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Using ventral striatum-prefrontal cortex (VS-PFC) functional connectivity signals to predict intrinsic motivation: New ideas from a machine learning perspective

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Abstract
Over the past decade, educational neuroscience research has increasingly identified the functional connectivity between the ventral striatum (VS) and the prefrontal cortex (PFC) as a significant biomarker for intrinsic motivation in adolescent students. Despite these findings, there remains a dearth of methods for utilizing such connectivity indices to directly measure intrinsic motivation levels in educational settings. With the aims of informing educational and cognitive neuroscience researchers of intrinsic motivation about new technical ideas that can advance their research, this opinion paper presents an overview of the most important neuroscientific research on intrinsic motivation in human youths together with a new methodological proposal. Crucially, we proposed the use of VS-PFC functional connectivity signals, extracted from functional magnetic resonance imaging (fMRI) data analysis, as predictors of intrinsic motivation through a machine learning (ML)-based linear regression model. By developing a robust linear regression model buttressed by tried-and-tested ML techniques, our method aims to facilitate rapid and precise predictions of intrinsic motivation levels without the need for repeated assessments of intrinsic motivation, thereby saving time and resources in subsequent studies. To elucidate our model, we presented equations showing how regression parameters are computed using the conventional ordinary least squares (OLS) method and the ML-based gradient descent (GD) method, highlighting their differences in the process. Potential technical difficulties concerning the establishment and validation of our ML-based model are also discussed with concrete recommendations on how to resolve them. With the right implementation, we expect our method to benefit longitudinal fMRI studies examining developmental brain and behavioral changes in intrinsic motivation and educational intervention programs that require quick and accurate identification of students' intrinsic motivation levels. Also noteworthy is that our proposed methodology is not limited to predicting intrinsic motivation alone and can be adapted for other functional connectivity and behavioral variables that may predict different outcome variables. The flexibility of our ML-based regression model will allow researchers to tailor the model by selecting alternative variables to suit their specific research needs.

Keywords Artificial intelligence, machine learning, gradient descent, intrinsic motivation, functional connectivity, prefrontal cortex, ventral striatum

1. Introduction

In the psychological literature on human development and education, Self-Determination Theory (SDT), as proposed by Ryan & Deci [1], was notable for defining motivation as a two-sided dispositional trait that takes on intrinsic and extrinsic dimensions. According to SDT, intrinsic motivation refers to the disposition to engage in a specific activity for the sake of extending and exercising one's skills and abilities, and for learning and self-discovery, rather than for the purpose of pursuing external or material rewards. As for extrinsic motivation, it relates to an externally driven incentive to engage in an activity because of the tangible rewards it can bring or is expected to bring. Importantly, respecting and supporting an individual's psychological needs for *autonomy* (freewill to pursue an activity), *competence* (capability to perform an activity to the best of one's ability), and *relatedness* (social ties with supportive individuals) provide the fertile grounds for the optimal development of intrinsic motivation [1]. In this article, the theoretical focus would be on intrinsic motivation in view of a large body of accumulating evidence in psychology and cognitive neuroscience showing that it is intrinsic motivation, *not* extrinsic motivation, which brings about positive effects for learning and mental well-being in the long run (for reviews, see [2-4]). When compared with individuals driven by extrinsic motivation, individuals driven by intrinsic motivation have been found to exhibit higher magnitudes of learning and performance, creativity, and emotional experience over longer stretches of time [2]. Conversely, extrinsic motivation contingent on monetary rewards has been shown to undermine an individual's intrinsic motivation to engage in cognitive performance to the best of his/her ability in the long-run [5]. Biologically, it is also worthy to note that a functional magnetic resonance imaging (fMRI) study by Lee et al. [6] has shown that intrinsic and extrinsic motivation can be physiologically separated from each other based on double-dissociation findings, which showed that higher insula activation was connected more with intrinsic motivation than with extrinsic motivation whereas higher posterior cingulate activation was tied more to extrinsic motivation than to intrinsic motivation.

The past few decades have witnessed a fruitful application of SOT to the scientific study of motivation in the cognitive neuroscience of education domain [4, 7], a discipline that has been popularly called "educational neuroscience" [8]. As such, in the sections below, we chose to highlight some of the most important fMRI studies on learning motivation in the educational neuroscience literature. Owing to the fact that the vast majority of them focused on intrinsic motivation, we chose to review the brain regions, pathways, and functional characteristics underlying this motivational construct. Specifically, we focused on fMRI studies showing the prominence of the functional connectivity between the ventral striatum (VS) and the prefrontal cortex in the sustenance of intrinsic motivation – and proposed how this VS-PFC connectivity can be harnessed as a neurophysiological predictor for an automated machine learning (ML)-based computation of intrinsic motivation scores for future samples of participants. In this regard, the current article is intended as an opinion paper seeking to inform researchers with a vested interest in intrinsic motivation about some exciting new ideas (i.e., concepts and methods) that can better shape the trajectories of their future studies.

