve the same goals. Lastly, investing in lifelong learning can enhance the *quality* of one's outcomes. Learning methods and strategies not only help individuals work more efficiently but also improve the quality of their work. Through lifelong learning, individuals can cultivate a diverse range of abilities and skills, empowering them to navigate the world more effectively and boosting their *confidence* in achieving their desired goals.

Individual differences in response to motivational conflicts

As seen in the previous sections, engaging in lifelong learning can be simultaneously viewed as both rewarding and aversive. When presented with an opportunity for learning, individuals may experience mixed motivations, and they must choose between behavioral approach or avoidance. Although the EVC theory addresses computations of the cost-benefit analysis for cognitive control allocation, not all individuals behave uniformly in a given situation [38].

Due to experience or personal traits, different incentives hold varying degrees of value for each individual. One personality trait strongly associated with engagement in voluntary learning is the need for cognition, reflecting the extent to which individuals enjoy and actively seek out thinking, problem-solving, and intellectual challenges [39]. Individuals with high scores in need for cognition are likely to have a more positive attitude towards engaging in lifelong learning than those with low scores. Other personality traits that can influence the inclination to engage in learning opportunities include novelty seeking [40], intolerance of uncertainty [41], as well as openness to experience and conscientiousness from the Five Factor Model [42,43].

In addition to individual differences in the valuation of learning, there are broader individual differences related to sensitivity towards positive and negative outcomes [44,45]. Some individuals are more strongly motivated to avoid the presentation of an aversive stimulus (e.g., expected high cognitive effort required to learn a new language) or the withdrawal of a rewarding stimulus (e.g., canceling a weekly activity one enjoys to accommodate language courses), while others are more strongly motivated to approach a rewarding stimulus (e.g., anticipated job opportunities due to language proficiency) or to obtain the withdrawal of an aversive stimulus (e.g., being excluded from conversations with colleagues conducted in the language being learned).

Motivational drives regarding aversive and rewarding stimuli have been assessed using questionnaires, experimental paradigms, and computational simulations. Stemming from the Reinforcement Sensitivity Theory [46–48], one of the most widely utilized questionnaires to measure these traits is the Reinforcement Sensitivity Theory of Personality Questionnaire (RST-PQ) [49–51]. This paradigm differentiates three components: 1) the Fight-Flight-Freeze system (FFFS), which responds to aversive stimulation; 2) the Behavioral Activation System (BAS), responsible for responding to rewarding stimulation; and 3) the Behavioral Inhibition System (BIS), responsible for monitoring and evaluating conflicting situations to select the appropriate response. Despite the widespread use of these scales, it remains inconclusive whether these traits correlate with behavioral measures [38].

A recent development of the EVC theory [7] has provided computational predictions of individual differences in sensitivity towards different incentives. This model incorporates the principles of the Drift Diffusion Model (DDM), which determines different response patterns in cognitive control allocation for different types of incentives [52,53]. In this model of the EVC theory, the motivational context is considered. Context refers to the type of incentive (e.g., punishments, rewards) guiding behavior. For example, in a cognitive decision-making task with increased rewards, participants are predicted to both accumulate evidence more rapidly to make a decision (increased drift rate) and become more willing to make decisions with less evidence (lower response threshold). Conversely, in response to increases in punishment, participants are predicted to primarily increase their response thresholds, indicating a more cautious approach where more evidence is required before making a decision. In this sense, in an experimental task with both rewarding and aversive incentives, individual response patterns can be taken as an indication of the predominant motivational drive (oriented more strongly towards positive or negative outcomes). This model, however, explains how cognitive control is affected by different sensitivities towards incentives but does not elucidate how this sensitivity affects the decision to engage in cognitive control itself.

In behavioral paradigms, several studies have investigated how individual differences in motivational drives influence decision-making processes in presence of motivational conflicts [54–58]. A motivational conflict involves the simultaneous presence of both aversive and rewarding outcomes. In these situations, individuals face two options: 1) opting for behavioral approach, where they receive both the appealing and aversive outcomes, or 2) opting for behavioral avoidance, where they receive neither. Typically, experiments are designed so that when individuals choose to approach different levels of monetary reward (often operationalized as low, medium, or high), there is a probability of encountering aversive stimuli, such as electrical stimulation [56] or exposure to aversive images and sounds [54].

The factors hindering individuals from approaching a reward in these paradigms have been limited to feelings of fear or anxiety. Approach-avoidance motivation paradigms share similarities with real-life contexts involving other types of aversive outcomes (e.g., effort). Consequently, one can draw parallels between these paradigms and the decision to allocate cognitive control for learning and professional development, where individuals can either a) opt for behavioral approach, engaging in costly cognitive control and receiving associated rewards for learning, or b) opt for behavioral avoidance and decide not to engage in the current learning opportunity. There is, therefore, a call for investigations integrating individual differences in mixed bundled motivation into the binomial decision of whether to allocate cognitive control for learning.

