From categorization to quantification: Stage-dependent neural and behavioral mechanisms of facial emotion recognition

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Abstract

Backgrounds: Facial emotion recognition (FER) is a core process in social communication, involving identifying emotion categories and estimating intensity. Although both are essential for adaptive social functioning, whether they rely on shared or dissociable neural mechanisms remains unresolved.Methods: The present study examined this question by combining event-related potential (ERP) measures with trial-by-trial brain-behavior modeling using (generalized) linear mixed-effects models, i.e., (G)LMMs, in 44 healthy adults performing emotion categorization and intensity rating on morphed faces varying in category (happiness, anger, fear, and sadness) and intensity (25%, 50%, 75%, and 100%).Results: Behaviorally, categorization reflected categorical distinctions, whereas intensity estimation revealed emotion-specific patterns that did not align with categorization. At the neural level, ERP results revealed a progressive processive sequence. Early (P100, N170) and mid-latency (EPN) components were modulated by category, while sensitivity to intensity emerged only at the late stage (LPP), marking a temporal dissociation between structural encoding and evaluative integration. Brain-behavior modeling further revealed task-dependent, stage-specific neural effects. In categorization, early and mid-latency components increased processing costs, while the late components (LPP) facilitated performance; in intensity estimation, these effects varied with emotion category and intensity.Conclusions: These findings support a multi-stage processing architecture of FER, where intensity estimation constitutes a functionally distinct aspect of affective representation rather than a secondary byproduct of categorical processing. By leveraging trial-by-trial brain-behavior modeling, this study uncovers neural contributions that traditional condition-average analyses cannot capture, distinguishing early cost-like from late benefit-like effects and linking them directly to performance.

Full Text

Preamble

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Abstract

Backgrounds Facial emotion recognition (FER) process social communication, involving identifying emotion categories estimating intensity.

Although essential adaptive social functioning, whether shared dissociable neural mechanisms remains unresolved.

Methods

present study examined question combining event-related potential (ERP) measures trial-by-trial brain-behavior modeling using (generalized) linear mixed-effects models, i.e., (G)LMMs, healthy adults performing emotion categorization intensity rating morphed faces varying category (happiness, anger, fear, sadness) intensity (25%, 100%).

Results

Behaviorally, categorization reflected categorical distinctions, whereas intensity estimation revealed emotion-specific patterns align categorization. neural level,

results

revealed progressive processive sequence. Early (P100, N170) mid-latency (EPN) components modulated category, while sensitivity intensity emerged stage (LPP), marking temporal dissociation between structural encoding evaluative integration.

Brain- behavior modeling further revealed task-dependent, stage-specific neural effects. categorization, early mid-latency components increased processing costs, while components (LPP) facilitated performance intensity estimation, these effects varied emotion category intensity.

Conclusions: These findings support multi-stage processing architecture where intensity estimation constitutes functionally distinct aspect affective representation rather secondary byproduct categorical processing. leveraging trial-by-trial brain-behavior modeling, study uncovers neural contributions traditional condition-average analyses cannot capture, distinguishing early cost-like benefit-like effects linking directly performance.

Keywords

facial emotion recognition, neural-behavior connection, emotional categorization, emotional intensity estimation

1. INTRODUCTION

Facial expressions constitute structured visual signals convey affective states, intentions, action tendencies (Ekman Cordaro, 2011).

Effective social functioning depends capacity decode these signals rapidly accurately (Calvo 2016). decoding involves least aspects: identifying which emotion expressed (i.e., categorization) estimating strongly expressed (e.g., intensity estimation).

Although categorization intensity estimation essential adaptive social functioning, previous research dominated categorical framework, emphasizing distinct features discrete emotional categories, while treating intensity variation secondary attribute within those categories (e.g., Calvo 2016; 2017). example, Calvo (2016) operationalized emotional intensity index recognition thresholds facial emotion perception demonstrated minimum intensity required accurate categorization varied across expressions: approximately happiness, basic emotions (i.e., sadness, surprise, anger, disgust), fear.

However, despite their shared functional importance, categorization intensity estimation reflect distinct fundamental units affective coding, associated different cognitive demands.

Theoretical accounts emotion representation offer competing perspectives constitutes fundamental affective coding, these perspectives directly whether emotion processing primarily organized around discrete categorical distinctions graded evaluations.

Discrete emotion theories propose emotions organized limited distinct categories (e.g., Ekman, Hutto 2018), defined characteristic configurations expressive physiological features 2026).

Within framework, conceptualized threshold-based process which perceptual input matched category-specific templates, successful identification depends whether sufficient diagnostic present cross categorical boundary. contrast, dimensional models conceptualize emotions positions within continuous space defined several dimensions (e.g., Cowie

Russell,1980 perspective, emotional meaning constructed through graded evaluation along continuous scales rather discrete classification.

