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**Information Diagnosticity and Uncertainty Mitigation: Integrated
Physiological, Cultural, Contextual, and Ethical Perspectives in
Consumer Behavior**

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Statement of Originality

I hereby declare that this dissertation, titled “Information Diagnosticity and Uncertainty Mitigation: Integrated Physiological, Cultural, Contextual, and Ethical Perspectives in Consumer Behavior,” represents my own original work conducted under the supervision of my advisors. The research presented herein has been carried out independently, and all sources of information and assistance have been appropriately acknowledged.

This doctoral dissertation contributes to the fields of consumer behavior, sensory marketing, and human-computer interaction. The work originates in the observation that, in the emerging “Hybrid Marketing Environment,” consumers do not process these domains in isolation but rather navigate a continuous, multimodal stream. The originality of this research lies in the construction and validation of the Consumer Information Diagnosticity Framework, a hierarchical model that unifies these disparate cues under the single theoretical construct of “diagnostic signals” used for uncertainty reduction, and conceptualizes passive visual systems and active algorithmic systems under a common theoretical lens.

This research presents four original studies employing rigorous mixed-methods approaches. Study 1 provides novel physiological evidence, using eye-tracking and pupillometry, demonstrating that brightness modulates processing depth via temporal resource allocation rather than merely affecting salience. Study 2 offers original insights into the effects of color configuration in Chinese gift-giving contexts, revealing the cultural-diagnostic function of dark red as a social shield for consumers with intermediate wine knowledge. Study 3 conducts a phenomenological investigation, identifying the privacy-precision concern in Douyin/TikTok e-commerce and documenting the trust crisis emerging from algorithmic opacity. Study 4 experimentally validates cognitive scaffolding mechanisms through which ethical design features restore system diagnosticity across four countries.

This research advances theoretical integration across multiple disciplines, extending Information Richness Theory, Adaptive Strategy Selection Framework, Cue Utilization Theory, Face Theory, Stimulus-Organism-Response Model, Expectancy-Value Theory, Dual-process Theory, and Scaffolding Theory into a diagnostic framework spanning physiological, cultural, contextual, and systemic dimensions.

This work has not been previously submitted for any degree or diploma at this or any other institution. In collaborative work, my specific contributions have been clearly delineated in the respective chapters. One study (Study 3) has been published by Emerald Publishing, while three others remain under review and are subject to revision. Study 1 was carried out under an approved ethics protocol. For the questionnaire and interview studies, written or oral informed consent was obtained from all participants before data collection commenced. All data collection, analysis, and interpretation procedures conformed to established ethical guidelines.

Statement on the use of generative AI: During the preparation of this thesis, the author used ChatGPT, Grammarly, and QuillBot in order to improve the language, readability, and grammar of the manuscript. After using this tool/service, the author reviewed and edited the content as needed.

I certify that this dissertation represents genuine scholarly inquiry conducted with academic integrity, and I take full responsibility for its content.

Dedication

Dedicated to my parents, for your endless encouragement and support. I could not have done this without you.

And to the loving memory of my grandparents. Forever in my heart, forever watching over me.

Abstract

This research investigates consumer information diagnosticity in hybrid marketing environments by examining how consumers reduce uncertainty through visual and algorithmic signals. Adopting a hierarchical framework spanning physiological, cultural, contextual, and systemic dimensions, four studies explore diagnostic evaluation across physical product displays and digital recommendation systems. Study 1 employs eye-tracking and pupillometry ($N = 32$) to demonstrate that wine label brightness modulates processing intensity rather than breadth. High brightness induces a front-loading of cognitive resources, enabling efficient early encoding, whereas low brightness triggers compensatory back-loading, leading to prolonged late-stage effort. Study 2 uses a $4 \times 2 \times 2$ factorial experiment ($N = 435$) and qualitative interviews ($N = 30$) to reveal that dark red wine color configurations function as highly diagnosticity cultural schemas in Chinese gift-giving contexts, particularly for intermediate wine knowledge consumers facing social uncertainty. Study 3 conducts phenomenological interviews ($N = 36$) with Douyin/TikTok users, identifying a privacy concern: excessive recommendation precision triggers privacy anxiety despite enhancing convenience, creating systemic uncertainty from algorithmic opacity. Study 4 tests AI ethical design features through a between-subjects experiment ($N = 278$) across four countries, establishing that transparency, fairness, privacy, and autonomy restore system diagnosticity through cognitive scaffolding rather than direct affective pathways. The research constructs a unified information diagnosticity framework demonstrating that physical sensory cues and algorithmic signals follow parallel psychological principles. Brightness serves as a physiological moderator, lowering perceptual thresholds; cultural schemas provide social shields, reducing face-related risks; and ethical design features function as cognitive scaffolds, enabling trust reconstruction. Findings offer actionable insights for visual marketing design and algorithmic system transparency.

Abstract (Versione Italiana)

Questa ricerca esamina la *information diagnosticity* (la diagnosticità informativa) del consumatore nei contesti di marketing ibridi, analizzando come gli individui riducano l'incertezza attraverso segnali visivi e algoritmici. Adottando un quadro gerarchico che comprende le dimensioni fisiologiche, culturali, contestuali e sistemiche, quattro studi indagano le modalità di valutazione diagnostica sia nelle esposizioni fisiche dei prodotti sia nei sistemi digitali di raccomandazione.

Lo Studio 1, mediante l'eye-tracking e la pupillometria ($N = 32$), dimostra che la luminosità dell'etichetta del vino modula la intensità piuttosto che l'ampiezza dell'elaborazione cognitiva. Un'elevata luminosità induce un *front-loading* (allocazione anticipata) delle risorse cognitive, consentendo una codifica precoce ed efficiente, mentre una bassa luminosità innesca un *back-loading* (allocazione posticipata) compensatorio, portando a uno sforzo prolungato nelle fasi tardive dell'elaborazione.

Lo Studio 2, attraverso un esperimento fattoriale $4 \times 2 \times 2$ ($N = 435$) e interviste qualitative ($N = 30$), rivela che le configurazioni cromatiche scure del rosso funzionano come schemi culturali ad alta diagnosticità nel contesto del dono in Cina, soprattutto per i consumatori con conoscenze intermedie di vino che affrontano situazioni di incertezza sociale.

Lo Studio 3 conduce interviste fenomenologiche ($N = 36$) con utenti di Douyin/TikTok, identificando un paradosso privacy-comodità: un'eccessiva precisione delle raccomandazioni genera un'ansia da sorveglianza nonostante ne migliori la comodità, creando un'incertezza sistemica derivante dall'opacità algoritmica.

Lo Studio 4 esamina elementi di design etico dell'IA tramite un esperimento tra soggetti ($N = 278$) condotto in quattro paesi, evidenziando che trasparenza, equità, privacy e autonomia ripristinano la diagnosticità del sistema attraverso meccanismi di *cognitive*

scaffolding (impalcature cognitive) piuttosto che mediante vie affettive dirette.

La ricerca sviluppa un quadro unificato della *information diagnosticity*, mostrando che i segnali sensoriali fisici e quelli algoritmici seguono principi psicologici paralleli. La luminosità agisce come moderatore fisiologico, abbassando le soglie percettive; gli schemi culturali forniscono protezioni sociali, riducendo i rischi legati alla perdita di faccia; e le caratteristiche di etica design operano come impalcature cognitive, facilitando la ricostruzione della fiducia. I risultati offrono indicazioni operative per il design del marketing visivo e per la trasparenza dei sistemi algoritmici.

Acknowledgement

Completing this dissertation has been an extraordinary journey in my life. Looking back over the past three years, this experience has not only shaped my academic abilities but has also profoundly reshaped my mindset. As I write this final section of the thesis, I pause to look out the window, and memories take me back to the day of my doctoral interview, a moment that now feels both distant and vivid, as though time has moved faster amid the busyness of the journey. There are truly so many people to whom I owe gratitude.

First and foremost, I would like to express my sincere appreciation to my supervisor, **Professorssa Michelina Venditti**. Thank her for providing me with the opportunity to pursue my PhD at the Università degli Studi “G. d’Annunzio” Chieti-Pescara, and for offering the resources and environment that made this research possible. What I am most grateful for, however, is her guidance, not only her academic support, but also her encouragement during moments of confusion, frustration, and emotional struggle. All of this has helped me reach where I stand today. I am also deeply grateful to my second supervisor, **Professor Gianluca Antonucci**, whose academic advice, care, and encouragement have made my doctoral journey more complete.

A doctoral study is, at its core, an act of courage, a test of will, an all-in exploration. And as with any exploration, it is filled with uncertainty and situations beyond one’s control. Is a PhD solely about producing academic outcomes? I believe the answer varies from person to person. For me, the PhD has been less of a results-driven pursuit and more of a process of accumulation, adjustment, and skill refinement. I owe this understanding to our **Department of Management and Business Administration**. I consider myself incredibly fortunate, for the department has taught us that a PhD is not the end of an academic journey; rather, it is a beginning. It is here that we prepare ourselves to face greater challenges ahead. Academic research rarely demands that every PhD student become a world-changing figure; instead, it is a slow and steady

progression, where even a small breakthrough, one that slightly disrupts the established circle of knowledge, is worthy of celebration. This philosophy has shaped me profoundly over the years. I am grateful for this experience, which taught me how to navigate an unmapped landscape and how to construct logic amid uncertainty.

I would also like to thank my host supervisor during my visiting period, **Professor Guojie Ma**. He is a man of few words, yet he supported me in countless ways and opened the door to the psychological foundations of consumer research. This turning point allowed me to approach management studies from new scientific perspectives. I am equally thankful to everyone at the Mazhuang Food Behavior Lab, who consistently provided advice and assistance whenever I needed it.

Lastly, I want to thank myself, the version of me who never gave up. Despite obstacles and pressure, I persisted. As I close this chapter today, what I hold is a heart full of gratitude and a spirit filled with hope for the future.

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List of Abbreviations

AI - Artificial Intelligence

AI-PPR - AI-Powered Personalized Recommendation

ANOVA - Analysis of Variance

AOI - Area of Interest (Study 1)

AR - Augmented Reality

ASSF - Adaptive Strategy Selection Framework

CCT - Consumer Culture Theory (Study 2)

CI - Confidence Interval

CIELUV - Commission Internationale de l'Éclairage Luv* color space (Study 1)

CLM - Cumulative Link Model (Study 2)

CLMM - Cumulative Link Mixed Model (Study 2)

CNNIC - China Internet Network Information Center (Study 3)

CPV - Consumer Perceived Value

DE - Direct Effect (Study 4)

ELM - Elaboration Likelihood Model (Study 4)

EVT - Expectancy-Value Theory

FDR - False Discovery Rate

FFT - First Fixation Time (Study 1)

GLM - Generalized Linear Model

GLMM - Generalized Linear Mixed-Effects Model

HC3 - Heteroscedasticity-Consistent Covariance Matrix Estimator (Study 2)

HCI - Human-Computer Interaction

HSD - Honestly Significant Difference (Tukey's test)

ICC - Intraclass Correlation Coefficient

IDT - Information Diagnosticity Theory

IE - Indirect Effect (Study 4)

IoT - Internet of Things

IQR - Interquartile Range

IRT - Information Richness Theory

K - Knowledge score (referencing participant wine knowledge in Study 2)

KOL - Key Opinion Leader

LMM - Linear Mixed-Effects Model

LOSO - Leave-One-Subject-Out (Study 1)

LR - Likelihood Ratio

LRT - Likelihood Ratio Test

ML - Maximum Likelihood

NHST - Null Hypothesis Significance Testing (Study 1)

OLS - Ordinary Least Squares (Study 2)

OR - Odds Ratio (Study 2)

PLR - Pupillary Light Reflex (Study 1)

QR - Quick Response (code) (Study 3)

REML - Restricted Maximum Likelihood (Study 1)

RMB - Renminbi (Chinese currency)

RQ - Research Question

SD - Standard Deviation

SE - Standard Error

SESOI - Smallest Effect Size of Interest (Study 1)

S-O-R - Stimulus-Organism-Response (model)

TAM - Technology Acceptance Model

TOST - Two One-Sided Tests (Study 1)

Ubicomp - Ubiquitous Computing

UTAUT - Unified Theory of Acceptance and Use of Technology

UTAUT2 - Unified Theory of Acceptance and Use of Technology 2

VIF - Variance Inflation Factor (Study 2)

VR - Virtual Reality

XAI - Explainable Artificial Intelligence (Study 4)

List of Publications

Part I: Papers included in this dissertation

1. **Ding, L.**, Ma, G. J., Antonucci, G., & Venditti, M. (2026). Brightness and temporal reallocation in wine label processing: An eye-tracking and pupillometry study. (Accepted) - *Chapter 4*
2. **Ding, L.**, Ma, G. J., Antonucci, G., & Venditti, M. (2026). Dark Red as High-End? How Wine Label Color Configurations Guide Chinese Consumers' Perceived Value Judgements. (Under Review) - *Chapter 5*
3. **Ding, L.**, Antonucci, G., & Venditti, M. (2025). Unveiling user responses to AI-powered personalised recommendations: A qualitative study of consumer engagement dynamics on Douyin. *Qualitative Market Research: An International Journal*, 28(2), 234–255. (Published) - *Chapter 6*
4. **Ding, L.**, Antonucci, G., Iaia, L., & Pironti, M. (2026). From Overlooked to Central: How Ethical AI Design Fosters User Acceptance through Cognitive and Affective Processes. (Presented at the 22nd Conference of the Italian Chapter of AIS) - *Chapter 7*

Part II: Other scientific contributions

1. **Ding, L.**, Antonucci, G., & Venditti, M. (2026). Constraint-Conditioned Women's Empowerment: How Psychological Needs Gate Social-Cognitive Mechanisms in Male-Dominated Industries. (Under Review)

Chapter 1 General Introduction

1.1 Research background

The emergence of Internet of Things (IoT), augmented reality (AR), ubiquitous computing (ubicomp), and generative artificial intelligence (Generative AI) has given rise to a new ecosystem that scholars call the “Omnichannel Marketing Environment”. It provides the broad theoretical context for integrating customer touchpoints (Verhoef et al., 2015). In this interwoven ecosystem, consumers no longer interact solely by touching products offline or browsing web pages. They exist within a continuous multimodal interaction stream (Paul et al., 2024). However, effectively managing this stream requires a focused strategic approach. Therefore, this research adopts the term “Hybrid Marketing,” defined as the organizational capability to leverage the distinct advantages of physical and digital modalities, following the logic of Kotler et al. (2017). Crucially, while these modalities differ in form, they share a common function, that is, they act as diagnostic signals that consumers use to reduce uncertainty. In the physical domain, consumers actively decode passive sensory cues (e.g., brightness, color) to infer product quality. In the digital domain, dynamic shifts mean consumers must evaluate active algorithmic signals (e.g., recommendation precision) to infer platform intent. Therefore, the core challenge of hybrid marketing is not merely managing channels, but understanding how consumers seamlessly migrate their diagnostic strategies from processing visual signals to evaluating an algorithmic agent.

This structural transformation raises a central theoretical and practical question: how do consumers integrate heterogeneous cues from multiple sources to reduce decision uncertainty (He & Rucker, 2023). Regardless of the setting, consumers must quickly identify which cues provide diagnostic value under limited cognitive resources. Furthermore, the endpoint of the consumption invariably lies with consumers, who constitute the direct users of the product or service (Kardes et al., 2004). Existing

information-processing theories typically treat sensory input and cognitive evaluation in isolation. They thus cannot explain how trust is formed, maintained, or lost when vivid visual stimuli interact with opaque algorithmic systems. Consumers enjoy the convenience of low-cost search algorithms while facing new forms of cognitive friction (Ding et al., 2025). They must balance visual attraction, culturally specific norms, and anxieties about algorithmic manipulation.

From a theoretical perspective, information diagnosticity has been central to decision research since Feldman and Lynch (1988) proposed the accessibility-diagnostics framework. That framework holds that cue use depends on cue accessibility in memory and the cue's diagnostic relevance to the judgment. Cue utilization theory (Olson & Jacoby, 1972) further distinguishes intrinsic cues (product physical attributes) from extrinsic cues (price, brand, packaging), emphasizing consumers' reliance on extrinsic cues to infer unobservable quality. Signal theory (Spence, 1973), later adapted to consumer research by Kirmani and Rao (2000), explains how sellers convey quality through costly signals such as advertising expenditure or warranty commitments.

These accounts, however, remain domain specific. Visual marketing research examines how packaging color affects perception (Labrecque & Milne, 2012) but pays limited attention to underlying physiological processing and configurational effects. The literature on recommendation algorithms documents algorithm aversion (Dietvorst et al., 2015) and users' demand for transparency (Castelo et al., 2019), yet rarely integrates these findings with cue utilization theory. This fragmentation overlooks a key fact: in hybrid marketing environments, consumers encounter both physical products and digital recommendations. Do their diagnostic evaluations follow common psychological principles across these domains?

From a practical perspective, marketers face two linked challenges. In the physical domain, winemakers rely on color heuristics for label design but lack clarity about how consumers process visual cues at the physiological level. For example, does brightness as an independent visual dimension alter processing intensity for hue and saturation? Which color combinations carry the highest diagnostic value in specific cultural

contexts, such as gift-giving in China? In the digital domain, short-video platforms invest heavily in AI recommendations while confronting the privacy paradox: users appreciate personalization yet fear data misuse (Ding et al., 2025). Excessive recommendation precision can induce surveillance anxiety. How can designers deliver recommendations that are both accurate and trustworthy? Through what psychological pathways do design features such as transparency and user control build trust?