Integrated framework: approach-avoidance motivation of cognitive control allocation in the context of lifelong learning

In this article, we propose integrating the literature on approach-avoidance motivation with the literature on cognitive control allocation to elucidate the decision-making process underlying engagement in learning opportunities for personal and professional development. To achieve this, we will elucidate the background of the integrating framework by explaining the parameters that make approach-avoidance motivation paradigms suitable for understanding the decision to engage in lifelong learning. Furthermore, we explain why these specific two lines of research greatly influence individual learning choices. In doing so, we describe and illustrate the decision-making process from the presentation of a learning opportunity to the achievement of the learning goal, if decided to approach. We also elucidate the application of this integrated framework to different fields of psychology and conclude by discussing the personal and societal implications of developing the framework.

Relevance of the Integrated Framework

There are various paradigms designed to test individual differences in decision-making in the presence of mixed motivations. However, approach-avoidance motivation tasks can be distinguished from decision-making tasks involving the potential loss of points or money, which can be viewed as a form of negative punishment in operant conditioning terms, as individuals forfeit a reward. Approach-avoidance motivation tasks are rooted in positive punishment, entailing the delivery of aversive stimuli to individuals [59].

The operationalization of cognitive effort as aversive varies across different experimental paradigms [6], as it can be perceived either as a form of negative or positive punishment. Some researchers argue that cognitive engagement depletes energy or metabolic resources, thereby depriving an individual of a positive resource [60–62]. However, these studies are controversial as they have been difficult to replicate [63]. Conversely, other studies frame effort as an action inducing cognitive fatigue or boredom, thereby eliciting unwanted feelings [4,64,65]. From this perspective, it is suggested, following the Law of Effect [66], that physical or mental effort is linked to discomfort and therefore minimized or avoided. When viewed from this standpoint, it becomes vital to embed lifelong learning engagement within the framework of approach-avoidance motivation. This classification facilitates a comparison of this type of decision-making process with others studied under the same paradigm, highlighting both similarities and differences and extending the application of approach-avoidance motivation beyond the clinical context.

Approach-avoidance motivation, as a behavioral binomial outcome (to approach or to avoid mixed-valence incentives), has not been extensively applied to the field of learning. However, decision-making processes in voluntary learning have been studied under other experimental paradigms. Usually, these paradigms reflect the cost of cognitive control allocation by making individuals choose between tasks requiring different amounts of cognitive control and offering varying rewards in exchange for completion [18,22,67]. While it is acknowledged that individuals are constantly learning from their environment, this article focuses on lifelong learning as a voluntary and conscious process that necessitates cognitive control allocation to consolidate new knowledge. Therefore, these paradigms, along with the contribution of the EVC theory and its further extensions, are of great value to understand the neuronal and behavioral patterns behind the decision of cognitive control allocation.

Decision Making Process Towards Lifelong Learning Opportunities

The integrated framework views lifelong learning as a mindset toward self-development that can be reflected when presented with learning opportunities (Figure 1). Opportunities can arise from internal or external prompts. For instance, an internal prompt could stem from personal interest; one might develop an interest in a musical instrument and actively seek out courses or instructional guides for learning to play it. Conversely, an external prompt could be a course offered within one's company to acquire new skills that enhance efficiency in the workplace. The difference between the two is that in the former, individuals first become aware of their interest and then actively seek a learning program. In the latter, individuals first become aware of a learning program and evaluate its utility based on their interest. In the last decade, rapid technological advancements have led to significant growth in both information and learning platforms, providing individuals with abundant opportunities to engage in a fulfilling learning process and make progress in their chosen development areas [68].

Although there are countless opportunities for learning and self-development, they only become an option when individuals become aware of them. For each perceived learning opportunity, individuals engage in cognitive evaluation to determine whether to engage in the process. This evaluation involves a decision-making process, requiring different brain mechanisms to compute the expected value of control, determined by the expected required cognitive effort and the expected reward of mastering the learning goal. In this evaluation, individual differences in sensitivity to aversive and rewarding outcomes have a significant impact on the cost-benefit analysis. An individual more sensitive to rewarding rather than aversive incentives can tend to perceive learning opportunities as more valuable than an individual more sensitive to aversive rather than rewarding incentives.