In the sections below, we first provide a mini-review of the most well-known and cited fMRI studies on intrinsic motivation before explaining the purpose of our ML-based method. Please note that our review is not intended to be exhaustive as this article is not meant as a formal review paper. Rather, we want to stimulate thinking among both educational and neuroscience researchers, update them about some of the state-of-the-art techniques that they can leverage in the current digital age, and encourage them to use such trendy tools to elevate research development in the educational neuroscience field.

2. Insights from educational neuroscience

In the extant educational neuroscience literature, reward-based cognitive processes associated with motivation are functionally mediated by the circulation of the neurotransmitter dopamine along the frontostriatal neural pathways connecting the prefrontal cortex (PFC) with the subcortical limbic system. Two well-known dopaminergic pathways, the mesolimbic and mesocortical pathways, each of which connects the ventral tegmental area (VTA) to the striatum and PFC, respectively, enable the effective channeling and release of dopamine in the presence of any stimuli that is perceived as rewarding or motivational [9] [see Figure 1]. Notably, the ventral striatum (VS), which comprises the nucleus accumbens, the olfactory tubercle, and parts of the caudate nucleus and putamen ventral to the rostral internal capsule [10], has long been observed as a core node involved in the execution of motivation-related reward-driven behaviors [9, 11].

Both the VS and the PFC are major brain regions innervated by dopaminergic neurons emanating from the lower mid-brain areas (e.g., VTA, substantial nigra) [12-15]. In this article, we chose to focus on VS-PFC functional connectivity and not merely on blood-oxygen-level-dependent (BOLD) activation localized to the VS because elevated VS BOLD activation is context-dependent and can either reflect a source of opportunity associated with positive behaviors/rewards (e.g., academic motivation, healthy peer relations) [9] or a source of vulnerability associated with negative behaviors/rewards (e.g., risky sexual behaviors, negative peer influence) [9, 16]. Such contextual variability in the interpretation of VS BOLD activation does not apply to VS-PFC functional connectivity, which has been shown to exhibit a positive and linear relationship with intrinsic motivational behaviors across numerous contexts – as the following paragraphs will explain. This unique feature of VS-PFC functional connectivity would thus greatly ease statistical analysis and interpretation when a linear regression model is applied, as proposed in the sections below.

Another reason for investigating VS-PFC functional connectivity is that it is engendered by a plethora of neuroanatomical pathways (i.e., neural fibers) constituting the "reward circuit" linking different subregions of the PFC with the VS via the thalamus, which functions as a relay hub [17]. In the developmental neuroscience literature, the PFC has been widely seen as the "chief executive" of a top-down cognitive control system or network that mediates executive functioning and decision-making in posterior and subcortical parts of the brain [9, 16, 18]. The PFC has also been shown to be involved in the processing of self-efficacy beliefs related to academic performance in the form of significant positive correlation between functional activity in the medial PFC (mPFC) and self-reported ratings of self-efficacy beliefs related to academic matters [19]. Under general academic situations concerning whether to engage in a motivational task or not, the insula is another PFC subregion that was shown to be highly activated when individuals were processing their subjective feelings and reasons to act [6]. In the more specific context of cognitive learning and performance, when compared with their counterparts with lower levels of intrinsic motivation, college-aged students with higher levels of intrinsic motivation have been shown to exhibit increased VS-PFC functional connectivity over three task blocks when assessed using a computerized Go/No-Go test of inhibitory control [20]. Change in false alarm rate on the Go/No-Go test, a measure of cognitive performance decline, also showed a significant negative linear relationship with change in the strength of VS-PFC functional connectivity within the full sample of participants [20].

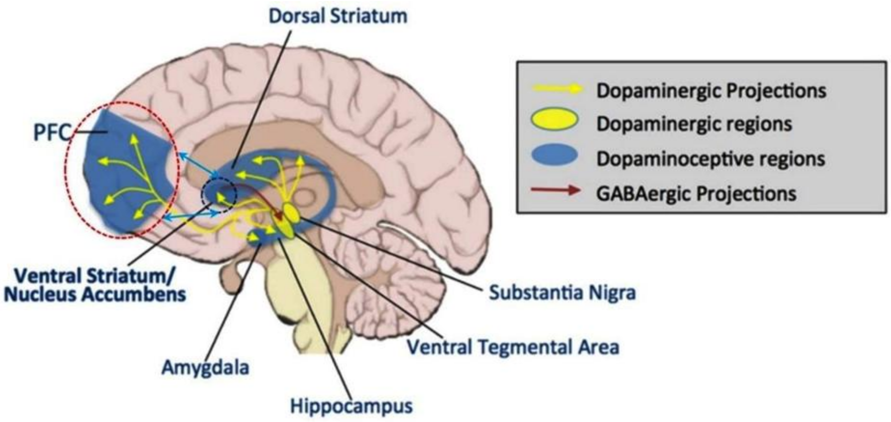

Figure 1 A schematic diagram showing two dopaminergic pathways (mesocortical and mesolimbic) and the associated brain regions where dopamine is generated and received. Double headed light blue arrows depicts the functional connectivity between the ventral striatum (VS, circled in dark blue) and the prefrontal cortex (PFC, circled in red) [Source: Figure 1 in Telzer [9]. Adapted and reproduced with permission. Dotted circles and double-headed arrows were added to the original figure by the first author.]