This dissertation addresses that gap. Moving from observed phenomena to underlying consumers' diagnostic evaluations follows shared psychological principles. The study constructs a systematic framework spanning four dimensions: physiological processing, cultural schemas, contextual features, and ethical design. The focus extends beyond the probability that a cue will be noticed to the diagnostic depth with which it is interpreted. The research examines how sensory cues lower the threshold of cognition and how ethical design functions as cognitive scaffolding to rebuild the consumer-system contract when algorithmic opacity undermines trust. Through this framework, the dissertation aims to explain how hybrid marketing environments transform consumer information diagnosis and reduce uncertainty.

1.2 Overview of research gaps and questions

1.2.1 Research gaps

In hybrid marketing environments, uncertainty is no longer a unidimensional concept but a complex construct that evolves as consumer agency shifts. Building on Feldman and Lynch's (1988) information diagnosticity theory (IDT), this research posits that consumers face a chain of uncertainty: starting from basic perceptual uncertainty (Can I see and process it?), moving to social uncertainty (is it culturally appropriate?), and culminating in systemic uncertainty (is the algorithm manipulating me?). Different sources of uncertainty require cues with distinct attributes. This dissertation identifies four core gaps corresponding to these layers, each addressed in one of four studies.

Visual Perceptual Challenges and Cognitive Effort: In environments rich with visual stimuli, consumers must efficiently identify relevant information while conserving biological resources (Chen et al., 2024). This pertains to the physical accessibility of cues. Traditional perspectives often conflate salience with attention (Parr & Friston, 2019), but this research differentiates mere visibility from deeper processing. Study 1 (brightness) explores how variations in visual brightness functions as an accessibility modulator that reconfigures the temporal processing strategies and processing intensity of visual information, instead of merely increasing search breadth.

Social Implications of Consumption in Cultural Contexts: In cultures like China, where social context is highly influential, consumption decisions carry symbolic weight (Witt, 2010). Consumers may worry about both practical shortcomings and potential social repercussions, such as loss of face (Gao & Ting-Toomey, 1998; Goffman, 1967). Study 2 (color configuration) examines how color configurations (hue $\times$ brightness $\times$ saturation) carry differential diagnostic value in Chinese gift-giving contexts, demonstrating that dark red configurations serve as high-diagnosticity cultural schemas that mitigate face-related social uncertainty.

Challenges of Algorithmic Opacity in Digital Platforms: As consumers engage with intelligent systems like Douyin/TikTok, uncertainty arises from the dynamic, opaque nature of algorithms (Eslami et al., 2015), which can feel like independent agents shaping content. Unlike static products, algorithmic platforms actively filter information. The third gap lies in the “Privacy-Convenience” paradox: how does excessive recommendation precision, intended to increase diagnosticity, paradoxically trigger privacy anxiety and reduce trust?

Building Trust in Algorithmic Systems: A key issue in recommendation platforms is their lack of transparency and fairness, as users observe results without insight into underlying processes (Sonboli et al., 2021). While factors like usefulness and ease of use promote adoption (Davis, 1989), they may not fully account for the need for cognitive comprehension to foster emotional trust in AI (Dimoka, 2010). Ethical elements (e.g., transparency, fairness, privacy, autonomy) can help address these

aspects. Study 4 (AI ethics) investigates how ethical design features (transparency, fairness, privacy, autonomy) function as cognitive scaffolds that restore system diagnosticity, enabling users to evaluate algorithmic quality through comprehensible design signals instead of opaque black-box outputs.

Based on these gaps, the dissertation proposes a hierarchical model of consumer information processing, explaining the transformation from physiological input to social cognition and system-level trust:

Sensory layer (Study 1): Examines how information is prioritized physiologically for acquisition (brightness → temporal reallocation of cognitive resources).

Cultural layer (Study 2): Examines how perceived value and sensory information are interpreted socially (color → cultural concern).

Contextual layer (Study 3): Examines the dynamic interaction of consumers' evaluation within digital platforms (AI-driven platform experience → privacy value).

Systematic layer (Study 4): Examines how trust is systematically reconstructed (AI ethical design → cognitive scaffolding).

1.2.2 Research questions

Based on these gaps, the overarching research question is:

In the hybrid marketing ecosystem, how do sensory physiological mechanisms, socio-cultural schemas, AI recommendation systems, and ethical designs interact to collectively constitute the cognitive mechanisms through which consumers alleviate perceptual, social, and systemic uncertainties?

This question is operationalized through four studies:

RQ1 (Study 1): How does wine label brightness modulate the temporal allocation of cognitive resources and the depth of visual information processing?

- RQ1a: Does brightness affect processing depth (mean fixation duration) independently of processing breadth (fixation count)?
- RQ1b: Does brightness trigger distinct temporal patterns of cognitive effort allocation, as revealed through pupillary response dynamics across early encoding, middle integration, and late evaluation stages?

RQ2 (Study 2): How do wine color configurations (hue $\times$ brightness $\times$ saturation) function as cultural schemas to influence consumer perceived value and mitigate social risk in Chinese gift-giving contexts?

- RQ2a: Do color effects arise from configurational interactions rather than additive main effects of individual attributes?
- RQ2b: How does face anxiety in Chinese gift-giving culture moderate consumers' reliance on color configurations as diagnostic cues?
- RQ2c: Do intermediate-knowledge consumers demonstrate higher reliance on color cues compared to novices and experts, and what psychological mechanisms explain this pattern?

RQ3 (Study 3): How do Douyin users experience AI-powered personalized recommendations, and how does personalization trigger concerns about privacy-value threats?

- RQ3a: What experiential factors drive user engagement with AI-powered recommendations on Douyin, and what tensions emerge between convenience and privacy concerns?
- RQ3b: How do users describe the threshold at which recommendation precision triggers privacy anxiety and defensive behaviors?
- RQ3c: What institutional trust mechanisms do users perceive as mitigating algorithmic opacity and uncertainty?

RQ4 (Study 4): How do AI ethical design features affect user acceptance through cognitive and affective pathways?

- RQ4a: Do ethical design features (transparency, fairness, privacy, autonomy) indirectly influence trust via a cognitive scaffolding effect?
- RQ4b: Do different ethical dimensions follow heterogeneous psychological processing paths?

1.3 Overview of literature review and theoretical frameworks

To support the logic above, this section reviews four core theoretical pillars that underpin this study: Information Richness and Adaptive Strategy Selection; Face Theory and Symbolic Consumption; the Stimulus-Organism-Response Model and Expectancy-Value Theory; and Dual-process Theory with Cognitive Scaffolding. These theories are interwoven to form an explanatory network for consumer behavior in hybrid marketing environments.

1.3.1 Physiological accessibility of sensory information: information richness and adaptive strategy selection (sensory layer)

At the base of hybrid marketing environments lies physical information input. Marketing studies often conflate salience, the probability that a stimulus will be seen, with accessibility, the ease with which that stimulus is encoded. Salience concerns low-level visual prominence, while accessibility concerns the fluency with which information enters cognitive systems. To clarify this distinction, this study draws on Information Richness Theory (IRT) and the Adaptive Strategy Selection Framework (ASSF).

Daft and Lengel (1983) proposed IRT in organizational communication, linking a medium's ability to transmit nonverbal cues to its effectiveness in reducing equivocality. This study extends IRT to consumer visual psychology within hybrid marketing. Under this view, brightness functions not only as an aesthetic property but also as a key moderator of information accessibility. Higher brightness increases extractable detail, raising objective information richness and lowering the threshold for decoding. As richer media reduce uncertainty, a high-brightness visual environment supplies more explicit cues and reduces perceptual uncertainty, increasing diagnosticity.

Payne et al.'s (1988, 1993) ASSF holds that decision makers are cognitive misers who trade off accuracy and effort given environmental constraints. Working memory limits force dynamic adjustments of decision strategy. Building on this, the study proposes that high-brightness, high-accessibility contexts induce a front-loading strategy: consumers exploit the low-cost extraction environment by investing substantial cognitive resources during the first few hundred milliseconds of exposure to form a rapid, stable cognitive representation and reduce downstream processing load. Low-brightness environments compel back-loading or compensatory strategies, producing inefficient cognitive expenditure. This intertemporal allocation explains why an object that is merely aesthetically pleasing (e.g., low-brightness mood design) may fail in high-diagnosticity e-commerce contexts, as it overlooks processing intensity dynamics.

1.3.2 Cultural configuration of value: face theory and symbolic consumption (cultural layer)

Once retinal input reaches the cortex, it becomes a cultural symbol, not just a physical signal. In China and other East Asian markets, face (*miànzi*) concerns offer a powerful account of risk-avoidance in consumption. In hybrid environments, the operation of face extends from offline interpersonal contexts into online symbolic display.

Hu's (1944) classical distinction "face" separates *liǎn* and *miànzi*. *Liǎn* refers to moral

integrity and social membership; its loss implies social death. Miànzi denotes external prestige accumulated through achievement, wealth, and relationships; it can be gained or spent. Yau (1988) adapted this concept to consumer behavior, arguing that consumption, especially gift-giving, is a performance of social competence. Consumers purchase not only functional value but also social safety. In gifting or public consumption, choosing the wrong product constitutes a face-threatening act and risks social harm (Qian et al., 2007).

Face anxiety creates a high-risk decision environment in hybrid marketing. This anxiety concerns more than personal preference; it concerns positional security within social networks. Integrating the Consumer Perceived Value (CPV) model (Zeithaml, 1988; Sheth et al., 1991), this study suggests that specific color configurations (e.g., dark red) evolve into high-diagnosticsity schemas in this culture (Arnould & Thompson, 2005). For intermediate wine-knowledge consumers, those aware of risk but lacking confident expertise, such color configurations provide a heuristic shortcut. Because dark red associates with steadiness, prestige, and historical depth, selecting products in this color minimizes the risk of losing face. This explains why, on digital shelves, some visual symbols retain decision weight that can surpass algorithmic recommendations.

1.3.3 Experience paradox under algorithmic contexts: Stimulus-Organism-Response (S-O-R) model and Expectancy Value Theory (EVT) (contextual layer)

This transition from packaging (Studies 1 & 2) to algorithms (Studies 3 & 4) represents a shift in the locus of agency, not a break in theoretical logic. We conceptualize this as a continuum from Passive Visual Systems to Active Algorithmic Systems.

In the physical context (Passive), the product is silent; the consumer must exert cognitive effort to “pull” diagnostic information from visual cues like brightness and color. In the digital context (Active), the AI system takes over the agency, actively

“pushing” decisions to the consumer. Consequently, the consumer’s diagnostic task evolves: they no longer just judge the product’s quality, but must now diagnose the system’s benevolence. Thus, the “privacy anxiety” in Study 3 is structurally equivalent to the “social risk” in Study 2; both are forms of uncertainty that require specific diagnostic cues to resolve.

Mehrabian and Russell’s (Mehrabian & Russell, 1974) S-O-R model is foundational for environmental psychology. It explains how physical atmospherics elicit organismic emotional states, such as pleasure, arousal, and dominance, that lead to approach or avoidance behavior. This study conceptualizes AI-powered personalized recommendations (AI-PPRs) as a novel environmental stimulus. Unlike traditional atmospherics, this stimulus has invisible, dynamic, and intentional properties. The organismic response includes not only pleasure or arousal but cognitive dissonance: a conflict between desire for convenience and concern about privacy invasion. Here, the organismic focus is cognitive states, for example, perceived value, privacy concern, and affective states, such as trust, anxiety, and their interaction.

Wigfield & Eccles’s (2000) EVT offers an economic perspective on user motivation: behavior depends on expected success and subjective task value. Applied to Douyin, EVT explains the algorithm’s double-edged effects. Precise recommendations lower search costs and raise utility value and enjoyment value. Excessive precision, however, can infer sensitive information and produce a negative privacy value. When privacy costs outweigh informational gains, users adopt defensive avoidance (Ding et al., 2025). This framing clarifies the essence of the trust deficit in hybrid environments: it is not purely affective but the result of users’ rational value computation.

1.3.4 Psychological mechanisms for trust reconstruction: dual-process theory and cognitive scaffolding (systematic layer)

Sensory optimization alone cannot resolve algorithm-induced trust crises. Deeper

psychological mechanisms are required to explain how ethical design exerts its effect.

Dual-process theory (Kahneman, 2011; Evans, 2003, 2008) distinguishes fast, intuitive System 1 and slow, deliberative System 2. System 1 relies on heuristics and is error-prone; System 2 performs analytic processing and consumes cognitive resources. Although the two systems are considered distinct and relatively independent, they may interact dynamically in real decision contexts.

Existing AI trust research often assumes a single pathway to trust. This study contests that view and posit that ethical design features (e.g., transparency statements) must first engage System 2 (algorithmic awareness and understanding) to enable System 1 affective trust. The proposal is a sequential mediation model: cognitive understanding precedes affective response. Only when users deploy System 2 to process ethical information and clear cognitive ambiguity can System 1 generate a sense of safety logically.

Inspired by Vygotsky's Zone of Proximal Development (Berk & Winsler, 1995), the scaffolding concept is introduced into the human-machine interaction field (Collins et al., 1989). AI ethical features (transparency, privacy, fairness, autonomy) function as cognitive scaffolds. Ordinary users often lack the capacity to comprehend black-box logic; ethical design does not aim to make users algorithm experts but to provide cognitive handles that bridge the gap from unknown to controllable. By rendering the black box more intelligible, ethical design restores system diagnosticity and converts fear into informed trust. This approach addresses the comfort-growth paradox and shifts human-machine interaction from passive acceptance to active collaboration.

1.3.5 Integration logic of the unified framework

The core argument of this model is: visual cues and algorithmic features are, in essence, diagnostic information signals. Consumers' evaluations of these signals follow common psychological principles but show adaptive variation across different layers of

contexts. This framework unifies the following research fields that appear independent: (see Table 1)

Table 1 Integrated uncertainty mitigation across different layers

Research level	Type of uncertainty	Diagnostic cues	Function	Mitigation mechanism	Support Study
Sensory layer	Perceptual ambiguity	Brightness	Modulates processing depth of hue/saturation	Front-loading of cognitive resources	Study 1
Cultural layer	Social risk	Color configuration	Activates high-value cultural schema	Social shield for intermediate consumers	Study 2
Contextual layer	Algorithmic opacity	AI recommendation precision	Over-precision reduces diagnosticity	Privacy value threshold awareness	Study 3
Systemic layer	Trust/agency deficit	Ethical design features	Restores system diagnosticity via transparency	Cognitive scaffolding: understanding → trust	Study 4

1.4 Overview of research methods

This section outlines the four core studies that comprise this dissertation. The four studies follow a strict, progressive mixed-methods design, using eye-tracking, surveys, qualitative interviews, and experimental methods to analyze mechanisms of uncertainty reduction in the hybrid marketing environment.

1.4.1 Overall design logic

This dissertation is rooted in pragmatist epistemology and acknowledges the plurality and complexity of social reality, which require complementary methods (Creswell & Plano Clark, 2018). The four studies follow the logical sequence: mechanism identification → cultural validation → contextual exploration → causal confirmation.

1.4.2 Study 1: Physiological basis of information accessibility: brightness as moderator of processing depth

Objective: This study addresses perceptual uncertainty. It investigates physiological mechanisms of visual attention, especially how brightness functions as a primary variable determining information accessibility and processing intensity.

Research question: In visual information streams, how does brightness influence the temporal allocation of cognitive resources? Is it merely increasing visibility, or does it change when and how intensely we process information?

Methodology: Within-subjects design (N = 32), combining eye-tracking and high-resolution time-resolved pupillometry. Physiological measures capture temporal processing dynamics that questionnaires cannot.

Stimuli: 256 wine labels systematically varied in hue, saturation, and brightness, simulating high-diagnosticity visual presentations. Each participant views 16 trials.

Eye-tracking metrics:

- Mean Fixation Duration is an indicator of processing intensity. More prolonged fixation intensified encoding of a single piece of information.
- Fixation Count is an indicator of search breadth or sampling frequency.

Pupillometry: Analyze pupil diameter change rates across three time windows after stimulus onset (early 200-500 ms, middle 500-1000 ms, late 1000-2500 ms) as a continuous physiological index of cognitive effort.

Core findings: Data support the idea that brightness fundamentally restructures the temporal process and the intensity of cognitive processing as opposed to search breadth.

- Depth prevails over breadth: high brightness significantly increased mean fixation duration (+14.8 ms, about +4.6 %), with no significant difference in fixation count. This shows that brightness does not make a label more likely to be discovered

(salience) but does make it more efficiently processed when fixated. It shifts consumers from rapid scanning to intensified encoding.

- Front-loading: pupil data show significant attenuated constriction (larger relative pupil size) in early- and middle-window dilation under high brightness, indicating that cognitive resources are front-loaded, with intensified encoding within the first second. This strategy is adaptive because high brightness provides a high signal-to-noise ratio, making early investment in resources worthwhile.
- The cost of compensatory processing: low brightness induced greater late-window pupil dilation, reflecting sustained cognitive effort to integrate less accessible visual cues. This back-loading strategy is compensatory and prone to decision fatigue.

Conclusion: High brightness, as an accessibility modulator, lowers the threshold of information extraction and front-loads cognitive effort. In hybrid marketing environments, especially on small mobile screens, high-brightness design is key to ensuring information is intensively encoded early in the viewing stream.

1.4.3 Study 2: Cultural configuration of value: color and face

Objective: After establishing the physiological mechanism of brightness, Study 2 extends the analysis to social interpretation. Brightness determines accessibility, but color determines social appropriateness. This study investigates how color configurations combine into culturally specific value signals and social shields in the Chinese market, and how this process is moderated by face culture.

Methodology: Mixed methods with triangulation to enhance validity:

- Quantitative experiment (N = 435): 4 (hue: red/blue/green/yellow) × 2 (saturation: high/low) × 2 (brightness: high/low) between-subjects full factorial design. Participants rated CPV dimensions (quality, emotional, social, sensory) and purchase intention, yielding 1,740 observations.
- Qualitative interviews (N = 30): stratified by wine knowledge level (novice,

intermediate, advanced, expert) to probe social learning of color schemas.