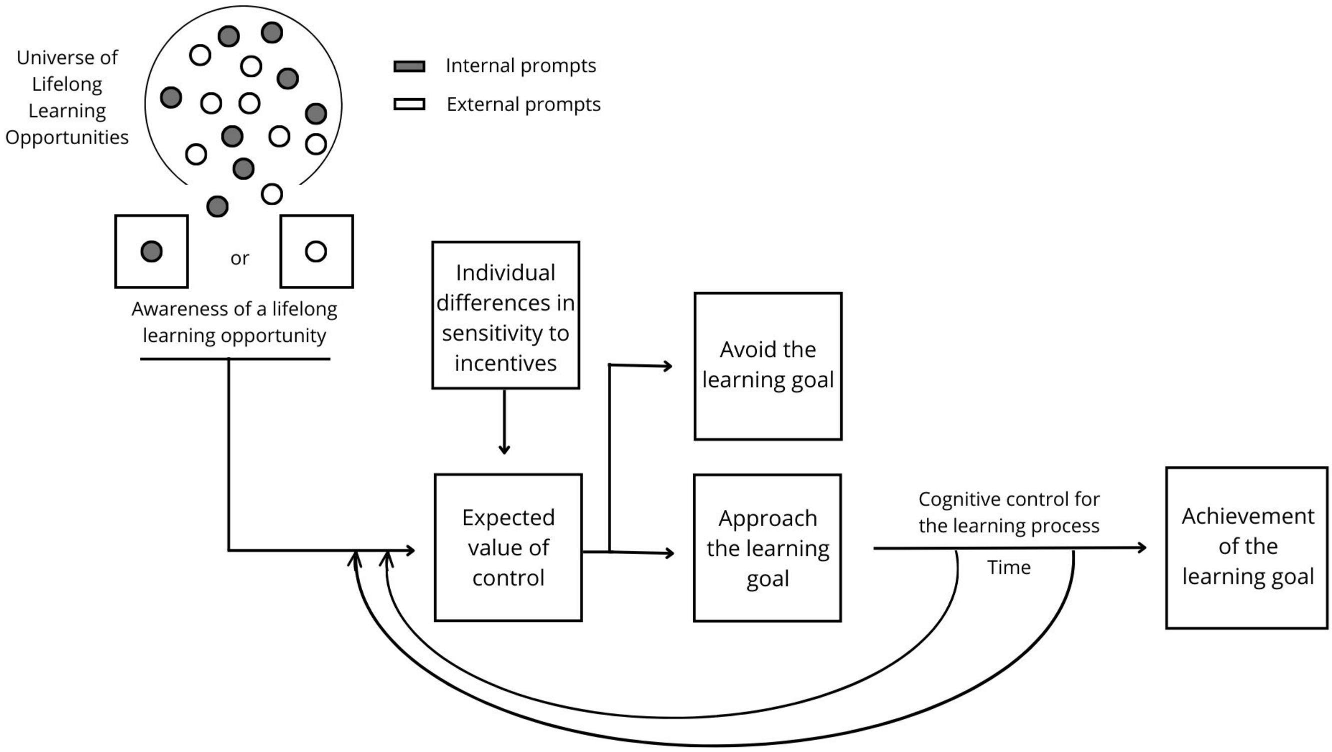

Figure 1. Different components of the integrated framework reflecting approach-avoidance motivation towards learning goals within the context of lifelong learning.

The outcome of this evaluation is a behavioral response of either approaching or avoiding the specific learning opportunity. Approaching the learning opportunity implies allocating cognitive control by maintaining an active representation of the situation, inhibiting dominant immediate responses, and considering the rules in place within the current context [15]. During the process of control allocation individuals carry out a re-evaluation to determine, on one hand, if the cost of cognitive control is adapting to their previous expectations, and on the other, if the value of the reward has increased [69], decreased [70], or remained the same. According to the result of this evaluation process, individuals choose again whether to approach and remain engaged in the learning goal, or to avoid and decide to no longer commit.

It is important to note that lifelong learning as a mindset implies the continued development of learning, for which current learning goals build up in the already mastered previous goals. Viewed as a whole, the costs of cognitive control allocation and the rewards of self-developing imply a long-term process. Not only the individual learning opportunities must be considered, but also a combination of them as key factors in personal and professional development. As indicated by the LEVC model [9], opting for an option that allows learnability has more value if there is an intention to keep learning.

Applications of the integrated framework

Applications to Neuropsychology

As both lines of investigation encompass detecting motivational conflicts to determine the best behavioral outcome, their neural mechanisms share many similarities. Numerous studies have provided empirical support for the vital role of the dorsal anterior cingulate cortex (dACC) in the decision-making process, valuation, and performance monitoring [5,71–74], as it represents outcome information from past trials and signals behavioral adjustments in subsequent trials [75]. The dACC plays an important role in these paradigms as it integrates expected positive and negative outcomes into a mixed motivational value [59]. The prefrontal cortex (PFC) and the striatum, in turn, are associated with dopamine's involvement in the representation of current goals, attention shifting, or task updating [76,77]. Serotonin, on the other hand, has been noted to increase with the anticipation of negative outcomes [78,79] in both paradigms.

