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REVIEW ARTICLE

A Stage-Mapped Framework for Neuroentrepreneurship: Linking Real-Time Decision Processes to Entrepreneurial Behavior

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Entrepreneurship demands rapid judgments, timely commitments, and effective learning from outcomes—yet we know remarkably little about the moment-to-moment neural processes underpinning these abilities. This review synthesizes existing neuroscience and decision-science evidence within a 3-stage framework of entrepreneurial decision-making: evaluation of opportunities, commitment to action, and feedback-based learning. Using this structure, we highlight key field limitations—including small and selective samples, task and measurement heterogeneity, and weak linkage between laboratory paradigms and real-world entrepreneurial behavior—and introduce a stage-mapped, computationally explicit framework that renders these processes empirically testable. We propose practical steps to support cumulative progress, such as portable tasks suitable for field testing, single-trial analyses linking computational choice parameters to neural dynamics, and preregistration practices that preserve confirmatory rigor while allowing bounded exploration. Drawing on established decision-science paradigms (e.g., multi-armed bandit and foraging), we specify stage-linked behavioral and neural relationships that characterize how entrepreneurs evaluate uncertain opportunities, decide when to act, and update beliefs following success or failure. We conclude with research priorities and a roadmap toward a coherent science of neuroentrepreneurship that links brain processes to proximal decision behaviors, which, across repeated cycles, may contribute probabilistically to entrepreneurial success.

Introduction

Why neuroentrepreneurship needs a process-level model

Entrepreneurship is widely recognized as a central engine of innovation and economic growth, yet understanding why some individuals consistently identify, pursue, and exploit opportunities more effectively than others remains a longstanding challenge [1,2]. Traditional research has examined the phenomenon primarily through economic and management lenses, identifying market, organizational, and resource-based drivers of venture outcomes. However, entrepreneurial success also hinges on individual differences in the interplay of personality traits, moment-to-moment cognitive processes, and underlying brain function [3,4]. More precisely, entrepreneurship demands complex decision-making under uncertainty, rapid problem-solving, and adaptive behavior, all of which rely on multiplexed cognitive and neural processes that standard self-reports, retrospective interviews, and case studies cannot capture in real time [1,5].

With the rise of behavioral economics, neuroscience, neuroeconomics, and social cognitive psychology, researchers now possess tools for deeper exploration of the cognitive and neural processes that shape entrepreneurial thinking and strategic decision-making [6–10]. Accordingly, scholars have increasingly called for a neuroscientific approach, one that uses direct, real-time observations of brain function while individuals engage in opportunity recognition, risk-taking, and strategic thinking [11–13] . This emerging perspective promises deeper mechanistic insights into how entrepreneurs perceive or create opportunities [11,14], make decisions [15], act despite uncertainty [16], and differ from non-entrepreneurs [7,11,17].

Despite growing interest, much of the neuroentrepreneurship literature has organized findings around neural correlates of traits, intentions, or isolated task contrasts (e.g., [18,19]). While these syntheses establish the relevance of neuroscience for entrepreneurship, they do not provide a unified, temporally explicit architecture of entrepreneurial decision processes. In particular, the field lacks a formal mapping linking task manipulations to computational parameters, neural indices, and proximal behavioral outputs within a single testable model. Empirical progress is further constrained by small and heterogeneous samples, divergent task implementations, and inconsistent reporting standards, limiting cross-study comparability and cumulative inference. As a result, findings remain fragmented and insufficiently anchored to founder-relevant decision dynamics.

These limitations motivate a process-level framework specifying when decisions unfold, how neural signals index underlying computations, and under which task conditions those signals can be meaningfully interpreted. Formal definitions, population scope, and boundary conditions are specified in the Definitions, boundary conditions, and outcome scope section.

Review methods (narrative, task-based synthesis)

This review synthesizes empirical and methodological work at the intersection of entrepreneurship and cognitive neuroscience, organizing evidence around temporally resolved decision processes. Searches were conducted in PubMed, PsycINFO, and the Web of Science Core Collection (Science Citation Index Expanded; Social Sciences Citation Index; Emerging Sources Citation Index) for peer-reviewed studies published between 1990 and 2025 (search dates: 2025 October 1 to 3). In Web of Science, searches were performed using the Topic field and refined to relevant research domains (Business and Management; Engineering and Technology; Life Sciences; Social and Behavioral Sciences). Keywords combined entrepreneurship terms (e.g., entrepreneur, startup founder, venture, and opportunity recognition) with neuroscience and decision-science terms [e.g., electroencephalography (EEG)/event-related potential (ERP), functional magnetic resonance imaging (fMRI)/functional near-infrared spectroscopy (fNIRS)/magnetoencephalography (MEG), reinforcement learning, bandit, foraging, decision-making], using database-specific Boolean operators.

Searches yielded 13,274 records. After duplicate removal, 2,123 records were screened at the title/abstract level and 127 full texts were assessed for eligibility. The large initial yield primarily reflected clinical, neurological, and rehabilitation-focused studies indexed under decision or neural processing terms but not relevant to entrepreneurial decision-making. Fifteen studies were retained as most directly relevant to informing or testing the proposed stage-mapped framework.

Studies were included if they: (a) reported task-based neural measures during decision processes relevant to evaluation, commitment, or feedback; (b) provided mechanistic neural or computational evidence informing stage-specific computations; or (c) compared entrepreneurial and non-entrepreneur populations using structured decision paradigms with interpretable behavioral outputs. Most excluded articles lacked task-based decision measures (e.g., resting-state only), used non-decision paradigms, or did not link behavior to computational variables. Among the 15 retained studies, 2 were included for mechanistic anchors: a resting-state fMRI study in entrepreneurs [20], contextualizing population-level network differences, and a parameterized volatile 6-armed bandit study [21], providing a behavioral benchmark for volatility, change-point learning, and exploration dynamics relevant to commitment and feedback stages.

Given heterogeneity in samples, paradigms, and analytic approaches, evidence is synthesized narratively and organized by decision stage; Table 1 summarizes sample definitions, paradigms, neural methods, stages analyzed, key findings, and limitations. Evidence type is labeled as Direct (task-based neural data in entrepreneurial populations) or Translational (mechanistic neural or behavioral evidence from non-founder samples relevant to stage-specific computations). Direct founder-level task-based neuroimaging evidence remains limited (fewer than 10 studies), reinforcing the need for the mechanism-first synthesis adopted here.

Overall pattern of methodological heterogeneity

Across studies, cumulative inference is challenged by several recurrent features: (a) inconsistent sample definitions/matching, (b) variable task parameterization (volatility, deadlines, opportunity cost, trial counts), (c) uneven preprocessing transparency [region of interest (ROI)/latency/baseline/artifact handling], (d) rare reliability reporting, (e) limited linkage to longitudinal outcomes, and (f) analytic heterogeneity (aggregate contrasts versus single-trial computational modeling). Post-2018 studies demonstrate improved preprocessing transparency and analytic sophistication; however, heterogeneity in reporting practices and ecological task design remains substantial.

Scope, contributions, and roadmap

This review synthesizes the emerging field of neuroentrepreneurship and proposes a concrete, testable framework for its next decade of research. Rather than cataloging neural correlates or discussing decision processes descriptively, we focus on how specific entrepreneurial decision stages map onto measurable ERPs (ERP markers) and how this mapping can be specified within a structured, falsifiable research model. The aim is not to introduce additional neural correlates but to organize existing evidence into a temporally explicit architecture linking task structure, computational parameters, neural indices, and proximal behavioral outputs within a unified stage-based framework. By locating founder and contextual influences at the level of computational parameters rather than neural traits, the framework supports mechanistic analysis without implying direct neural prediction of success. This structured mapping is intended to enhance comparability, preregistration, and cumulative testing across laboratories.

A core goal of this review is to promote cumulative science in neuroentrepreneurship— research that builds systematically on shared paradigms, preregistered predictions, and comparable metrics, rather than isolated self-reports or one-off correlates. The field remains emerging and fragmented, characterized by disconnected collaboration networks and inconsistent methods that hinder replicability and synthesis [18,22].

We deliver 4 contributions: (a) a stage-mapped conceptual framework (Fig. 1) that decomposes entrepreneurial decision-making into 3 recurring stages—evaluation → commitment → feedback—anchored to well-established, millisecond-resolution ERP markers (Table 2) and formalized as a falsifiable model (Fig. 2 and Table 3); (b) a task lens based on 2 decision-science paradigms [multi-armed bandits (MABs) and ecological foraging] that directly operationalize these stages and provide quantifiable manipulations of core entrepreneurial dilemmas; (c) a practical method roadmap (Fig. 3) emphasizing ecological validity, single-trial computational modeling, and transparent preregistration with bounded robustness checks; (d) a reporting checklist (Table 4) and prediction map (Table 5) aligning task manipulations, neural signatures, and behavioral outcomes to support comparability and cumulative science.

By providing a unified framework, standard tasks, and explicit stage-linked mappings, we aim to address identified gaps and accelerate progress toward mechanistic, testable accounts of entrepreneurial decision-making.

The review proceeds as follows: The Definitions, boundary conditions, and outcome scope section specifies definitions and boundary conditions; the Theoretical foundations: How neuroscience informs entrepreneurship section outlines the theoretical foundations; the The Neuroscience of Entrepreneurial Decisions: The Stage-Mapped Framework section presents the stage-mapped ERP framework; the Task Lenses for Entrepreneurial Decision-Making section introduces the task lenses; the Neuroimaging

Table 1. Summary of task-based neuroentrepreneurship and decision-neuroscience studies included in the review. This table summarizes studies selected for mechanistic relevance to stage-specific entrepreneurial decision processes and is not intended as an exhaustive census. The "decision stage" column indicates evaluation, commitment, and/or feedback components analyzed. Evidence type distinguishes direct from translational sources.

Study	Task paradigm/ decision context	Neural method and analysis	Mapped decision stage(s)	Primary neural–behavioral finding	Evidence type; sample definition and recruitment characteristics	Key methodological constraints and reporting scope
Ortiz-Terán et al. (2013)	Visual Stroop (conflict) decision task	EEG/ERP	Evaluation	Founders exhibited altered early control-related neural signals during conflict processing.	Direct; $n = 50$ (25 founders, 25 non-entrepreneurs); Founders defined broadly as "founders of enterprises" (no reported venture stage or performance metrics); recruited via professional networks; no demographic or matching information reported	Sample: Modest *n* per group; no demographic matching or venture-stage information reported. Task: Visual Stroop (conflict) paradigm; no volatility, deadlines, or opportunity-cost manipulation. Neural method: Conventional peak-based ERP analysis; no reported single-trial modeling or reliability metrics. → Reporting reflects early-stage task-ERP contrasts without behavioral linkage to real-world entrepreneurial outcomes.
Aydın et al. (2023)	Creative thinking (AUT-style) + opportunity recognition (text-based sector judgment)	EEG (time–frequency band power analysis)	Evaluation	Entrepreneurs exhibited beta-dominant frontal/temporal activity during opportunity recognition, whereas non-entrepreneurs showed relatively higher theta/alpha/gamma power.	Direct; $n = 35$ (17 entrepreneurs, 18 non-entrepreneurs); Entrepreneurs defined broadly (no reported venture stage or performance metrics); recruitment procedure not clearly specified; no demographic matching information reported	Sample: Small *n* per group; broad entrepreneur definition; limited recruitment and demographic detail. Task: Static opportunity-recognition paradigm; no volatility, deadlines, or opportunity-cost manipulation. Neural method: Time–frequency band-power contrasts; limited preprocessing transparency; no ERP components or computational modeling. → Reporting emphasizes group-level frequency differences without real-world behavioral linkage.
Shane et al. (2020)	Pitch evaluation	fMRI	Evaluation	Neural responses during pitch exposure were associated with stated investment interest.	Translational; $n = 28$ (investors); Investors (not founders); recruited via professional networks; no founder-level behavioral or venture outcome metrics assessed	Sample: Investors (not founders); modest *n*; no founder-level behavioral metrics. Task: Decontextualized pitch videos; no volatility or dynamic decision structure. Neural method: fMRI activation contrasts; no reported reliability metrics; limited ecological context inherent to scanner environment. → Mechanistic valuation evidence from investors rather than entrepreneurial decision-makers.