Core findings:

- The hegemony of dark red: Robust hue $\times$ brightness interaction. Low-brightness red (dark red) outperformed all other combinations on quality, emotional, social perception, and purchase intention. High-brightness red lost this advantage compared to the others. Hue alone is insufficient as a diagnostic cue; it must pair with low brightness to activate high-value cultural schemas.
- Intermediate consumers and the knowledge-skill gap: Qualitative data reveal that intermediate consumers rely most on color cues. Novices are often uninformed or rely on other attributes. Experts have intrinsic cue knowledge and can ignore packaging. Intermediates know enough to fear social risk but lack sensory confidence, so dark red becomes their safest social shield.
- Cross-domain analogies: Users' interpretations of color derive from everyday experience transfer, not formal wine education. For example, associations with dark red fruits or premium dark beverage packaging transfer to wine perception. This cross-domain learning explains the persistence of the preference.

Conclusion: Color configuration in the Chinese market is more than an aesthetic choice; it is cultural currency that reduces social uncertainty (face loss risk).

1.4.4 Study 3: Phenomenon under algorithmic contexts: engagement drivers and privacy anxiety

Objective: Moving from static labels to dynamic platforms, Study 3 examines user experience on Douyin. As a phenomenon-level study, it reveals the core contradiction in hybrid marketing: the trade-off between push-based convenience and privacy invasion, establishing the practical necessity for subsequent ethical research.

Methodology: In-depth phenomenological interviews with 36 active Douyin users, coded deductively. The study deconstructs micro-experiences of user-algorithm

interaction, focusing on content presentation, recommendation timing, and social influence.

Core findings:

- The double-edged push mechanism: Douyin's push seamlessly integrates product discovery into entertainment, significantly lowering search costs, aligning with EVT's utility maximization. Users need not search; content auto-matches preferences.
- Privacy value: The critical tension identified. Users want precise recommendations (high diagnosticity), but excessive precision (for example, inferring undisclosed sexual orientation or secret preferences) becomes a threat. This "being spied on" feeling creates negative privacy value, triggering defensive avoidance behaviors, such as choosing "not interested" to confuse the algorithm.
- Recommendation timing: A holiday-period push recommendation may elicit negative sentiment, as consumers are more inclined to savor the in-person holiday shopping ambiance.
- Trust stratification and payment stickiness: Payment innovations such as Douyin Monthly Payment serve as institutional trust mechanisms, increasing platform stickiness by reducing transactional financial uncertainty.
- Fragility of KOL trust: Users distinguish between "content experts" and "sales machines"; trust in overly commercialized KOLs declines. Social influence diagnosticity weakens, pushing users to seek other trust anchors, such as platform ethical mechanisms.

Conclusion: This study establishes the core phenomenon of "trust deficit." In the face of algorithmic opacity, visual appeal (Studies 1 & 2) is fragile. Without addressing perceived manipulation and privacy anxiety, user relationships cannot persist. This provides a direct logical entry for Study 4 on AI ethical design.

1.4.5 Study 4: Causal mechanisms: ethical design and cognitive scaffolding

Objective: Responding to the trust crisis revealed in Study 3, this study uses an experimental design to test the effectiveness of AI ethical design as a solution and to validate the dual-process psychological mechanism. The study asks: if we open the algorithmic black box, will users look, and after looking, will they trust?

Methodology: Between-subjects design (N = 278), comparing high-ethics and low-ethics AI recommendation interfaces. Samples include participants from China, Italy, South Korea, and the United States to enhance cross-cultural generalizability.

Stimulus: High Ethical Design: clear data-use indicators, explanations of recommendation logic, and prominent user control options. On the contrary, Low Ethical Design: hidden recommendation logic, scarcity urgency cues (countdowns), and lack of data control.

Measurement model: Sequential Mediation Model: Design → Algorithmic awareness (cognitive) → Affective trust (affective) → Usage intention.

Core findings:

- Dominance of sequential mediation: Statistical results strongly support the dual-process sequential integration. All 16 tested sequential mediation paths (design → awareness → affect → intention) reached significance. Simple affective mediation was non-significant. This implies users cannot directly trust an AI system they do not understand. Understanding is a necessary route to trust.
- Cognitive scaffolding effect: Transparency functions as cognitive scaffolding. It first activates users' algorithmic awareness (System 2), dispels black-box doubts, and this epistemic clarity converts into affective security (System 1 trust).
- Dimensional heterogeneity: Different ethical dimensions operate via distinct psychological paths. Privacy: highly dependent on cognitive processing. Users must cognitively comprehend privacy policies before feeling secure affectively;

Autonomy: triggers immediate instinctive response. Its direct pathway to reduced reactance has the highest coefficient. Seeing a control option, even without clicking, can instantly reduce psychological resistance, reflecting an instinctive desire for control.

Conclusion: Ethical design is not mere compliance; it is an integral system function. By converting the algorithmic black box into a transparent, controllable glass box, ethical design restores system diagnosticity. It transforms Study 3's "being spied on" anxiety into "understanding-enabled control" confidence.

1.5 Theoretical integration and contributions

1.5.1 Theoretical contributions

Contribution 1: Constructing the consumer information diagnosticity framework (CIDF) across the physical-digital domains

This research advances marketing theory by synthesizing findings across sensory and algorithmic domains to propose the Consumer Information Diagnosticity Framework (CIDF). Unlike prior fragmented approaches that segregate sensory marketing from human-computer interaction, the CIDF integrates physiological accessibility (Layer 1), cultural schema activation (Layer 2), contextual privacy evaluation (Layer 3), and systemic cognitive scaffolding (Layer 4) into a single hierarchical model. This framework demonstrates that physical visual cues (e.g., label brightness) and digital algorithmic features (e.g., ethical transparency) function as homologous diagnostic signals: both serve the fundamental purpose of reducing decision uncertainty. This framework provides the theoretical bridge requested to link passive product interactions with active algorithmic mediations.

Contribution 2: Extending the dimension of "salience": from visual to ethical

This research expands the conceptual evolution of "salience" by proposing

multidimensional salience. Visual Salience: It renders information physically accessible, serving as the starting point for all interactions; Cultural Salience: It makes the product “readable” within social norms, endowing it with social significance; and Epistemic Salience: It makes the system’s “logic” visible, bringing hidden rules to the surface to serve as the basis for user decision-making.

Contribution 3: Revealing configurational causal mechanisms in color perception

Study 2 demonstrates that color effects in consumer perception arise from specific combinations of hue $\times$ brightness $\times$ saturation, as opposed to additive main effects of single attributes. This extends the mainstream paradigm of main-effect analysis in consumer research literature, which typically examines hue effects in isolation. By introducing a configurational perspective grounded in complexity theory, this reveals that color diagnosticity is inherently combinatorial, that the same hue carries different diagnostic value depending on its brightness and saturation configuration.

Contribution 4: Extending the sequential mediation mechanism of dual-process theory

Study 4 finds that ethical design features cannot directly activate affective trust; instead, they must first engage algorithmic awareness before affective responses emerge. All 16 tested sequential mediation paths were statistically significant, with moderate effect sizes, while the direct affective paths remained non-significant. This finding extends the independence of System 1 and System 2 in dual-process theory by demonstrating temporal sequence dependence: understanding precedes feeling. Furthermore, the research reveals dimensional heterogeneity: Privacy operates through a heavily cognitive-dependent path, requiring detailed comprehension before security feelings emerge; Autonomy triggers immediate instinctive responses, where merely seeing a control option instantly reduces psychological reactance without requiring cognitive elaboration. This heterogeneity suggests that different ethical dimensions engage different processing routes, necessitating differentiated design strategies.

Contribution 5: Integrating cultural psychology and information processing theory

Study 2, by introducing “face theory,” demonstrates how cultural schemas moderate consumers’ reliance on diagnostic cues. The diagnostic value of dark red in Chinese gift-giving contexts originates from its function as a “face” protection mechanism that reduces social uncertainty. In Study 3, this anxiety extends into the digital space: users fear that algorithmic recommendations may expose their “backstage” identities (e.g., sexual orientation, peculiar predilection) in public settings, which is essentially a form of “digital face threat.” Therefore, the “autonomy” function in Study 4 carries a “digital face” protection role. By providing privacy control and preference adjustment functions, it protects users’ dignity and social safety in algorithmic interactions.

1.5.2 Practical contributions

Contribution 1: Packaging design optimization strategies

Study 1, through eye-tracking and pupil data, provides design principles based on physiological evidence: high-diagnostic products that carry complex information should adopt high-brightness designs; products that rely on aesthetic appeal may use low-brightness designs to encourage prolonged, compensatory processing, though this risks fatigue.

Contribution 2: Color configuration guidelines for the Chinese market

Study 2 demonstrates that low-brightness red holds the highest perceived value in Chinese gift-giving contexts. Intermediate consumers, as the group most dependent on color cues, constitute the core target segment of the gift-wine market.

Contribution 3: User-experience optimization for AI recommendation systems

Study 3 identifies three major challenges: the contextual sensitivity of push timing, privacy-value thresholds (to avoid revealing hidden identities), and payment innovation as a trust-enhancing tool.

Contribution 4: Priority framework for AI ethical design

The path analysis in Study 4 reveals that privacy protection requires detailed interactive explanations; autonomy requires surface-level visible control buttons; transparency requires explanations of algorithmic logic. This differentiated framework helps product teams determine priorities.

1.6 Research scope and boundaries

Domain boundaries: This research focuses on consumer goods and digital platforms (AI recommendations) and does not extend to service or B2B contexts.

Theoretical boundaries: It concentrates on information diagnosticity and uncertainty reduction and does not examine all uncertainty-reduction paths (such as social influence from a sociological perspective).

Methodological boundaries: First, the physical domain studies (Studies 1 & 2) and digital domain studies (Studies 3 & 4) were conducted with separate samples; this dissertation does not include a within-subject comparison that directly tests whether the same individuals apply identical diagnostic principles across both domains. The parallel structure is conceptually and theoretically matched. Second, all four studies employ cross-sectional designs and do not track longitudinal changes in trust formation or diagnostic strategy adaptation over time. The dynamic evolution of consumer-algorithm relationships, for example, how initial diagnostic strategies may shift with accumulated platform experience, remains beyond the current scope. Third, while Study 4 includes cross-cultural samples (China, Italy, South Korea, USA), the primary theoretical development draws heavily from Chinese consumer contexts (Studies 1, 2, and 3). The generalizability of face-related cultural moderation effects to Western gift-giving contexts requires future investigation.

Contextual boundaries: Studies 1 and 2 were conducted in mainland China; Study 3 focuses on the Chinese version of TikTok; Study 4 covers four countries but is limited to online experiments.

Cultural boundaries: Study 2 introduces Face Theory as a cultural moderator in the Chinese context but does not systematically compare differences between China and Western contexts.

1.7 Conclusion

In summary, this research demonstrates that, in hybrid marketing environments, whether through millisecond-level pupil dilation or complex algorithmic interactions, consumers consistently seek to diagnose value beyond surface cues. Although sensory cues initiate attention, only the cognitive scaffolding constructed through ethical design can sustain long-term trust in AI-mediated hybrid environments. The transition from the algorithmic “black box” to the ethical “glass box” is not only a moral imperative but also a functional necessity for reducing uncertainty and achieving commercial effectiveness. This provides a solid theoretical foundation and empirical guidance for future marketing practices aimed at building high-diagnostics and high-ethics digital ecosystems.

Chapter 2 Contextual Background

The hybrid marketing environment has fundamentally reshaped the landscape of consumer behavior research over the past decade (Kotler et al., 2017). This chapter provides the empirical contextual background for four empirical studies, including visual processing, color configuration, AI recommendation, and ethical design. Based on this, the present research adopts an integrated perspective. The visual cues consumers encounter at offline shelves and the algorithmic cues they encounter in online AI recommendation systems are, in essence, informational signals that require diagnostic evaluation. In other words, in the contemporary hybrid marketing environment, the consumer decision journey overlaps between physical touchpoints and the multiple digital touchpoints of different channels.

2.1 The evolution of the hybrid marketing environment: from omni-channel integration to algorithmic mediation

2.1.1 Structural transformation of retail formats: seamless integration between physical and digital

Verhoef et al. (2015) pointed out that the rise of digital channels has fundamentally changed the retail business model. The key transformation is the evolution from “multi-channel” to “omni-channel.” The multi-channel model assumes boundaries between channels (Neslin et al., 2006). In contrast, omni-channel retail represents a paradigm shift in which the distinction between physical and online gradually disappears, making the world become a “showroom without walls” (Brynjolfsson et al., 2013). However, in the present research, omni-channel does not refer solely to the integration of logistics or inventory; it also encompasses the hybridization of sensory environments. As Grewal et al. (2017) argued, when envisioning the future of retail, modern consumers in fact

inhabit a “hyper-connected” space composed jointly of physical cues and digital augmentations. This dissolution of boundaries between physical and digital provides the empirical foundation for the “hybrid marketing environment” examined in this research: consumers no longer distinguish between online and offline and instead process a continuous stream of information.

2.1.2 The algorithmic turn of marketing logic: from “digitization” to “AI mediation”

With the maturation of big data and machine learning technologies, the hybrid marketing environment is undergoing a second leap: from basic digitization to deep algorithmic mediation.

De Bruyn et al. (2020) pointed out that AI is no longer merely an analytical tool but has become an autonomous agent in the marketplace. Traditional omni-channel retail relied primarily on consumer-initiated search (the pull strategy), whereas in the algorithmic era, platforms actively push products to consumers through predictive models (the push strategy) (Ding et al., 2025). This transformation reconstructs the relationship between consumers and the information environment. Transfer of decision authority: consumers gradually “outsource” the cognitive tasks of filtering, comparing, and even deciding to algorithmic systems (Puntoni et al., 2021). Predictive personalization: The “four-stage AI service strategy model” proposed by Huang and Rust (2018) argues that marketing AI is evolving from analytical intelligence toward emotional and intuitive intelligence. These mean that the marketing environment not only provides product information but also attempts to understand and influence the consumer’s emotional states. This background explains why the present research shifts its focus from traditional advertising visuals to the dynamic recommendation streams of AI-powered platforms. In environments such as Douyin or TikTok, the algorithm is not only a channel but also an interlocutor with “intent,” continuously adjusting content distribution strategies in real time based on user browsing behavior (Liu et al., 2019).

2.1.3 The paradox of efficiency and autonomy: the trust crisis in the algorithmic era

Although algorithmic mediation brings unprecedented efficiency, it also generates profound human-AI tension, which forms the empirical background for the ethical perspective of the present research.

Academic discussions on this phenomenon focus primarily on the binary opposition between “algorithm aversion” and “algorithm appreciation” (Dietvorst et al., 2015; Logg et al., 2019). However, in the marketing context, this tension manifests in more complex ways. Puntoni et al. (2021) argued that while AI enhances functional experience, it often erodes the consumer’s existential experience: the consumer’s sense of autonomy and privacy boundaries are disrupted. When recommendation systems become overly precise, consumers experience surveillance anxiety (Ding et al., 2025). This condition of “simultaneous comfort and fear” provides the empirical basis for introducing dual-process theory in the present research. The current market environment requires a new design paradigm that preserves the efficiency of algorithms (the convenience of System 1) while restoring users’ sense of control through transparency and explainability (the rational engagement of System 2). Therefore, the “AI ethical design” proposed in this research is not only a technological issue but also an institutional response to the trust deficit of the contemporary marketing environment.

2.2 Structural characteristics of the empirical context:

China’s digital ecosystem

2.2.1 The “Super App” architecture and closed-loop consumption

China’s digital marketing ecosystem offers a unique structural context distinct from Western markets, characterized by the dominance of “Super Apps” (e.g., WeChat).

Unlike fragmented Western ecosystems where consumers switch between social media, search engines, and independent e-commerce sites, the Chinese model integrates content, socialization, and transaction into a single “closed-loop” architecture. This structural integration has profound behavioral implications. The seamless transition from social interaction to purchase within a single platform significantly lowers the cognitive threshold for impulse buying. Underpinning this ecosystem is the phenomenon of “Swift Guanxi” (Chong et al., 2018), a digital adaptation of traditional interpersonal connections. In the absence of physical proximity, digital consumers rely heavily on mediated cues to establish rapid trust. Guo et al. (2021) demonstrated that in live-streaming contexts, swift guanxi mediates the link between trust and engagement. This unique trust formation mechanism is critical to this research. It suggests that in China’s high-velocity digital environment, visual signals (such as brightness and color explored in Study 1 & Study 2) act not merely as aesthetic properties, but as highly diagnostic surrogates for interpersonal trust, compensating for the lack of physical interaction.

2.2.2 The paradigm of “Interest E-commerce”: from search to algorithmic push

Douyin (the Chinese counterpart to TikTok) represents the evolution of this ecosystem into “Interest E-commerce” (Interest-based commerce). Unlike traditional e-commerce (e.g., Amazon or Taobao), which relies on a “Search” model driven by explicit user intent, Douyin employs a “Push” model driven by algorithmic prediction. In this environment, the algorithm proactively curates and feeds content to users, creating a distinct informational environment where an active algorithmic system precedes passive visual decision-making. Academic research has begun to dissect this shift. Xiao et al. (2019) found that, in short-video environments, users’ perceived usefulness, playfulness, and influencers’ involvement positively influence consumers’ purchase intentions. Similarly, Yin et al. (2024) found that short video engages users by

instigating a desire for postponing closure, which mitigates defensive evaluations of advertising and promotes potential demands. These findings provide the empirical grounding for this thesis. The “Push” mechanism reduces search costs but simultaneously creates new psychological tensions between convenience and privacy. This tension is the central focus of Study 3, which investigates the paradox of algorithmic personalization.