Accordingly, intensity merely secondary attribute within category intrinsic dimension affective representation, emotion processing entails continuous scaling affective magnitude rather binary decision-making.

Thus, examining temporal functional relationship between categorization intensity estimation provides empirical competing models Specifically, operates categorical system graded refinements, intensity information should emerge byproduct categorical processing without establishing independent contributions. contrast, relies multi-stage processing architecture, categorization intensity estimation should exhibit partially dissociable temporal dynamics distinct functional contributions. adjudicate between these competing accounts, necessary examine whether categorization intensity estimation differ behaviorally, temporally expressed neural processing.

Electroencephalography (EEG), millisecond-level temporal resolution, widely

methods

examining facial emotion processing suitable tracing temporal unfolding process (e.g., 2017; associated sequence reflecting successive processing phase Early midlatency components, including N170, Vertex Positive Potential (VPP), Early Posterior Negativity (EPN), typically linked rapid perceptual encoding selective allocation attention emotional information, while Positive Potential (LPP) associated sustained evaluative processing 2014). neural level, distinction generates specific predictions: categorical system predicts that, present, intensity effect should emerge parametric modulations co-localized components support categorical discrimination, whereas multi-stage processing architecture predicts partial temporal dissociation which intensity-related modulation emerges different processing stages.

Thus, temporal profile components provides critical empirical whether categorization intensity estimation shared processes reflect distinct levels representational granularity within affective system.

Crucially, temporal dissociation alone insufficient establish functional differentiation between categorization intensity estimation. stronger involves determining whether component-specific brain-behavior coupling patterns differentially predict categorical intensity-related performance. brain- behavior level, multi-stage processing architecture suggests neural variability different stages should independently predict intensity-related performance beyond categorical effects.

However, implemented predominantly categorical system graded refinements, intensity would establish independent neural- behavior predictive pathway would instead amplify attenuate category-driven effects. directly functional relevance, present study employs (G)LMMs single-trial amplitudes behavioral indices accuracy reaction times (RTs).

Unlike traditional condition-level analyses prior

studies facial emotion processing (e.g., Kashihara Shinguu, 2024; 2026), (G)LMMs allow simultaneous modeling within-subject neural- behavioral associations between-subject variability, providing rigorous framework assessing component-specific contributions distinct cognitive processes 2018, 2021). integrating neural behavioral measures unified framework, approach allows beyond descriptive effects whether categorization intensity estimation reflect distinct levels representational granularity within affective system. present study examines whether categorical graded refinements multi-stage processing integrating three converging levels analysis: behavioral performance across emotion categorization intensity rating, stimulus- locked spanning early perceptual evaluative stages, single-trial brain- behavior associations modeled (G)LMMs. categorical identification intensity estimation shared neural processes, emotional intensity should establish independent predictive effect should instead modulate category- driven effects across behavioral performance, neural responses, brain-behavior coupling patterns. contrast, emotion recognition reflects multi-stage processing architecture, intensity estimation should exhibit partially independent predictive effects. multi-level approach allows beyond descriptive effects directly whether intensity estimation constitutes functionally independent aspect affective processing merely graded extension categorical representation.

2.1 Participants

priori power

analysis

conducted using G*power software (Faul 2007) determine required sample size. account potential methodological variability, conservatively estimated effect desired power 0.95,

analysis

indicated minimum sample healthy adults recruited study. participants excluded excessive artifacts, resulting final sample participants females; years). analyses conducted complete cases.

Participants right-handed, normal corrected-to-normal vision, reported history neurological disorders. provided written informed consent (Chinese Yuan) $14.04) participation. study conducted accordance Declaration Helsinki approved Scientific Research Ethics Committee South China Normal University (SCNU- PSY-2024-376).

2.2 Apparatus

Stimuli Participants completed

experiment

individually soundproof room.

Stimuli presented 24-in. color monitor (refresh resolution pixels).

Stimulus presentation acquisition controlled using E-Prime (Psychology Software Tools, Pittsburgh, study employed modified emotion-labeling task. ensure identification accuracy, neutral facial images selected based identification scores provided Tsinghua Facial Expression Database (Yang Specifically, images correctly identified young female raters accuracy included. total models males, females) selected. selected neutral face, emotional expressions (anger, happiness, fear, sadness) included. facial images (neutral, fear, iness underwent standardized preprocessing.

First, image cropped elliptical shape using Adobe Photoshop remove external facial contours

background

distractions. Second, images converted grayscale standardized size, background, spatial frequency, contrast, brightness using Python Imaging Library (PIL; Clark, 2015) Python independent sample healthy college students majoring psychology females; years) further participated emotion-rating task. evaluated stimulus terms valence arousal using 9-point Likert scales highly negative arousal; highly positive arousal).

Emotion category rated 5-point scale neutral, happy, angry, fearful, sad), emotional intensity rated 10-point scale weak, intense) Supplementary Material detailed validation results).