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Table 1. (Continued)

Study	Task paradigm/ decision context	Neural method and analysis	Mapped decision stage(s)	Primary neural–behavioral finding	Evidence type; sample definition and recruitment characteristics	Key methodological constraints and reporting scope
Hassall et al. (2019)	Two-armed bandit (stationary)	EEG/ERP	Evaluation; Commitment	N2 and P300 amplitudes differentiated exploratory versus exploitative choices in non-entrepreneur samples.	Translational; $n = 23$ (students); Undergraduate convenience sample (psychology participant pool); no founder-level behavioral or venture outcome metrics assessed	Sample: Small *n*; no entrepreneurial population. Task: Stationary 2-armed bandit; explicitly no volatility manipulation. Neural method: ERP (N2/P300); limited reporting of trial-level reliability and artifact-handling transparency.→ Laboratory exploration–exploitation effects without ecological or entrepreneurial linkage.
Laureiro-Martínez et al. (2014)	Four-armed bandit (dynamic)	fMRI: standard GLM	Commitment	Entrepreneurs exhibited reduced neural recruitment during exploitative choices, interpreted as greater neural efficiency.	Direct; $n = 50$ (24 entrepreneurs, 26 managers); Entrepreneurs and managers recruited via professional networks/executive programs; no reported venture stage or performance metrics; no demographic matching details reported	Sample: Modest *n* per group; entrepreneurs vs. managers; no venture-stage or performance metrics. Task: Dynamic 4-armed bandit; no explicit volatility quantification or deadline manipulation. Neural method: fMRI GLM contrasts; limited reporting of trial-level modeling and reliability metrics. → Neural efficiency interpreted within lab-based exploitation contexts without longitudinal behavioral linkage.
Bourdaud et al. (2008)	Four-armed bandit (dynamic)	EEG + time–frequency (oscillatory power)	Commitment	Frontal alpha/beta and parietal oscillatory activity differentiated exploratory versus exploitative choices.	Translational; $n = 9$ (non-entrepreneurs); Small convenience sample; no founder-level behavioral or venture outcome metrics assessed	Sample: Very small *n*; non-entrepreneurs. Task: Dynamic 4-armed bandit. Neural method: EEG time–frequency contrasts (alpha/beta focus); limited spatial specification and preprocessing transparency; no reliability metrics reported. → Frequency-band differentiation of explore/exploit without single-trial modeling or ecological validation.
Tzovara et al. (2012)	Exploration–exploitation task	EEG (single-trial decoding)	Commitment	Exploratory decisions were decodable from pre-response neural activity.	Translational; $n = 14$ (non-entrepreneurs); Small convenience sample; no founder-level behavioral or venture outcome metrics assessed	Sample: Small *n*; non-entrepreneurs. Task: Exploration–exploitation task; no explicit volatility manipulation. Neural method: Single-trial decoding; moderate classification accuracy; limited preprocessing detail and reliability reporting. → Proof-of-concept decoding of exploration decisions without behavioral linkage to real-world contexts.

(Continued)

Table 1. (Continued)

Study	Task paradigm/ decision context	Neural method and analysis	Mapped decision stage(s)	Primary neural–behavioral finding	Evidence type; sample definition and recruitment characteristics	Key methodological constraints and reporting scope
Twomey et al. (2015)	Perceptual decision task	EEG/ERP	Commitment	CPP activity reflected evidence accumulation to a decision bound independent of motor response.	Translational; $n = 48$ (students); Undergraduate convenience sample (university participant pool); no founder-level behavioral or venture outcome metrics assessed	Sample: $n = 48$ split across small experiments; no entrepreneurial population. Task: Perceptual decision paradigm; no reward, volatility, or opportunity-cost structure. Neural method: ERP (CPP accumulation signal); strong perceptual modeling but non-entrepreneurial context. → Mechanistic accumulation evidence from low-uncertainty perceptual decisions.
Kolling et al. (2014)	Foraging task (dynamic)	fMRI	Commitment	dACC activity signaled pressure to pursue unlikely choices and interacted with vmPFC/PCC during foraging decisions.	Translational; $n = 18$ (general sample); General convenience sample (university/community); no founder-level behavioral or venture outcome metrics assessed	Sample: Small n; non-entrepreneurs. Task: Foraging paradigm; dynamic but limited explicit volatility manipulation. Neural method: fMRI (dACC/vmPFC/PCC interactions); no reported neural reliability metrics; limited temporal precision inherent to fMRI. → Value-based foraging mechanisms without entrepreneurial sampling or ecological deadlines.
Cavanagh et al. (2012)	Dynamic reward-learning task (RT-based)	EEG/ERP + TF	Commitment → Feedback	Frontal theta activity reflected uncertainty-driven exploration and unsigned prediction errors, with asymmetry for negative outcomes.	Translational; $n = 17$ (students); Undergraduate convenience sample (psychology participant pool); no founder-level behavioral or venture outcome metrics assessed	Sample: Small n; non-entrepreneurs. Task: RT-based reward-learning; no discrete arms or volatility manipulation. Neural method: EEG/TF (frontal theta); limited reporting of reliability metrics; no ecological linkage. → Theta dynamics in laboratory reward learning without entrepreneurial behavioral integration.
Zuluaga et al. (2025)	Simulated business decisions	GSR + EEG (performance metrics)	Commitment → Feedback	Experienced entrepreneurs exhibited higher stress responses in remuneration/layoff contexts but greater relaxation in familiar domains, whereas novices showed higher emotional intensity during planning/distribution phases	Direct; $n = 40$ (20 novice entrepreneurs, 20 experienced entrepreneurs); recruitment procedure not specified; Experience defined by self-report (no reported venture stage or objective success metrics)	Sample: Modest n per group; entrepreneurs defined by self-report; no objective venture-performance metrics. Task: Simulated business decisions; limited dynamic structure. Neural method: GSR + EEG performance metrics; no computational modeling; no reliability metrics reported. → Physiological differentiation in simulated contexts without validated performance linkage.

(Continued)

Table 1. (Continued)

Study	Task paradigm/ decision context	Neural method and analysis	Mapped decision stage(s)	Primary neural–behavioral finding	Evidence type; sample definition and recruitment characteristics	Key methodological constraints and reporting scope
Payzan-LeNestour (2012)	Six-armed bandit (dynamic)	Behavioral + computational modeling (Bayesian model; no neural measures)	Feedback → Commitment	Participants approximated Bayesian learning in a volatile bandit environment.	Translational; $n = 62$; (students); Undergraduate convenience sample; Behavioral study only (no neural measures); no founder-level behavioral or venture outcome metrics assessed	Sample: non-entrepreneurs; behavioral only; no entrepreneurs. Task: Restless 6-armed bandit; limited ecological deadlines or opportunity costs. Neural method: Bayesian computational modeling (no neural measures). → Computational learning dynamics without neural or entrepreneurial validation.
Holroyd and Coles (2002)	Probabilistic reinforcement learning task and modified Eriksen flanker task	EEG/ERP integrated with computational reinforcement-learning modeling	Feedback	ERP and feedback-related error activity were interpreted as neural correlates of dopamine-dependent reinforcement-learning prediction-error signaling.	Translational; two ERP experiments ($n = 15$), (non-entrepreneurs); Small convenience sample; no founder-level behavioral or venture outcome metrics assessed	Sample: Small n non-entrepreneurs. Task: Laboratory reinforcement-learning and response-conflict paradigms; no volatility or real-world entrepreneurial complexity. Neural method: Foundational ERP// computational framework predating contemporary preprocessing, source localization, single-trial modeling, and current reliability standards. → Historically influential hybrid theoretical–computational–empirical model of neural prediction-error signaling.
Cavanagh (2015)	Three-armed bandit (dynamic)	EEG/ERP + TF	Feedback	Cortical delta activity reflected reward prediction error and associated behavioral adjustments at temporally dissociable intervals.	Translational; $n = 23$ (students); Undergraduate convenience sample (psychology participant pool); no founder-level behavioral or venture outcome metrics assessed	Sample: Small n. Task: Three-armed bandit; limited exploration complexity; no deadline or exit-cost manipulation. Neural method: EEG time–frequency (delta); no formal reliability metrics reported. → Advanced oscillatory dissociation within laboratory reward tasks without ecological entrepreneurial linkage.
Ooms et al. (2023)	Resting-state (no active task; eyes-closed fMRI scan)	fMRI	Resting-state (not stage-mapped)	Resting-state insula connectivity differences were associated with entrepreneurial self-reported cognition.	Translational (entrepreneurs; resting-state only); $n = 40$ (20 serial entrepreneurs, 20 managers); Serial entrepreneurs defined as having founded multiple ventures; recruited via professional networks; no reported venture stage or performance metrics; no task-based decision paradigm.	Sample: Modest n per group; serial entrepreneurs vs. managers; no task-based decision paradigm. Task: Resting-state only; no volatility, deadlines, or behavioral decisions. Neural method: fMRI connectivity; limited behavioral correlates reported. → Resting-state differences without task-based stage mapping or decision metrics.

Fig. 1. Stage-mapped conceptual framework of entrepreneurial decision-making (neural dynamics). Note: The 3 stages recur iteratively throughout the entrepreneurial process.

Methods for Neuroentrepreneurship section reviews neuroimaging methods; the Empirical Evidence and Founder-Relevant Patterns from the Literature section synthesizes empirical evidence and founder-relevant patterns; and the Discussion, Limitations, and Future Directions section discusses limitations and future directions. A complete glossary of ERP components, time–frequency terms, and novel constructs introduced in this review is provided in Appendix A.

Reader's guide

This review is intentionally interdisciplinary. Readers interested in neural decision mechanisms may focus on the stage-mapped framework and ERP signatures (The Neuroscience of Entrepreneurial Decisions: The Stage-Mapped Framework, Task Lenses for Entrepreneurial Decision-Making, and Neuroimaging Methods for Neuroentrepreneurship sections). Scholars in entrepreneurship and innovation may focus on how decision stages relate to entrepreneurial behavior and learning under uncertainty (Introduction, Empirical Evidence and Founder-Relevant Patterns from the Literature, and Discussion, Limitations, and Future Directions sections). Readers concerned with methods and study design will find guidance on task construction, computational modeling, and reporting standards in Task Lenses for Entrepreneurial Decision-Making, Neuroimaging Methods for Neuroentrepreneurship, and Design improvements and analytic standards sections. Applied audiences (e.g., entrepreneurs, investors, incubator leaders, and educators) may focus on Definitions, boundary conditions, and outcome scope and Discussion, Limitations, and Future Directions sections, which clarify boundary conditions, outcome measures, and implications for evaluation and training. Together, these entry points converge on a shared mechanistic framework.

Definitions, boundary conditions, and outcome scope

This section clarifies the framework's conceptual scope, boundary conditions, populations, venture contexts, and outcome interpretation. Given neuroentrepreneurship's interdisciplinary nature, we provide precise definitions of entrepreneurial constructs while anchoring neural interpretations in founder-relevant contexts.

Core definitions

Entrepreneurship (process-level definition)—This review adopts a process-oriented definition whereby entrepreneurship refers to the discovery, evaluation, and exploitation of opportunities under uncertainty [23,24]. This foregrounds 3 recurring decision stages—opportunity evaluation, resource commitment (including pivoting), and feedback-driven updating—which serve as core units of analysis and bridge to time-resolved neuroimaging.

Startup founder (actor-level definition)—Terms such as "entrepreneur" and "founder" are used inconsistently in the literature (from students at business/entrepreneurship programs to individuals with entrepreneurial intentions to accomplished venture leaders and corporate managers). We define a startup founder as an individual who initiates and leads a new venture oriented toward scalable, innovation-driven growth, retains meaningful decision authority in the formative years, and actively shapes strategy, resource allocation, and learning under uncertainty (consistent with Danilovska et al. [25]).

Population differences and interpretive scope

Reviewed evidence spans heterogeneous samples (students, managers, investors, entrepreneurs; see Table 1). Non-founder studies provide mechanistic insight into decision processes, whereas studies of active founders or entrepreneurial professionals offer direct founder-level evidence. The framework avoids assuming equivalence across populations, specifying that core decision computations (e.g., evidence accumulation, exploration, and feedback updating) are likely shared, while their weighting, timing, and strategic expression may differ—requiring interpretive caution.