Although similar decision-making processes are in place, it is relevant to note the disparities of both lines of research to understand the neural implications of the integrated paradigm. One observation of interest in the approach-avoidance motivation paradigms is that motivational conflicts using emotional punishment instead of pain elicit different patterns of brain activation when the motivational conflict is presented [80]. Much remains to be explored, especially if we include cognitive effort as a potential aversive stimulus. Another interesting aspect worth exploring is the lateralization of the response observed in approach-avoidance motivation paradigms. Specifically, there is a higher degree of right prefrontal cortex (PFC) activation when individuals approach and a higher degree of left PFC activation when individuals avoid [74]. Given the association of the right hemisphere of the brain with emotional responses [81], it would be intriguing to explore whether similar lateralization occurs when individuals engage in lifelong learning, an action less directly related to emotional valence. Finally, one should explore the noteworthy pattern of gender difference in the approach-avoidance motivation paradigms, with women exhibiting a greater inclination toward avoidance behaviors compared to men [55]. This gender disparity potentially corresponds to the higher prevalence of anxiety disorders observed in the female population [82]. As the proposed paradigm is not inherently linked to fear, it could prove instrumental in determining whether these gender differences stem from aversive stimuli or the nature of the behavior itself. Studying lifelong learning under the realms of approach-avoidance motivation would help us explore a wide range of research questions related to the mechanisms underlying deliberate cognitive engagement.

Applications to Experimental Psychology

Given that much remains to be explored in the realm of individual differences in the decision to approach or avoid learning opportunities oriented towards personal and professional development, this framework has utility in the design of novel experimental paradigms. As lifelong learning involves discerning which opportunities for development are worthwhile pursuing, experimental designs should incorporate variations in the parameters of the tasks being presented. This approach will help identify which types of prompts can motivate an individual to approach lifelong learning. It is important to note that the goal is not to make individuals choose between different tasks but rather to present a task (with specific parameters) giving individuals the opportunity to approach it and engage in cognitive control to obtain a given reward or to avoid it and abstain from both. The dichotomy of the proposed design would account for ecological validity, as in different situations in life, we are presented with offers or opportunities for which we must execute a cost-benefit analysis to understand if it is worth committing.

At the same time, experimental designs should aim to measure the effect of individual differences in the valuation of the aversive and appetitive stimuli being presented. This can be achieved through questionnaires or Likert scales that assess the subjective costs of mental effort and the subjective rewarding experience of the incentives, which have been proven to correlate with individuals' behavioral cognitive avoidance [24]. Although it is difficult to measure the objective cognitive effort individuals exert when cognitively engaged in a task, it is often monitored through heightened activity of the sympathetic nervous system [83]. This is indicated by physiological measures such as sweat, elevated blood pressure, pupil dilation, and reduced heart rate variability [84–87]. Response parameters should also be collected as an indication of individual differences.

Ideally, brain measures such as EEG or fMRI should be carried out to clearly delineate the brain areas involved in this specific motivational conflict. This would help forge the bridge between the two lines of research and provide answers to the related research questions. Finally, individual traits that can affect the decision to engage in learning (e.g., need for cognition, academic motivation, intolerance of uncertainty, novelty seeking, openness to experience, and conscientiousness) should be measured to better understand the differences in behavioral responses when avoiding or approaching lifelong learning. Designing specific investigations that allow us to test this united framework can facilitate its implementation and practical application.

Applications to Educational Psychology

Having a broader understanding of the process behind the decision to engage in learning goals within the realm of lifelong learning can have significant implications for educational psychology. There has been a call for theoretical contributions to guide the personalization of learning experiences to improve their efficacy [88]. By considering individual differences in the evaluation of rewarding and aversive incentives to allocate the value of control, educators can tailor instructional approaches to optimize student engagement and commitment to learning endeavors. Simultaneously, by developing knowledge of the mechanisms behind lifelong learning engagement, educators can leverage this understanding to cultivate a growth mindset and instill a sense of purpose and autonomy in learners. Encouraging reflection, fostering metacognitive awareness, and cultivating a supportive learning community are essential strategies for nurturing a lifelong learning orientation among students.

Conclusion

Lifelong learning holds significance for both individual and societal advancement. By integrating both lines of research, we can understand how individual differences in sensitivity to incentives can influence the cost-benefit analysis of self-developmental learning opportunities. Implications of this framework are crucial for informing educational policies that foster the creation of such scenarios. Building flexible learning programs that cater to diverse motivations related to cognitive control allocation is of great relevance, as it can increase the likelihood of individuals approaching, rather than avoiding, various aspects of lifelong learning.

Ethical considerations

No ethical approval was required as human participants were not involved in the article.

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The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT in order to improve language and readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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