IJEMD-SS, 4 (2) (2025) https://doi.org/10.54938/ijemdss.2026.05.1.510

International Journal of Emerging Multidisciplinaries: Social Science

Research Paper
Journal Homepage: www.ojs.ijemd.com
ISSN (print): 2957-5311

Drive As a System: Applying Lagun's Law to Education

Sudikshya Baniya [1]*

1. Pokhara United Academy, Bhadra kali Marga, Pokhara, Nepal

Abstract

Human drive, the energy that pushes us to begin, persist, and complete tasks, is one of the most important forces in learning and daily life. Most existing theories of motivation describe it in broad, qualitative terms. In 2025, Lagun's Law was introduced as a mathematical formula for drive, grounded in Cognitive Drive Architecture (CDA). The model defines drive through six interacting components: ignition (Primode), amplification (CAP), adaptability (Flexion), stability (Anchory), resistance (Grain), and variance (Slip). A published analysis of secondary student datasets showed that this law predicts academic performance, providing the first empirical support. This article summarizes the core model and proposes a practical framework for applying it in high school settings. By showing how each component can be measured with everyday student behaviors, the article opens a path for future primary research and highlights the promise of Lagun's Law as a foundation for the science of drive.

Keywords: Cognitive drive architecture; Lagun's law; Motivation; Drive science; Educational psychology; Structural equation model

1. Introduction

Why do some students persist with a difficult math problem while others give up quickly? Why do some athletes stay after practice to keep training, while others stop as soon as they are allowed? These differences are often described as "motivation," a concept that has been central to psychology for over a century [14].

The challenge is that most theories of motivation are broad and descriptive. [11] framed motivation as a progression from basic survival to self-actualization. Self-Determination Theory [4],[14] emphasized autonomy, competence, and relatedness. Expectancy–Value Theory [5] proposed that people act when they expect success and value the outcome. Achievement Goal Theory focused on mastery versus performance orientations [6]. These approaches have shaped decades of research, yet they tend to rely on surveys and qualitative descriptions rather than precise equations.

Some progress has been made in mathematical modeling. For instance, risk-taking model by [2] expressed motivation as the product of motive, probability, and incentive value. More recently, researchers have used computational models to link motivation to effort-based decision-making [15]. Still, such approaches are exceptions. Motivation is most often treated as a psychological state rather than a structural system with measurable components.

In 2025, a new proposal sought to change that. Lagun's Law, derived from the Cognitive Drive Architecture (CDA), introduced a structural equation for drive (Lagun, 2025b). Rather than defining drive as a general trait, CDA identifies six interacting variables: ignition (Primode), amplification (CAP), adaptability (Flexion), attentional stability (Anchory), resistance (Grain), and variance (Slip). A validation study applying this model to secondary student datasets (N = 480) showed that these variables significantly predicted performance outcomes [7].

The present article builds on that foundation. Its aim is not to present new data but to propose a conceptual framework for applying Lagun's Law in high school contexts. By translating each component of the equation into measurable classroom behaviors, this paper highlights how the law can move from abstract theory to practical application. Such a framework may also guide future primary research designed to test the law directly.

2. Theoretical Framework

Cognitive Drive Architecture (CDA) has been proposed not merely as a new model, but as the foundation of a new field within cognitive psychology [8]. Traditional motivational theories emphasize needs, goals, or values [11] , [4] , [5], but they typically stop short of providing a unifying structural science of drive. CDA, by contrast, argues that the drive itself can be expressed through interacting cognitive variables that obey systematic principles.

In this sense, CDA is to motivation what ACT-R or SOAR were to cognition more broadly: an attempt to formalize a messy psychological construct into an architecture that can generate predictions and be tested against data [1] , [9]. By presenting drive as an emergent product of six interacting components, CDA aims to launch a research program, what could be called a new subfield of "drive science" within cognitive psychology.