Boundary conditions and venture contexts

The framework applies most directly to opportunity-driven, growth-oriented entrepreneurship, where repeated decisions under high uncertainty, resource commitment, and feedback-driven adaptation are central and excludes purely intention-based or necessity-driven samples. Necessity-driven entrepreneurship, often urgency-driven and constraint-based, may compress evaluation and accelerate commitment, with feedback focused on short-term viability rather than scaling. Lifestyle-oriented or small-scale local ventures (e.g., solopreneurship and family-run businesses) may involve prolonged evaluation and conservative commitment thresholds, with feedback oriented toward stability rather than growth. Corporate intrapreneurship, operating within established organizational structures, may involve formalized evaluation, moderated personal commitment thresholds, and distributed feedback loops. Core computational mechanisms (e.g., evidence accumulation, threshold adjustment, and updating)

Table 2. ERP components and measurement parameters. Latencies indicate approximate peak windows derived from major reviews [42,47,58,59]. These components have been reported across value-based and/or perceptual decision-making paradigms, although their functional interpretation depends on task structure, timing, and analysis choices [111]. General reporting recommendations for all components: baseline interval, filters (HP/LP), reference, artifact handling (ICA/rejection), electrode montage, ROI selection rationale, and split-half reliability (e.g., [44,47,112])

Component	Latency (ms)	ROI (electrodes)	Functional interpretation	Measurement notes
P2 (salience/early categorization)	~150–250	Fronto-central/parietal (FCz, Cz, CPz)	Attentional gating to diagnostic cues; larger = stronger early selection	Baseline −200 to 0 ms; average ref or mastoids; report cluster and peak/mean window
N2 (stimulus-locked; early conflict/control)	~200–350	Fronto-central (FCz/Cz)	Mismatch detection and inhibitory control; more negative = greater conflict/top-down engagement	Include rare-target/no-go probes when feasible; report trial counts and artifact thresholds
CPP (evidence accumulation/commitment)	Response-locked, pre-response ramp	Central–parietal (CPz/Pz)	Buildup of decision evidence toward a bound; steeper slope or higher pre-response amplitude = faster/stronger commitment	Response-locked (−700 to + 100 ms); quantify slope (linear fit) and pre-response area/mean
Midfrontal theta (4–8 Hz; control at decision bound)	Pre-/peri-response	Midfrontal (FCz)	Control recruitment and decision-threshold adjustment under conflict or urgency; a cross-stage control signal that modulates speed–accuracy trade-offs rather than an event-related potential	Time–frequency (e.g., Morlet); report baseline correction/window
RewP (prediction error)	~200–300	Fronto-central (FCz)	Signed prediction error (δ); larger for better-than-expected outcomes and attenuated/negative-going for worse-than-expected outcomes.	Feedback-locked; specify feedback onset precision; model-based single-trial regressions
P300 (context updating)	~300–500	Parietal (Pz/CPz)	Task model updating; scales with volatility/informativeness	Report peak/mean window; target versus standard contrast (if used); scalp distribution
LPP (motivational meaning/reappraisal)	~500–900+	Posterior/parietal	Sustained evaluative processing; strategy-level meaning	Long-window drift sensitivity; report segment length and high-pass filter

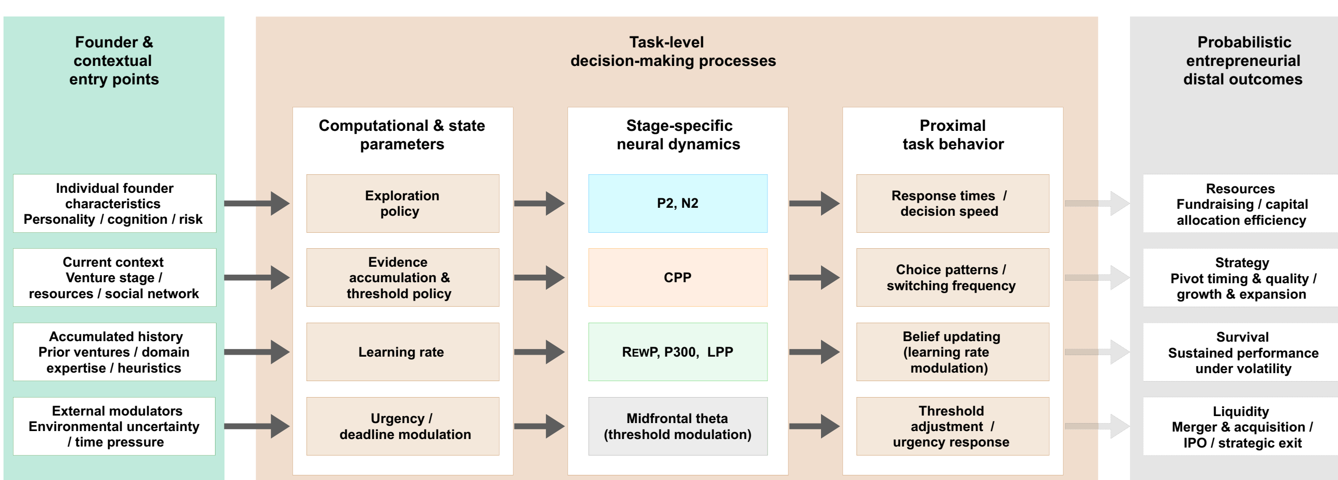

Fig. 2. Stage-mapped mechanistic research model of entrepreneurial decision-making. Note: Founder history and situational context are hypothesized to influence decision-making via computational parameters spanning evaluation (exploration policy), commitment (evidence accumulation; decision threshold), and feedback (learning rate). These parameters manifest as stage-specific neural dynamics and give rise to proximal behavior. Across repeated cycles, such behaviors contribute probabilistically to downstream outcomes. Solid arrows denote within-task mechanistic pathways; dashed arrows denote cumulative distal relationships.

Table 3. Formal research model linking decision stages, cognitive operations, neural signatures, and founder-relevant behavior. Founder and contextual variables are hypothesized to influence entrepreneurial outcomes indirectly through computational parameters and stage-specific neural dynamics. No deterministic pathway from neural markers to venture success is assumed.

Decision stage(s) analyzed	Core cognitive operation	Task instantiation (examples)	Primary neural markers	Founder-relevant behavioral interpretation	Representative empirical support
Evaluation	Rapid salience detection and early screening of opportunity cues	Cue-based valuation; early option preview in bandit tasks; opportunity cue exposure; rare/no-go probes	P2 (150–250 ms); N2 (200–350 ms); midfrontal theta (4–8 Hz)	Efficient early opportunity screening; inhibition of low-value or ambiguous options before full evaluation	Crowley and Colrain (2004); Folstein and Van Petten (2008); Cavanagh and Frank (2014); Hassall et al. (2019)
Evaluation	Pattern recognition and novelty detection	Manipulation of cue diagnosticity; novelty versus familiarity contrasts in bandits	P2 amplitude modulation	Faster identification of high-potential opportunities based on learned templates	Baron (2006); Beugré (2017); Wittmann et al. (2007)
Commitment	Evidence accumulation toward an action threshold	Forced-choice bandits; stay/leave foraging decisions; deadline-constrained choices	CPP slope; response-locked N2; midfrontal theta	Decisiveness under uncertainty; adaptive speed–accuracy trade-offs during commitment	O'Connell et al. (2012); Twomey et al. (2015); Kelly and O'Connell (2015)
Commitment	Dynamic adjustment of decision thresholds under conflict or urgency	Deadline pressure; balanced value gaps; increased exit or switching costs	Midfrontal theta (4–8 Hz); response-locked N2	Strategic caution when stakes are symmetric or time-pressured; flexible threshold control	Cavanagh and Frank (2014); Shenhav et al. (2014)
Feedback learning	Trial-wise prediction error processing	Outcome feedback in bandits; first post-switch outcome in foraging tasks	RewP (200–300 ms; FCz)	Sensitivity to informative gains and losses; trial-wise updating efficiency	Holroyd and Coles (2002); Sambrook and Goslin (2015)
Feedback learning	Context updating and belief revision	Volatility manipulation; change-point detection; unexpected outcome shifts	P300 (300–500 ms; Pz)	Flexible strategy updating in dynamic or nonstationary environments	Donchin and Coles (1988); Polich (2011); Cavanagh (2015)
Feedback learning	Meaning-level appraisal and reappraisal of outcomes	High-magnitude outcomes; sunk-cost release; rare or consequential failures	LPP (500–900+ ms; posterior)	Resilience; adaptive reappraisal of failure versus perseverative rumination	Hajcak et al. (2010); Bechara and Damasio (2005); Ding et al. (2022)

are likely shared across contexts, but their relative weighting and strategic expression may vary systematically. Implications for task design and sampling are revisited in the Discussion, Limitations, and Future Directions section.

Entrepreneurial behavior and venture performance

Entrepreneurial behavior refers to proximal decision processes observable in task paradigms [e.g., choice patterns, response times (RTs), switching, and learning rates]. Venture performance, by contrast, is conceptualized as the longitudinal, probabilistic aggregation of repeated decision cycles shaped jointly by founder characteristics, behavior, and market context, and operationalized through measurable real-world indicators.

Recommended minimum outcome measures

To link stage-specific mechanisms to venture performance, future studies should report ≥1 standardized metric per domain, with observation window and key covariates (e.g., industry, venture stage, founder experience, capital access, and macroeconomic context). These domains include:

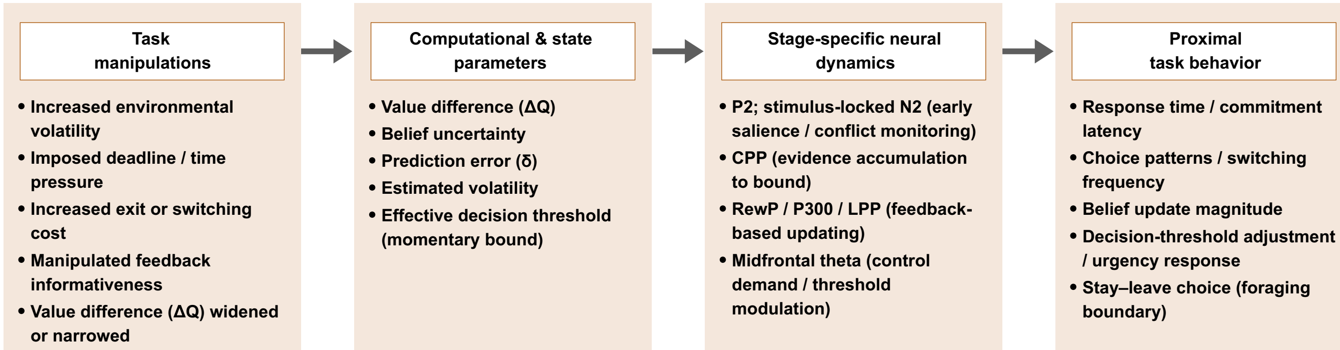

Fig. 3. Summary pipeline linking task manipulations to computational and state parameters, neural indices, and behavior. Note: Analytic pipeline linking task manipulations → computational and state parameters → stage-specific neural indices → proximal task behavior. This schematic represents an operational mapping rather than a causal or outcome model. Shared neural indices reflect common computational mechanisms that are differentially engaged under specific task parameterizations.

a. Financial/capital allocation: funding stage progression (e.g., seed, series A), cumulative capital raised, capital allocation efficiency (e.g., burn rate/runway), valuation;
b. Strategic adaptation: pivot frequency and timing, post-pivot performance indicators (e.g., revenue and/or employee growth trajectories);
c. Performance/survival: sustained operation under adverse conditions, continued operation at predefined intervals, or time-to-failure;
d. Liquidity/investor-return: merger, acquisition, initial public offering (IPO), multiple on invested capital (MOIC), internal rate of return (IRR), time-to-liquidity.

Outcomes should be modeled probabilistically relative to covariates, consistent with the cumulative mapping in Fig. 2 and Table 3.

Theoretical foundations: How neuroscience informs entrepreneurship

Entrepreneurship theory rests on several competing traditions. Trait approaches view entrepreneurs as possessing stable characteristics such as high risk tolerance and innovativeness [26]. Process-oriented models instead emphasize dynamic cognition, notably opportunity recognition and enactment [27,28] and the contrast between effectuation (intuitive, means-driven logic under uncertainty; Sarasvathy [29]) and causation (goal-driven analytical planning). Dual-process theory has become a dominant integrative lens by mapping effectuation-like behavior to fast, intuitive system 1 processing and causation-like behavior to deliberate system 2 processing [15,30].

However, neuroscience evidence indicates that the classic system 1/system 2 distinction is best understood as continuous gradients of cognitive control allocation rather than 2 discrete neural systems [31,32]. A stage-mapped perspective on entrepreneurial decision-making naturally aligns with this continuous view. By anchoring each stage to graded, parametrically sensitive ERP markers (Figs. 1 and 2; component definitions in Table 2; operational mappings in Table 5; e.g., midfrontal theta scaling with conflict and central–parietal positivity (CPP) slope varying with value clarity), our model offers a mechanistic, testable extension of effectuation/causation distinctions and reframes ostensibly static traits as dynamic modulations of evidence accumulation, conflict monitoring, and feedback learning. It also preserves the psychological usefulness of the system 1/system 2 heuristic with the temporal precision and objective neural implementation that prior entrepreneurial theories lack.

Neuroscience is uniquely positioned to deliver these advances. As Nicolaou et al. [33] summarize, it can (a) capture hidden mental processes missed by self-reports, (b) test the validity of purported entrepreneurial traits, (c) characterize developmental trajectories of cognition, and (d) adjudicate between competing theories by supplying objective physiological markers. Accordingly, the present framework uses time-resolved ERPs to render effectuation/causation differences as stage-specific, falsifiable predictions (formalized in Table 3; operationalized in Table 5).

The Neuroscience of Entrepreneurial Decisions: The Stage-Mapped Framework

Mechanism-first perspective in neuroentrepreneurship

We adopt a mechanism-first stance and organize entrepreneurship literature through 3 decision stages—evaluation, commitment, and feedback learning—and their EEG/ERP signatures (indexed by well-characterized components; see the Overview of the stage-mapped framework section). This structure improves construct specificity (which part of the decision is affected), methodological alignment (which task parameters isolate that stage), and interpretability (which neural markers should change). It also supports stage-specific hypotheses linking founder characteristics to neural signals that index stage-specific processing and to proximal task behaviors in MAB/foraging-type paradigms.