Final stimuli chosen ensure recognizabilities, defined weighted recognition accuracy (weighted sample size) exceeding across original database norms current validation sample, while maintaining balanced gender representation. procedure yielded total pictures emotion category without neutral faces; gender ratio).

Emotional intensity levels (25%, 100%) created morphing neural faces emotion expressions using FantaMorph Deluxe (Abrosoft Lincoln, USA), resulting final stimuli. two-stage selection ensured stimulus reliably recognizable systematically manipulable intensity.

Additionally, based current validation, neutral faces gender ratio selected included materials filler trials.

2.3 Procedure

Before experiment, participants instructed actively evaluate emotional category intensity face. trial began fixation cross presented 200ms, followed facial image displayed center screen 1000ms.

Afterward, blank screen appeared after which participants asked categorize emotion neutral, happy, angry, fearful, emotional intensity neutral, weak, relatively relatively strong, strong) (Figure responses promote consistent responding across trials

reduce variability. There limit responses. participant selected neutral during emotion categorization, response required intensity rating task, thereby minimizing forced-choice emotional ambiguous reducing response predictability.

Before formal experiment, participants completed practice trials facial expression category) using separate images included task. procedure practice trials identical formal ensure participants familiarity procedure. formal

experiment

consisted eight blocks, containing trials, total trials (including selected neutral faces filler trials). unique image, varying emotion category emotional intensity, presented times throughout experiment. image repeated within block minimize potential habituation recognition effects. procedure stimuli.

Sequence typical trial. Following fixation presentation, delay interval preceded response phase, where participants categorized emotion rated intensity.

Example stimuli depicting emotion categories (happiness, anger, sadness, fear) intensity levels (25%-100%).

2.4 Statistical

Analyses

Behavioral analysis. Because non-normally distributed (emotion category labeling: kurtosis 7.96, skewness 2.01; emotion intensity rating: kurtosis 42.40, skewness 4.95), participant log-transformed.

Trials exceeding individual removed. After preprocessing trials remained 98.15%), distributions approximated normality (emotion category labeling: kurtosis 3.01, skewness emotion intensity rating: kurtosis 5.11, skewness 2013).

tasks, accuracy analyzed using GLMMs binomial function. predictors emotional category, emotional intensity, their interaction Accurate modeled using predictors. assess trial-by-trial effects neural signals behavioral performance, expanded hierarchical model-building framework.

Starting baseline model, including baseline amplitude (z-scored within participants), sequentially introduced interaction terms emotional intensity category systematically investigate their moderating effects brain-behavior relationship.

Trial number added these other models nuisance regressor account trends time, learning fatigue effects Additionally, ensure reliability stability parameter estimates, rigorous model diagnostics performed (G)LMMs.

First, model singularity assessed using isSingular() function (Bates 2020), complex model consistent experimental design, removing terms required allow nonsingular (Barr 2013).

Second, multicollinearity among fixed effects evaluated using adjusted Generalized Variance Inflation Factor (GVIF). predictors their interactions final models yielded 1/(2* value below scaled index allows comparison across terms differing degrees freedom, indicating reported

results

biased excessive collinearity Monette, recording, preprocessing analyses. recorded standard in-cap Ag/AgCl electrodes, following extended international system (Brain Products GmbH, Germany). served online reference.

Electrode impedance below throughout recording. continuously collected sampling 1,000 online filtered using bandpass filter.

Following recording, preprocessed offline using MATLAB R2022b software, EEGLAB v2024.2 (Delorme Makeig, 2004), ERPLAB v12.00 (Lopez-Calderon Luck, 2014). re-referenced average mastoids TP10) filtered bandpass filter notch filter remove noise filter; Luck, 2014).

Independent component

analysis

(ICA) correct major artifacts, including ocular movements, blinks, muscle-related potentials (Delorme Makeig, 2004; 2012). decomposition performed using EEGLAB default runica algorithm, which implements extended Infomax (Dien 2007).

ICLabel plug-in (Pion-Tonachini 2019) applied identify remove components containing artifacts according plug-in default criteria.

Continuous

epoched relative stimulus onset, baseline-corrected using amplitude before event onset (-200 single-trial baseline activity included covariates statistical models.

Epochs voltage exceeding automatically rejected. focused analyses these event-related potentials, quantified agnostic condition window determined priori based previous literature Liang, 2023; 2010; 2014): (85-135 averaged across (125-175 averaged across (150-200 averaged across (250-300 averaged across (475-650 averaged across included emotional category, emotional intensity, their interaction, trial number predictors regressors.

Similar behavioral analyses, underwent rigorous diagnostics ensure reliability stability parameter estimates.