In addition, through an analysis of resting-state functional brain connectivity in young female adolescents (mean age = 11.2 years), Myers et al. [21] further showed that self-reported questionnaire scale scores of a growth mindset underpinned by intrinsic motivation (i.e., the belief that one can "grow" his/her intelligence through hard work and dedication) were positively correlated with the degree of functional connectivity strength between the VS (centered on the left and right nucleus accumbens) and the right dorsolateral prefrontal cortex (dlPFC). On the other end, there were also studies which showed that excessive smartphone usage among adolescents could lead to diminished VS-PFC functional connectivity [16, 22]. Such findings suggested that the VS-PFC pathway is highly crucial for top-down cognitive control and any impairment or disruption can result in negative behaviors that are driven by external rewards.

Taking into account all these studies, which provided replicable evidence of the crucial role played by VS-PFC functional connectivity in pinpointing the intrinsic motivation levels of adolescents and young adults, we hereby propose the use of a VS-PFC functional connectivity variable, representing the parameter estimates of signal intensities emanating from a target PFC region coupled with a seed VS region, as a sensitive neurophysiological predictor of intrinsic motivation levels in future samples of human participants. Although the aforementioned studies demonstrated that the strength of VS-PFC functional connectivity was positively and significantly correlated with one's intrinsic motivation level under different contexts [9, 20, 21], they did not argue for the use of VS-PFC connectivity signals as predictors of intrinsic motivation performance in future replications or extensions of their studies.

This endeavor can only be achieved using ML-based linear regression and a technical overview of this highly efficient computational method is presented in the sections below.

3. Purpose of new method

Before discussing how ML-based regression modelling is done, we deem it important to state that the impetus for the proposed new method is driven by a call to translate neuroimaging findings, especially those from fMRI, into feasible applications for educational research and practice [8]. Seghier et al. [8] identified a series of challenges in the translation of fMRI findings into practical applications within educational settings and through our proposed new method, we aim to address several of these challenges – that is, how to better (i) investigate heterogenous cohorts of individuals with varying learning abilities, (ii) assess changes in brain functions related to the development of such abilities, and (iii) conserving research resources related to longitudinal studies. Specifically, we advocate an active use of correlational patterns of brain activations for making predictions about intrinsic motivation at the individual level, ensuring that valuable fMRI data is used with greater utility in a prospective fashion. Consequently, longitudinal fMRI studies on intrinsic motivation following up on an initial fMRI study conducted using the same protocol can be done much faster. Educational intervention programs seeking to recruit and compare students with varying levels of intrinsic motivation can also be conducted more swiftly with speedier identification of such individuals using our predictive model.

In our model, we will use VS-PFC connectivity as the primary predictor of intrinsic motivation due to its neurophysiological nature and origins in the brain. As such, this variable can offer a more sensitive and non-biased measure of intrinsic motivation compared to non-physiological variables, such as self-reported questionnaire ratings or cognitive test scores. By proposing a new ML-based regression method, we build on the significant contributions made by developmental and educational neuroscientists who have linked VS-PFC connectivity to intrinsic motivation (as mentioned above). Our goal is to develop this foundation and advance motivation-related research by leveraging the best computational techniques offered by artificial intelligence (AI).

In addition, due to the fact that intrinsic motivation assessments can be difficult to design and time-consuming to execute, we expressed our methodological ideas herein with the purpose of facilitating rapid and precise predictions of participants' intrinsic motivation levels in future studies. The following sections will elucidate these ideas through the validation and testing of a ML-based linear regression model. As this article is not a research paper, we did not provide experimental data and results to establish the regression parameters. However, this lack of proof does not, in any way, imply that our proposed method is erroneous or flawed, but that it serves as a "call to action" for investigators in future studies to test our ideas and assess their merit. As the statistical model-building process outlined below is based on rigorous, tried-and-tested mathematical formulas and principles, we guarantee the lay reader that our method would work to generate the required regression parameters for predictive analysis contingent on the availability of research data from a future sample of participants.