2.2.3 A natural experiment in algorithm governance

Beyond commercial architecture, China provides a unique regulatory context for studying AI ethics. As one of the world’s first jurisdictions to implement comprehensive algorithm regulation, China’s “Provisions on the Management of Algorithmic Recommendations in Internet Information Services”¹ (effective March 1st, 2022) explicitly addresses issues of user autonomy and ethical transparency. Unlike the self-regulatory approach often seen in other markets, this framework legally mandates that platforms provide options to “turn off” recommendations and prohibits addiction-inducing algorithms (Xu, 2024; Zou & Zhang, 2025). This creates a high-awareness environment in which consumers are increasingly conscious of their interactions with AI systems. This distinct regulatory landscape serves as a natural experimental setting for Study 4. By comparing consumer reactions to AI ethics design in this highly regulated environment versus other contexts, this research can isolate the impact of regulatory protection on consumer trust, offering insights into how external institutional frameworks interact with internal psychological mechanisms (System 2 processing) to shape acceptance of AI.

¹ “Provisions on the Management of Algorithmic Recommendations in Internet Information Services” (2022), Cyberspace Administration of China, State Internet Information Office, Ministry of Industry and Information Technology of the People’s Republic of China, Ministry of Public Security of the People’s Republic of China, State Administration for Market Regulation, Order No. 9. https://www.chinalawtranslate.com/en/algorithms/?__cf_chl_tk=qNU47esmSsFz6r6fvSL1Wpc042JvI_mnag_boSRqTRw-1764171434-1.0.1.1-N.mtpG_RQk2dJ5s9luV3LY9dwJUtk2RvmNzUa6R1zxQ#gsc.tab=0; Original Chinese Website: https://www.cac.gov.cn/2022-01/04/c_1642894606364259.htm

2.3 Theoretical traditions in algorithmic recommendation research

2.3.1 Rational adoption paradigm: the information systems tradition and its limitations

In the early stages of algorithmic recommendation research, the Technology Acceptance Model (TAM) and its extensions in the information systems field, such as UTAUT and UTAUT2, dominated the literature (Davis, 1989; Venkatesh et al., 2003, 2012). The central logic of this tradition is rational calculation. Users are viewed as rational decision-makers who adopt a technology based on perceived usefulness and perceived ease of use. The application of this paradigm to contemporary hybrid marketing environments faces several challenges. First, the TAM and UTAUT traditions originated from instrumental technologies in workplace settings and assume that technology functions as a passive tool. In the Douyin and TikTok environments examined by the present research, the algorithm operates as an active agent. Users often receive content passively instead of adopting technology actively. More importantly, the TAM framework has limited capacity to explain psychological processes that do not follow rational logic. For example, users may be aware that the algorithm violates privacy, which signals low usefulness, yet they remain unable to stop watching videos due to strong addictive tendencies. For these reasons, Study 3 does not rely on the rational adoption perspective and instead uses the S-O-R framework to capture emotional reactions to environmental stimuli.

2.3.2 Interaction and explanation paradigm: the human-computer interaction (HCI) tradition

In contrast to the information systems focus on adoption, the HCI tradition concentrates

on user experience and transparency. The central concern of this tradition is resolving algorithmic opacity, often referred to as the black-box problem. Liao et al. (2020) argued that accuracy alone is insufficient to establish trust and that explainability must be provided. The 18 design guidelines proposed by Amershi et al. (2019) emphasize the importance of user control. This tradition provides important design variables for the present research, such as transparency and explanation mechanisms. Chen et al. (2024) demonstrated that post-hoc explanations can enhance trust. Study 4 builds on these insights but further extends them. HCI studies often focus on interface design itself, while the present research focuses on the psychological mechanisms behind design features. The concept of cognitive scaffolding proposed in this research aims to explain how ethical design features rebuild trust by reducing cognitive load.

2.3.3 Manipulation and persuasion paradigm: the marketing communication tradition

Marketing perspectives on algorithms focus on their persuasive capacity. Fogg (2003) established the research domain of persuasive technology. In the algorithmic era, this line of work has evolved into attention to dark patterns. Gray et al. (2018) and Mathur et al. (2019) documented how applications use interface interference and forced actions to manipulate user behavior. The concept of hyper-relevance proposed by Darmody and Zwick (2020) is particularly important. It argues that marketers attempt to mask manipulation with extreme precision. This viewpoint forms the central tension in Study 3, namely the privacy-convenience paradox. When recommendations become extremely precise, they trigger defensive responses from users. By incorporating EVT, the present study provides a quantitative economic-psychological explanation for this phenomenon.

2.3.4 Theoretical choices of the present research

TAM is suitable for instrumental adoption contexts that involve decisions such as whether to use a software tool at work. The present research investigates experiential consumption, specifically users' psychological states while watching short videos. The S-O-R framework captures the dynamic process in which environmental stimuli generated by algorithms or visual cues influence psychological states such as anxiety or pleasure, which in turn shape avoidance or immersion behaviors. This aligns with the analytical needs of Study 3.

Table 2 Comparison of theoretical paradigms and present research positioning

Paradigm	Key theories	Focus	Limitations for this context	How present research differs
Information systems	TAM, UTAUT, UTAUT2	Rational adoption, Utility	Assumes technology is a passive tool; ignores emotional complexity	Views AI as an active agent and emphasizes ongoing experience
HCI	XAI	Transparency, Interface	Often emphasizes design features over psychological mechanisms	Focuses on cognitive scaffolding
Persuasion/Marketing	Dark patterns	Influence, Manipulation	Often emphasizes the negative or manipulative aspects	Use EVT to evaluate the trade-off between convenience and privacy
Present research	S-O-R model, EVT, Dual-processing	Psychological mechanism	High theoretical complexity; sacrifices parsimony for explanatory depth in specific contexts.	Combines visual, algorithmic, and ethical elements

EVT addresses the privacy value. TAM has difficulty explaining why users continue to use algorithmic services while expressing privacy concerns. EVT offers a trade-off

perspective. Users evaluate the benefits generated by accurate recommendations and the costs created by privacy risks. This interpretation is consistent with the findings of Study 3.

Dual-process theory explains the mechanism through which ethical design becomes effective. Existing information systems studies often assume a single trust pathway. The present research finds that ethical design must first activate slow cognitive processing in System 2 to generate understanding before it can unlock rapid emotional trust in System 1. TAM and UTAUT cannot capture this sequential mediation mechanism.

Table 2 provides a comparative overview of these dominant theoretical paradigms, juxtaposing their primary focuses and limitations with the distinct psychological approach adopted in this thesis.

2.4 The crisis of trust: ethical challenges and psychological tensions

2.4.1 The “Black Box” problem: opacity, bias, and loss of agency

The rapid proliferation of algorithmic systems has outpaced the development of ethical governance, leading to what scholars describe as a “crisis of trust” (Liao et al., 2020). This crisis is structurally rooted in the “Black Box” nature of modern AI. First, the inherent opacity of deep learning models creates an explainability gap. While explainable Artificial Intelligence (XAI) scholars strive for technical transparency (Arrieta et al., 2020), they suggest a disconnect between technical explainability and human understanding (Fazi, 2021). Second, this opacity often masks systemic bias. As highlighted by Noble’s (2018) concept of Algorithms of Oppression and Eubanks’ (2019) Digital Poorhouse, algorithms can perpetuate historical inequalities. However, unlike the sociological critique that calls for policy intervention, Study 4 adopts a psychological lens: focusing on how the perception of fairness acts as a prerequisite for consumer trust. Third, the “Black Box” erodes human agency. Nokhiz and

Ruwanpathirana (2025) argue that algorithms narrow choice spaces through path dependence. This suggests that the core of the trust deficit is not just about error, but about the loss of autonomy. This theoretical backdrop necessitates the examination of “autonomy-supportive designs” in Study 4.

2.4.2 The privacy value: from rational calculation to contextual integrity

In the domain of privacy, the traditional “Privacy Calculus” model, which assumes a rational trade-off between risk and benefit (Dinev & Hart, 2006), is increasingly challenged by the complexity of hybrid environments. Nissenbaum’s (2009) theory of Contextual Integrity offers a more robust explanatory framework for the current algorithmic era. It posits that privacy violation stems not from the act of data collection itself, but from the flow of information violating context-specific norms. This distinction is crucial for understanding the “Privacy Value” identified in Study 3. When Douyin’s algorithm infers sensitive attributes (e.g., sexual orientation) based on viewing behavior, it violates the contextual norm of an “entertainment platform,” triggering a defensive reaction even if the user technically consented to data collection.

2.4.3 The psychology of resistance: algorithm aversion vs. appreciation

The consumer response to these ethical challenges is not uniform. The literature presents a dichotomy between Algorithm Aversion (Dietvorst et al., 2015), which is a punitive reaction to algorithmic error, and Algorithm Appreciation (Logg et al., 2019), which is a preference for algorithmic advice in objective tasks. Recent scholarship suggests this response is highly context-dependent. Castelo et al. (2019) and Puntoni et al. (2021) highlight that aversion peaks in tasks requiring subjective taste or creating a sense of “identity threat” (e.g., “unique” medical conditions). This view supports the overarching logic of this thesis: consumers do not simply “reject” or “accept” AI. Instead, they navigate a complex landscape where visual cues (Study 1 & 2) engage

System 1, while ethical features (Study 4) appease System 2, collectively determining the final level of trust.

2.5 Research gaps and the positioning of the present research

Based on the above analysis and the overview of research gaps in the previous chapter, the review of the evolution of hybrid marketing environments, the characteristics of the Chinese digital ecosystem, the major traditions of algorithmic recommendation research, and the current state of algorithmic ethics research reveals five gaps. These gaps provide the foundation for the four studies in the present research.

Gap 1: Integration of physical cues and digital cues

Existing studies often treat sensory marketing, which examines physical cues such as product packaging, and algorithmic recommendation research, which examines digital cues on platforms, as separate domains. In hybrid marketing contexts, consumers process cues from both domains simultaneously. One theoretical contribution of the present research is proposing information diagnosticity as a unifying concept for physical and digital cues. Whether the cue is packaging brightness and color configuration or the ethical features of AI recommendations, each serves as a diagnostic signal that reduces decision uncertainty.

Gap 2: Physiological mechanisms of visual processing depth

Most research on packaging color design relies on self-reported measures and provides limited insight into the physiological processes that underlie visual processing. Study 1 of the present research uses eye tracking and pupillometry to uncover how brightness modulates the temporal reallocation of cognitive resources and processing intensity at the millisecond level.

Gap 3: Configurational nature of color effects

Mainstream color psychology studies often examine the main effects of single attributes, such as the hue effect, and overlook the configurational interactions among hue, brightness, and saturation. Study 2 of the present research demonstrates that color effects are configurational. Distinct perceptual value effects arise from different configuration conditions.

Gap 4: Privacy value in AI recommendation contexts

Existing privacy research often treats privacy concerns as a continuous variable and assumes a linear relationship between privacy cost and disclosure intention. Study 3 of the present research identifies a nonlinear threshold effect. Moderately accurate recommendations are welcomed, but when accuracy exceeds a threshold, such as inferring undisclosed sensitive identities, negative reactions intensify sharply.

Gap 5: Psychological mechanisms of AI ethical design

Most studies on AI ethics focus on normative principles, such as how systems should be designed, or on technical implementation issues, such as how transparency can be achieved. The psychological mechanisms through which ethical design affects consumer responses need to be applied. Study 4 of the present research uses a sequential mediation model to identify the psychological pathway from ethical design to usage intention and reveals heterogeneous pathways across different ethical dimensions.

Chapter 3 Methodology: A Progressive Mixed-Methods Framework

3.1 Philosophical foundations and epistemological positioning

The present research adopts pragmatist epistemology as its overarching philosophical foundation. This stance originates from the classical philosophical tradition of Dewey and James, and was later reinterpreted in contemporary scholarship by Rorty (1991). Pragmatist epistemology rejects binary ontological choices and does not insist on selecting between positions such as reality as an objective entity or reality as socially constructed. Instead, it emphasizes the primacy of the research question, where the choice of methodological tools is guided by the nature of the research question (Morgan, 2014).

In the context of the present research, the pragmatist stance recognizes the complementarity of causal inference and meaning interpretation. Studies 1, 2 (sub-study 1), and 4 use experiments to identify causal effects, such as whether brightness regulates visual processing (Study 1), whether color configuration affects perceived value (Study 2), and whether ethical design influences acceptance intention (Study 4). Studies 2 (sub-study 2) and 3 use phenomenological interviews to understand meaning construction processes, such as how consumers perceive red under low-brightness conditions evoke cultural consciousness, how consumers experience AI algorithmic recommendations, and why excessive accuracy evokes resistance. This quantitative-qualitative-quantitative progression across independent studies aligns with pragmatist principles of methodological pluralism.

3.2 Design logic

3.2.1 Conceptual integration: passive visual systems and active algorithmic systems

Traditional research places “shelf wine label design” within sensory marketing and “AI recommendations on Douyin” within digital marketing. These two domains use different theoretical vocabularies, measurement tools, and participant groups. As conceptualized in Section 1.3.3, this research operationalizes the distinction between Passive Visual Systems (Studies 1 & 2) and Active Algorithmic Systems (Studies 3 & 4). The methodological design reflects this theoretical continuum, transitioning from measuring physiological responses to passive cues towards analyzing psychological evaluations of active agents.

Physical product shelf display = Passive visual system

- Visual cues in retail environments or product packaging, such as brightness and color configuration, present products to consumers passively.
- Mechanism: salience enhancement and schema activation.
- Consumer role: actively scan the environment and assess the diagnostic value of visual cues.

AI platforms = Active algorithmic system

- Algorithms analyze data and actively push content to users.
- Mechanism: personalization and predictive modeling.
- Consumer role: passively receive recommendations and evaluate the algorithm’s intention and credibility.

The key to this unified framework is that both systems address information diagnosticity. Consumers must evaluate diagnosticity in both contexts, although the systems differ in their level of proactivity. This difference produces different types of uncertainty and various strategies for reducing such uncertainty.

3.2.2 Four-stage logic of methodological progression

Based on this conceptual framework, the four studies follow a progression from basic mechanisms to complex systems:

Stage 1 (Study 1): Objective measurement of physiological mechanisms

Research indicates that decision-making is often habitual and rapid, with visual fixations on packaging lasting merely milliseconds (Pieters & Warlop, 1999). This necessitates a reliance on high-salience sensory cues (passive visual system). To establish the theoretical foundation of “visual cues as diagnostic signals”, it is essential to understand how consumers process packaging or design signals over time. Self-report measures cannot capture pre-conscious processes. Eye-tracking and pupillometry are therefore used (N = 32, within-subject design to control individual differences and increase statistical power). Fixation duration reflects the intensity of information extraction, which is an unconscious process that cannot be recalled accurately through self-report (Rayner, 1998). Pupil dilation is a physiological indicator of cognitive load (Sirois & Brisson, 2014). Time-window analysis (early 200-500 ms, mid 500-1000 ms, late 1000-2500 ms) reveals temporal strategies of resource allocation. These results provide key evidence for the “front-loading vs. back-loading” hypothesis, demonstrating how brightness functions as an accessibility modulator.

Stage 2 (Study 2): Extending from single dimensions to configurational effects

Study 1 identified brightness as a physiological moderator. In real consumption contexts, however, color information appears in multi-dimensional configurations. A mixed design combining a large-scale experiment and qualitative interviews is therefore used (N = 435 for the experiment; N = 30 for interviews). A simple “hue main effect” design would overlook configurational interactions. In real settings, hue, saturation, and brightness always co-occur. A full-factorial design is the only rigorous method for testing the configuration hypothesis, such as “dark-red tones produce higher

perceived value than bright tones”. The experiment includes 16 cells with at least 26 participants per cell to ensure sufficient power for detecting interactions (Cohen, 1992). Quantitative data identify effects such as “dark-red tones increase perceived value”. They cannot explain why consumers with intermediate wine knowledge rely on color cues more strongly. Qualitative interviews using stratified sampling (novice, intermediate, advanced, expert) reveal the cultural mechanism of “face anxiety”.

Stage 3 (Study 3): Phenomenological exploration of cross-domain transfer

Studies 1 & 2 establish diagnosticity principles in the physical domain. Whether these principles transfer to the digital domain cannot be answered through deduction. A phenomenological approach is required. At this stage, the key variables in the digital domain are still unclear. Semi-structured interviews are used (N = 36, active Douyin users). The openness of qualitative inquiry allows phenomena to emerge. Following the principle of theoretical saturation (Guest et al., 2006), no new themes appeared after the 32nd interview; four additional interviews confirmed saturation. The S-O-R model helps distinguish stimulus (recommendation mechanism) and response (engagement or avoidance). EVT helps identify the construct of “privacy value”. This construct provides the theoretical motivation for Study 4.

Stage 4 (Study 4): Experimental validation of causal mechanisms

Study 3 identifies a trust crisis, but causal verification of solutions is still required. To estimate the causal effect of ethical design on user intentions, random assignment is necessary to control confounding variables with the goal of unpacking the mechanism by testing a dual-process path. Ethical features do not influence users directly. They influence intention only after users understand the algorithm cognitively and then respond affectively. The data do not meet normality assumptions. A bias-corrected percentile bootstrap method with 5,000 resamples is used. This non-parametric approach does not rely on distributional assumptions and provides robust estimates for sequential mediation effects. The results validate the “cognitive scaffolding” theory. Although this study does not conduct formal cross-cultural comparisons, sample

recruitment covers participants from China, Italy, Korea, and the United States. All sixteen sequential mediation paths are significant, while purely cognitive or purely emotional paths are only partially significant. These patterns confirm the existence of the cognitive scaffolding effect: users must first understand transparency or privacy awareness, then experience trust or resistance, and finally decide whether to adopt the system.