Following recommendations Alday (2019), baseline activity electrode sites included nuisance regressor. approach controls pre-stimulus variability might otherwise induce spurious effects single-trial analysis, where assumption stationary baseline often fails hold, thereby ensuring observed effects biased pre-stimulus noise spill-over previous trials. mixed() function package Singmann assess significance fixed effects Likelihood Ratio Tests (LRT), comparing models without target effect Brown, significant reduction model removal specific effect indicated factor provided independent significant information explaining dependent variable.

Significant effects interactions further examined using follow-up contrasts based model-derived Estimated Marginal Means (EMMs) Maslej Lenth, providing interpretable comparisons across multi-level factors higher-order interactions.

Multiple comparison control applied using Tukey correction.

results

categorization task, accurate (split-half reliability based trials: revealed emotional category 193.93, .001) intensity 75.80, .001) significantly influenced identification speed, significant interaction between 24.17, .004) Figure Happy faces consistently yielded fastest across intensities .001).

Interestingly, while negative emotions followed clear hierarchy lowest intensity level (i.e., Anger Fear, .050), performance between these categories narrowed became non-significant intensity increased. accuracy (split-half reliability: .92), found significant effects

emotional category 44.55, .001) intensity 177.02, .001) Figure Post-hoc comparisons revealed robust happy superiority effect happy faces 2.67, confidence intervals (CIs) [2.24, 3.10]) being identified accurately anger, fear, sadness .001).

Among negative expressions, anger 1.26, 95%CI [.84, 1.68]) identified accurately 95%CI [.10, .94]) sadness 95%CI [.20, 1.03]) .050).

Additionally, identification accuracy exhibited significant upward trend emotional intensity increased .010), peaking intensity 2.41, 95%CI [1.98, 2.83]) further significant gains 2.64, 95%CI [2.21, 3.06]) .797). intensity rating task,

analysis

accurate (split-half reliability: demonstrated significant effect emotional intensity only, 23.27, Figure Specifically, faces presented lowest level (i.e., 5.92, 95%CI [5.80, 6.03]) processed faster those higher intensity levels (e.g., 100%: 6.04, 95%CI [5.92, 6.15]), Regarding rating accuracy (split-half reliability: .81), significant effects emotional category 52.16, .001) intensity 53.67, .001) observed, along significant interaction between them, 72.43, Figure Notably, fearful expressions demonstrated highest overall rating accuracy among negative emotions, reaching level comparable observed happy faces (fearful anger: .010; fearful sadness: .001).

Follow-up analyses revealed distinct patterns across negative emotion categories. fearful expressions, happy ones, rating accuracy increased linearly emotional intensity .050). contrast, angry expressions, accuracy followed inverted U-shaped pattern, accuracy medium intensity levels (i.e., significantly higher (25%) (100%) intensity levels .050). expressions, rating accuracy highest intensity level (100%) significantly lower other intensity levels .050).

Overall, behavioral

results

revealed clear differences across emotion categories.

Happy expressions showed robust advantage tasks, evidenced faster higher recognition accuracy, consistent classic happy superiority effect (e.g., Nummenmaa Calvo, 2015). contrast, processing negative emotions homogeneous. emotion categorization task, angry expressions recognized faster accurately fearful expressions; moreover, emotional intensity rating task, negative emotions exhibited distinct behavioral patterns varied across intensity levels.

Together, these findings indicate differentiated processing characteristics among negative emotions behavioral level.

Behavioral

results

categorization intensity rating. Interaction emotion category intensity categorization (log-transformed). effect intensity during intensity rating task. effect emotion category intensity categorization accuracy.

Interaction effect intensity rating accuracy across emotion categories. plots represent derived (G)LMMs; error indicate

- $p < .050$, ** $p < .010$, *** $p < .001$.

Results

Across components, emotional category exerted robust effects early mid-latency components Figure Specifically, significant effects emotional category observed 10.19, .017), 17.13, .001), 24.78, .001).

P100, angry 3.98, 95%CI [-4.73, -3.23]) -4.02, 95%CI 4.77, -3.27]) faces elicited smaller amplitudes happy faces -3.64, 95%CI [-4.38, -2.89]) .050).

Similarly, fearful -.58, 95%CI [-1.12, -.03]) -.53, 95%CI [-1.07, .00]) expressions evoked reduced amplitudes relative happy -.24, 95%CI [-.77, .30]) .010). negative emotional faces (Anger: 1.03, 95%CI [.66, 1.39]; Fear: 95%CI [.55, 1.30]; 95%CI [.54, 1.27]) elicited larger amplitudes happy faces 95%CI [.31, 1.03] .050).

However, significant effects found component .050).

Interestingly, significant effects emotional category 8.92, .030) intensity 47.82, .001) observed. comparisons indicated happy faces 3.11, 95%CI [2.85, 3.38] elicited larger amplitudes angry 2.83, 95%CI [2.56, 3.10] .050) addition, amplitudes exhibited significant increase increasing emotional intensity (25%: 2.53, 95%CI [2.22, 2.83]; 2.83, 95%CI [2.56, 3.09]; 3.04, 95%CI [2.78, 3.31]; 100%: 3.35, 95%CI [3.09, 3.61]; .010). interaction effects reached statistical significance.