Prior work suggested that neuroscience advances entrepreneurship research by opening the brain's "black box", validating/contrasting candidate traits, tracking change over time, and discriminating among theories that predict similar behavior but posit different mechanisms [33,34]. Complementary foundations motivate a stage approach: Dual-process perspectives imply separable mechanisms—fast, affective, experience-based judgments [35] versus slower, analytical control [30,36]; neuroplasticity and reinforcement learning show how practice and feedback tune these mechanisms over time [33,37,38], and the somatic marker hypothesis explains why affective guidance can be adaptive under uncertainty [39–41].

Table 4. Reporting and preregistration checklist. Checklist items draw on EEG/ERP reporting and preregistration recommendations [113,114] and reliability/timing guidance [115].

Domain	What to preregister/report	Examples/specifics
Stage-specific hypotheses	Predicted direction, latency windows, ROIs for evaluation (P2/N2), commitment (CPP slope; midfrontal theta/N2), feedback (RewP → P300 → LPP)	E.g., larger P2 to diagnostic cues; steeper CPP slope with larger ΔQ
Model-based linkage	Trial-wise regressors and mapping to ERPs	δ (prediction error), ΔQ (value gap), volatility, leave threshold/opportunity cost
Behavior–signal coupling	Planned couplings between neural measures and behavior	CPP slope ↔ RT/accuracy; RewP ↔ trial-wise δ; midfrontal theta ↔ post-error adaptation; N2 ↔ inhibitory control
Task parameters	Core manipulations and primary outcomes	MAB: volatility/horizon/feedback richness; Foraging: depletion/travel cost; outcomes: directed vs. random exploration, optimal leave times
Timing fidelity	Hardware/timing QA and lag corrections	Monitor refresh, trigger path, feedback onset precision
EEG preprocessing	Filters, reference, baselines, epochs, ICA/rejection, component extraction	HP 0.1–0.5 Hz; LP 30–40 Hz; CPP slope method; feedback-locked windows
Power and reliability	Sample size justification, trial counts, reliability metrics	Split-half reliability; noise metrics per component
Exclusions/QC	Participant/trial exclusion criteria; handling unbalanced cells	Minimum usable trials per condition/component
Transparency	Sharing commitments	Task code, preprocessing pipeline, analysis scripts, anonymized summaries, prereg link
Deviations	How you'll disclose/analyze deviations	Sensitivity analyses; robustness checks

This stage-based map specifies when founder characteristics should matter in the decision stream and how they should appear neurally—improving construct precision, study design, and interpretation. To operationalize the framework in later sections, we use 2 canonical paradigms as task lenses—MABs (explore–exploit trade-off) and foraging stay–leave (opportunity cost/thresholding; see the Task Lenses for Entrepreneurial Decision-Making section).

Overview of the stage-mapped framework

Entrepreneurial decision-making is not a single act but a recurring cycle of 3 psychologically and temporally distinct stages: evaluation (is this opportunity worth pursuing?) → commitment (how much to invest and when to pivot?) → feedback (what did the outcome teach me?). In this framework, these stages are treated as temporally distinct and neurally tractable components of a recurring decision cycle, each anchored to well-established ERP markers with millisecond precision (Fig. 1; component definitions in Table 2).

Midfrontal theta (4–8 Hz) is conceptualized as a cross-stage control signal: When observed pre-response (typically over FCz), it indexes control recruitment following conflict detection and dynamic adjustment of decision thresholds at the bound, while when observed post-response or post-feedback, it reflects adaptive control and performance monitoring following conflict or error [42].

The N2 is distinguished by lock type: stimulus-locked N2 during early evaluation versus response-locked N2 during pre-response control at commitment, with latency windows specified throughout.

The CPP is a response-locked, pre-response ramping positivity over central–parietal sites (typically CPz/Pz) that indexes evidence accumulation toward a decision bound (∼300 to 800 ms preceding response; [43,44]).

ERP terminology follows contemporary conventions (e.g., RewP rather than FRN; CPP rather than choice-P3), with formal definitions provided in Table 2 and Appendix A.

The detailed stage-by-stage mapping, including operationalization strategies and founder-relevant patterns, is presented in the Detailed stage descriptions and predictions section. Table 5 translates these mappings into preregistrable signal–behavior relationships.

A stage-mapped research model of entrepreneurial decision-making

Whereas the previous section outlined the conceptual structure of entrepreneurial decision-making, this section formalizes it as a directional, testable research model linking founder characteristics and situational context to computational parameters, stage-specific neural dynamics, and proximal task behavior.

Evaluation, commitment, and feedback are instantiated through computational parameters (e.g., exploration policy, evidence-accumulation rate, decision threshold, and learning rate), which manifest as temporally specific neural signatures and give rise to observable behavior (e.g., choices, RTs, and updating). Figure 2 embeds the conceptual stage framework

Table 5. Computational variables for stage-specific entrepreneurial decision processes. All predictions in this table are within-subject, specifying how trial-wise computational variables modulate ERP components and proximal behavior at the individual level.

Computational variable (within-subject prediction)	ERP component (timing/ROI)	Expected neural pattern	Behavioral correlates
Cue diagnosticity/salience	P2 (150–250 ms; fronto-central/parietal)	Larger P2 with more informative cues	Faster, accurate filtering; fewer spurious explorations
Initial value ambiguity/early conflict	N2 (200–350 ms; FCz/Cz)	More negative N2 with higher ambiguity	Slower but more controlled screening; relates to no-go accuracy (if probed)
Value gap ($\Delta Q = Q\_best - Q\_next$)	CPP (response-locked; CPz/Pz)	Steeper CPP slope/higher pre-response amplitude as ΔQ increases	Shorter decision times without accuracy loss
Urgency/deadline (speed–accuracy setting)	Midfrontal theta (4–8 Hz; FCz; time–frequency control signal) and response-locked N2	Theta increases with tighter deadlines/conflict (bound raising); response-locked N2 scales with control	Better speed–accuracy trade-off; predicts post-error adjustments
δ (prediction error)	RewP (200–300 ms; FCz)	More positive RewP for better-than-expected outcomes; attenuated or negative-going responses for worse-than-expected outcomes	Larger $\lvert\delta\rvert$ predicts stronger next-trial updating and switching probability
Volatility/unexpected uncertainty	P300 (300–500 ms; Pz)	Larger P300 when the context/model must be updated	Increased belief updating following regime shifts
Outcome salience/appraisal	LPP (500–900 ms+; posterior/parietal)	Larger LPP when outcomes carry strategic meaning (e.g., big losses and pivots)	Persistence versus adaptive switching (e.g., reduced sunk-cost bias under reappraisal)

introduced in Fig. 1 within a mechanistic architecture, specifying how each stage is implemented at computational and neural levels. Distal entrepreneurial outcomes are conceptualized as cumulative, probabilistic consequences of repeated decision cycles (e.g., exploration policies shaping pivot timing and learning rates influencing adaptation under volatility) rather than one-to-one readouts of neural signals. The model therefore targets proximal cognitive mechanisms and does not posit direct neural prediction of venture success.

Established psychological constructs (e.g., decisiveness, resilience, and tolerance for ambiguity) remain conceptually indispensable. Neural markers are treated as temporally resolved indices of decision processes through which such constructs may operate, not as trait substitutes.

Stage-specific markers draw on both direct founder studies and translational decision-neuroscience evidence (see Table 1). Formal testable mappings are specified in Table 3.

Explicit, testable hypotheses derived from the model

In the following hypotheses, value gap (ΔQ) refers to the difference between the highest and next-best option value at the moment of commitment, and prediction error (δ) refers to the trial-wise discrepancy between expected and obtained outcomes in reinforcement-learning models.

- H1 (Evaluation stage): Greater cue diagnosticity will be associated with increased P2 amplitude and reduced stimulus-locked N2 under low ambiguity. Under high ambiguity, diagnostic cues are expected to preferentially recruit conflict-related activity (N2 and/or midfrontal theta), reflecting structured uncertainty screening rather than indiscriminate salience enhancement. Trial-wise modulation of these signals will predict faster rejection of low-value options.
- H2 (Commitment stage): Trial-wise value gap magnitude (ΔQ) will positively predict CPP slope and shorter decision latency, reflecting steeper evidence accumulation. The strength of this coupling [$\beta(\text{CPP slope} \sim \Delta Q)$] will index value-sensitive commitment dynamics.
- H3 (Feedback stage): Prediction-error magnitude (δ) will scale with RewP amplitude, and downstream belief updating will be indexed by P300 amplitude. The coupling between δ and feedback-locked neural responses is expected to be stronger when outcomes are informative (e.g., under volatility), consistent with adaptive learning.
- H4 (Founder-level modulation): Founder-level differences are hypothesized to manifest as systematic modulation of computational parameters and their neural couplings (e.g., exploration policy, learning rate, and decision threshold), rather than as direct trait-level differences in ERP amplitude independent of trial-wise task variables.
- H5 (Cross-stage urgency control): Urgency/deadline pressure will modulate pre-response midfrontal theta and decision thresholds. Adaptive performance will be characterized by proportional scaling of control recruitment relative to

evidence strength (ΔQ), rather than uniform increases in theta power or indiscriminate threshold elevation.

Testability and empirical falsification

The framework would be challenged if (a) stage-targeted manipulations selectively modulated neural markers assigned to other stages without affecting stage-appropriate signals, (b) hypothesized neural signatures failed to track their corresponding computational variables at the trial level (e.g., ΔQ not predicting CPP slope; δ not predicting RewP), or (c) stage-specific neural–computational couplings showed no reliable association with proximal behavioral adjustments.

Consistent with single-trial computational approaches (e.g., [45]), ERP components are treated as temporal indices of underlying computations rather than trait readouts.

Detailed stage descriptions and predictions

The following patterns are presented as model-derived, stage-specific predictions rather than established founder biomarkers. ERP components are treated as process indicators of stage-specific computations, and any links to founder-relevant characteristics (e.g., decisiveness and resilience) are framed as hypotheses about differential parameterization of shared mechanisms—not as neural readouts or replacements of psychological constructs.

Stage 1: Evaluation—Early salience and conflict monitoring

During evaluation, the brain rapidly screens options for relevance and flags conflict (e.g., ambiguity and rule violations) before full evidence integration. Salient or novel cues trigger an early positive deflection (P2), while conflict or ambiguity elicits N2 and midfrontal theta, signaling the need for heightened cognitive control.

Core neural indices indexing evaluation-stage processing (see Table 2 for component definitions and Table 3 for model mapping):

- P2 (~150 to 250 ms; fronto-central/parietal): early positive peak reflecting rapid orienting to salient or novel information [46,47];
- Stimulus-locked N2 (~200 to 350 ms; fronto-central negativity, typically FCz/Cz): signals early detection of conflict or need for cognitive control [42,48,49];
- Midfrontal theta (4 to 8 Hz): transient increases during evaluation reflect conflict and ambiguity detection and the recruitment of control resources; this cross-stage control signal reflects early control recruitment and may precede later threshold adjustments [42].

Opportunity recognition aligns with memory–association systems that support rapid pattern completion and insight [12,50]. In ERP terms, cues matching learned "high-potential" templates evoke larger P2, whereas ambiguous or rule-conflicting cues recruit control (larger N2) via anterior cingulate cortex (ACC)/prefrontal cortex (PFC) [51]. Apparent "risk tolerance" can reflect valuation conflict at this stage—i.e., stronger N2 when cues imply both upside and hazard [4,52].

Operationalization: This stage is elicited by varying how informative the cues are and how predictable the environment feels (raised or lower cue validity, introduced or removed regularities, or manipulated initial value ambiguity). It also helps to include occasional rare-target or no-go trials for a clean assay of early control readiness while keeping participants engaged in opportunity scanning.

Founder-relevant patterns: A testable hypothesis derived from the model is that more efficient opportunity screening will be associated with larger P2 responses to diagnostic cues [46] and adaptive inhibitory control reflected in scaled N2 amplitudes under ambiguity [49].

Stage 2: Commitment—Evidence accumulation and action thresholding

At commitment stage, noisy evidence is converted into a categorical choice under time/uncertainty—exactly where entrepreneurial decisions often diverge from managerial ones [28,53].

Core neural indices indexing commitment-stage processing (see Tables 2 and 3):

- CPP slope (~300 to 800 ms pre-response ramp, typically CPz/Pz): neural index of evidence accumulation whose slope tracks the moment-by-moment accumulation of evidence toward a decision threshold [43,44]; steeper slope/higher pre-response amplitude → faster/stronger commitment;
- Response-locked N2 (FCz/Cz) and midfrontal theta (4 to 8 Hz), ~200 to 400 ms before response: increase when caution, deadlines, or strategic adjustment is required — reflecting prospective online threshold control [42].