3.2.3 Rationale for methodological diversity across diagnostic layers

The selection of distinct methodologies for each study was not eclectic but strategically aligned with the specific nature of the uncertainty being investigated at each layer of the CIDF framework. Physiological methods (Eye-tracking/Pupillometry in Study 1) were mandated because the mechanism of processing intensity operates at a pre-cognitive, biological level (System 1) that self-reports cannot accurately capture. Conversely, the “social risk” examined in Study 2 is a culturally constructed phenomenon embedded in inter-subjective norms, necessitating a mixed-methods approach to uncover the “everyday learning” mechanisms that pure experimentation would miss. For Study 3, a phenomenological approach was selected because the “privacy-concern” is a subjective lived experience of the user feeling “spied on,” a nuance that variance-based quantitative models often obscure. Finally, Study 4 required an experimental causal-chain design to validate the cognitive scaffolding mechanism, effectively isolating the sequential path from ethical transparency to affective trust. Thus, the methodological progression from physiological measurement to causal experimentation mirrors the consumer’s own journey from sensory perception to systemic trust.

3.3 Logic of methodological triangulation

Beyond simply collecting diverse data, this research employs a rigorous triangulation

strategy to enhance validity. Following Denzin (1978), the research design employs not only data triangulation (e.g., combining physiological, behavioral, and self-reported data) but also methodological triangulation, integrating experimental and phenomenological approaches. This strategy operates on three converging levels.

3.3.1 Convergence across methods and domains

The first level of triangulation seeks to achieve convergence across different measurement modalities to minimize the measurement error inherent in any single method. For instance, the construct of “information accessibility” is verified through both unconscious physiological metrics (pupillometry and eye-tracking in Study 1) and behavioral choices (conjoint analysis in Study 2). The consistency between objective physiological resource allocation and subjective behavioral decision-making provides internal validity for the proposed sensory mechanisms. The second level extends this convergence across domains. The core theoretical construct of “diagnosticity” is examined in parallel across the physical (Study 2) and digital (Study 3) domains. In comparison, the specific cues differ; one manifested as visual configurations in physical gifting, and the other as algorithmic precision in digital recommendations. Yet the underlying principle remains the same: reduce uncertainty. This parallel evidence structure supports the cross-domain applicability of the unified framework.

3.3.2 Complementarity of evidence

In line with Greene et al. (1989), the mixed methods design also serves a complementary function, in which different methods reveal distinct facets of the same phenomenon. Objective mechanisms reinforced subjective mechanisms; for example, physiological data (Study 1) uncovered System 1’s intuitive processing, of which consumers are often unaware. Conversely, the interview data (Studies 2 & 3) reveal System 2’s conscious meaning-making processes. Together, they provide a holistic

view of decision-making that neither method could achieve in isolation. Micro-process worked in tandem with macro-pattern; for example, experimental designs capture decision-making in millisecond timeframes, explaining how processing occurs. Phenomenological interviews capture long-term usage patterns and explain the consequences of these processes over time. Control validity was counterbalanced with external validity; the laboratory and online experiments (Studies 1 & 4) prioritize internal validity through strict control of variables and sample parameters, while the qualitative fieldwork (Studies 2 & 3) prioritizes ecological validity within real-world digital platforms. Similarly, the lack of causal inference in the qualitative study is compensated for by the rigorous factorial designs of the experimental studies. This “replication logic” (Yin, 2018) enhances the external validity of the overarching framework.

3.4 Summary

This chapter has outlined the methodological architecture of the thesis, characterizing it as a multiphase explanatory sequential design rooted in a pragmatist philosophy. By integrating physiological, behavioral, and phenomenological data through a rigorous triangulation protocol, the research design addresses the complexity of hybrid marketing environments. The subsequent chapters (Chapters 4-7) present the specific empirical studies executed within this framework.

Chapter 4 The Sensory Mechanism: Visual Accessibility and Cognitive Resource Allocation (Study 1)

Publication status:

This chapter is based on the article: “Brightness and temporal reallocation in wine label processing: An eye-tracking and pupillometry study,” which is accepted at the *British Food Journal*.

Author contribution:

The candidate contributed to: conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing-original draft, and visualization; Author Guojie Ma: conceptualization, methodology, software, validation, resources, and writing-review & editing; Author Gianluca Antonucci: conceptualization, methodology, writing-review & editing, supervision, and project administration; Author Michelina Venditti: conceptualization, methodology, writing-review & editing, supervision, and project administration.

Contextual link to the dissertation

As outlined in the general introduction (Chapter 1) and methodology (Chapter 3), this research investigates consumer decision-making in hybrid marketing environments through a multi-layered framework of information diagnosticity. While the ultimate goal is to understand trust in complex algorithmic systems, the investigation must follow a logical progression from micro-level mechanisms to macro-level systems.

Chapter 4 represents the foundational sensory layer of this framework. Before

consumers can interpret cultural symbols (Chapter 5) or evaluate algorithmic intentions (Chapters 6 & 7), they must first physically perceive and encode visual information. This research, titled “The sensory mechanism: visual accessibility and cognitive resource allocation,” investigates visual accessibility as the physiological antecedent to trust. Using eye-tracking and pupillometry, it tests the biological basis of the adaptive strategy selection framework. The findings presented in this chapter establish that high-brightness environments facilitate a “front-loading” of cognitive resources, allowing consumers to extract diagnostic information rapidly. Study 1 provides the baseline for the present research. It demonstrates that diagnosticity is not just a psychological construct but triggers an unconscious physiological response (pupil dilation) aimed at reducing entropy. By validating the mechanism of sensory optimization here, this chapter lays the empirical groundwork for the subsequent chapter (Chapter 5), which will examine how these optimized sensory inputs are further processed through a cultural lens to form social judgments.

4.1 Abstract

We examine whether wine label brightness modulates processing intensity and the temporal allocation of cognitive effort, drawing on principles from Information Richness Theory and the Adaptive Strategy Selection Framework. In a within-subjects task, thirty-two participants viewed 16 labels varying in brightness, hue, and saturation. Eye-movements indexed orienting and sustained attention allocation; time-resolved pupillometry (200-2500 ms) tracked cognitive effort dynamics across early, middle, and late processing stages. Higher brightness lengthened fixation duration (+14.8 ms), revealing intensified processing of attended targets without altering sampling frequency. Pupillometry demonstrated adaptive temporal reallocation: high brightness front-loaded cognitive resources (allocated earlier in processing), enabling intensive early encoding that reduced late-stage compensatory demands; low brightness back-loaded resources (sustained in later stages), reflecting compensatory processing during later evaluation. This temporal reversal pattern varied in magnitude across hues in exploratory analyses. This study provides evidence distinguishing salience-related capture from processing intensity mechanisms in packaging design. By demonstrating that brightness reconfigures when cognitive effort is invested rather than merely attracting attention, we reframe wine packaging design from visibility enhancement to information processing facilitation.

4.2 Introduction

Consumers cannot taste wine before purchase, relying on packaging as the primary information source (Chamorro *et al.*, 2020; Lick *et al.*, 2017). Digital retail intensifies this reliance by further constraining available cues to visual information alone. Colour, brightness, and typography on wine labels therefore become critical determinants of perceived quality, brand impressions, and purchase decisions (Anagnostou *et al.*, 2025;

Spence, 2020). Among these design elements, colour and brightness function as essential dimensions that guide consumer responses (Sunaga *et al.*, 2016; Tijssen *et al.*, 2017). Despite evidence of brightness effects, underlying cognitive mechanisms remain inadequately characterised.

Visual marketing literature frequently combines three separate constructs: (1) salience refers to the probability of capturing bottom-up attention via low-level feature contrast (Itti and Koch, 2000). (2) Accessibility denotes the efficiency with which information can be extracted and encoded once attention is allocated (Feldman and Lynch, 1988). And (3) diagnosticity concerns the extent to which extracted information reduces decision uncertainty. Packaging research often conflates attentional capture with post-selection processing efficiency and cue usefulness, blurring the lines between these separate processing stages. Although salience, accessibility, and diagnosticity are analytically distinct, the present study focuses on post-selection processing efficiency during visual encoding and does not assess diagnosticity, which concerns the decision relevance of extracted information. Existing research treats brightness predominantly as a salience enhancer. This limits understanding of when visual manipulations may influence processing strategies versus merely redirecting attention (Orquin and Mueller Loose, 2013). Consumers display considerable adaptivity to visual information density, adjusting their search strategies based on task demands (Meißner *et al.*, 2020). While the adaptive strategy selection framework predicts that information availability modulates processing patterns (Payne *et al.*, 1993), empirical evidence mapping temporal dynamics in visual tasks remains limited. Pupillometry provides continuous physiological indices of cognitive effort (Mathôt, 2018), but remains underutilised in food and beverage packaging research.

We address these gaps by applying core principles of information richness theory (Daft and Lengel, 1983) that signal quality shapes processing strategies, and the adaptive strategy selection framework (Payne *et al.*, 1993) to conceptualise brightness as a processing intensity modulator. Using eye-movement analysis and time-resolved pupillometry, we examine how brightness influences processing intensity and temporal

organisation. The findings provide evidence distinguishing salience-related capture from post-selection processing mechanisms, offering design principles for enhancing label visibility and processing efficiency.

4.3 Literature review

Recent research frames packaging as vehicles for evidential accessibility instead of mere visual attraction (Tonkin *et al.*, 2015). By enhancing legibility and improving signal-to-noise ratios, effective label design encourages elaborate information processing and steers consumers away from superficial heuristics (Ankiel and Grzybowska-Brzezińska, 2020). This perspective aligns with the Accessibility-Diagnosticity Framework, which posits that the utility of a cue depends on both accessibility (ease of retrieval) and diagnosticity (relevance to judgement) (Feldman and Lynch, 1988). In the wine sector specifically, readability and layout shape quality expectations well before the point of consumption, extending beyond simple salience interpretations (Piqueras-Fiszman and Spence, 2015). This conceptual framework aligns with the packaging design model of Orth and Malkewitz (2008), who frame visual elements as diagnostic cue systems. While their framework concerns the diagnostic value of design elements, we focus on how brightness modulates processing intensity once such cues are attended, specifically examining the temporal dynamics of cognitive effort allocation. Within retail and digital contexts, label colour has been shown to influence purchase intention through the mediation of authenticity and quality cues, a process that reinforces the link between enhanced accessibility and more intensive processing (Pelet *et al.*, 2020). Consequently, when labels are designed to facilitate high accessibility, consumers are significantly more likely to engage in attribute-based comparison, not relying on more superficial, surface-level impressions (Orquin and Mueller Loose, 2013).

As defined earlier, visual salience refers to bottom-up attentional capture, while accessibility concerns the efficiency of extracting and encoding information once

attended. A critical distinction exists between visual salience, the likelihood of being seen, and accessibility, the ease of information extraction (Itti and Koch, 2000), increased brightness or contrast relative to the background merely captures attention without guaranteeing effective comprehension (Portengen *et al.*, 2023). For instance, a bright but complex label might capture attention without facilitating efficient information extraction (Barbierato *et al.*, 2023). True accessibility encompasses the entire cognitive sequence of accurate encoding and integration within limited time constraints (Ansorge *et al.*, 2010). This is essential for wine labels, where decision-relevant cues such as certification badges or appellations often appear in fine print (Escandon-Barbosa and Rialp-Criado, 2019). Without sufficient accessibility, these critical details are often overshadowed by more familiar but less decision-relevant brand elements (Velasco Vizcaíno and Velasco, 2019). Thus, identifying design variables that facilitate early information encoding is essential, as this may reduce the effort for later compensatory processing (Feldman and Lynch, 1988; Payne *et al.*, 1988).

The transition from initial visual examination to sustained post-selection processing is most effectively characterised through contemporary process tracing techniques such as eye-tracking and pupillometry (Motoki *et al.*, 2021; Mormann *et al.*, 2020). While metrics such as first fixation time and fixation count index orienting, mean fixation duration within areas of interest (AOI) reflects processing intensity once a target is selected (Holmqvist *et al.*, 2011). Research indicates that wine label colour and layout affect taste and quality expectations and brand personality (Lick *et al.*, 2017; Galati *et al.*, 2018; Bortolotti, 2023), effects that may involve differential information processing strategies. Label graphics and colours influence purchase intentions and brand personality judgements through associations and readability, with information density and arrangement surpassing colour saturation in importance (Laeng *et al.*, 2016). Extending adaptive strategy logic, we propose that individuals reallocate mental effort over time as visual evidence becomes available: high-brightness enables front-loaded resources towards early encoding; low-brightness necessitates back-loading effort for later compensatory integration (Payne *et al.*, 1993; Meißner *et al.*, 2020). By

supplementing these gaze metrics with pupil dilation, a continuous measure of task-evoked effort, researchers can achieve a more granular understanding of visual processing dynamics (Van Der Wel and Van Steenbergen, 2018; Van Loon *et al.*, 2022).

Although brightness is known to affect consumer judgements. For instance, higher brightness signals vibrancy and healthfulness, while darker packaging suggests richness and premium quality (Sunaga *et al.*, 2016; Lick *et al.*, 2017; Tijssen *et al.*, 2017; Steiner and Florack, 2023). The underlying processing mechanisms remain underexplored. Specifically, whether brightness modulates the temporal allocation of cognitive effort during visual encoding has received limited empirical attention. Prior studies show that colour and brightness influence perception (Lick *et al.*, 2017; Pelet *et al.*, 2020; Steiner and Florack, 2023) and design salience alters attentional allocation (Alvino *et al.*, 2021; Barbierato *et al.*, 2023). These studies often rely on summary metrics (e.g., total fixation count, total dwell time) that conflate initial orienting with subsequent processing. Distinguishing these stages requires tracking when cognitive effort is deployed across the viewing period. Pupillometry offers this capability by providing continuous, time-resolved indices of cognitive effort (Mormann *et al.*, 2020), yet it remains underutilised in food and beverage packaging research. The present study addresses this gap by examining whether brightness modulates the temporal distribution of processing effort during wine label viewing.

4.4 Theoretical background and hypotheses

Information Richness Theory (IRT) (Daft and Lengel, 1983) asserts that the capacity of a medium to transmit information influences processing strategies and decision-making quality. While IRT was originally formulated to compare organisational communication media, recent applications have extended this framework to consumer decision-making contexts (Maity *et al.*, 2018). We argue that the underlying principle, that information transmission capacity influences processing strategies, provides a useful organising framework for visual accessibility effects. Maity *et al.* (2018) demonstrate that media

richness affects consumer information search costs and processing strategies, supporting the extension of IRT principles to stimulus-level attributes. In the present study, we conceptualise brightness as modulating signal quality, treating it as a form of “channel capacity” for visual information extraction, that parallels how media richness affects communication efficiency. This extension is supported by visual perception research demonstrating that brightness affects feature detectability (Ghodrati *et al.*, 2019), thereby governing the information yield per unit of attentional investment. Applied to visual marketing, this theory suggests that stimulus attributes enhancing information accessibility alter how consumers extract and process visual information (Pieters and Wedel, 2004).

In consumer visual processing, stimulus brightness determines the accessibility of visual information. According to Maity *et al.* (2018), higher media richness reduces information search costs and encourages reliance on stimulus-based information over memory-based heuristics. Higher brightness improves the signal-to-noise ratio and facilitates differentiation, enabling extraction of more detailed visual information. This enhanced information accessibility alters processing strategy: instead of relying on heuristic shortcuts in low-information environments, consumers engage in elaborate processing to maximise information extraction when more details are visually accessible (Pieters and Wedel, 2004). Brightness affects detectability of subtle design elements, texture variations, and typographic details on wine labels that together signal quality and authenticity (Zhang *et al.*, 2023; Pelet *et al.*, 2020). Higher brightness enhances the visibility of wine label information, encouraging extended visual exploration beyond fast, surface-level processing. Beyond simply enhancing visibility, this effect increases the information cognitively available for processing.

The Adaptive Strategy Selection Framework (ASSF) (Payne *et al.*, 1993) explains how consumers modify their processing strategies based on information availability. Originally developed for multiple-alternative choices, we extend its core principle of adaptive resource allocation to within-stimulus processing. Visual processing involves sequential decisions (e.g., which features to encode, how long to dwell, when to

terminate) that function as resource allocation choices conceptually similar to ASSF's strategy adaptations, though operating at a finer temporal scale (Payne and Bettman, 2004; Wedel *et al.*, 2023). When visual information is rich and accessible (e.g., high-brightness), consumers engage in attribute-based processing, extracting and encoding available features (Payne *et al.*, 1988; Payne and Bettman, 2004). This elaborate processing, reflected in longer fixations, initially imposes greater cognitive burden as multiple aspects must be encoded simultaneously, but subsequent stages require less effort once information is integrated (Wedel *et al.*, 2023). Under visually degraded conditions (e.g., low-brightness), the immediate extraction of label information is constrained. Consequently, consumers demonstrate sustained cognitive involvement in later stages, reflected in extended pupillary dilation (Pomplun and Sunkara, 2019). This reflects compensatory processing mechanisms that require sustained cognitive effort (Payne *et al.*, 1988). This physiological response indicates ongoing integrative effort, particularly in the later stages of visual attention allocation (Zénon, 2019).

We combine principles from IRT and ASSF in a two-mechanism framework. IRT principles inform the accessibility mechanism that may influence information extractability per fixation. ASSF logic informs the temporal allocation mechanism: specifically, consumers may front-load resources (allocating effort primarily during early encoding) when information is accessible, or back-load resources (sustained allocation during later evaluative stages) when information is constrained. This integration produces testable predictions: brightness reconfigures effort timing, not total amount. High-brightness enables elaborate early encoding (longer fixations, elevated early-to-middle pupil dilation), potentially allowing earlier completion of encoding and reducing late maintenance demands. Low-brightness constrains early encoding (shorter fixations, lower early dilation) but sustains evaluative effort (elevated late dilation) as viewers integrate incomplete cues (Pomplun and Sunkara, 2019). This temporal reallocation implies an inversion: high accessibility advantages encoding stages but reduces late effort; low accessibility shows the reverse. Based on this integrated framework, we propose the following hypotheses:

H1: Higher brightness increases information accessibility, eliciting longer fixation durations on attended targets (with hue and saturation as statistical controls to isolate brightness mechanisms within a representative colour space).