Taken together,

results

reveal temporal dissociation facial emotion processing: early components (i.e., N170) primarily involved distinguishing happy non-happy expressions, mid-latency components reflected enhanced attention negative emotions, later stages, indexed neural activity become sensitive emotional intensity.

These findings support progressive processing sequence categorization quantification. framework, emotional intensity perception automatic perceptual process rather complex evaluative operation requires late-stage attentional resources achieve quantification integrative appraisal emotional significance.

Modulation components emotional intensity category.

Statistical

results

amplitudes P100, N170, Plots illustrate derived (G)LMMs, depicting effects emotional intensity category.

Error represent Grand average waveforms representative electrode clusters topographical component.

Shaded areas denote specific windows amplitude quantification.

- $p < .050$, ** $p < .010$, *** $p < .001$.

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3.3 Neural-behavioral

relationships relationships between single-trial amplitudes behavioral performance summarized Table During categorization task, clear dissociation emerged between early/mid-latency components Supplementary Material Larger amplitudes early mid-latency components (P100, N170, associated slower correct trials .001) reduced accuracy .010).

However, larger amplitudes predicted faster -.06, .001) higher accuracy 1.08, .010). contrast, intensity rating task, brain-behavior relationships generally weaker.

Although significant effects components observed (i.e., amplitudes showed positive negative associations respectively, .050), effects accuracy evident. example, moderated emotional category, association between amplitude accuracy significant .050).

Taken together, these

results

indicate neural activity underlying facial emotion processing exerts stage-dependent influences categorization performance (i.e., cost-like effects early/mid-latency components benefit-like effects component), while impact intensity rating performance limited primarily reflected accuracy.

Brain-Behavior Relationships: Effects Amplitudes Behavioral Performance Components Categorization Intensity Rating Accurate Accuracy Accurate Accuracy Notes. standardized regression coefficient LMMs; Ratio GLMMs.

Positive values indicate larger amplitudes associated slower indicates larger amplitudes associated higher accuracy. models included trial number baseline amplitude covariates, random intercepts participants pictures. indicates non-significant effect .05). .050, .010, Superscripts indicate significant moderation effects figures details). pecifically, LMMs, including either emotional intensity category, specified separately tasks, components interacting emotional category categorization task, emotional intensity intensity rating Effect moderated emotional intensity (G)LMMs, including either emotional intensity category;

Effect moderated emotional category (G)LMMs, including either emotional intensity category; Effect moderated emotional intensity (G)LMMs, including emotional intensity category; Effect moderated emotional category (G)LMMs, including emotional intensity category; Effect moderated emotional intensity category (G)LMMs, including emotional intensity category. examined whether either emotional category intensity independently moderated these brain-behavior relationships adding task-relevant factor (G)LMMs (i.e., category categorization intensity estimation; Supplementary Material Overall, moderated effects predominantly observed accuracy rather Table categorization accuracy, positive association amplitude moderated emotional category 12.39,

.006), suggesting larger amplitudes predicted higher accuracy specifically happy faces 1.15, 95%CI [1.05, 1.27]) faces 1.13, 95%CI [1.05, 1.22]), angry fearful faces. intensity rating accuracy, significant moderation emotional intensity observed 9.95, .019) 35.66, .001).

Specifically, negative P100-accuracy relationship emerged highest intensity level (i.e., 100%: 95%CI [.84, .95]), whereas positive accuracy relationship specific highest intensity (i.e., 100%: 1.22, 95%CI [1.14, 1.30]).

Finally, emotional category intensity entered simultaneously examine whether their interactive moderation relationships between components behavioral performance Supplementary Material accurate dependent variable, neither emotional intensity emotional category significantly moderated relationships between components .050).

Further analyses revealed that, except predictive effects remaining components accuracy moderated emotional intensity category Table categorization accuracy, negative association amplitude moderated emotional category 13.34, .010) intensity 23.61, .001), significant effects observed specifically happy expressions, intensity levels.

LPP-accuracy relationship jointly moderated emotional category intensity 20.48, .050) Figure amplitude negatively predicted accuracy low-intensity fearful faces (25%: -.32, 95%CI [-.53, -.12]), positively predicted accuracy medium intensity happy faces (50%: 95%CI [.03, .45]) intensity faces (100%: 95%CI [.16, .45]).

Interestingly, intensity rating accuracy, predictive effect moderated emotional category 7.83, .050), significant negative association observed exclusively faces 95%CI

.00]), possibly reflecting increased processing difficulty expressions, which require greater top-down evaluative modulation.