The central formulation of this proposed field is Lagun's Law, which expresses drive mathematically as:

$$Drive = \left(\frac{Primode^{CAP} \times Flexion}{Anchory + Grain} \right) + Slip$$

Each variable represents a distinct aspect of drive:

- **Primode (Ignition Readiness)**

  Primode acts as the ignition switch. Without initiation, no amount of energy or adaptability produces drive. In the equation, this variable is treated as binary (on/off). Its inclusion reflects research showing that readiness to start a task is a unique predictor of engagement [16].

- **CAP (Cognitive Activation Potential)**

  CAP represents intensity, the "voltage" of motivation. When Primode is engaged, CAP magnifies the output nonlinearly (through exponentiation). This echoes empirical findings that higher motivational arousal produces disproportionate increases in effort [3].

- **Flexion (Adaptability)**

  Flexion measures how effectively a person adjusts to changing conditions. High flexibility allows students or workers to sustain effort even when obstacles appear. Flexibility has been tied to resilience and learning adaptability in education research [10].

- **Anchory (Attentional Stability)**

  Anchory anchors attention to a focal point. Stability prevents drive from dissipating across distractions. Cognitive psychology has long emphasized sustained attention as critical for performance [17].

- **Grain (Resistance or Friction)**

  Grain represents the "drag" on drive: effort costs, fatigue, or the external barriers. High Grain reduces effective drive, paralleling theories of effort discounting [18].

- **Slip (Variance/Entropy)**

  Slip accounts for randomness and unpredictability in human behavior. No model perfectly predicts performance; Slip acknowledges this by introducing a variance term. Such "noise" terms are common in cognitive and decision models [12].

Taken together, the equation embodies several principles: drive cannot occur without ignition, it scales nonlinearly with intensity, it is enhanced by adaptability, it is constrained by attention–resistance balance, and it always contains some randomness. Unlike traditional motivational theories, Lagun's Law is not metaphorical: it is structural, equation-based, and designed for empirical testing [7], [8]. Figure 1 illustrates this structure, showing how the six CDA variables combine to yield an overall drive output.