H2: If brightness modulates sustained processing rather than attentional capture, it should lengthen fixation duration on selected targets without necessarily altering fixation count or time to first fixation.

H3: High accessibility front-loads resources to early encoding (elevated early-to-middle dilation); low accessibility back-loads resources to later evaluation (elevated late dilation).

H4: The accessibility advantage inverts across processing stages, transitioning from encoding-dominant to maintenance-dominant patterns.

4.5 Methodology

4.5.1 Overview

We employed a two-phase analysis: eye-movement metrics to quantify attentional and processing patterns (phase 1) and pupillometry to index physiological effort (phase 2). To analyse task-evoked cognitive load, we examined pupil dilation from 200 ms post-stimulus onset (after the typical Pupillary Light Reflex (PLR) onset latency), as colour processing typically requires 200-300 ms to become effective (Mathôt, 2018; Palmer *et al.*, 2019; Mathôt and Vilotijević, 2022). Mean fixation duration and baseline-corrected pupil percentage were pre-specified as primary endpoints; all other eye-movement indices served as secondary outcomes to minimise multiplicity and improve inferential precision.

4.5.2 Participants

Forty-two participants were recruited. Ten were excluded due to colour vision deficiency ($n = 1$), unreliable pupil tracking ($n = 1$), or corrective lens interference ($n = 8$). The final sample ($N = 32$; 16 males; $M_{age} = 23.41$, $SD = 2.93$) provided approximately 80% power to detect a medium effect size ($f = 0.25$) in our repeated-measures design. This study was approved by the institutional review ethics committee of the participating institution (Approval No. HR2024-12-01). Procedures aligned with the Declaration of Helsinki. Written informed consent was obtained from all participants after they were fully informed about the study purpose, procedures, data anonymisation, and their right to withdraw at any time.

4.5.3 Design and stimuli

We employed a within-subjects $4 \times 2 \times 2$ full factorial design: Hues (warm colour: red and yellow; cold colour: blue and green) $\times$ Saturation (high, low) $\times$ Brightness (high, low), yielding 16 conditions. This design strikes a balance between external validity by using a realistic multidimensional colour space, and theoretical parsimony. While all factors are varied to maintain ecological validity, our hypotheses specifically concentrate on brightness effects. Hue and saturation are included as statistical controls to isolate brightness mechanisms within a representative colour space. Labels preserved realistic Italian wine label aesthetics while standardising non-colour elements (typography, layout, and content) to prevent confounding.¹ All text used a uniform sans-serif typeface with consistent size and placement (Joshi *et al.*, 2024). Minimalist graphic backgrounds were used to isolate colour effect (Galati *et al.*, 2018; Lunardo and Rickard, 2019), while avoiding imagery known for shielding effects, such as brand, castles or award stickers (Velasco Vizcaíno and Velasco, 2019). Label layout followed

¹ The design adhered to the current European Union regulations, including Regulation (EU) No 1308/2013, Commission Delegated Regulation (EU) 2019/33, Regulation (EU) No 2021/2117, and Italy's Legislative Decree No 61/2010. These regulations mandate that wine labels must include specific elements: the product name, designation of origin, alcohol content, net quantity, allergen declaration, and country of origin.

a vertical hierarchy (Figure 1).

Colour attributes were manipulated in Pixelmator Pro 3.0: saturation at +70% (high) and –20% (low); brightness at +70% (high) and –70% (low). This ensured perceptible contrast while preserving hue recognisability without greyscale reduction (Cutler *et al.*, 2024). While prioritising ecological validity over strict CIELUV calibration, we statistically controlled for hue and saturation variations in our models to accommodate real-world complexity (Witzel and Gegenfurtner, 2018).

From the full set of 256 labels ($4 \text{ hues} \times 2 \text{ brightness} \times 2 \text{ saturation}$), each participant viewed 16 labels, pseudo-randomly sampled so that they saw each hue 4 times and each level of brightness and saturation 8 times. This structure ensured a within-subjects comparison across all factorial levels, though it resulted in one exemplar per factorial cell per participant.

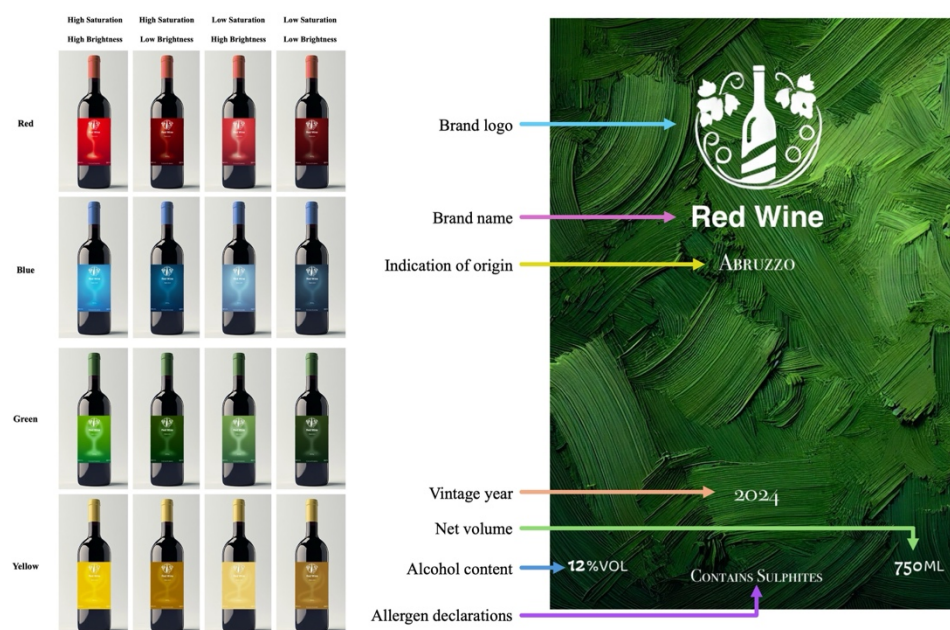


Figure 1 Sample Wine-Label Stimulus

4.5.4 Apparatus and procedure

Eye-movements were recorded using an EyeLink 1000 Plus (1000 Hz) with accuracy

< 0.5°. Stimuli were presented on a 1920 × 1080 monitor (144 Hz) at 62 cm viewing distance. After a 5-point calibration and practice trials, participants performed 16 self-paced viewing trials in randomised order. Each trial presented a single wine label, and participants were instructed to examine the label naturally, as if considering a wine purchase. Following each trial, participants provided evaluative ratings (quality, liking, purchase intention) to maintain engagement; however, these subjective evaluations fall outside the scope of the current study, which focuses exclusively on the temporal dynamics of visual information processing as indexed by eye-tracking and pupillometry. Trial order and hue repetition were recorded as covariates to control for sequence effects. Raw data were filtered to exclude fixations < 80 ms or > 1200 ms.

4.5.5 Data processing and modelling analysis

The label region defined the AOI. Pupil data (0-2500 ms) were interpolated for blinks (< 10% per trial), smoothed (Savitzky-Golay filter), and baseline-corrected using the – 200-0 ms pre-stimulus period. Baseline correction converted pupil size to percent change, where negative values indicate pupil constriction (smaller than baseline) and positive values indicate pupil dilation (larger than baseline) relative to the pre-stimulus baseline. Data were aggregated into 50 ms bins for analysis (Franzen *et al.*, 2022). Statistical comparisons report the difference between high-brightness and low-brightness conditions (high minus low), with positive differences indicating relatively larger pupil size under high brightness. Analyses focused on three theory-driven windows: early (200-500 ms), middle (500-1000 ms), and late (1000-2500 ms) (Mathôt, 2018; Palmer *et al.*, 2019; Wedel *et al.*, 2023).

Data were analysed using mixed-effects models (lme4/lmerTest). Specifically, mean fixation duration and first fixation time were analysed via linear mixed-effects models (LMMs) with Gaussian error assumptions; fixation count assessed with a Poisson GLMMs; pupil percent change was modelled with brightness, time window, and their interaction as fixed effects, including participant-level random slopes for brightness.

Robustness was verified through 1-99% Winsorization, parametric bootstrapping ($n = 2000$), and leave-one-subject-out (LOSO) analysis. We further conducted equivalence tests (TOST) against a $\pm 3\%$ smallest effect size of interest (SESOI) for the middle and late pupil windows (Lakens, 2017). False discovery rate (FDR) corrections were applied to all post-hoc comparisons.

4.6 Results

4.6.1 Overview

Omnibus analyses indicated that brightness exhibited consistent effects across both phases. In eye-movement analyses (Phase 1), hue and saturation did not reach significance; in pupillometry (Phase 2), hue showed significant effects which are reported below as exploratory findings. We therefore report focused brightness comparisons while including hue and saturation as covariates to statistically account for colour space variance and improve the precision of brightness effect estimates (Baguley, 2012).

4.6.2 Phase 1: Eye-movement analysis

Following our pre-specified testing hierarchy, we report mean fixation duration as the primary endpoint without alpha adjustment, with first fixation time and fixation count as secondary outcomes. The primary endpoint, mean fixation duration, showed a consistent increase for high-brightness labels ($M = 337$ ms, $SD = 94.6$) compared to low-brightness labels ($M = 322$ ms, $SD = 76.3$). Mean fixation duration showed a 14.8 ms increase for high-brightness labels. The base model without covariates showed marginal significance ($p = .053$). When hue and saturation were added as covariates to control for colour-space variance, the brightness effect became statistically significant ($\beta = 14.8$ ms maintained, $p = .026$), indicating a 4.6% increase. This significance

persisted after 1-99% Winsorization (+13.3 ms, $p = .028$), with a parametric bootstrap 95% CI of [1.8, 27.6] ms, and remained consistent under LOSO analysis (11-18 ms). Likelihood-ratio testing favoured the model with brightness ($\chi^2(1) = 5.10$, $p = .024$). First fixation time and fixation count showed no reliable brightness effects (FFT = -10 ms, $p = .75$; Poisson GLMM rate ratio high-low = 0.95, $p = .072$), suggesting that brightness primarily prolonged dwell processing on already selected targets, with no detectable effects on initial orienting or sampling frequency in the present paradigm. This pattern is consistent with a post-selection processing mechanism rather than attentional capture.

4.6.3 Phase 2: Pupillometry analysis

Omnibus model

The omnibus LMM revealed a significant brightness $\times$ window interaction $F(2, 22,124.2) = 360.86$, $p < .001$; time-window, $F(2, 22,111.4) = 5216.25$, $p < .001$; brightness, $F(1, 32.6) = 14.57$, $p < .001$. Saturation was not significant ($p = .397$), whereas hue was significant overall, $F(3, 22,107.9) = 4.18$, $p = .006$. Random-effects SD s were 4.686 (intercept) and 3.117 (brightness slope; $\text{corr} = -0.54$); residual $SD = 10.501$. As pre-specified, we excluded the 0-200 ms interval (prior to typical PLR onset) from inference and set $\pm 3\%$ pupil change as the SESOI for TOST in the middle and late windows. Model assumptions passed standard residual diagnostics, and sensitivity checks (alternative random-effects structures; adding or removing colour covariates) yielded consistent conclusions.

Temporal dynamics

To decompose the significant brightness $\times$ window interaction, we examined simple effects at each time window. Critically, although high-brightness stimuli provide a stronger physical impetus for the PLR, these conditions exhibited significantly larger

pupil size relative to low-brightness conditions (i.e., attenuated constriction). This suggests that early task-evoked cognitive arousal was sufficiently robust to modulate and partially override the stronger reflexive constriction typically associated with higher brightness.

The early window (200-500 ms) encompasses the onset and active constriction phase of the PLR, which begins approximately 200 ms post-stimulus and continues beyond this window (Espinosa *et al.*, 2015; Mathôt, 2018). However, several features suggest the observed pattern reflects task-evoked cognitive components in addition to reflexive responses: (1) PLR produces directionally consistent effects (bright stimuli cause constriction, dark stimuli cause dilation), whereas our observed temporal reversal (early high-brightness advantage reversing to late low-brightness advantage) indicates dynamic cognitive resource allocation; (2) the convergence between pupil patterns and fixation duration effects supports a cognitive interpretation; and (3) if brightness differences were purely reflexive, the directional offset should remain constant across time windows instead of reversing. Considering the convergence with fixation duration patterns, we interpret these results cautiously, acknowledging that early-window effects likely reflect a combination of PLR and early cognitive encoding processes.

Estimated marginal means revealed the following temporal pattern. Early window: despite the reflexive tendency for brighter stimuli to induce stronger constriction, high-brightness labels exhibited +6.01% larger pupil size relative to low-brightness targets (95% CI [+4.70, +7.33], FDR(BH)-adjusted $p < .001$; within-subject $d_z = 1.37$), indicating that cognitive effort significantly modulated the physiological light reflex. Middle: high-low = +3.77% (95% CI [+2.55, +5.00], FDR(BH)-adjusted $p < .001$; $d_z = 0.82$). Late window showed a reversed effect: high-low = -3.18% (95% CI [-4.32, -2.04], FDR(BH)-adjusted $p < .001$; $d_z = -0.94$), indicating that low-brightness conditions now exhibited larger pupils, consistent with sustained compensatory processing. TOST against a $\pm 3\%$ SESOI indicated that neither the middle nor the late effects were equivalent to zero (middle: TOST $p_1 = .888$, $p_2 < .001$; late: $p_1 < .001$, $p_2 = .621$; both NHSTs significant), implying effects exceeding the $\pm 3\%$ threshold.

Physiological interpretation

Figure 2 visualises the temporal evolution of these effects and provides a physiological context for the statistical findings. Percent change from baseline is plotted in 50 ms bins. Both conditions show the initial light-reflex dip emerging around 200 ms. Thereafter, the high-brightness trace rises earlier and remains higher through 500-1000 ms, consistent with attenuated constriction potentially reflecting concurrent cognitive demands. From 1000-2500 ms, the low-brightness trace overtakes, indicating greater sustained dilation, consistent with prolonged processing demands at later stages. Vertical dashed lines at 200, 500, and 1000 ms mark physiological landmarks; statistical inferences were based on the 200-500 ms, 500-1000 ms, and 1000-2500 ms windows. Shaded ribbons depict $\pm SE$ to visualise uncertainty.

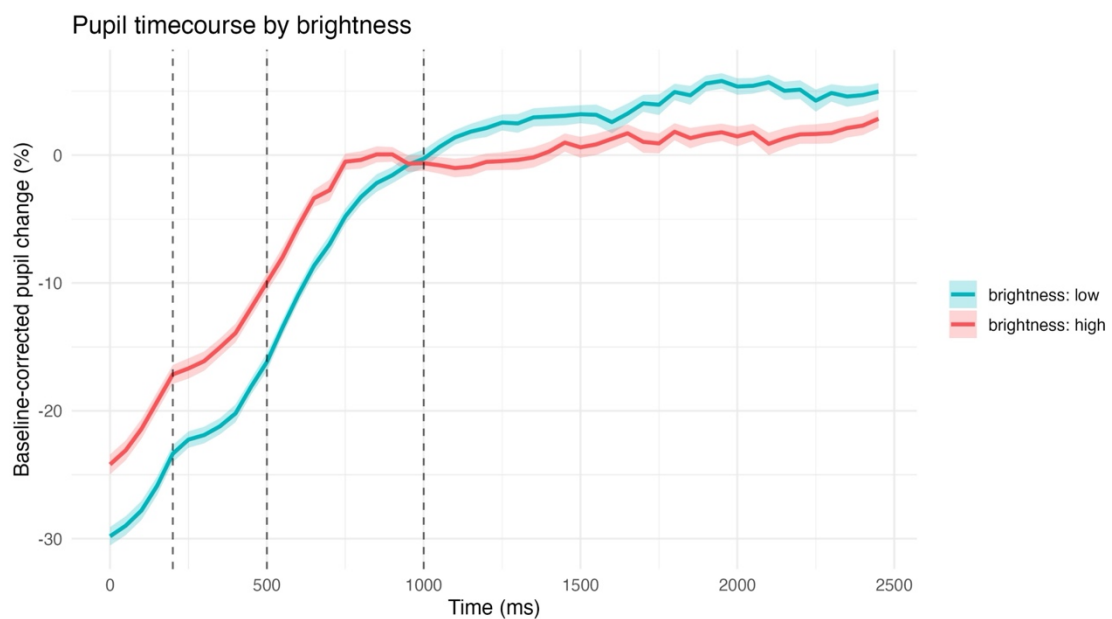


Figure 2 Pupil Percent Change from Baseline (50 ms Bins)

4.6.4 Integration of findings and additional covariate effects

Across both measures, brightness was associated with differences in sustained post-selection processing: eye-movement data showed prolonged fixations, while pupillometry showed attenuated constriction and higher early-to-middle pupil responses for high brightness, alongside stronger late dilation for low brightness. This convergent pattern is consistent with a temporal reallocation of cognitive effort across early encoding and later evaluative stages during visual processing.