Operationalization: This stage is surfaced by manipulating deadlines, value gaps, and switching/exit costs, which force trade-offs between speed, accuracy, and opportunity cost.

Founder-relevant patterns: The model predicts that wider value gaps will be associated with steeper CPP slopes, reflecting faster evidence accumulation and more decisive choices. In contrast, increased strategic caution (e.g., under tight deadlines or balanced costs) is expected to be indexed by stronger midfrontal theta. Behaviorally, this pattern corresponds to risk-sensitive decisiveness: rapid commitment when advantage is clear, adaptive slowing when caution is warranted [54].

Stage 3: Feedback learning—Prediction error, updating, meaning integration

In feedback stage, outcomes are converted into updates, noise is distinguished from signal, and motivational meaning is integrated, which forms the base of entrepreneurial learning from wins and failures.

Core neural indices indexing feedback-stage processing (see Tables 2 and 3):

- RewP (~200 to 300 ms; reward positivity, fronto-central, FCz)—sharp positivity (or reduced negativity) when outcomes are better than expected; larger amplitude indexes stronger reward prediction error and reinforcement-learning signal [55,56].
- P300 (~300 to 500 ms; parietal, Pz)—broad positivity that indexes context updating and surprise; amplitude scales with outcome volatility and feedback informativeness [57,58].
- Late positive potential (LPP) (~500 to 900 ms+; parietal/posterior)—sustained late positivity that indexes deeper emotional and motivational appraisal; amplitude increases with motivational importance and the need for reappraisal [59].

- Midfrontal theta oscillations—increased power in the 4- to 8-Hz band that reflects post-outcome adaptive control demands (e.g., error processing or strategy adjustment), complementing its pre-response role in threshold regulation [42].

Operationalization: This stage is isolated by varying reward volatility, feedback richness (full versus partial/counterfactual), and including occasional high-magnitude outcomes to probe meaning-level appraisal. The plasticity and reinforcement-learning claims are operationalized via the RewP → P300 → LPP sequence: larger δ and higher volatility are expected to increase RewP and P300, while consequential outcomes that demand reappraisal increase LPP. Behaviorally, these patterns align with higher learning rates, faster post-error correction, and adaptive policy shifts.

Founder-relevant patterns predicted by the model include robust RewP responses to informative errors, P300 scaling with volatility (reflecting update weight), and LPP patterns favoring reappraisal over sustained affective engagement. A testable hypothesis is that founders who exhibit more adaptive feedback processing will show these neural signatures. Where examined to date, primarily in translational decision-neuroscience studies and a small number of founder samples, such patterns are associated with faster post-error correction and greater performance stability under environmental drift [60,61].

Implementation—Linking model to signals (applies across evaluation, commitment, and feedback stages)

For each trial-wise regressor—diagnosticity, ambiguity, value gap, urgency/deadline, prediction error, and volatility—researchers should fit single-trial ERP/time–frequency models and report signal–behavior couplings, such as CPP slope ↔ RT; RewP ↔ trial-wise prediction error (δ); midfrontal theta ↔ post-error adaptation. Regions of interest, latency windows, and preprocessing parameters should be specified a priori. Recommended methodological guidance and a preregistration/reporting checklist are provided in Tables 4 and 5.

Model map (operational): Computational variables → ERP signatures → behavioral correlates

Table 5 summarizes the review's conceptual mapping between core decision variables (e.g., cue diagnosticity, ambiguity, value gap, urgency/deadline, prediction error, volatility, and outcome salience), their expected ERP correlates, and the behavioral measures with which those signals should covary. The mapping is task-agnostic and organized within the evaluation → commitment → feedback framework; specific paradigms instantiate the same variables with different manipulations (e.g., volatility and horizon in bandits and depletion rate and travel cost in foraging). Presented in this way, the table functions as a model-based framework for interpreting prior findings and for preregistering signal–behavior predictions in future studies. The empirical implementation of these model-derived predictions is outlined in the Near-term priorities for cumulative progress section.

Task Lenses for Entrepreneurial Decision-Making

A mechanism-first account of entrepreneurial choice benefits from paradigms that involve uncertainty, commitment, and learning in controlled yet ecologically meaningful ways—while permitting millisecond-resolved tests with EEG/ERPs. Two families of tasks do this particularly well. MAB tasks instantiate the continual tension between exploiting known options and exploring uncertain alternatives [62,63]. Foraging (stay–leave) tasks formalize the pivot decision: whether to persist in a depleting opportunity or incur a cost to search elsewhere [64]. Both naturally express the evaluation → commitment → feedback learning sequence and therefore map cleanly onto ERP markers that index P2/N2 (early evaluation and control), CPP and midfrontal theta (evidence accumulation and threshold control at commitment), and RewP → P300 → LPP (prediction-error updating and meaning integration during feedback).

MABs: Explore–exploit under volatility

The modern cognitive version of the bandit problem was developed for human decision neuroscience by Daw et al. [65]. On each trial, individuals choose among options with uncertain payoffs, observe feedback, and update expectations. This sequential structure is ideal for staging the decision stream: cues and early summaries drive evaluation; evidence accumulation under time and uncertainty drives commitment; and outcomes trigger feedback learning via prediction-error-based updating. Reinforcement-learning accounts map neatly onto EEG: Outcome prediction errors are expressed in the RewP and subsequent context updating in the P300, while the commitment moment is indexed by the CPP and control at the bound by midfrontal theta.

Crucially, how the task is built determines which neural signals might be prominent. Hassall et al. [66] used a stationary 2-armed bandit where the superior option remained stable within blocks. In that setting, the feedback-locked P300 was larger before exploratory choices, consistent with a noradrenergic "interrupt" that flags the need to revise one's internal model, whereas the RewP did not differ between exploration and exploitation. Choice-locked N2 was larger for exploration, suggesting higher conflict costs when considering a switch away from the currently favored option. The lesson is that stationary designs damp novelty and mute some aspects of context updating: Once a respondent has identified the good arm, further exploration yields little new information, and the neural signature reflects conflict more than learning.

In contrast, Cavanagh [67] pushed in the opposite direction with a dynamic 3-armed bandit that re-introduces novelty and context change across trials. By combining ERPs and time–frequency analyses, he dissociated reward prediction error (indexed by RewP and delta activity) from state-updating processes (P300 and delta) and showed that cue-locked delta—activity time-locked to the bandit display before the next choice—predicted subsequent behavior through faster reaction times and stronger parietal–motor coupling. Dynamic environments thus amplify context revision demands and elicit larger P300 when the context truly needs to be revised. Read through our stage lens, informative cues sharpen evaluation (larger P2 when summaries are diagnostic, larger N2 when ambiguity or rule conflict is high), clear value gaps steepen commitment signals (faster CPP ramp and shorter RTs), and surprising outcomes magnify feedback signals (larger RewP and P300), especially when volatility is high [55].

When the time point at which individuals start to "explore" is variable, classical averaging can wash out the signal. Bourdaud et al. [68] addressed this in a nonstationary 4-armed bandit by using discriminant methods rather than fixed latency ERPs.

They found that exploratory decisions were best distinguished by activity over left frontal and bilateral parietal regions, especially in alpha and beta bands—topographies consistent with executive attention and sensory–decision integration during exploration. Extending the temporal argument further, Tzovara et al. [69] showed that explore versus exploit can be predicted well before the button press: On average, around half a second after feedback and nearly a second before the motor act, the EEG already carries sufficient information to classify the upcoming decision. Source estimation implicated dorsolateral PFC and right supramarginal gyrus, fitting the view that exploration recruits control and re-framing systems while a policy is being set [65,70].

Entrepreneurship-relevant contrasts emerge when we look at populations and network-level data. Laureiro-Martínez et al. [54] used an n-armed bandit with fMRI and found that entrepreneurs, compared with managers, exhibited greater decision efficiency alongside stronger recruitment of control and reward networks. The ERP framework provides the time-resolved counterpart to that result: In founders, one would expect to observe a sharper CPP modulation by value gap and midfrontal theta recruitment when caution is warranted (risk-sensitive control).

Finally, the way people learn in bandits matters for what neural signals can be expected. Payzan-LeNestour [21] used a restless 6-armed bandit with abrupt regime shifts to ask whether people approximate Bayesian updating in volatile settings. Behavior aligned more with Bayesian tracking than with simple model-free reinforcement learning, especially at change points—precisely when we would expect larger RewP and P300 because prediction errors are both big and informative. Zhang and Yu [71] analyzed a larger dataset and reported that a recency-weighted ("forgetful") Bayesian learner paired with a Knowledge Gradient choice rule provided the best account of human choices across participants. That recency-weighted, horizon-aware strategy is a natural cognitive readout for entrepreneurship, where time horizon, volatility, and the value of information fluctuate. It also implies specific EEG predictions: As horizons shorten and exploration becomes less valuable, CPP should ramp more quickly for the best-known option, midfrontal theta should drop with reduced conflict, and RewP and P300 should shrink as outcomes become less surprising.

Together, the bandit literature gives a precise map from design choices to neural readouts. Stationary tasks emphasize conflict costs at the moment of switching; dynamic or volatile tasks emphasize context updating and prediction-error-driven learning. Across both paradigms, the 3 stages are temporally dissociable, with ERP markers providing anchors in the expected order: Diagnostic cues and ambiguity modulate P2/N2 during evaluation; value gaps and deadlines modulate CPP and midfrontal theta during commitment; and surprise, volatility, and outcome meaning modulate RewP → P300 → LPP during feedback.

Foraging/stay–leave: Thresholded switching by opportunity cost

Foraging frames the entrepreneurial pivot as a threshold problem: Do you stay in a patch with declining returns, or do you leave, pay a travel cost, and search elsewhere? Kolling et al.'s [72] work with fMRI shows that this computation recruits a distributed network in which posterior cingulate cortex couples with ventromedial PFC (vmPFC) during safer choices and with dACC during riskier switches. Circuit-level accounts similarly emphasize coordinated medial prefrontal, cingulate, and parietal engagement during exploration and patch-leaving [73]. The network view is consistent with our time-resolved staging. When local and global value signals conflict—returns are depleting but travel costs are high—evaluation should elicit larger N2, and when cues forecast richer alternatives, P2 should rise with salience. At the leave boundary, commitment unfolds as evidence accumulation toward a new action: When leaving clearly dominates, the CPP should ramp more steeply; under conflict or time pressure, midfrontal theta should increase and predict stronger post-error adaptation if the switch turns out suboptimal. The first outcomes after leaving then anchor feedback learning: "was the switch worth it?" shows up as larger RewP for informative outcomes, a P300 that scales with how much the policy should be updated (raise or lower the leave threshold), and a late LPP when outcomes carry motivational meaning—precisely where sunk-cost reappraisal and affect regulation live.

This mapping also helps integrate adjacent literatures on loss aversion and loss chasing. Individual differences in how people respond to adverse outcomes—whether they double down or recalibrate—are exactly the differences that should change LPP and the coupling between LPP and subsequent behavior. In entrepreneurial language, resilient founders are the ones who use negative outcomes to update without being captured by them; in EEG terms, that looks like robust RewP and P300 to informative losses and an LPP pattern that favors reappraisal over rumination.

Although most foraging evidence is network-level and fMRI-based, EEG predictions are immediate and testable. Depletion rate, travel cost, environment richness, and time pressure stress different elements of the decision process and should therefore produce distinct stage-specific effects: greater evaluation conflict should increase N2; greater commitment to the selected action should be reflected in a steeper CPP ramp, whereas conflict or time pressure should increase midfrontal theta; and more informative feedback should increase RewP and P300, with consequential outcomes additionally enhancing LPP. In this sense, foraging is the natural complement to bandits: Where bandits illuminate directed exploration within a menu of alternatives [74], foraging illuminates exit/leave thresholds when opportunity cost is explicit [64].

Integrating the paradigms: What changes, what generalizes

Across both MAB and foraging paradigms, the evaluation → commitment → feedback sequence provides a common temporal scaffold for decision-making under uncertainty. What differs across tasks is not the underlying computational architecture, but which task parameters modulate the timing and strength of stage engagement. This section therefore clarifies (a) which aspects of the framework generalize across paradigms, (b) which aspects are task-specific, and (c) which neural signals constitute mechanistic invariants.

What generalizes across paradigms

Both task families reliably instantiate the same 3 decision stages and their associated neural markers. Early evaluation is indexed by P2 and stimulus-locked N2, reflecting salience detection and early conflict monitoring [42,47]. Commitment is expressed as evidence accumulation toward a bound, indexed by the CPP, with midfrontal theta and response-locked N2 reflecting control and threshold adjustment under conflict, deadlines, or urgency [43,44,75]. Feedback learning is indexed by RewP (trial-wise prediction error), followed by P300 (context updating) and LPP when outcomes carry motivational salience or personal meaning [58,59,76].