4. ML-based linear regression modelling

Linear regression is a highly used statistical technique used in numerous academic fields for predicting the value of a continuous outcome variable (y) using one (x) or more predictor variables $(x_1 + \cdots + x_j)$ by fitting a linear equation to the observed data (see Equation 1). The goal is to find the best-fitting line that minimizes the difference between the predicted and observed outcome values. In the simplest case with only one predictor, the model is written algebraically as:

$$y_i = \beta_0 + \beta_1 x_{1i} + \epsilon_i \tag{1}$$

where y_i represents the observed outcome value for the i^{th} individual and x_{1i} represents the value of the first predictor for the i^{th} individual. β_0 represents the intercept of the line with the y-axis, β_1 represents the regression slope or coefficient, and ϵ_i represents the error term (i.e., residual) that represents the difference between the predicted and observed y values for the i^{th} individual.

When dealing with two or more predictors, the model is written as:

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_j x_{ij} + \epsilon_i \tag{2}$$

where β_1 through β_j represent the regression coefficients associated with the first predictor up to the j^{th} predictor. The subscript of "i" represents the value associated with a particular individual, as shown in equation (1) above.

In linear regression, the primary objective is to find the intercept (β_0) and regression coefficients (β_1 to β_j) that minimize the loss function (L) of mean squared error (MSE) between the observed (y_i) and predicted $(\hat{y}_i)$ outcome values over n observations [23]:

$$L = \text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{3}$$

The conventional method for finding the regression coefficients is through the ordinary least square (OLS) technique using the formula:

$$\beta = (X^T X)^{-1} X^T y \tag{4}$$

Based on this formula, the matrix of predictor variables (with a column of ones to represent the intercept) (X) is first multiplied with its transposed counterpart (X^T) to generate a matrix product that gets inversed and multiplied further with X^T and the vector of observed outcome values (y) to output the vector containing the regression coefficients and intercept $(\boldsymbol{\beta})$ [24]. This computation is carried out by default when one executes linear regression using most statistical packages (e.g., SPSS, STATA) and provides the analyst with a single set of intercept and regression coefficient values. For foundational mathematical details of linear regression and proofs of OLS formula, the reader is advised to the statistical handbook by Gelman et al. [24] [open access version available via URL under its reference].

The OLS technique is perfectly suitable for examining the linear relationship between the predictor and outcome variables within a given sample but may be insufficient for predicting outcome values in future samples if the model parameters (i.e., the regression coefficients and intercept) are not calibrated carefully for generalization purposes. In view of this concern, ML-based regression through gradient descent (GD) is called for. Unlike OLS, which works in the form of a closed formula that finalizes results after a single computational cycle, GD is an iterative differential technique that refines the regression model through multiple iterations to find the optimal intercept and regression coefficients that minimize the loss function (i.e., MSE) to the largest extent possible [23].

Specifically, GD works in linear regression by updating an initial set of regression coefficient and intercept values through partial differentiation using the following formulas:

$$\beta_j \leftarrow \beta_j - \alpha \frac{\delta L}{\delta \beta_j} \tag{5}$$

$$\beta_0 \leftarrow \beta_0 - \alpha \frac{\delta L}{\delta \beta_0} \tag{6}$$

where L denotes the loss function shown in equation (3), with β_j and β_0 on the left of the leftward pointing arrow representing the updated regression coefficient for the j^{th} predictor and the updated intercept, respectively. α represents the learning rate, a hyperparameter that can be set in advance by the analyst to control the size of each update.

Following the first iteration, the regression coefficients and intercept are updated by subtracting the partial derivatives (multiplied by the learning rate) from their current values. These updated values are then reinserted into the regression model shown in equation (2), followed by the computation of a new set of partial derivatives using equations (5) and (6). This process is repeated, with the regression coefficients and intercept being recomputed again at the end of the second iteration. The cycle continues until convergence is reached, that is, when there are negligible or no changes in the regression coefficient and intercept values. The constant value of the learning rate and the initial values of the regression coefficients and intercept (usually zeros for both), as well as the number of iterations (usually 10,000 or more), must be set by the analyst in advance. The total number of iterations required for convergence depends on several key factors, such as sample size, the number of predictors, learning rate, and multivariate normality [23]. For more details concerning GD, such as the programming codes and software to implement it, the reader is advised to refer to the online eBook by Burkov [23] [see URL under its reference].

For all mathematical formulas and explanations herein, please note that we presented them in the simplest form possible for a non-technical audience. For basic information about the fundamentals of linear regression and matrix algebra, we advise the reader to peruse relevant statistical works, such as the eBooks by Burkov [23] and Gelman et al. [24] cited above.