Additionally, similar pattern emerged Figure where amplitude consistently predicted better performance intensity happy (100%: 95%CI [.16, .38]), fearful (100%: 95%CI [.06, .28]) faces (75%: 95%CI [.05, .29]; 100%: 95%CI [.12, .41]), angry ones.

These findings indicate brain-behavior relationships depend specific combinations emotional category intensity, instead being uniform across conditions.

Emotional category intensity jointly moderated relationship between amplitude categorization accuracy intensity rating accuracy derived (G)LMMs including emotional intensity category. represent error represent color highlights statistically significant effects .050). vertical dashed indicates effect.

4. DISCUSSION

present findings support multi-stage processing architecture which categorical intensity-related processing temporally organized functionally dissociable.

Converging evidence across behavioral, neural, brain- behavior levels consistently points stage-dependent progression: early latency components selectively encoded categorical distinctions, evaluative processing integrated categorical intensity information, component- specific brain-behavior coupling patterns differed systematically between categorization intensity estimation.

These

results

challenge purely categorical account, which intensity would function merely graded byproduct category- level processing, instead provide functional evidence intensity estimation constitutes partially independent aspect affective representation.

4.1 Behavioral

Dissociation Between Emotion Categorization Intensity Evaluation Categorization intensity evaluation exhibited heterogeneous patterns During categorization task, robust anger superiority effect emerged.

Specifically, lowest intensity level, negative emotions followed clear processing hierarchy, indicating relative advantage (i.e., faster anger detection.

Additionally, categorical accuracy angry expressions higher fearful faces. superiority effect reflect functional specificity anger signals.

Unlike other emotions, anger closely linked approach-related motivation systems signal potential aggression (Carver Harmon-Jones, Malezieux 2023).

Crucially, facial ambiguous, observers often tendency interpret uncertain social signals hostile direction (Dodge 2015; Milich Dodge, 1984). biases social interpretation shift decision thresholds toward anger detection, potentially facilitating faster identification angry faces under ambiguous conditions.

However, intensity increases, emotional become perceptually salient across categories, reducing ambiguity consequently diminishing relative advantage anger.

Moreover, anger expressions characterized relatively distinctive perceptual features (e.g., lowered brows, tightened eyelids), which enhance early perceptual discrimination (Ekman, 1993).

Beyond anger, clear happy superiority effect observed (Nummenmaa Calvo, 2015), happy expressions recognized faster accurately other categories. advantage consistent diagnostic value hypothesis (Calvo 2014) affective uniqueness hypothesis (Flowe 2016), which suggest happy expressions contain highly distinctive perceptual features configural information, allowing rapid categorical identification. occurrence anger happy superiority effects suggests governed least partially independent optimization pressures, i.e., threat-priorization mechanism accelerates detection socially dangerous signals under ambiguous conditions, feature-diagnosticity mechanism supports accurate categorical discrimination expressive sufficiently distinctive.

These

pressures highlight recognition advantage unitary construct rather multidimensional outcome interplay between stimulus properties adaptive processing priorities.

Unlike categorical identification, intensity estimation requires assessing magnitude affective signals, which revealed different patterns among negative emotions. fearful expressions, rating accuracy increased linearly emotional intensity, mirroring pattern observed happy faces.

However, angry expressions, different patterns emerged.

Notably, intensity ratings fearful faces significantly accurate those angry faces, comparable happy expressions. pattern reflect that, compared anger expressions, which primarily signal presence social threat aggression, fearful faces convey graded information about environmental danger uncertainty (Malezieux 2023).

Variations intensity directly correspond changes perceived magnitude urgency environmental threat. graded signals therefore provide observers particularly informative evaluating strength affective states. distinction suggests different emotions provide differentially informative intensity evaluation, depending strongly their expressive variations ecologically meaningful changes environmental threat. broadly, these findings indicate emotion categorization intensity evaluation partially dissociable processing principles.

Emotion categorization primarily requires identifying qualitative identity expression, process often perceptually diagnostic features distinguish category another. contrast, intensity estimation requires estimating magnitude affective signals, which depend categorical distinctiveness functional meaning conveyed expression. difference highlights involve multiple layers information processing, which perceptual distinctiveness supports rapid categorical decisions, whereas functional meaning supports graded evaluations emotional intensity.

4.2 Temporal

Dynamics Structural Encoding Meaning Integration Early mid-latency components revealed biases primarily associated categorical processing.

Specifically, happy faces elicited significantly larger amplitudes other expressions, suggesting enhanced early perceptual encoding these stimuli. pattern consistent previous research indicating perceptual advantage happy faces, which contain highly distinct features, upward curvature mouth, facilitate rapid discrimination (Calvo Flowe 2016). subsequent mid-latency stage indexed different pattern emerged: happy expressions elicited smaller amplitudes angry, fearful, expressions, indicating enhanced neural responses negative emotions. pattern consistent well-established negativity bias, suggesting negative stimuli preferentially capture attentional resources (e.g.,

2010; 2007). adaptive perspective, prioritization facilitate rapid detection socially significant signals, including potential threat, distress, interpersonal conflict. contrast early components associated primarily categorical processing, emotional intensity effects emerged during later stage Specifically, higher emotional intensity levels (i.e., 100%) elicited larger amplitudes lower levels (i.e., 50%).