Across paradigms, task manipulations do not introduce new stages, but instead modulate the timing, amplitude, and coupling of these stage-specific signals. This supports the central claim that the framework is mechanism-first rather than paradigm-specific, enabling principled comparison across task families.

What changes by paradigm

Where paradigms differ is in how uncertainty and opportunity cost are expressed.

In MABs (explore–exploit) tasks, exploration occurs within a fixed option set. The primary control variables are volatility and horizon, which tune commitment and learning dynamics. Stationary designs emphasize conflict costs at the moment of switching: Hassall et al. [66] show increased choice-locked N2 for exploratory moves and muted P300 when exploration yields little new information. Dynamic or volatile designs instead highlight learning and model revision: Cavanagh [67] demonstrates that RewP and cue-locked delta activity predict faster, more consistent policy use, consistent with amplified P300 when the task model must be updated. Computationally, Bayesian and recency-weighted learners [71,77] explain why change points amplify RewP and P300 and why horizon manipulations modulate CPP slope and midfrontal theta (greater exploration early; tighter bounds late).

In foraging (stay–leave) tasks, uncertainty is framed as an explicit exit threshold problem governed by depletion rate, travel/exit cost, environment richness, and time pressure. Conflict between local and global value signals elevates N2 during evaluation, while cues forecasting richer alternatives increase P2. At commitment, a clear advantage for switching produces a steeper CPP ramp, whereas conflict or urgency increases midfrontal theta, reflecting online threshold control [64,72]. Feedback after a switch is especially informative: RewP and P300 scale with whether the pivot paid off, and LPP rises when outcomes require sunk-cost reappraisal or affective regulation [58,59].

Thus, bandits and foraging engage the same neural machinery but differ in the control variables that stress each stage. CPP indexes evidence accumulation regardless of whether the choice is among arms or between staying and leaving a patch [43,44]. Midfrontal theta indexes control at the decision bound whether conflict arises from exploit–explore trade-offs or stay–leave opportunity costs [42]. RewP and P300 index learning and belief updating regardless of reward distributions, volatility structure, or environmental richness [58,76].

Shared neural indexing does not imply cross-task performance equivalence. Individuals may recruit the same decision mechanisms under different parameter regimes, producing dissociations in observable performance. By making explicit which components generalize and which depend on task structure, the framework supports principled comparison across studies and avoids overgeneralization from any single paradigm. Figure 3 summarizes these shared mechanisms and paradigm-specific parameterizations.

Neuroimaging Methods for Neuroentrepreneurship

Overview of methods: Strengths, limitations, and recommended uses

Entrepreneurial decision-making unfolds on rapid timescales and recruits partially dissociable neural operations for option evaluation, commitment to action, and feedback-based learning. Neuroimaging and neurophysiology methods therefore serve 3 complementary goals: when a computation occurs (temporal dynamics), where it is implemented in the brain (spatial localization), and how it is influenced by neurochemistry or structural connectivity (mechanistic drivers).

Accordingly, different neuroimaging tools answer different questions:

EEG with ERPs

EEG/ERP is particularly well-suited for implementing the stage-mapped framework because it offers millisecond temporal resolution, allowing evaluation, commitment, and feedback stages to be temporally dissociated and modeled at the single-trial level (Table 3). Other neuroimaging methods provide complementary spatial, network-level, or neurochemical information (see Table 6), but lack the temporal precision required to resolve these stages within individual trials.

Functional near-infrared spectroscopy

fNIRS complements EEG by indexing hemodynamic recruitment of superficial cortical regions—particularly lateral and medial prefrontal cortices—during ambiguity resolution, inhibitory control, and reappraisal. Portable fNIRS enables semi-naturalistic or field settings while preserving sensitivity to sustained control states that complement the temporal resolution of ERPs [78,79]. In tandem, EEG + fNIRS links fast control signatures to localized prefrontal activation, improving inferences about the engagement of evaluative and regulatory processes under uncertainty [80,81].

Functional magnetic resonance imaging

fMRI offers high spatial resolution to situate stage-level operations within valuation and control networks. Work on decision-making consistently implicates vmPFC and ventral striatum in value representation and prediction error, and dorsal anterior cingulate and lateral prefrontal cortices in conflict monitoring, control, and threshold adjustment [15,82,83]. In the present framework, fMRI specifies where evaluation, commitment, and feedback computations are embedded—particularly when testing whether manipulations that modulate ERP components are associated with recruitment shifts within vmPFC–striatal or cingulo-frontal circuits. It may also be informative in resting-state contexts (Ooms et al. [20]).

Positron emission tomography

Positron emission tomography (PET) complements fMRI when theory requires explicit neurochemical tests, such as dopaminergic prediction-error signaling or noradrenergic arousal linked to exploration and threshold control. PET can resolve transmitter-specific accounts of feedback learning and urgency, albeit with practical limitations related to radiation exposure, cost, and task simplicity requirements [78,80].

Table 6. Methods overview—temporal/spatial resolution, core strengths, and inferential level. "Inferential level" indicates the primary level of inference each method supports (e.g., within-subject trial-wise dynamics, between-participant contrasts, structural moderation, and neurochemical mechanisms). Methods are complementary, not hierarchical.

Method	Temporal resolution	Spatial resolution	Core strengths (entrepreneurship fit)	Main limitations	Best used for (stage → signals)	Typical analyses/notes	Inferential level
EEG/ERPs	Milliseconds	Low–moderate (scalp)	Time-locking of transient computations; established components; portable; task-friendly under deadlines/volatility	Poor deep-source localization; artifact sensitivity; requires adequate trials and reporting	Evaluation: P2 (salience), N2 (early conflict). Commitment: CPP (evidence), midfrontal theta/response-locked N2 (bound control). Feedback: RewP → P300 → LPP (PE, updating, meaning).	Single-trial regressions (diagnosticity, ΔQ, δ, volatility, deadline) onto ERPs/TFR; behavior–signal couplings (CPP↔RT, RewP↔prediction error (δ); updating parameters (α) estimated via behavior, theta↔post-error adaptation).	Within-subject, time-resolved (trial-wise dynamics)
fNIRS	Seconds (hemodynamic)	Cortical, superficial (PFC)	Portable/localizable PFC indices in semi-naturalistic contexts (incubators, pitch sims); complements EEG timing with frontal localization	Limited depth/coverage; motion/saturation; slower than EEG	Evaluation/Commitment: lateral/medial PFC engagement under ambiguity, inhibition, reappraisal; control state during deadlines.	Block/event-related HbO/HbR in ROIs (dlPFC/vmPFC/ACC proxies); ideal as EEG + fNIRS tandem in field-proximal sessions.	Between-condition/participant (cortical localization)
fMRI	Seconds	High (whole brain)	Networks for valuation (vmPFC/VS) and control (dACC/lPFC); localizes where ERP-moved processes sit	Cost; immobility; task simplification; limited time precision	All stages (localization): vmPFC/VS for value and δ; dACC/lPFC for conflict/threshold; PCC/dACC in foraging switches.	Model-based GLM (parametric ΔQ, δ, volatility); ROI/whole-brain with task "dials" aligned to ERP endpoints.	Between-condition/participant (whole-brain networks)
PET	Minutes	Moderate–high	Neurochemical specificity (dopamine, noradrenaline) for hypotheses about prediction error, arousal/urgency	Radiation, cost, simple tasks only; small N	Feedback: transmitter-specific modulation of prediction error signaling (δ) and learning rate (α); Commitment: neuromodulatory contributions to urgency and threshold regulation.	Ligand binding vs. task conditions; pairs with fMRI/EEG for convergent evidence.	Neurochemical/transmitter-specific
MEG	Milliseconds	Better cortical source resolution than EEG	Oscillatory sources of control/accumulation; coupling across frontal–parietal during deadlines/ΔQ	Cost; magnetically shielded room; less portable	Commitment: midfrontal theta sources; CPP-like parietal buildup; Evaluation/Feedback: delta/theta/beta dynamics.	Time–freq beamforming; source-level connectivity (frontal–parietal) under ΔQ/deadlines.	Within-subject, time-resolved (source-level)

(Continued)

Table 6. (Continued)

Method	Temporal resolution	Spatial resolution	Core strengths (entrepreneurship fit)	Main limitations	Best used for (stage → signals)	Typical analyses/notes	Inferential level
DTI	–	Structural (white-matter tracts)	Links trait-like connectivity (fronto-parietal, cingulo-opercular) to variability in ERP magnitude/reliability and computational parameters (e.g., learning rate α, decision threshold)	Correlational; no temporal information	Cross-stage moderators: explains individual differences in learning rate, decisional threshold, control efficiency.	Tractography metrics (FA/MD) as predictors of ERP–behavior couplings across participants.	Between-participant correlational (structural moderation)

Magnetoencephalography

MEG combines millisecond temporal resolution with improved source estimation relative to EEG, providing a stronger bridge between time-resolved dynamics and cortical generators [84,85]. For the commitment stage in particular, MEG identifies the cortical origins of midfrontal theta and the buildup of central–parietal activity associated with bound crossing, and it can track large-scale oscillatory coordination between frontal control areas and parietal accumulation sites during deadlines and shifting value gaps. In addition, MEG's spectral sensitivity supports tests of how directed exploration and post-error control map onto midfrontal theta and beta dynamics in ways that complement ERP measures.

Diffusion tensor imaging

Diffusion tensor imaging (DTI) quantifies white-matter microstructure and long-range connectivity. Within the present framework, DTI can relate stable individual differences in learning rate, decisional threshold setting, or control efficiency to the integrity of fronto-parietal and cingulo-opercular pathways, potentially explaining variance in ERP magnitude, reliability, and behavior–signal coupling across participants [86]. Structural predictors of ERP/behavior relationships offer a way to connect plastic, stage-specific computations to more trait-like neuroanatomical constraints relevant for entrepreneurial performance.

Choosing a method for each decision stage

The stage-mapped framework is not modality-exclusive: Different neuroimaging techniques contribute complementary insights depending on whether the research question concerns timing, localization, network coordination, or neurochemical mechanisms. The following recommendations summarize how each technique most directly supports testing of the 3 stages (see also Table 6):

Evaluation (P2/N2). EEG/ERPs are primary for timing early salience and conflict [87–89]; fNIRS helps localize prefrontal control recruitment during ambiguous or rule-conflict conditions; fMRI clarifies the extent to which anterior cingulate and lateral prefrontal networks scale with cue diagnosticity and ambiguity.

Commitment (CPP; midfrontal theta). EEG quantifies evidence-accumulation slope and threshold control [42,75,90–92]. MEG improves source localization for oscillatory processes supporting bound adjustments and pre-response control, while fMRI identifies network-level shifts under deadlines or widened value gaps.

Feedback (RewP → P300 → LPP). EEG captures trial-wise prediction error, context updating, and meaning integration [57,58,60,93–95] . fMRI localizes prediction-error responses to striatum/vmPFC; PET is appropriate when transmitter-specific hypotheses are important; DTI relates learning-rate variability and resilience to connectivity profiles.

A common concern is that many entrepreneurial decisions appear to unfold over days or weeks, making millisecond-level EEG seem irrelevant. This view overlooks that even the longest strategic choices are built from thousands of rapid cognitive events that recur constantly throughout the process, for example, scanning a market report and spotting an anomaly → P2/N2 (<300 ms), reading a venture capital (VC) term sheet and feeling conflict about dilution → midfrontal theta (<1 s), hearing "our burn rate doubled" and weighing whether to pivot →

CPP evidence accumulation (400 to 800 ms), and receiving a customer complaint or sales update → RewP/P300 prediction error and learning (<500 ms). The evaluation → commitment → feedback cycle proposed here is not a single macro-event but a repeating micro-loop triggered every time new information arrives. EEG/ERP is particularly well-suited to isolating these elementary operations, as demonstrated in other high-stakes, extended-timeline domains such as medical diagnosis, financial trading, and military decision-making. Slower methods (e.g., fMRI, fNIRS, and resting-state approaches) can capture sustained states, spatial organization, or cumulative effects, while EEG/ERP most directly resolves the moment-by-moment dynamics through which these processes unfold and ultimately influence longer-term outcomes.

The following sections put this measurement strategy into practice using 2 well-validated decision-science paradigms—MABs and ecological foraging—and translate them into concrete, pre-registrable predictions that link task manipulations, ERP signatures that index stage-specific processing, and proximal entrepreneurial task behavior.

Empirical Evidence and Founder-Relevant Patterns from the Literature

Where available, direct founder evidence is discussed first; translational mechanistic evidence is clearly indicated.