5. A proposed case study of ML-based linear regression at work

With all these technical knowledge in mind, we now introduce a framework of how ML-based linear regression, which harnesses GD, could be applied to future studies investigating the relevance of VS-PFC functional connectivity for intrinsic motivation. To do so, we will refer to a previous fMRI study conducted by Telzer et al. [20] as a starting point. In that study, the authors performed functional connectivity analysis in the form of psychophysiological interaction (PPI). Through this technique, the authors identified the target PFC regions-of-interest (ROIs) whose task-dependent hemodynamic functions (HRFs) covaried with the HRF-deconvolved time series of the ventral striatum, which serves as the seed ROI. Based on ROI-to-ROI connectivity analysis, the authors identified a cluster in the inferior frontal gyrus (IFG), centered around the standardized xyz coordinates of (40, 28, -5), as the target ROI that was functionally coupled with the VS beyond the voxel-wise significance threshold of $p = 0.005$. Based on a full sample of 29 participants, changes in VS-IFG connectivity strength (between the first and third task blocks) were found to be negatively and linearly correlated with corresponding changes in successful Go/No-Go task performance [$r = -0.53$, $p < 0.005$].

This brain-behavior correlation can also be represented in a linear regression model, with the predictor being the change in parameter estimates of fMRI signal intensities in the target IFG region between the first and final trial block, and the outcome variable being the change in false alarm rate, the percentage of incorrect responses on No-Go trials, between the first and final trial block. In equation form, the model can be represented nominally as:

$$\begin{aligned} &\Delta \text{ Observed Go/No-Go false alarm rate (\%)} = \\ &\qquad \beta_0 + \beta_1 * \Delta \text{ VS-PFC connectivity} + \epsilon_i \end{aligned} \tag{7}$$

In the case of Telzer et al.'s [20] study, β_1 in equation (7) will approximate the full sample correlational value of -0.53. Since only one predictor is used, its regression coefficient will be approximately equal to this correlational value.

Depending on the fMRI scanning protocol used, future investigators may also want to break down a scan run into several trial blocks, as done by Telzer et al. [20], or keep it intact as one block to ease data analysis. If the former option is chosen, then the predictor and outcome variables would need to be converted into difference values conveying changes in behavioral performance and VS-PFC connectivity between the start and final task blocks, as shown in equation (7). If not, the raw Go/No-Go performance and VS-PFC connectivity values can be used to simplify matters.

For any future fMRI study involving the Go/No-Go task and VS-PFC connectivity, the goal should not be about replicating Telzer et al.'s [20] fMRI experiment in order to establish the single-predictor regression model shown in equation (7), but to establish a new regression model with multiple predictors and a new outcome variable representing intrinsic motivation. This is because the VS-PFC connectivity variable shown in equation (7) is a task-dependent variable that is tied to performing the Go/No-Go task. Without performing the Go/No-Go task, this variable would cease to exist and the computation of any regression coefficient tied to it would be impossible. Hence, creating any regression model with the behavioral performance on the Go/No-Go task being the outcome variable would not carry any predictive value since the same task would have to be performed during fMRI in any future experiment. Consequently, we propose a multiple linear regression model that includes Go/No-Go task performance as a covariate or control variable entered alongside a primary predictor of VS-PFC connectivity. This model will have performance on an intrinsic motivation task (IMT_perf) as the outcome variable and is shown nominally in the equation below:

$$\begin{aligned}\text{IMT\_perf} &= \beta_0 + \beta_1 * \text{VS-PFC connectivity} \\ &\quad + \beta_2 * \text{Go/No-Go false alarm rate (\%)} \\ &\quad + \epsilon_i \end{aligned} \tag{8}$$

where β_1 and β_2 denote the regression coefficients tied to the observed VS-PFC connectivity signals generated from Go/No-Go task performance and the observed false alarm rate on the Go/No-Go task, respectively.

With respect to the IMT, we have no particular preferences and recommend it to be any task that involves making decisions or responses concerning intrinsic motivation. In line with a previous proposal by Zhong [25], this task can be either a behavioral task requiring visuomotor responses or a questionnaire that assesses one's intrinsic motivation to learn and improve in a specific activity of interest. Specially, for a behavioral measure of intrinsic motivation, one can use a task that require them to exercise their free will to learn about the responses taken by others concerning a certain activity [26] or a task that assesses their persistence in performing a highly challenging cognitive task in the absence of monetary rewards [25]. As for questionnaires, one can consider the *Intrinsic Motivation Inventory* [27, 28], a classical and well-recognized self-report tool for assessing an individual's motivation to engage in an activity of interest by measuring seven dimensions of intrinsic motivation. For educational research on intrinsic academic motivation among adolescents and young adults, one can consider the *Academic Motivation Scale* [29, 30] and (ii) *Internalization of Learning Motivation Scale* [31], both of which assess a student's motivation to work hard and excel in academic activities. Depending on the research question(s) at hand, a relevant subscale score can be taken from any of these three questionnaires for use as an outcome variable.