Although our primary analyses focused on brightness, the findings revealed time-dependent hue contributions in pupillometry ($F(3, 22,107.9) = 4.18, p = .006$). Exploratory analysis revealed a significant three-way interaction (brightness $\times$ time window $\times$ colour, $F(6, 22,091.6) = 10.52, p < .001$), indicating that hue modulates the temporal dynamics of brightness effects. Decomposition of this interaction revealed that all hues exhibited the theorised temporal reversal, but with different magnitudes. Early and middle windows showed a consistent gradient: yellow demonstrated the strongest brightness advantage (+9.69% and +5.49%), followed by green (+6.88%, +3.80%), red (+4.41%, +3.74%), and blue (+3.03%, +2.09%; all $p < .001$ except blue middle $p = .009$). Late-window reversal was significant across all hues (range: +2.35% to +3.70%, all $p < .001$). Post-hoc comparisons confirmed yellow differed from all other hues. These findings suggest warm hues may amplify processing intensity advantages, while the temporal reallocation mechanism operates consistently across colours. Supplementary Tables S1-S8 include full statistical outputs, descriptive statistics, and robustness checks (see Appendix A).

4.7 Discussion

This study combines principles from IRT and ASSF as organising framework instead of direct mechanistic models. By extending information richness principles to within-stimulus visual processing, this study provides evidence that design attributes

such as brightness are associated with post-selection processing intensity, consistent with accessibility mechanisms, thereby shaping how cognitive resources are deployed over time. Examining brightness as a processing intensity modulator, our results suggest that brightness is associated with the transition from “search and orientation” to “encoding and integration” processing pathways (Pieters and Wedel, 2004). High-brightness labels induce a front-loading resource allocation during early encoding, whereas low-brightness labels trigger compensatory back-loading during late evaluation. These findings reveal how brightness reconfigures temporal processing strategies, offering design principles that may enhance processing intensity beyond visual appeal.

H1 supported: Brightness increased fixation duration (+14.8 ms, 4.6%) without altering fixation count, indicating intensified processing per attended target rather than altered sampling strategy. Unlike perceptual fluency, which hastens processing, high-brightness here affords information richness, encouraging deeper elaboration instead of rapid skimming. This 4.6% gain translates to approximately 120-180 ms cumulative processing advantage across typical label viewing (8-12 fixations on average in our data). Robustness checks, model comparisons, and pupillometric convergence triangulate this effect. By improving signal-to-noise ratios, brightness rendered subtle design elements more extractable, promoting elaborate encoding beyond heuristic processing (Piqueras-Fiszman and Spence, 2015). This dissociation between duration and count is consistent with an accessibility mechanism distinct from attentional capture.

H2 partially supported: Brightness influenced sustained processing, with no detectable effects on initial orienting (first fixation time) or sampling frequency (fixation count) in the present paradigm, although equivalence to zero was not formally established for these metrics. Although we did not collect direct spatial coverage metrics, the absence of detectable differences in fixation count suggests that brightness may not have significantly modified sampling frequency across label regions. This pattern is consistent with brightness modulating how information is processed once selected,

instead of affecting how visual attention is distributed across the stimulus, suggesting brightness functions as a post-selection modulator rather than a driver of search behaviour (Payne *et al.*, 1988, 1993).

H3-H4 supported: pupillometry revealed adaptive temporal allocation of cognitive resources contingent on brightness level. High brightness front-loaded effort with relatively larger pupil size in early and mid-stage dilation, indicating intensive encoding accompanied by reduced constriction (less negative pupil change) and heightened early task-induced arousal (Van Der Wel and Van Steenbergen, 2018). Conversely, low-brightness back-loaded effort with greater late dilation, reflecting compensatory processing to integrate incomplete visual cues (Payne *et al.*, 1988, 1993; Pomplun and Sunkara, 2019). Together, the eye-movement and pupillometry results indicate that brightness reshapes the temporal structure of visual processing, favouring early encoding under high brightness and prolonged evaluation under constrained conditions.

These temporal dynamics reveal how brightness modulates information processing. The selective effect of brightness on fixation duration, in the absence of changes in fixation count or initial orienting, indicates that brightness reconfigures post-selection processing rather than attentional capture (Ansorge *et al.*, 2010). This finding reframes brightness from an “eye-catching” property to a cue associated with processing efficiency during encoding, thereby moving beyond salience-focused models of packaging design by incorporating accessibility-based mechanisms (Itti and Koch, 2000). The temporal reversal in pupil dynamics suggests that brightness is not limited to physiological light responses, but is associated with changes in the timing of task-evoked effort. Brightness reorganises the sequence of cognitive operations during visual evaluation, accelerating encoding under high accessibility conditions while postponing integrative effort when accessibility is constrained. The significant three-way interaction indicates that colour modulates the magnitude and timing of brightness effects. While the front-loading-to-back-loading temporal pattern persisted across all hues, effect sizes varied substantially: yellow and green showed stronger early advantages, while red and blue showed attenuated patterns. This exploratory colour-

contingent modulation suggests that semantic or perceptual properties of hue may amplify or dampen processing intensity mechanisms, though replication with multiple exemplars is needed before drawing firm conclusions (Witzel and Gegenfurtner, 2018).

4.8 Theoretical and practical implications

This study contributes to the literature by providing evidence for the link between IRT and processing intensity dynamics. Using time-resolved pupillometry, we provide evidence that brightness functions as a modulator of information accessibility, not as a tool for visual salience. Specifically, the inversion of pupil responses across time windows suggests adaptive reallocation of cognitive effort contingent on visual accessibility. By suggesting that brightness alters when cognitive effort is invested rather than how much attention is allocated overall, this study shifts the focus of packaging research from attentional capture to temporal dynamics in information processing.

These findings have potential implications for packaging design practices and consumer welfare:

E-commerce and digital platforms: Brands should use high-brightness labels when conveying high-quality information. Longer fixations under high-brightness may support more detailed information processing, particularly on mobile interfaces where reducing task-evoked effort is critical for sustained engagement.

Physical retail strategy: To mitigate decision fatigue caused by compensatory processing of low-brightness labels, designers should simplify information hierarchies on matte or dark-surface materials. Our findings suggest that global brightness offers a practical means of modulating visual processing strategy in wine labelling. Designers could therefore explore varying overall brightness to influence consumer attention, particularly for red wines. Future studies should investigate interactions with wine category (white, rosé, sparkling) and consumer cross-modal associations, enabling

more tailored strategies such as leveraging global brightness to match category expectations or applying selective brightness to diagnostic elements. When shelf space is limited, prioritising brightness at already-attended regions may offer more effective processing gains than global salience.

Sustainable packaging and public policy: When eco-materials constrain brightness (recycled paper, matte finishes), accessibility should be compensated through information aggregation and hierarchy simplification. Policymakers can use these principles to ensure that critical cues, such as health warnings or legal labels, remain easily extractable by maintaining sufficient contrast against low-reflectance substrates, thereby protecting consumer interests in fast-paced shopping environments.

Cross-category applicability: This mechanism extends to beverages where brightness influences health/richness perceptions (e.g., milk, fruit juice, beer labels) and low-inspection products (coffee, olive oil, canned beverage), where quality cues are typographic; strategic brightness may facilitate sensory detail processing during initial scan.

4.9 Limitations and future research

Although we interpret fixation count as an index of sampling frequency, comprehensive spatial coverage metrics (e.g., convex hull area, saccade amplitude distributions, spatial dispersion) would provide more direct evidence of search breadth. The observed increase in fixation duration without corresponding increase in fixation count suggests that brightness primarily affected intensified processing, but we cannot definitively rule out subtle spatial breadth changes without explicit spatial scan-path analyses. Future studies should include these metrics to fully validate this characterisation. The relatively small sample size reflects resource constraints and the intensive nature of within-subjects eye-tracking paradigms requiring extensive calibration and individual baseline correction. Whilst our within-subjects design provides approximately 80% power for medium effects, and sensitivity analyses confirmed result robustness,

replication with larger samples would strengthen generalisability confidence. Our measures capture processing intensity and cognitive effort rather than extraction accuracy. Longer fixations and pupil responses align with accessibility mechanisms but do not directly demonstrate successful information extraction. Future research should use behavioural measures (e.g., recognition accuracy, recall) to confirm that brightness improves extraction success. Our design employed one label exemplar per factorial cell, which prioritises within-subject statistical power for brightness comparisons but prevents full separation of colour-factor effects from stimulus-specific variance. This design choice limits the generalisability of colour-specific findings (particularly the three-way interaction effects) beyond the tested stimuli. Future research should employ multiple exemplars per condition to disentangle factor-level from item-level variance. The early temporal window (200-500 ms) likely reflects a combination of ongoing PLR and early cognitive encoding, as this window overlaps with the active constriction phase of the light reflex. While our temporal reversal pattern and behavioural convergence support a cognitive interpretation, future research should include control trials with brightness-matched stimuli under passive viewing conditions (no task instructions) to definitively isolate task-evoked from luminance-evoked pupil responses and establish a baseline PLR profile for comparison. To preserve ecological validity, we relied on statistical controls instead of strict CIELUV calibration, a compromise that enhances realism but leaves residual variance in colour space (Witzel and Gegenfurtner, 2018). While our factorial design revealed selective brightness effects, the null findings for saturation and limited main effects for hue should be interpreted cautiously, as the limited observations per cell may have underpowered our ability to detect subtler effects or complex interactions (Cramer *et al.*, 2016). The three-way interaction revealed colour-contingent modulation of temporal dynamics, with warm hues (particularly yellow) amplifying early brightness advantages. Future research should replicate findings using perceptually uniform colour spaces and systematically examine brightness $\times$ hue interactions to delineate boundary conditions and determine whether brightness effects generalise across hues. This study only allowed precise capture of visual processing dynamics but does not replicate real shopping environment

complexity. Future research should examine the stability of brightness effects in immersive shopping contexts (e.g., shelf displays, VR, or AR) (Motoki *et al.*, 2021), testing whether findings generalise to natural decision-making. The present study did not explore boundary conditions such as domain expertise (e.g., wine professionals versus novices) and cross-cultural variation in colour meanings (Tang *et al.*, 2015), which may substantially alter evaluative load.

4.10 Conclusion

This study addresses a methodological gap by simultaneously capturing attentional and cognitive effort dynamics via eye-tracking and pupillometry. By integrating IRT and ASSF into a cohesive framework, we provide physiological evidence that brightness functions as an accessibility modulator that reconfigures the temporal organisation of visual processing resources. While our findings demonstrate processing mechanisms such as intensified encoding and front-loaded resource allocation under high brightness, the downstream consequences for decision quality await behavioural validation. Ultimately, these findings position brightness as a critical lever for managing consumer cognitive load, shifting the packaging design paradigm from “catching the eye” to “facilitating the brain”.

4.11 References

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Chapter 5 The Cultural Mechanism: Visual Configuration and Social Diagnosticity (Study 2)

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Author contribution:

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Contextual link to the dissertation

Having established the sensory layer in Chapter 4, which showed how consumers optimize cognitive resources to extract physical information, the present research now moves up to the cultural layer. This study, titled “The cultural mechanism: visual configuration and social diagnosticity,” explores how visual configurations (hue, saturation, brightness) function as diagnostic signals for social competence. Combining Face Theory (Miànzi) with the configurational perspective, this chapter shows that specific visual configurations, for example, red under low brightness, are not just aesthetic choices but are interpreted as signals of steadiness and prestige, therefore

protecting the consumer's social face. This expands the present research definition of diagnosticity from a physiological function role (Chapter 4) to a sociological one. However, both Chapter 4 and Chapter 5 focus on static visual cues of product packaging. Since the modern hybrid marketing environment is characterized by its dynamism, the next chapter (Chapter 6) will shift focus from a static view to the dynamic, algorithmic environment.

5.1 Abstract

Research on wine label color has focused predominantly on hue effects while neglecting brightness and saturation dimensions. This mixed-methods study examined how color configurations influence Chinese consumers' perceived value through a $4 \times 2 \times 2$ experimental design ($N = 435$) combined with 30 stratified qualitative interviews. Our results revealed a robust color $\times$ brightness interaction across all perceived value dimensions (quality, emotional, social) and purchase intention. Low-brightness red labels significantly outperformed, whereas high-brightness red labels lost this advantage compared to other colors. Qualitative interviews revealed that consumers construct these associations through everyday cross-domain learning (fruit ripeness, premium packaging schemas) instead of wine knowledge. Face-related anxiety in gifting contexts amplified reliance on dark red configurations, particularly among less experienced consumers. Findings demonstrate that brightness operates as a critical perceptual dimension. For wine marketers targeting Chinese premium segments, low-brightness red labels enhance perceived value and purchase intentions, particularly in face-sensitive gift-giving contexts.

5.2 Introduction

Color is a central cue in food and beverage perception, shaping consumers' sensory expectations and evaluations (Spence, 2015). Packaging colors convey product symbolism and expectations of quality, emotion and taste (Liang & Hangeldiyeva, 2024). Brighter packaging is perceived as healthier than darker (Steiner & Florack, 2023), and red is perceived as higher in calories than green (Tian et al., 2025). Color interacts with food type and positioning: warmer colors (e.g., red, yellow) increase willingness to buy indulgent foods, whereas cooler colors (e.g., blue, green) suit foods positioned as healthy (Su & Wang, 2024). Green enhances perceived trustworthiness of organic food (Nagy & Temesi, 2024), and premium value is higher when packaging color is congruent with food attributes and positioning (Lyons & Wien, 2018). Overall,

package color conveys “value” dimensions including perceived quality, emotion, social meaning, purchase intention and sensory expectations.

In wine, label color is a key external cue influencing perceived quality and selection preferences (Spence, 2020). Without physical or prior tasting experience, consumers rely heavily on visual cues for initial assessment (Lick et al., 2017; Crichton-Fock et al., 2023). Wine labels convey brand value and influence perceptions (Chamorro et al., 2020), particularly in e-commerce (Pelet et al., 2017). Warm colors are seen as premium and expensive (Boudreaux & Palmer, 2007), while darker heraldic or muted tones convey authenticity (Pelet et al., 2020). Label colors are also linked to specific flavor and taste expectations (Lick et al., 2017; Petit et al., 2024; Heatherly et al., 2019). Therefore, label color is a central informational cue through which consumers infer sensory and symbolic meanings.

However, many studies hold saturation and brightness constant or unspecified, implicitly treating hue as the primary determinant. As Spence and Piqueras-Fiszman (2016) emphasize, color-flavor correspondences are not fixed to hue alone but are constructed from multidimensional attributes such as brightness and saturation. A low-brightness red may evoke richness and maturity, whereas a high-brightness red may signal vibrancy and playfulness, even though both are categorically “red”. Bortolotti (2023) argues that wine label color research should examine hue, saturation and brightness jointly to capture configurational effects.

In the Chinese cultural context, red occupies a distinctive position beyond a basic perceptual hue (Xu, 2024). Red is associated with prosperity, auspiciousness, and national symbolism (Tian et al., 2024), leading wine marketing to assume red reliably enhances preferences and purchase intentions. Industry and academic discourses often treat “red means good fortune and passion” as self-evident (Neo, 2020). Tang et al. (2015) found that younger Hongkonger consumers preferred fashionable labels with red as the dominant hue because red was considered lucky. However, Galati et al. (2018) report that although Chinese consumers state they like red, this does not necessarily mean they are willing to pay a premium for it and Bortolotti (2023) notes that red’s

meaning differs between Chinese and Western contexts. Such culturally deterministic accounts risk oversimplifying the socially constructed nature of color perception. Recent research has begun questioning this stereotype and points to cognitive mechanisms beyond cultural preference (Zhao & Guan, 2023). Overall, existing studies acknowledge red's cultural salience in China but rarely examine how brightness and saturation within red influence perceptions.

Wine expertise influence how consumers use extrinsic cues. Alba and Hutchinson (1987) conceptualize expertise as richer and better-organized category knowledge. Experts rely more on intrinsic attributes, such as flavor, taste, structure, whereas less knowledgeable consumers depend more on packaging and other extrinsic attributes (D'Alessandro & Pecotich, 2013). Raju et al. (1995) identify an intermediate group combining relatively high declarative knowledge with lower task-specific skill, who continue drawing extensively on heuristics. How color-attribute associations are acquired has received limited attention. Bandura and Walters (1977) and Holt (1995) argue that everyday marketplace experiences, alongside formal education and media, contribute to consumption-related schemas. Consumers encounter recurrent pairings between particular colors and product positions. Such associations involve both broad distinctions and fine-grained mappings of brightness variations within a hue onto different social contexts or usage situations (Palmer & Schloss, 2010). Attribution theory suggests people revise stimulus-based explanations when disconfirming experiences are perceived as systematic instead of idiosyncratic (Kelley, 1973). Studies also distinguish between inferential uses of color to predict product attributes and communicative uses to signal meanings in social interaction, such as formality, respect or festivity (Goffman, 1967; Piqueras-Fiszman & Spence, 2015; Yang & Paladino, 2015). Practice-based accounts emphasize that repeated engagement with market environments can embed such associations in dispositions and aesthetic preferences (Bourdieu, 1990).

This study addresses these gaps in the Chinese wine consumption context. We examine how label color configurations influence perceived value. We ask a core question: how

do Chinese consumers, drawing on cultural color schemas, construct links between wine label color and perceptions, and how are these schemas formed, shared and enacted across groups with different levels of expertise? This core question is specified in four research questions:

RQ1: How do wine label color configurations (hue, brightness and saturation) influence Chinese consumers' perceived quality, emotional, social, sensory value and purchase intentions?

RQ2: How does wine expertise condition cognitive schemas and behavioral reliance on color configurations in wine evaluation and choice?

RQ3: Through which social learning processes and information sources do Chinese consumers acquire wine-related color-attribute schemas?

RQ4: When color-based expectations are disconfirmed, how do consumers account for these violations, and what consequences does this have for their subsequent use of color cues?