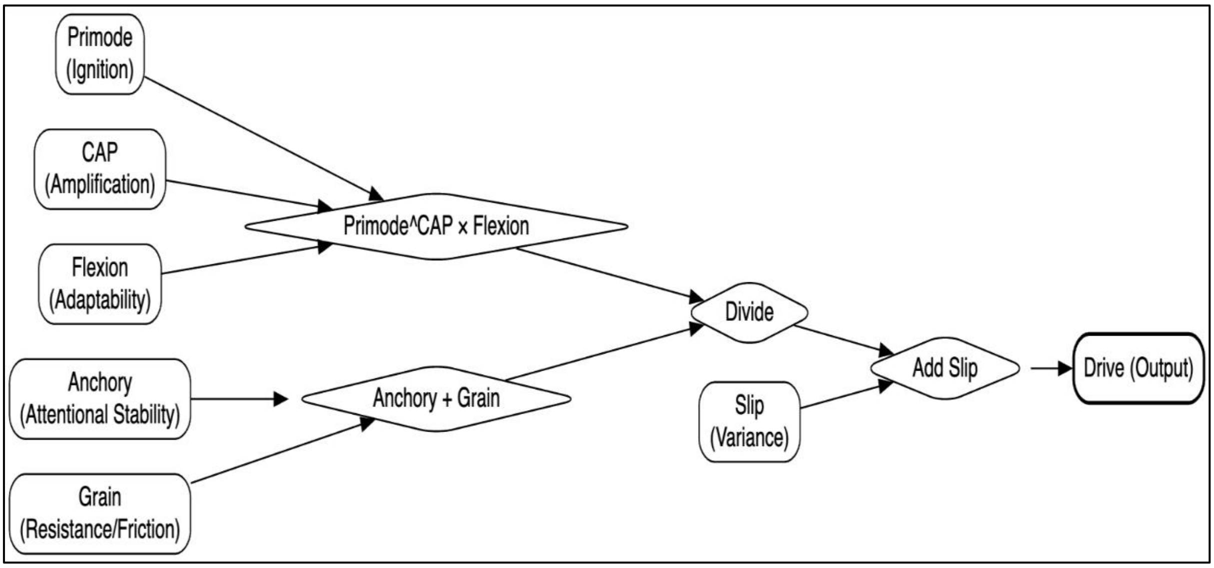

Figure 1: Structural diagram of Lagun's Law within Cognitive Drive Architecture (CDA). Primode is exponentiated by CAP, multiplied by Flexion, divided by the sum of Anchory and Grain, and Slip is added to yield Drive.

3. Empirical Evidence

Although Cognitive Drive Architecture (CDA) is primarily a theoretical proposal, it has already received preliminary empirical support. In a validation study, Lagun (2025a) tested Lagun's Law against secondary datasets drawn from approximately 480 students. These datasets included measures of academic readiness, reported effort, and performance outcomes. While not originally collected for the purpose of evaluating CDA, they provided a practical opportunity to examine whether the six components of the law could predict real-world educational performance.

The analysis employed regression and structural equation modeling to map dataset variables onto CDA constructs. For example, task readiness indicators were used as a proxy for Primode, measures of energy and effort intensity for CAP, adaptability indices for Flexion, attentional ratings for Anchory, and difficulty ratings for Grain. Slip was modeled as residual variance in performance not explained by the other terms.

The results were broadly consistent with the predictions of Lagun's Law. Students with higher ignition readiness (Primode) and stronger motivational amplification (CAP) performed better across tasks. Moreover, outcomes were influenced by the balance between stabilizing focus (Anchory) and resisting friction (Grain). Importantly, these findings emerged even though the data were not originally designed to test the CDA model, suggesting that the law captures real dynamics of drive present in educational contexts.

However, the reliance on secondary data is both a strength and a limitation. On one hand, it demonstrates that Lagun's Law can account for patterns already present in existing educational datasets. On the other hand, secondary data lacks the precision needed to fully test each component of the architecture. For example, Flexion was represented by limited adaptability measures rather than a robust, task-specific flexibility index. Future research will require primary data collection designed explicitly to operationalize each CDA variable.

4. Proposed Framework for New Applications

The initial validation of Lagun's Law provides promising evidence that drive can be modeled as a structural system [7]. Yet its true value lies in whether the model can guide new research and practice. To advance CDA as a proposed field, this section outlines a framework for applying the six components of Lagun's Law in high school learning contexts. The goal is to translate abstract constructs into measurable, observable indicators that educators and students can recognize.

4.1 Primode (Ignition Readiness)

Ignition reflects whether a student begins a task at all. In high school classrooms, this could be operationalized as *time-to-start* measures, how quickly students engage once instructions are given. Digital learning environments also provide natural data: login times, submission timestamps, or frequency of skipped assignments.

4.2 CAP (Cognitive Activation Potential)

CAP captures intensity or motivational "voltage." In practice, this could be measured by time-on-task (e.g., minutes spent studying) or self-report ratings of energy and effort. Physiological proxies such as heart rate variability have also been explored in related research on effort mobilization [13].

4.3 Flexion (Adaptability)

Flexion reflects the ability to adjust when conditions change. In a school context, adaptability could be measured through revision-based tasks (e.g., improvement across multiple essay drafts) or responses to corrective feedback in math problems. Students who maintain drive despite needing to change strategies would exhibit high Flexion.

4.4 Anchory (Attentional Stability)

Anchory refers to the tethering of attention. One proxy is sustained concentration on assignments, measurable through classroom observation or digital tools that track off-task clicks. Individual differences in attentional control are known to predict learning outcomes [17], making Anchory a critical component.