Evaluation stage: Opportunity recognition and early conflict/inhibition

Entrepreneurial opportunity recognition has been linked to rapid pattern completion and salience extraction, supported by hippocampal–associative and valuation systems [12,50,96]. Within the present framework, ERP markers provide temporal anchors for these early evaluation processes. Diagnostic cues that match learned opportunity templates are expected to elicit larger stimulus-locked P2 (∼150 to 250 ms), indexing rapid salience detection and early selection, whereas value ambiguity or rule conflict is associated with larger fronto-central N2 amplitudes (∼200 to 350 ms), indexing early control and inhibition demands. Insight-style findings [97] are consistent with this interpretation, showing enhanced early categorization when solutions cohere suddenly. fMRI studies of entrepreneurial and opportunity-evaluation tasks further indicate co-activation of pattern-recognition and valuation systems during early screening [12,50]. Although EEG evidence in entrepreneurship remains sparse, pilot findings suggest that founders may recruit more efficient early control under ambiguity [98], consistent with cleaner downstream accumulation. Additional EEG work reports distinct frontal–temporal frequency patterns in entrepreneurs during opportunity recognition [99], while valuation-network activity during investor pitch evaluation predicts perceived opportunity quality [13].

Commitment stage: Decisiveness, cognitive flexibility, and threshold policy

Commitment reflects evidence accumulation toward an action bound under uncertainty and time pressure. In this stage, ERP markers index stage-specific commitment processes rather than defining the stage itself. The CPP tracks the buildup of decision evidence, with steeper slopes and higher pre-response amplitude as the value gap widens, while midfrontal theta (4–8 Hz) and response-locked N2 index control at the bound under conflict, deadlines, and post-error adjustment [42,75].

Task manipulations in bandit and foraging paradigms systematically modulate accumulation rate and threshold policy: In MABs, horizon and volatility modulate commitment dynamics; in foraging, depletion rate and travel or exit cost shift the leave threshold. These computational adjustments are temporally anchored by CPP and control-related signals, allowing commitment processes to be operationally dissociated from earlier evaluation and later feedback stages.

Feedback stage: Prediction error, updating, and meaning integration

Feedback converts outcomes into policy updates and meaning-level appraisals. In this stage, ERP markers provide temporal anchors for distinct feedback computations. Trial-wise prediction error is indexed by reward positivity/feedback-related negativity (RewP; ∼200 to 300 ms), followed by P300 (∼300 to 500 ms), which indexes context updating and belief revision. The LPP (∼500 to 900+ ms) scales with motivational salience and reappraisal.

Dopaminergic accounts predict larger RewP and P300 responses at change points and under volatility, consistent with volatile bandit behavior and recency-weighted Bayesian strategies [21,71,100]. The somatic marker framework positions the LPP as indexing meaning-level evaluation following consequential outcomes, such as sunk-cost release versus renewed persistence [39]. Stress and resilience research further indicates tighter coupling between error signals and adaptive behavior under effective regulation [101,102], with GSR–EEG evidence showing context-dependent stress modulation in experienced versus novice entrepreneurs [103].

Population contrasts rendered at the stage level

Across studies, group differences are most consistently expressed in when specific computations are engaged within the decision stream, rather than as global trait differences. Where founder studies indicate greater decision efficiency than comparison groups, the present model predicts that such differences may be expressed as stronger CPP modulation by value gap (faster ramps) and shorter reaction times when one option clearly dominates, together with context-appropriate midfrontal theta under deadlines or conflict [42,54,75]. Pilot EEG work also points to founder-related differences in early conflict processing [98].

Within the proposed framework, resilience-related differences are hypothesized to manifest during the feedback stage as systematic modulation of feedback-locked neural responses. Specifically, individuals with more adaptive feedback processing are expected to show RewP and P300 amplitudes that scale with prediction error and environmental volatility, alongside LPP patterns more consistent with cognitive reappraisal than sustained affective rumination. At the task level, these neural dynamics are expected to covary with faster post-error correction and more stable performance under environmental drift.

Trait constructs rendered as testable stage-specific hypotheses

Framing founder characteristics at the stage level renders trait constructs empirically testable. For example, "opportunity recognition" corresponds to larger P2 responses to diagnostic cues and larger N2 responses under ambiguity during evaluation [50,52,88]; "decisiveness" appears as value gap-sensitive CPP dynamics at commitment; "tolerance for ambiguity" and "cognitive control" as indexed by context-appropriate midfrontal theta near the bound [42,104]; and "resilience"-related processing is hypothesized to involve RewP and P300 responses that scale adaptively with feedback, together with LPP patterns consistent with reappraisal during feedback [58,76,105].

Expressed this way, founder–manager–aspiring entrepreneur contrasts can be tested using preregistered models that specify task manipulations (e.g., volatility, horizon, depletion, and exit cost), fix regions of interest and latencies for P2/N2, CPP/midfrontal theta, and RewP → P300 → LPP, and assess whether group-by-regressor couplings differentiate populations in behavior-linked, stage-specific ways.

Discussion, Limitations, and Future Directions

Limitations and current gaps

Despite growing interest, neuroentrepreneurship remains a young and fragmented field [18]. Weak experimental designs, vague sample definitions, poorly matched comparison groups, and tasks that omit volatility, deadlines, or opportunity cost all reduce the visibility of the neural signatures predicted by our framework. Uneven reporting—missing preprocessing details, regions of interest/latency justification, or reliability metrics—further complicates integration of findings and slows cumulative progress [1,16,106]. Because direct neuroentrepreneurship datasets remain limited, the framework draws substantially on convergent translational decision-neuroscience evidence. This limitation is treated explicitly and directly motivates the empirical roadmap outlined in the Near-term priorities for cumulative progress section.

Many studies labeled "entrepreneurial" recruit students or mixed community samples and do not define who counts as a founder (e.g., venture creation/ownership, venture type and scale—lifestyle-oriented or small-scale local ventures versus growth-oriented regional/national/global firms, innovation/tech status, funding and growth stage, and revenues). Comparison groups are seldom matched on age, gender, education, or cognitive baselines, inviting confounds. When lab tasks omit volatility, deadlines, switching/exit (sunk) costs, and partial or counterfactual feedback, they remove the very computations our framework targets—change-point detection, bound control under pressure, thresholded exits, and learning from sparse/structured feedback—so the expected ERP/EEG signatures may be altered or attenuated (e.g., smaller sensitivity of RewP and P300 at change points, reduced midfrontal theta under deadlines, and weaker CPP adjustments at leave boundaries) [1,107]. Moreover, entrepreneurial behavior is incentive-sensitive: Flat payments in tasks often damp exploration and threshold policies. Finally, many studies use too few trials per condition, omit clear payoff functions, and provide limited preprocessing or regions of interest/window/baseline details. This undermines component reliability and statistical power for all key markers (P2/N2, CPP, RewP → P300 → LPP, and midfrontal theta).

Design improvements and analytic standards

While the present framework emphasizes EEG/ERP for temporal staging, its predictions are explicitly intended to be tested using convergent, multimodal approaches where feasible, including EEG–fNIRS, EEG–fMRI, and MEG designs. A convergent methodological path emphasizes design refinement over conceptual proliferation. Ecological richness can increase without sacrificing temporal precision by combining portable EEG and fNIRS with carefully preserved cue-, response-, and feedback-locked events—thereby keeping the evaluation → commitment → feedback sequence intact while observing behavior in contexts such as incubator tasks or time-pressured pitches. Longitudinal or repeated-measures designs could offer a stronger basis than one-off cross-sections for separating relatively stable propensities from practice effects and for estimating stage-specific parameters within person (e.g., evidence-accumulation rate at commitment or learning rate during feedback). Moreover, tasks must use real incentives (or other meaningful stakes) that are clearly documented. Flat or trivial incentives make participants indifferent and suppress the very behaviors (exploration, cautious pivoting, learning from losses) that the framework aims to measure.

Analytically, the field should adopt model-based, single-trial analyses. On every trial, researchers can extract computational variables (cue diagnosticity, ambiguity, value gap, urgency/deadline, prediction error, volatility) and regress them directly onto both ERP amplitudes/latencies and behavior. This directly tests the stage-specific couplings outlined in the Detailed stage descriptions and predictions section and Table 5 (applied in Task Lenses for Entrepreneurial Decision-Making, Neuroimaging Methods for Neuroentrepreneurship, and Empirical Evidence and Founder-Relevant Patterns from the Literature sections), for example, steeper CPP slope with faster commitment decisions, larger RewP with stronger learning from feedback, and increased midfrontal theta with adaptive slowing after conflict. Power and reliability (split-half or G-coefficients) must be calculated for these single-trial neural and behavioral effects. Only then will studies have enough trials to detect the predicted relationships reliably.

A tiered analysis plan can balance rigor and discovery. Tier 1 (confirmatory) should preregister a minimal set of stage-focused tests: (a) value gap predicting the response-locked CPP slope at commitment, (b) δ predicting feedback-locked RewP (optionally interacting with volatility) and downstream P300, and (c) deadline/conflict elevating midfrontal theta near the bound (FCz). Windows, regions of interest, and primary contrasts should be fixed in advance, with multiplicity controlled across Tier-1 tests [e.g., Benjamini–Hochberg false discovery rate (FDR)]. Tier 2 (exploratory) may include additional contrasts, time–frequency probes, tentative source/localization, and subgroup slices, all labeled hypothesis-generating. Preregistration should specify task measures (volatile versus stable blocks, value gap bins, deadline versus fixed horizon), primary neural endpoints with latency windows/regions of interest (CPP, midfrontal theta, RewP → P300), core trial-wise regressors (diagnosticity, value gap, prediction error, volatility, deadline), and a small menu of allowable pipelines (e.g., robust versus ordinary least squares (OLS) and baseline and reference choices). A brief specification curve can document robustness. Reporting can be consolidated via a checklist table (see Table 4).

Practical implications: Reframing traits and trainability

Downstream outcomes and interpretive scope

While the framework focuses on proximal decision processes observable in task paradigms, entrepreneurship unfolds over longer-horizon venture outcomes, including growth trajectories, funding acquisition, pivot timing and quality, capital allocation efficiency, and sustained performance under volatility.

Table 7. Empirical roadmap: Linking tasks, neural signals, and behavior. Rows are labeled by inferential level: within-subject (task manipulations affecting computational variables, ERP indices, and behavior), between-group (matched contrasts, e.g., founders versus controls), and exploratory/predictive (out-of-sample analyses). Between-group inferences require matched samples, preregistered stage-specific contrasts (e.g., CPP slope by value gap at commitment; RewP by δ at feedback; midfrontal theta by conflict/deadline at the bound), with predefined ROIs/latencies, power justification, and multiple-comparison control. Predictive uses should be positioned as exploratory, out-of-sample validated, and ethically constrained.

Mechanism	Stage and EEG markers	Paradigm and manipulation	Neural prediction	Behavioral prediction	Design/prereg notes
(Within-subject) Targeted exploration	Evaluation: P2 (~150–250 ms)	MAB: high- vs. low-information cues/summaries	Larger P2 to high-diagnostic cues	More directed (less random) exploration; improved regret profile	Within-subject; single-trial regressor for cue diagnosticity → P2; preregister P2 latency window/ROI and filters; FDR plan; link P2 to exploration-policy parameters
(Within-subject) Decisiveness under clear value gaps	Commitment: CPP (response-locked; CPz/Pz)	MAB: large ΔQ (best–next) vs. small ΔQ	Steeper CPP slope; higher pre-response amplitude	Shorter RT without accuracy loss; higher choice confidence	Within-subject; regress ΔQ → CPP slope; preregister parietal ROI and response-locked window; power on single-trial slope effects; CPP–RT coupling specified a priori
(Within-subject) Risk-sensitive control under time pressure	Commitment: midfrontal theta (4–8 Hz), response-locked N2	MAB: deadline vs. no-deadline; conflict manipulations	Increased midfrontal theta/N2 under deadlines/conflict	Improved speed–accuracy trade-off; adaptive post-error slowing	Time–frequency (2–7 Hz) at FCz; preregister baseline, tapers, trial counts/reliability; model conflict/deadline → midfrontal theta/N2; link to DDM bound estimates
(Within-subject) Learning from informative errors	Feedback: RewP (~200–300 ms), P300 (~300–500 ms)	MAB: volatile vs. stable blocks; change points	RewP scales with trial-wise δ; P300 scales with volatility and model updating demands	Greater behavioral updating (higher estimated learning rate α), reflected in faster post-error correction and policy shifts at change points	Fit RL/Bayesian model to get δ and volatility; single-trial regress δ/volatility → RewP/P300; preregister windows/ROIs and multiple-comparison control; test next-trial updates
(Within-subject) Meaning/reappraisal after large outcomes	Feedback: LPP (~500–900+ ms)	Foraging: rare large losses/gains blocks	Larger LPP to consequential outcomes; sustained positivity	Reduced sunk-cost bias; more adaptive subsequent switching	Outcome-locked LPP; preregister posterior ROI and long window; include affect ratings as covariates; link LPP to next-trial stay/leave
(Within-subject) Switch-threshold calibration	Commitment: CPP at leave boundary; midfrontal theta with conflict	Foraging: high vs. low travel cost; local–global value conflict; depletion rate	Clear advantage → steeper CPP; higher conflict → increased theta	Leave times track marginal-value predictions; orderly hazard of leaving	Preregister leave-boundary operationalization; response-locked CPP; theta at FCz; parametrize travel cost/depletion; relate CPP/midfrontal theta to stay/leave latency and threshold parameter
(Between-group) Founder–manager contrast (stage-linked)	Commitment: CPP slope; Feedback: RewP/P300; Control: midfrontal theta	MAB: ΔQ bins; volatility blocks; deadline vs. no-deadline	Founders show stronger CPP modulation by ΔQ; larger RewP/P300 to informative errors; theta scales with conflict/deadline	Faster RT without accuracy loss at high ΔQ; higher learning rate to informative errors; better speed–accuracy under deadlines	Between-group matched (age/education/cog baseline); preregister contrasts: CPP slope~ΔQ; RewP~δ; theta~conflict/deadline; fix ROIs/latencies a priori; power on single-trial effects; FDR plan
(Exploratory/predictive) Early identification	Evaluation: P2; Commitment: CPP slope; Feedback: RewP/P300	MAB: info/ΔQ/volatility; Foraging: depletion/travel-cost	Multivariate stage-linked signal profile predicts later outcomes	Predict directed-exploration index, decisiveness (RT–accuracy), learning rate; prospectively predict venture-entry/intent	Out-of-sample prediction (train/test or k-fold); preregister models/priors; report AUC/Brier/MAPE; fairness checks; label exploratory; no profiling claims without replication

Within this framework, such outcomes are conceptualized as probabilistic aggregations of repeated decision cycles rather than direct neural readouts. Venture survival, for example, must be interpreted relative to strategic intent (e.g., growth-oriented persistence versus planned acquisition).