Taken together, the examples cited are just a small sample of the potential IMTs future investigators can use and we encourage innovation and creativity in the design of new IMTs. Ideally, any IMT used should exhibit significant correlation with the Go/No-Go task in a preliminary pilot experiment before being used formally in an fMRI experiment. Doing so would lower the risks of failure and increase the likelihood of finding a significant VS-PFC connectivity coefficient in the multiple regression model shown in equation (8).

In the event that a new IMT is designed and shown to correlate significantly with the Go/No-Go task, a new fMRI experiment can be conducted with participants performing the Go/No-Go task in the fMRI scanner. The false alarm rate on the Go/No-Go task, the VS-PFC connectivity signals recorded while performing this task, and performance on an IMT measured by a suitable metric, will then be recorded for each participant for entry as variables into the model shown in equation (8). Following this, ML-based regression using GD can be employed to determine the optimal values for the intercept and regression coefficients. To facilitate this process, note that the variables can be normalized to a standard range (see section below, for details).

Assuming all parameters in the multiple regression model are found to be significant, they can be applied in a second future experiment involving fMRI scanning using Go/No-Go task to compute estimates of IMT performance. In this case, re-administering the IMT will be unnecessary, since the most accurate regression parameters, derived through GD, will be used to predict IMT performance. Accordingly, a lot of time and effort can be saved.

By using a well-established regression model to predict participants' levels of intrinsic motivation instead of assessing them repeatedly using the same IMT, the time and resources spent on data collection can be more effectively reallocated to data analysis and interpretation. For an example, if a future need arises to develop an intervention program aimed at boosting intrinsic motivation in students, particularly among those with lower motivation levels, our ML-driven approach will be particularly useful for expediting the identification of suitable candidates for the program. Another example will apply to longitudinal fMRI studies investigating how developmental brain changes affect intrinsic motivation [25]. By using a ML-based regression model, follow-up fMRI studies can shorten the experimentation time by requiring returning participants to undergo only fMRI scans with the Go/No-Go task. Using the model, subsequent IMT performance for these participants can be predicted with ease through the recorded VS-PFC connectivity signals and Go/No-Go task performance scores.

6. Important technical considerations

In order to implement the ML-based regression model we proposed successfully, it is quite understandable that one would encounter some doubts and technical difficulties. Such challenges can concern issues such as data preparation, sample size, and participant characteristics. In this section, we will discuss some of the most important matters that future investigators ought to be explicitly aware of and the specific steps to manage them.

6.1 Data preparation: Variable selection and normalization

In the regression model shown in equation (8), there is only one predictor for VS-PFC connectivity. Considering that the PFC is a voluminous brain region that comprises many subregions with different functions, one may query about the ways in which the target PFC region should be selected and if more than one subregion can be chosen. Our recommendation is to select a target PFC subregion that exhibits the highest and most significant signal intensity in its functional coupling with the seed VS region, as done previously by Telzer et al. [20]. If there are more than one PFC subregion exhibiting significant functional coupling with the VS, the PFC subregion with the highest signal intensity should be chosen. Although it is all right to create two or more VS-PFC connectivity predictors in the aforementioned scenario (e.g., a VS-IFG connectivity predictor and a VS-dlPFC connectivity predictor), we do not recommend the use of multiple VS-PFC predictor simply because the sample size required for training and validating the ML-based regression model would have to be increased with each additional predictor – by at least 20 participants for a model exhibiting a medium-sized effect [32]. Unless one has a lot of research personnel and monetary resources, we do not recommend the fMRI scanning of additional participants simply to satisfy the insertion of additional predictors into the model. Instead, what we recommend is a resource-efficient analytical approach that combines significant PFC clusters into a bigger ROI and testing whether that ROI demonstrates significant functional coupling with the VS. If the outcome is positive, then the signal intensity parameter estimates from this combined ROI will represent the values of the single VS-PFC connectivity predictor used in the model.

In the same vein, one can query about the right way forward if there are multiple outcome variables derived from the use of several IMTs. In this scenario, should one train multiple ML-based regression models, each with a unique outcome variable? Our answer to this question is a staunch "no" since doing so would create lots of regression coefficients with different values for the same predictors, a process that would culminate in confusion during data analysis and interpretation in future studies. The right path forward, in our opinion, is to normalize the values of each IMT performance variable into a standard range of [0, 1] and average these normalized values to compute a composite IMT performance variable that represents the mean performance over all IMTs. Assuming that "0" represents the lowest score achieved on an IMT and "1" represents the highest score achieved, the normalization formula to be applied will be the following:

$$v' = \frac{v - \min(v)}{\max(v) - \min(v)} \tag{9}$$

where v' denotes the normalized version of the variable v, $\min(v)$ denotes the minimum value of v attained by a participant within a sample, and $\max(v)$ denotes the maximum value of v attained by a participant within the same sample.