4.5 Grain (Resistance or Friction)

Grain captures obstacles to drive. At the high school level, Grain could be assessed via self-reported "stuck points" (moments when students feel blocked) or logs of incomplete problem sets. External factors such as noise, workload, or competing responsibilities also contribute to Grain.

4.6 Slip (Variance/Entropy)

Slip recognizes the unpredictability of human performance. Even students with high readiness, energy, and focus sometimes underperform. In applied settings, Slip could be quantified by variability across repeated trials or test performances. By including Slip, Lagun's Law acknowledges that no model of drive can be perfectly deterministic.

4.7 Integrative Use

By combining these measures, educators could identify where the drive breaks down. For example, a student with strong Primode and CAP but high Grain might need structural support (clearer instructions, fewer obstacles). Another student with high Flexion but low Anchory might benefit from attention-management strategies.

This framework provides not only a pathway for primary research, designing studies that explicitly operationalize CDA variables, but also practical insights for teachers and students. By mapping abstract constructs to everyday behaviors, Lagun's Law becomes accessible as both a scientific model and an educational tool.

5. Implications and Future Research

The framework proposed here has several important implications for both science and practice.

First, it positions drive as a structural system rather than a descriptive state. Traditional motivational theories, whether [11], Self-Determination Theory [4], or expectancy-value models [5], have offered valuable insights, but they rely heavily on self-report surveys and qualitative constructs. Lagun's Law, by contrast, provides a quantitative formula that specifies how multiple variables interact to produce drive [8]. This opens the door to falsifiable predictions, a hallmark of scientific progress.

Second, the framework has direct educational applications. High school students, teachers, and administrators can use Lagun's variables to diagnose where drive falters. For example, if students fail to start tasks promptly, interventions can focus on Primode. If effort is high but progress is low, teachers may look for excessive Grain. If adaptability is strong but outcomes fluctuate, Slip may be the limiting factor. This structural lens transforms motivation from an abstract quality into something observable and improvable.

Third, the framework highlights the importance of primary research. The CDA validation study [7] demonstrated the law's predictive power using secondary data, but such proxies were limited. Primary studies, specifically designed to operationalize Primode, CAP, Flexion, Anchory, Grain, and Slip, are essential for rigorous testing. For example, digital learning platforms could track ignition, attention, and adaptability in real time, providing rich datasets for validating the law in authentic environments.

Fourth, the framework has interdisciplinary potential. Beyond education, CDA may offer insights into domains such as sports psychology, occupational performance, rehabilitation, and even artificial intelligence. Modeling drive as a system could improve our understanding of persistence, burnout, and resilience across diverse contexts [16] , [18].

Finally, the framework underscores a paradigm shift. By proposing CDA as the basis of a new field, Lagun's Law moves motivational research closer to status of cognitive architectures such as ACT-R [1] or [9]. Whether this emerging field will be fully realized depends on the accumulation of empirical evidence, theoretical refinements, and applied successes.

Taken together, these implications suggest that Lagun's Law is not just a novel formula, but a potential cornerstone for a broader "science of drive." The next step is to put this science to the test.

6. Conclusion

Lagun's Law and the broader proposal of Cognitive Drive Architecture represent an ambitious step toward reframing drive as a structural, measurable construct. Unlike traditional motivational theories, which often remain descriptive, CDA offers a precise formulation in which drive emerges from ignition, amplification, adaptability, stability, resistance, and variance. Early validation with secondary datasets suggests that this model captures a real dynamics of student performance, though much work remains to be done.

This article has extended that foundation by proposing a practical framework for applying Lagun's Law in high school contexts. By mapping each variable to observable behaviors, such as time-to-start, time-on-task, or adaptability to feedback, the model becomes accessible not only to researchers but also to educators and students.

The implication is straightforward: drive is not mysterious. It is a system that can be described, measured, and eventually improved. With targeted primary research and interdisciplinary application, CDA has the potential to establish itself as a new field within cognitive psychology, a science of drive that is both theoretically rigorous and practically useful.