A key implication is that classic entrepreneurial traits can be investigated as stage-specific modulations of computational and neural processes rather than treated solely as fixed dispositions. Under uncertainty, entrepreneurs combine fast, experience-based judgments with deliberate control. In neural terms, larger value gaps yield steeper CPP ramps and shorter commitment latencies (decisiveness), whereas ambiguity or deadlines increase midfrontal theta and response-locked N2, reflecting dynamically scaled cognitive control [31,42].

The CPP is the established neural signature of evidence accumulation: As the value difference between options increases, accumulation rate increases, producing a faster-rising CPP that reaches the decision bound sooner [43,44,108]. This relationship—replicated across perceptual and value-based decisions—extends directly to entrepreneurial task contexts instantiated via MAB and foraging paradigms, where value gaps systematically modulate accumulation dynamics [109]. Accordingly, the framework generates concrete, testable predictions linking task manipulations, ERP indices, and behavioral commitment latency (see Table 5).

Entrepreneurial cognition may therefore exhibit bounded plasticity. Repeated exposure to uncertain, feedback-rich environments produces meaningful change within limits—a form of bounded plasticity supported by reinforcement learning and experience-dependent tuning of control and accumulation processes. Consistent with this, entrepreneurial cognitive adaptability reflects feedback-driven metacognitive adjustment [110], aligning with our treatment of thresholds and learning parameters as dynamically modulated. Practice could alter evidence-accumulation and control-related signals; in principle, this would predict steeper CPP ramps, more informative RewP/P300 scaling, and more adaptive midfrontal theta responses in entrepreneurial-relevant tasks. In short, key aspects of entrepreneurial decision-making appear partially trainable, opening the door to targeted interventions and executive education programs.

Near-term priorities for cumulative progress

To move from scattered findings to genuine cumulative science, the field should focus on 4 concrete priorities. Priority 1—Standardize task families: Adopt MABs and foraging/stay–leave tasks with systematic variation of volatility, horizon, depletion rate, travel/exit cost, and deadlines. Priority 2—Scale samples via harmonized protocols: Use shared code, pre-registration templates (Table 4), and open data to enable meta-analysis of identical stage-specific contrasts. Priority 3—Close the lab–field gap without losing timing: Pair laboratory baselines with field-proximal sessions (e.g., incubator tasks and pitch simulations) using portable EEG/fNIRS while preserving event locks. Priority 4—Link models to signals at the single-trial level: Fit reinforcement-learning or drift-diffusion parameters trial-by-trial and regress trial-wise computational variables (e.g., ΔQ and δ) onto ERP amplitudes (e.g., CPP slope and RewP) and test behavioral couplings (e.g., RT and next-trial updating). Recommended minimum venture outcome indicators are summarized in the Definitions, boundary conditions, and outcome scope section to support longitudinal linkage between stage-specific mechanisms and real-world performance.

Direct EEG evidence in founders remains limited, and much of the current base is translational. Yet, the stage-mapped framework and formal model (Table 3), together with the detailed computational prediction table (Table 5), provide a clear, shared template for the next wave of comparable, pre-registered, mechanism-level research. Table 7 translates these model-derived predictions into a concrete empirical roadmap (with design and preregistration notes) for implementation.

Conclusion

This review clarifies why neuroentrepreneurship has struggled to converge, specifies the design and analytic standards required to test a stage-mapped decision framework, and outlines a shared template for cumulative, mechanism-driven research. It reframes entrepreneurial traits as dynamic modulations of stage-specific decision processes, bounded by context and plasticity. By moving from diagnosis of fragmentation to a concrete empirical roadmap, the paper positions entrepreneurial decision-making as a temporally structured and empirically testable neurocognitive process. The framework is offered not as a finished theory but as a shared scaffold to be tested, challenged, and iteratively refined.

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Appendix A. Glossary of Key Terms

Ambiguity – Uncertainty about value or rules; increases early conflict processing (N2, midfrontal theta).

Ambiguity-related processing – Task-dependent modulation of conflict- and control-related signals under uncertainty; not a direct neural readout of tolerance for ambiguity.

Bound/threshold – Amount of evidence required to commit to a choice; reflected in CPP slope and midfrontal theta.

Bound-control efficiency – Ability to flexibly adjust decision thresholds based on task demands.

Burn rate – Rate at which a venture spends cash reserves, typically measured monthly.

Capital allocation efficiency – Effectiveness with which invested capital is converted into measurable venture progress (e.g., revenue growth, product development milestones, customer acquisition).

Commitment stage – Decision moment when accumulated evidence triggers a choice; indexed by CPP and pre-response midfrontal theta.

CPP (centro-parietal positivity) – A response-locked, pre-response ramping positivity over central–parietal sites (typically CPz/Pz) reflecting the accumulation of decision evidence toward a response bound. The slope of the ramp indexes the rate of evidence accumulation (drift-like dynamics), whereas pre-response amplitude reflects proximity to bound crossing.

Cue diagnosticity – How strongly cues predict value; higher diagnosticity enhances P2.

Depletion rate – Speed at which returns decline in foraging tasks.

Decisiveness – Rapid, accurate commitment decisions; linked to steeper CPP slopes.

Deadline pressure – Time constraints that alter threshold settings and increase control signals.

DDM (drift–diffusion model) – A computational model of decision-making in which noisy evidence accumulates over time toward a decision bound. Key parameters include drift rate (speed of accumulation), boundary separation (decision threshold), and non-decision time.

Drift rate – The speed of evidence accumulation toward a decision bound; in EEG-informed models, often approximated by CPP slope.

Evaluation stage – Initial assessment of relevance and potential; associated with P2, N2, and midfrontal theta.

Event locking – Temporal alignment of EEG to cues, responses, or feedback.

Exploitation – Choosing the best-known option; associated with faster CPP ramps.

Exploration – Sampling uncertain options for information; may increase N2 and midfrontal theta when it involves greater conflict or control demand.

Feedback stage – Outcome interpretation and learning; reflected in RewP, P300, and LPP.

Foraging (stay–leave tasks) – Decisions about exploiting a current opportunity or searching elsewhere.

IRR (internal rate of return) – Annualized rate of return that equates the present value of invested capital with the present value of realized returns.

Learning rate (α) – Behavioral parameter indicating the weight assigned to prediction error (δ) when updating value estimates. Estimated from choice behavior rather than directly measured neurally.

LPP (late positive potential) – Late positivity reflecting emotional/motivational appraisal of outcomes.

MAB (multi-armed bandit) tasks – Sequential choices requiring exploration versus exploitation.

Midfrontal theta – The 4- to 8-Hz oscillatory activity over midfrontal sites (typically FCz) indexing control recruitment. When observed pre-response, it reflects conflict monitoring and dynamic threshold adjustment at the decision bound; when post-response or post-feedback, it reflects adaptive control and performance monitoring.

Meaning-level evaluation – Late interpretation of motivational importance; captured by LPP.

MOIC (multiple on invested capital) – Ratio of total value returned to investors divided by the original invested capital.

N2 – Fronto-central negativity reflecting conflict and early control demands.

Neuroentrepreneurship – Field integrating entrepreneurship with cognitive neuroscience to examine the neural basis of opportunity recognition, decision-making, and learning.

Opportunity-driven, growth-oriented founders – Founders building scalable, innovation-based ventures; primary population for neural predictions.

P2 – Early positivity indexing rapid salience detection and cue relevance.

P300 – Parietal positivity reflecting belief updating and outcome importance.

Post-error adaptation – Behavioral adjustments following errors; supported by midfrontal theta and feedback-related ERPs.

Prediction error (δ) – Trial-wise difference between received and expected outcome ($\delta = r - V$). RewP amplitude scales with the magnitude and valence of δ, indexing feedback-based updating.

Preregistration – Advance specification of hypotheses and analysis plans to reduce flexibility.

RewP (reward positivity) – Early signal of reward prediction error following positive or informative outcomes.

Resilience-related processing – Hypothesized adaptive modulation of feedback updating and outcome appraisal, potentially indexed by task-dependent RewP, P300, and LPP responses.

ROI (region of interest) – Electrode cluster or cortical region specified a priori based on prior literature before hypothesis testing (e.g., FCz for RewP).

RT (response time) – Time from stimulus or decision cue to behavioral response; typically inversely related to CPP slope in accumulation-to-bound tasks, particularly when value gaps are large.

Runway – Estimated time a venture can continue operating at its current burn rate before exhausting available capital.

Single-trial ERP modeling – Linking trial-specific computations (e.g., value gap) to ERP amplitudes.

Startup founder – Individual who initiates and leads a new venture oriented toward scalable, innovation-driven growth, retains meaningful decision authority during formative years, and shapes strategy and resource allocation under uncertainty.

Temporal precision – Millisecond-level resolution enabling fine-grained separation of cognitive processes.

Time–frequency analysis – Decomposition of EEG into frequency bands (e.g., theta 4 to 8 Hz) to capture oscillatory control processes not visible in time-domain ERPs.

Travel/exit cost – Cost of abandoning a current option; influences pivot decisions.

Value gap (ΔQ) – Difference between the highest and next-highest expected action values ($\Delta Q = Q\_best - Q\_next$). Larger ΔQ predicts steeper CPP slope and shorter decision latency.

Volatility – Rate of change in the environment; increases prediction error and updating demands.

Alternative/historically used ERP labels

ERN (error-related negativity) – Response-locked fronto-central negativity following internally generated errors; indexes action monitoring rather than feedback evaluation.

FRN (feedback-related negativity) – Legacy term historically used to describe feedback-locked negativity; in contemporary literature and in this review, this signal is treated as the Reward Positivity (RewP) reflecting prediction error.

Choice-P3 – Legacy term referring to a decision-locked parietal positivity; standardized here as the centro-parietal positivity (CPP) indexing evidence accumulation.

N200 – Older label for the N2 component; this review uses N2 consistently, distinguishing stimulus-locked and response-locked variants by timing and function.

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A Stage-Mapped Framework for Neuroentrepreneurship: Linking Real-Time Decision Processes to Entrepreneurial Behavior

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Entrepreneurship demands rapid judgments, timely commitments, and effective learning from outcomes—yet we know remarkably little about the moment-to-moment neural processes underpinning these abilities. This review synthesizes existing neuroscience and decision-science evidence within a 3-stage framework of entrepreneurial decision-making: evaluation of opportunities, commitment to action, and feedback-based learning. Using this structure, we highlight key field limitations—including small and selective samples, task and measurement heterogeneity, and weak linkage between laboratory paradigms and real-world entrepreneurial behavior—and introduce a stage-mapped, computationally explicit framework that renders these processes empirically testable. We propose practical steps to support cumulative progress, such as portable tasks suitable for field testing, single-trial analyses linking computational choice parameters to neural dynamics, and preregistration practices that preserve confirmatory rigor while allowing bounded exploration. Drawing on established decision-science paradigms (e.g., multi-armed bandit and foraging), we specify stage-linked behavioral and neural relationships that characterize how entrepreneurs evaluate uncertain opportunities, decide when to act, and update beliefs following success or failure. We conclude with research priorities and a roadmap toward a coherent science of neuroentrepreneurship that links brain processes to proximal decision behaviors, which, across repeated cycles, may contribute probabilistically to entrepreneurial success.
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