In the event that we want "0" to represent the highest score achieved and "1" to represent the lowest score achieved, as in the case of the Go/No-Go task, in which lower false alarm rate represents more accurate performance, and vice versa, the normalization formula to be applied will be the following:

$$v' = \frac{\max(v) - v}{\max(v) - \min(v)} \tag{10}$$

Equation (10) is noteworthy because performance on psychological tests can be assessed using negative indicators of performance and thus it is important to reverse this trend when computing the normalized scores for such indirect measures. More importantly, in the event where there is a mix of positive and negative measures, we will always recommend the default normalization for the positive measure [equation (9)] and the reverse normalization for the negative measure [equation (10)]. In this way, higher values on each variable can be interpreted as indicative of greater representation of the feature of that variable, lessening the chance for inaccuracy or confusion during data analysis. In addition, one must be aware that we recommend the use of normalization not just for the computation of composite variables, but for its extension to all variables. If an outcome variable is normalized, the predictor variables must be normalized as well. This normalization procedure is extremely important in the context of ML because having a smaller range of numerical values to work with will lead to more precise and faster convergence. By normalizing all predictors variables to the same range of [0,1], we will eliminate the possibilities for large partial derivatives belonging to predictors with higher values and longer ranges to dominate the update of the regression coefficients during each GD iteration, a process that can result in non-optimal parameters computed at the end of GD [23]. We will also eliminate the problem of numerical overflow (i.e., resetting large values beyond a finite range that can be stored to zero) that can happen during GD through the entry of large numerical values [23].

In summary, for the purpose of computational efficiency and ease of result interpretation, we recommend the training and validation of our ML-based regression model according to the following equation:

$$\begin{aligned} \text{IMT\_perf}_{\eta} &= \beta_0 + \beta_1 * \text{ VS-PFC connectivity}_{\eta} \\ &\quad + \beta_2 * \text{ Go/No-Go Accuracy}_{\eta} \\ &\quad + \epsilon_i \end{aligned} \tag{11}$$

where the subscript of η denotes default normalization with "0" representing the lowest value achieved and "1" representing the highest value achieved. Note that the false alarm rate from the Go/No-Go task is converted into its reverse normalized form representing performance accuracy using equation (10).

6.2 Sample size for model assessment

With this understanding of variable selection and normalization, the next task is to figure out the optimal sample size to assess our model. To do so, we performed a power analysis using G*Power version 3.1.9.4 [33], and found that the sample size for obtaining a power of at least 80% with a medium effect size (R^2) of 0.15 at the default alpha level of 0.05 for a regression model with two predictors to be 60. This is a conservative estimate given that we did not specify a high effect size ($R^2 \geq 0.25$) and would prefer future investigators to collect a sizeable number of participants to avoid the commission of Type I errors.

Hence, we recommend future studies to recruit around 60 participants for model assessment, a process which would involve cross-validation in ML terms. This means that the collected sample would be divided into a training subset and a testing subset in a pre-set ratio, with more participants in the former group than in the latter group. In line with a recent ML study [34], this ratio can be set at 4:1, meaning that 48 participants will be randomly selected for training the model, and the remaining 12 participants be used for testing the model. The data-splitting process can be repeated multiple times for up to 20 times [34] to ensure that the regression parameters are computed as precisely as possible. This means that the final regression parameters – β_0, β_1, β_2 in equation (11) – would each represent the mean values derived from the entire cycle of iterations. To test the model in each data-split iteration, the predicted IMT performance scores can be correlated with the observed IMT performance scores. A high correlational value of 0.75 or more would indicate high accuracy in the training process and averaging the correlational values over all iterations would provide the mean model accuracy over the entire training process. Ideally, a mean correlational value of at least 0.90 would give future investigators the greatest confidence in the model's internal validity and its subsequent ability to predict IMT performance accurately in the absence of IMT(s).

6.3 Participant characteristics

In addition to the two issues mentioned above, the third most important concern pertain to participant characteristics. Owing to the fact that motivation research focuses largely on students in their adolescence and young adulthood, and that the association of VS-PFC connectivity with intrinsic motivation was mainly found amongst them [9, 16, 20-22], we intend our regression model to apply only to this population of youths. Apart from this, there is one more variable that we want future investigators to be explicitly aware of – and that is culture. As shown by Telzer et al. [20], a participant's cultural background has the potential to moderate the strength of the VS-PFC connectivity, with Chinese young adults (born and raised in China) demonstrating stronger, albeit non-significant, correlation between VS-PFC connectivity and Go-No-Go task performance [$r(14)= -0.43$, $p = 0.11$] than White American young adults (born and raised in the USA) [$r(15) = -0.16$, $p = 0.59$]. The same East-West cultural differences have also been shown by Qu et al. [35] to affect brain-behavior correlations between PFC activations and risk-taking motivation. While Chinese young adults (born and raised in China) demonstrated significant positive correlations between activations in two PFC subregions (left dlPFC and right anterior insula) and risky exploration behaviors, White American young adults (born and raised in the USA) demonstrated non-significant correlations (close to a flat line) between the same sets of variables.