References

[1] Anderson, J. R. (2007). How can the human mind occur in the physical universe? Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195324259.001.0001

[2] Atkinson, J. W. (1957). Motivational determinants of risk-taking behavior. Psychological Review, 64(6, Pt.1), 359–372. https://doi.org/10.1037/h0043445

[3] Brehm, J. W., & Self, E. A. (1989). The intensity of motivation. Annual Review of Psychology, 40, 109–131. https://doi.org/10.1146/annurev.ps.40.020189.000545

[4] Deci, E. L., & Ryan, R. M. (1985). Intrinsic Motivation and Self-Determination in Human Behavior. New York: Plenum Press. http://dx.doi.org/10.1007/978-1-4899-2271-7

[5] Eccles, J. S., & Wigfield, A. (2002). Motivational beliefs, values, and goals. Annual review of psychology, 53(1), 109-132. https://doi.org/10.1146/annurev.psych.53.100901.135153

[6] Elliot, A. J., & McGregor, H. A. (2001). A 2 X 2 achievement goal framework. Journal of personality and social psychology, 80(3), 501–519. https://doi.org/10.1037/0022-3514.80.3.501

[7] Lagun, N. (2025a). Cognitive Drive Architecture: Derivation and Validation of Lagun's Law for Modeling Volitional Effort. https://doi.org/10.20944/preprints202507.0996.v1

[8] Lagun, N. (2025b). Lagun's law and the foundations of cognitive drive architecture: A first principles theory of effort and performance. International Journal of Science and Research Archive. https://doi.org/10.30574/ijsra.2025.15.2.1425

[9] Laird, J. (2012). The Soar Cognitive Architecture. United Kingdom: MIT Press.

[10] Martin, A. J., Nejad, H. G., Colmar, S., & Liem, G. A. D. (2013). Adaptability: How students' responses to uncertainty and novelty predict their academic and non-academic outcomes. Journal of Educational Psychology, 105(3), 728–746. https://doi.org/10.1037/a0032794

[11] Maslow, A. H. (1943). A theory of human motivation. Psychological Review, 50(4), 370–396. https://doi.org/10.1037/h0054346

[12] Ratcliff, R., Smith, P. L., Brown, S. D., & McKoon, G. (2016). Diffusion Decision Model: Current Issues and History. Trends in cognitive sciences, 20(4), 260–281. https://doi.org/10.1016/j.tics.2016.01.007

[13] Richter, M., Gendolla, G. H. E., & Wright, R. A. (2016). Three decades of research on motivational intensity theory: What we have learned about effort and what we still don't know. In A. J. Elliot (Ed.), Advances in motivation science (pp. 149–186). Elsevier Academic Press. https://doi.org/10.1016/bs.adms.2016.02.001

[14] Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. The American psychologist, 55(1), 68–78. https://doi.org/10.1037//0003-066x.55.1.68

[15] Shenhav, A., Musslick, S., Lieder, F., Kool, W., Griffiths, T. L., Cohen, J. D., & Botvinick, M. M. (2017). Toward a Rational and Mechanistic Account of Mental Effort. Annual review of neuroscience, 40, 99–124. https://doi.org/10.1146/annurev-neuro-072116-031526

[16] Steel, P., & König, C. J. (2006). Integrating theories of motivation. The Academy of Management Review, 31(4), 889–913. https://doi.org/10.2307/20159257

[17] Unsworth, N., & Robison, M. K. (2017). A locus coeruleus-norepinephrine account of individual differences in working memory capacity and attention control. Psychonomic bulletin & review, 24(4), 1282–1311. https://doi.org/10.3758/s13423-016-1220-5

[18] Westbrook, A., & Braver, T. S. (2015). Cognitive effort: A neuroeconomic approach. Cognitive, affective & behavioral neuroscience, 15(2), 395–415. https://doi.org/10.3758/s13415-015-0334-y