Given commonly interpreted reflecting sustained evaluative processing higher-order appraisal emotional stimuli 2014), finding suggests emotional intensity directly extracted early perceptual instead requires extended processing support refined decision-making.

Importantly, sensitive emotional category intensity, indicating stage reflect integrative phase affective processing.

While early perceptual stages appear rapidly differentiate between emotional categories, particularly happy versus non-happy faces, based diagnostic facial features, estimating intensity likely requires integrating multiple facial evaluating magnitude affective signals along continuous scale. coexistence category intensity sensitivity within points multi-stage processing rather strictly sequential architecture, which later evaluative stages integrate categorical identity affective magnitude concurrently rather discrete succession.

4.3 Brain

Behavior Relationships Critical Evidence Functional Significance present study investigated trial-by-trial variation amplitudes relates behavioral performance during showed clear stage-dependent pattern Early mid-latency components negative associat behavioral performance, whereas component exhibited facilitative relationship performance.

Early mid-latency components generally understood reflect rapid perceptual encoding automatic allocation attention emotional features 2014).

Larger amplitudes these components therefore index stronger bottom-up salience detection attentional capture emotional cues.

Although early attentional mechanisms essential detecting socially relevant signals, excessive attentional capture associated reduced efficiency goal-directed decision processes, categorization intensity estimation reflected slower accurate responses (Innes Todd, 2022). contrast, components consistently associated sustained evaluative processing motivationally relevant attentional allocation 2014). positive association between amplitudes behavioral performance, therefore, suggests late-stage evaluative integration facilitate efficient accurate decisions perceptual encoding completed.

Importantly, strength direction these brain-behavior relationships uniform across emotional categories intensity levels. categorization process, association between amplitude behavioral performance

selectively moderated happiness sadness higher intensity levels.

Since sensitive structural encoding facial features 2014), these moderation effects reflect differences perceptual processing demands across emotional expressions.

Happy expressions contain highly diagnostic visual cues, pronounced mouth curvature, which strongly engage early face- processing mechanisms (Calvo Nummenmaa Calvo, 2015). contrast, faces typically characterized subtle salient facial changes, making perceptually difficult discriminate 2023).

Larger responses these conditions therefore reflect increased structural encoding demands rather efficient perceptual processing. moderation medium-high-intensity level reflect different perceptual mechanisms. moderate intensity (50%), emotional signals remain relatively ambiguous, making extraction stable facial structural difficult.

Larger amplitudes reflect increased perceptual effort during structural encoding, which associated poorer behavioral performance. contrast, intensity (100%), facial feature changes become pronounced perceptual signals strengthened.

However, although stronger signals facilitate detection, increase amount structural information encoded, thereby placing greater demands early face-processing mechanisms.

Categorical intensity-specific effects observed Specifically, amplitude predicted poorer performance low-intensity fearful expressions better performance medium-intensity happiness high-intensity sadness.

Rather reflecting single uniform mechanism, these patterns likely indicate sustained evaluative processing plays different functional roles depending perceptual motivational characteristics stimulus. widely associated sustained attentional engagement motivationally relevant stimuli 2014). emotional signals sufficiently informative, sustained processing facilitate decision-making enabling deeper integration affective cues.

Conversely, perceptual evidence weak, elevated activity reflect uncertainty-driven monitoring rather effective evidence consolidation, potentially delaying categorical commitment. explain positive relationship between amplitude performance medium-intensity happiness high-intensity sadness. these conditions, emotional signal strong enough provide reliable diagnostic information (Calvo 2016).

Greater engagement therefore reflect effective evaluative processing helps consolidate perceptual evidence stable categorical judgement.

However, negative relationship between amplitude performance low-intensity fearful expressions likely reflects different functional process.

Fearful expressions closely linked threat detection mechanisms, signals trigger heightened vigilance uncertainty monitoring (Malezieux 2023) perceptual evidence threat weak, greater activity reflect prolonged evaluation potentially threatening ambiguous stimulus.

Rather facilitating categorical decisions, sustained vigilance reflect prolonged evaluative process associated delayed commitment

specific interpretation, potentially biasing processing towards threat-related alternatives under conditions perceptual ambiguity. similar logic explain pattern observed process intensity estimation.

Early-stage brain-behavior relationships emerged primarily intensity levels, particularly component. emotional signals become highly salient, increased early sensory amplification reflect heightened perceptual processing demands rather improved perceptual discrimination.