These findings are noteworthy because they suggest that individuals from cultures that place strong emphasis on intrinsic motivation for academic achievement and self-improvement, such as the Chinese culture, may activate brain regions that are functionally involved in intrinsic motivation to a larger extent and in a more linear fashion than individuals from cultures that place weaker emphasis on intrinsic motivation. This also means that future investigators of intrinsic motivation should take note of the cultural background of their participants and ensure that each cultural group is represented equally in the overall sample. If the sample size is large enough, one can compare the correlations between IMT performance and VS-PFC connectivity between the cultural groups and establish a ML-based regression model – based on equation (11) – befitting of each culture.

7. Limitations

In addition to the technical considerations highlighted above, there are some key limitations of the proposed methodology that we need investigators in future studies to be aware of. First, for any future study to run smoothly, we deem it crucial that effective communication and collaboration exist between different researchers with a diverse set of expertise. These experts could have been trained originally in biomedical engineering, computer science, neuroscience, educational science, sociology, etc., and it is essential that the principal investigator managing them plays an active guiding role in fostering teamwork, charting out team-oriented goals, facilitating interdisciplinary dialogues, and sharing knowledge – so that a sense of team identity and belonging is forged [36], Second, owing to the fact our methodology was originally designed with healthy, cognitively intact adolescents in mind, future studies focusing on adolescents with psychological disorders would need to recruit a separate sample to establish the regression parameters. Due to differences in sample characteristics, any regression parameters previously established using healthy adolescents cannot be applied unequivocally to another model involving non-healthy adolescents with psychological problems. Third, we must state that because fMRI research is an expensive endeavor, since substantial funding is necessary for compensating participants and purchasing equipment, we advise future investigators to conduct careful budgeting and planning. As training a reliable ML model would require a considerable number of participants, as mentioned in the previous section, a sizeable proportion of any research funding must be devoted to participant recruitment and compensation, and hence it is important for future investigators to plan their budget around this central fact.

8. Conclusion

In this article, we provided a short review of the most notable human neuroscience literature on intrinsic motivation and proposed a novel approach wherein VS-PFC connectivity signals, derived from functional magnetic resonance imaging (fMRI) data, can be used as predictors of intrinsic motivation through a machine learning (ML)-based linear regression model. By developing a robust linear regression model supported by ML techniques and applied to a substantial sample of students, this approach aims to facilitate rapid and precise predictions of intrinsic motivation levels without the need for repeated assessment of intrinsic motivation in follow-up studies. Our proposed method would greatly benefit longitudinal fMRI studies investigating developmental brain and behavioral changes in intrinsic motivation, as well as educational intervention programs seeking fast and accurate identification of students with varying levels of intrinsic motivation.

In addition, we want to state that our ideas do not have to be restricted to the investigation of intrinsic motivation alone. If there are other functional connectivity and behavioral variables that can predict another type of outcome variable, our ML-based regression model can be similarly applied using the same procedures outlined above. This means that our ideas can be recast in the form of a generic methodological framework that provides flexibility in determining the variables to suit the research questions at hand. For an example, we turn to the neuroscience of spatial navigation literature, which postulates that the functional connectivity between the PFC and the hippocampus (Hpc) plays a crucial role in human navigation, in processes such as landmark-direction binding [37], perspective-switching [38], and cognitive mapping [39]. Thus, it would be interesting to investigate whether task-dependent PFC-Hpc connectivity can predict performance on a visuospatial task it is known to support (e.g., associative learning of landmark locations and turning directions, [37]) after controlling for a performance variable (e.g., number of wrong turns, [37] from an in-scanner virtual navigation task.

Finally, we want to stress that the successful realization of our proposed ideas may very likely involve multidisciplinary collaboration between neuroscientists and AI/data scientists. This endeavor will require a substantial amount of technical knowledge and expertise from both sides, making active communication and effective project management crucial. With the right coordination of efforts, we believe that any technical problems that may arise during the research process can be overcome. Following this vein, we welcome all future investigators who are keen to apply our methodology to contact us for academic discussion and potential collaboration. On this positive note, we end this article, and hope that future investigators will build upon our ideas to further the frontiers of motivation research.

Author Disclaimer

All ideas and claims expressed in this article are solely those of the authors and do not represent those of their affiliated universities.

Author Contributions

JZ: Conceptualization, Data curation, Methodology, Visualization, Writing — original draft. SG: Methodology, Writing — review & editing. SU: Literature review, Writing — review & editing. All authors read and approved the manuscript. All authors participated sufficiently in the work and agreed to be accountable for all aspects of the work.

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Conflict of Interest

The authors declare no conflict of interest.

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