Similar

results

categorization, consistently supported accuracy higher intensity levels across several emotional expressions. emotional signals become stronger perceptually reliable, sustained evaluative processing increasingly contribute integration confirmation affective information, thereby promoting accurate behavioral responses. addition, predictive effect moderated emotional category, significant negative association observed exclusively faces.

Given expressions typically characterized relatively subtle distinctive facial 2023), increased responses reflect greater perceptual processing effort observers attempt extract structural signals. sense, stronger amplitudes indicate demand-driven processing effort rather encoding efficiency, consistent negative brain-behavior relationship observed other early components.

Taken together, these findings demonstrate behavioral relevance activity depends critically interaction between processing stage, emotional characteristics, cognitive demands.

Early perceptual components appear reflect stimulus-driven processes signal increased perceptual effort difficulty, which interfere efficient decision-making attentional resources excessively captured (Innes Todd, contrast, later evaluative processing appears support goal-directed integration affective information, particularly emotional signals provide sufficiently reliable perceptual evidence. broadly, these

results

highlight functional significance neural responses cannot inferred solely their magnitude understood relation their stage within processing hierarchy their contribution behavioral outcomes.

4.4 Limitations

future directions Despite contributions present study, several limitations should acknowledged.

First, current

experiment

focused basic emotions (i.e., happiness, anger, fear, sadness).

Although these emotions represent widely studie affective categories, other basic expressions, disgust surprise, included (Ekman, 1993).

Given different emotional categories exhibit distinct perceptual thresholds processing dynamics (Calvo 2016), restricted emotions limit generalizability present findings.

Future research could extend current paradigm broader range emotional expressions, including additional basic emotions complex socially

nuanced affective states, pride shame. Second, study employed static facial images stimuli. natural social interactions, emotional expressions typically unfold dynamically provide additional temporal influence emotion recognition perceived intensity.

Consequently, static images fully capture richness real-world emotion perception 2021).

Future could extend present paradigm using dynamic facial expressions video-based stimuli examine whether observed neural behavioral patterns generalize ecologically valid contexts.

Third, experimental tasks administered fixed order: emotion categorization always preceded intensity rating within trial. should noted order dependency limited impact analyses reported here, stimulus-locked neural responses recorded during presentation window, before overt behavioral response either task.

results

therefore reflect neural processing during active perceptual evaluation rather post-decisional stages either task.

Nevertheless, fixed order introduce subtle concern behavioral data: having already formulated categorical judgement, participants approach intensity rating pre-activated categorical frame could constrain evaluative processing fully captured trial-level covariates. possibility cannot entirely ruled present design.

Importantly, however, convergent evidence across behavioral, neural, brain-behavior levels suggests potential confound unlikely account overall pattern findings.

Future studies should address limitation adopting counterbalanced fully blocked design which categorization intensity rating administered separate experimental sessions randomized order across participants, thereby allowing cleaner dissociation neural processes supporting cognitive operation.

Fourth, components analyzed study defined using prior windows electrode clusters based previous literature Liang, 2023; 2010; 2014).

While hypothesis-driven approach commonly research facilitates theoretical interpretation, overlook neural effects occur outside predefined temporal spatial boundaries.

Future studies could complement component-based analyses data-driven approaches, cluster-based permutation tests mass-univariate analyses, provide comprehensive characterization neural dynamics underlying facial emotion processing.

Finally, sample consisted exclusively young adults, which limit generalizability findings broader populations.

Age-related cultural differences emotion perception reported prior research (Thomas 2007).

Future studies should therefore replicate present findings diverse samples, including participants different groups cultural backgrounds, further evaluate robustness generalizability observed effects.

Although present study these limitations, provides novel evidence regarding temporal dynamics linking categorical intensity-based aspects

integrating temporally resolved neural measures trial-by-trial brain- behavior modeling, study offers framework future further investigate representational architecture underlying affective perception.

5. CONCLUSION

present study demonstrates reflects multi-stage processing architecture rather unitary categorical system.

Behaviorally, categorization intensity estimation showed distinct sensitivity profiles across emotional categories intensity levels.

Neurally, early components selectively modulated emotional category, whereas component (i.e., integrated categorical intensity-related information, marking temporal boundary between rapid structural encoding evaluative appraisal.

Brain-behavior analyses further revealed stage-dependent architecture carries direct functional consequences, early components predicting cost-like effects evaluative processing predicting facilitative effects behavioral performance.

Collectively, these findings reframe intensity estimation functionally distinct aspect affective representation rather byproduct categorical processing, indicating categorical accounts alone insufficient capture computational architecture trial-by-trial brain-behavior modeling framework employed offers replicable approach future examining affective perception across clinical developmental populations.

AVAILABILITY generated study available Science Framework (OSF) relevant obtained reasonable request.

CONTRIBUTIONS Wenbin Conceptualization, methodology, software, formal analysis, investigation, curation, writing original draft preparation, writing review editing, visualization.

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