5.3 Material and methods

5.3.1 Study 1

We employed a 4 (Hue: red, blue, green, yellow) $\times$ 2 (Saturation: high, low) $\times$ 2 (Brightness: high, low) mix design, yielding 16 experimental conditions. Wine label stimuli were designed as realistic Italian wine labels (Figure B1) conforming to EU regulations, with color attributes were manipulated in Pixelmator Pro 3.0 (saturation: +70% high, -20% low; brightness: +70% high, -70% low). Through a paid online survey platform, 510 Chinese participants were recruited and assigned to one of four counterbalanced questionnaire versions. Following rigorous data screening, 435 valid responses were retained (85.3% retention rate), yielding 1,740 observations. Each participant viewed four label stimuli in their assigned version and completed identical

measures for each.

Based on Consumer Perceived Value (CPV) theory (Zeithaml, 1988; Sheth et al., 1991; Sweeney & Soutar, 2001), we assessed four core dimensions using 7-point Likert scales: quality (Spearman-Brown = 0.76), emotional (0.81), social perception (0.90), and purchase intention (0.88). Sensory dimensions included ordinal measures (sweetness, acidity, wine body) and binary measures (flavor profiles: fruity, floral, spice, oak, earthy; intensity descriptors: intense, subtle, complex, simple). All measures were adapted from established wine sensory research (Noble et al., 1987; Koone et al., 2014) and cross-culturally validated through forward-backward translation procedures (Beaton et al., 2000). Full details on survey items, reliability scores, stimuli, pilot testing, and procedure are in Appendix B (Table B1).

5.3.2 Study 2

We further employed theory-driven purposive stratified sampling to recruit 30 participants from the Study 1 sample via snowball procedures (Creswell & Creswell, 2017). Participants were stratified by wine knowledge scores into four theoretically meaningful categories: novice, intermediate, advanced and expert (Table C1). The final sample comprised 18 females and 12 males, aged 18-42 years ($M = 29.23$, $SD = 6.20$), with bachelor's or higher degrees, distributed across eight major Chinese cities (Table C2). Semi-structured online interviews (70-90 minutes) covered five modules: consumption background, sources of color associations, brightness semantics (including bright and dark red comparisons), anxiety in gift-giving decisions, and critical reflection on color-attribute links. All interviews were audio-recorded with informed consent and strictly anonymized.

We applied a hybrid coding approach integrating deductive and inductive analysis (Fereday & Muir-Cochrane, 2006) (Tables C3-C4). NVivo 15 supported systematic coding. Respondent validation was conducted with 6 participants (20%), and methodological triangulation was performed by comparing themes from semi-

structured interviews with survey findings to assess convergence and complementarity.

5.4 Theoretical framework and analytic approach

5.4.1 Theoretical framework

CPV theory has evolved from an economic view of value as a trade-off between functional attributes and price to a broader view of value as subjective, multi-dimensional judgement. Zeithaml (1988) defined customer perceived value as an overall assessment of benefits relative to costs, and the theory of consumption values formalized five core dimensions: functional, social, emotional, epistemic and conditional value (Sheth et al., 1991). Wine is a hedonic, experiential product in which sensory pleasure, affective experience and social signaling often outweigh functional or epistemic utility (Batra & Ahtola, 1991; Niimi et al., 2019). The original five-value framework is therefore coarse for capturing how visual cues such as label color inform fine-grained inferences about value, sensory expectations, and social meaning in wine consumption. Building on Sheth et al.'s (1991) model, we operationalize CPV through four perceptual dimensions and one behavioral outcome that are more sensitive to the sensory-emotional-social nature of wine. Value perception refines functional value by focusing on quality inferences triggered by visual cues. Sensory perception captures anticipated taste and aroma evoked by label color, addressing cross-modal correspondence. Emotional perception isolates affective responses directly elicited by color-induced expectations. Social perception reconceptualizes social value as signaling of face concerns and gifting appropriateness. Purchase intention is treated as the behavioral integration of these perceptual value dimensions.

Study 2 examines how consumers construct and rely on color-attribute associations. This requires theories that explain both cognitive structures encoding color meanings and social processes through which these structures are acquired and revised. Cultural capital theory (Bourdieu, 1984) provides a primary lens on expertise heterogeneity,

distinguishing embodied cultural capital (sensory competences internalized through practice) from objectified cultural capital (reliance on external legitimating symbols such as packaging). In wine consumption, novices lacking embodied knowledge tend to depend on visible cues to reduce marketplace uncertainty, whereas experts base judgements more on gustatory assessment (Yang & Paladino, 2015). Reliance on color cues can therefore be read as dependence on objectified capital, with increasing expertise involving a gradual shift towards embodied capital. Social learning theory (Bandura & Walters, 1977) specifies learning pathways: direct experiential learning (tasting and evaluating), observational learning (watching choices and justifications of role models), and symbolically mediated learning (acquiring knowledge through experts, books and digital platforms). In China's relatively young wine market, where many consumers have limited tasting experience, observational and symbolically mediated learning likely dominate (Balestrini & Gamble, 2006; Hu et al., 2008), making it possible to trace where color-attribute associations originate. Consumer culture theory (Arnould & Thompson, 2005) treats color meanings as culturally constructed schemas reproduced through ritual, media and marketplace practice. In Chinese culture, red is strongly associated with prosperity, celebration and auspiciousness (Tian et al., 2024), yet industry discourse often simplifies this symbolism, assuming red uniformly elevates preference for red wine or red labels (Neo, 2020). Consumer culture theory allows us to examine how these schemas are enacted: whether bright and dark reds activate different cultural codes, and how such codes interact with expertise. Wine purchasing in gifting contexts is also a socially embedded performance involving relational risk. Face theory (Gao & Ting-Toomey, 1998; Goffman, 1967; Qian et al., 2007) situates selection anxiety within Chinese interpersonal dynamics, where an inappropriate wine choice may lead to face loss, harming both reputation and relationship quality. This risk is particularly salient in gifting, where wine signals respect and competence (Yang & Paladino, 2015). Face concerns help explain why objectified capital remains important even for knowledgeable consumers. Finally, work on critical consciousness and consumer resistance suggests a continuum from unreflective acceptance of marketing codes

through ambivalent questioning to active resistance and reinterpretation (Carducci, 2006). When color-induced expectations are disconfirmed by tasting, some consumers may only downgrade a specific brand, whereas others may generalize and reduce their reliance on color cues more broadly. Overall, these five perspectives form the theoretical framework for Study 2: cultural capital theory conceptualizes expertise as movement from objectified towards embodied competence; Social learning theory specifies acquisition pathways for color-attribute schemas; Consumer culture theory situates these schemas within broader cultural meanings of color; Face theory explains persistent reliance on visible cues under social risk; and work on critical consciousness clarifies how consumers may question, revise or resist color codes.

5.4.2 Statistical modelling approach

For Study 1, nested data were analyzed in R 4.4.2. Continuous variables were modelled with linear mixed-effects models (LMMs; REML estimation), ordinal variables with cumulative link mixed models (CLMMs; logit link), and binary variables with logistic GLMMs. All models included hue, saturation, brightness, and their interactions as fixed effects, plus nested random intercepts. Type III tests used Kenward-Roger approximation; significant interactions were followed up with estimated marginal means (Tukey HSD). A planned contrast compared red labels against the mean of other colors under low brightness. Full details are in Appendix B.

For Study 2, interview data were coded deductively using the five theoretical perspectives as higher-order codes, then refined inductively based on emergent patterns and negative cases. Material was organized in case-by-theme matrices crossing four expertise levels (novice, intermediate, advanced, expert) with focal constructs, revealing expertise-related shifts in embodied capital, dominant learning pathways, and reliance on color cues. Particular attention was given to bright/dark reds and gifting episodes under social risk. Thematic patterns were compared with Study 1 for convergence and tension. Further details are in Appendix C.

5.5 Results

5.5.1 Survey results

Participant demographic characteristics and overall distribution across 1,740 stimulus evaluations are summarized in Table 3 (N = 435)

Table 3 Participant characteristics and overall distribution

Variable	Category	N	%
Gender	Male	172	39.5%
	Female	257	59.1%
	Others	4	0.9%
	Prefer not to say	2	0.5%
Age	Under 18yrs	0	0
	18-25yrs	163	37.5%
	26-35yrs	227	52.2%
	36-45yrs	32	7.4%
	46-55yrs	8	1.8%
	56 and above	5	1.1%
Educational level	Primary school or below	0	0
	Junior high school	6	1.4%
	High school	9	2.1%
	Junior college	89	20.5%
	Bachelor's degree	248	57.0%
	Master's degree or above	83	19.1%
Wine drinking frequency	Never	31	7.1%
	Less than twice a year	80	18.4%
	2-5 times a year	99	22.8%
	About once every two months	79	18.2%
	About once a month	50	11.5%
	About once every two weeks	46	10.6%
	About once a week	23	5.3%
	More than once a week	27	6.2%
Sweetness	Dry	245	14.1%
	Semi-dry	539	31.0%
	Semi-sweet	575	33.0%
	Sweet	311	17.9%
	Not sure	70	4.0%

Acidity	Very Low Acidity	165	9.5%		
	Low Acidity	492	28.3%		
	Medium Acidity	585	33.6%		
	High Acidity	346	19.9%		
	Very High Acidity	81	4.7%		
	Not sure	71	4.1%		
Wine body	Very light	96	5.5%		
	Light	376	21.6%		
	Medium	483	27.8%		
	Rich	464	26.7%		
	Full-bodied	266	15.3%		
	Not sure	55	3.2%		
Flavor	Fruity Flavors	519	29.8%		
	Herbal & Floral Flavors	530	30.5%		
	Spice Flavors (e.g., pepper, cinnamon, cloves, etc.)	633	36.4%		
	Oak Flavors (e.g., Vanilla, Toast, Smoke, Chocolate, coffee, etc.)	607	34.9%		
	Earthy Flavors (e.g., soil, forest floor, stone, etc.)	447	25.7%		
	Other Flavor	75	4.3%		
	Not perceived	39	2.2%		
Intense	Subtle	543	31.2%		
	Intense	680	39.1%		
	Simple	425	24.4%		
	Complex	684	39.3%		
	Others	73	4.2%		
	Not sure	65	3.7%		
Variable	N Valid	Mean	SD	Median	IQR (25 - 75)
Quality perception *	1740	4.85	1.16	5.00	4.00 - 5.50
Emotional perception *	1740	4.83	1.12	4.88	4.00 - 5.75
Social perception *	1740	4.34	1.60	5.00	3.00 - 5.50
Purchase intention *	1740	4.71	1.35	4.71	4.00 - 5.75

*: Skewness values -0.54 to 0.66, and Kurtosis values -0.68 to 0.39.

5.5.2 Main effects and interactions on CPV dimensions

Quality perception

For perceived quality, the LMM showed main effect of color, $\chi^2(3) = 23.27, p < 0.001$, $\eta^2p = 0.02$, robust color $\times$ brightness interaction, $\chi^2(3) = 86.15, p < 0.001$, $\eta^2p = 0.09$, and three-way interaction, $\chi^2(3) = 20.54, p < 0.001$, $\eta^2p = 0.02$. The model explained

17.2% of the variance (marginal R^2) and 53.6% when random effects were included (conditional R^2 ; ICC = 0.439). Under low brightness, red labels received higher quality ratings than the other colors, whereas high-brightness red lost this advantage and was rated lower than blue and green and slightly lower than yellow. A planned contrast confirmed a high-end for dark red labels: low-brightness red outperformed the average of all other color-brightness combinations, $d = 0.69$, 95% CI [0.48, 0.90], $t(1423) = 7.49$, $p < 0.001$.

Emotional perception

For emotional perception, there was a significant main effect of color, $\chi^2(3) = 20.50$, $p < 0.001$, $\eta^2p = 0.02$. These were qualified by a robust color $\times$ brightness interaction, $\chi^2(3) = 67.27$, $p < 0.001$, $\eta^2p = 0.08$, and the three-way interaction was significant, $\chi^2(3) = 12.70$, $p = 0.002$, $\eta^2p = 0.02$. The model explained 17.6% of the variance (marginal R^2) and 57.7% when random effects were included (conditional R^2 ; ICC = 0.486). Under low brightness, red labels received higher emotional value ratings than the other colors, while high-brightness red was evaluated lower than blue and green and comparable to yellow. A planned contrast again confirmed the advantage of dark red: low-brightness red exceeded the average of all other color-brightness combinations, $d = 0.77$, 95% CI [0.56, 0.98], $t(1423) = 8.35$, $p < 0.001$.

Social perception

For the social perception, there were significant main effects of color, $\chi^2(3) = 35.31$, $p < 0.001$, $\eta^2p = 0.03$, saturation, $\chi^2(1) = 14.20$, $p < 0.001$, $\eta^2p = 0.01$, and brightness, $\chi^2(1) = 10.25$, $p = 0.001$, $\eta^2p = 0.008$, qualified by a strong color $\times$ brightness interaction, $\chi^2(3) = 76.65$, $p < 0.001$, $\eta^2p = 0.10$; the three-way interaction was also significant, $\chi^2(3) = 22.83$, $p < 0.001$, $\eta^2p = 0.03$. The model explained 21.6% of the variance (marginal R^2) and 75.8% when random effects were included (conditional R^2 ; ICC = 0.692). Under low brightness, red labels received higher social value ratings than the other colors, whereas high-brightness red was evaluated lower than blue and green and

comparable to yellow. A planned contrast supported the high-end advantage of dark red labels, with low-brightness red yielding higher perceived social value than the alternative color-brightness combinations, $d = 0.66$, 95% CI [0.45, 0.87], $t(1423) = 7.14$, $p < 0.001$. Table 4 summarizes the LMM results for the three CPV dimensions and purchase intention, Table 7 provides the details of the post-hoc pairwise comparisons, and Table 8 reports the planned (a priori) contrasts.

Table 4 Summary of the LMM results for the three CPV dimensions and purchase intention

Dependent variable	Color	Saturation	Brightness	Color × Saturation	Color × Brightness	Saturation × Brightness	Color × Saturation × Brightness	R ² m	R ² c	ICC
Quality perception	$\chi^2(3) = 23.27, p < 0.001, \eta^2p = 0.02$	$\chi^2(1) = 3.82, p = 0.051, \eta^2p = 0.003$	$\chi^2(1) = 5.26, p = 0.022, \eta^2p = 0.004$	$\chi^2(3) = 6.06, p = 0.109, \eta^2p = 0.006$	$\chi^2(3) = 86.15, p < 0.001, \eta^2p = 0.09$	$\chi^2(1) = 1.80, p = 0.180, \eta^2p = 0.001$	$\chi^2(3) = 20.54, p < 0.001, \eta^2p = 0.02$	0.172	0.536	0.439
Emotional perception	$\chi^2(3) = 20.50, p < 0.001, \eta^2p = 0.02$	$\chi^2(1) = 1.22, p = 0.270, \eta^2p = 0.001$	$\chi^2(1) = 2.46, p = 0.117, \eta^2p = 0.002$	$\chi^2(3) = 8.42, p = 0.038, \eta^2p = 0.009$	$\chi^2(3) = 67.27, p < 0.001, \eta^2p = 0.08$	$\chi^2(1) = 0.61, p = 0.437, \eta^2p < 0.001$	$\chi^2(3) = 12.70, p = 0.0015, \eta^2p = 0.02$	0.176	0.577	0.486
Social perception	$\chi^2(3) = 35.31, p < 0.001, \eta^2p = 0.03$	$\chi^2(1) = 14.20, p < 0.001, \eta^2p = 0.01$	$\chi^2(1) = 10.25, p = 0.001, \eta^2p = 0.008$	$\chi^2(3) = 10.73, p = 0.013, \eta^2p = 0.01$	$\chi^2(3) = 76.65, p < 0.001, \eta^2p = 0.10$	$\chi^2(1) = 0.26, p = 0.613, \eta^2p < 0.001$	$\chi^2(3) = 22.83, p < 0.001, \eta^2p = 0.03$	0.216	0.758	0.692
Purchase intention	$\chi^2(3) = 13.49, p = 0.004, \eta^2p = 0.01$	$\chi^2(1) = 1.09, p = 0.297, \eta^2p = 0.001$	$\chi^2(1) = 2.54, p = 0.111, \eta^2p = 0.002$	$\chi^2(3) = 6.93, p = 0.074, \eta^2p = 0.007$	$\chi^2(3) = 70.11, p < 0.001, \eta^2p = 0.07$	$\chi^2(1) = 2.60, p = 0.107, \eta^2p = 0.002$	$\chi^2(3) = 15.57, p = 0.001, \eta^2p = 0.02$	0.169	0.514	0.415

Note: All models control for covariates, effect sizes for LMMs are reported as partial η^2 (η^2p), R^2m = marginal R^2 ; R^2c = conditional R^2 ; ICC = intraclass correlation coefficient.

Sensory perception

Table 5 summarizes the models for perceived sweetness, acidity and wine body. For sweetness, both the color $\times$ saturation interaction, $LR \chi^2(3) = 12.98, p = 0.005$, and the color $\times$ brightness interaction, $LR \chi^2(3) = 8.33, p = 0.040$, were significant. High-saturation blue labels showed higher odds of sweeter ratings ($OR = 1.26, 95\% CI [1.08, 1.47]$), and high-brightness green labels were modestly associated with higher sweetness expectations ($OR = 1.18, 95\% CI [1.01, 1.37]$). For acidity, there was a strong main effect of color, $LR \chi^2(3) = 17.87, p < 0.001$: red labels were associated with lower perceived acidity ($OR = 0.77, 95\% CI [0.66, 0.90]$), and green labels with higher perceived acidity ($OR = 1.19, 95\% CI [1.02, 1.38]$). Higher saturation increased acidity expectations, $LR \chi^2(1) = 5.60, p = 0.018, OR = 1.11, 95\% CI [1.02, 1.22]$, and the color $\times$ saturation interaction, $LR \chi^2(3) = 11.56, p = 0.009$, indicated that high-saturation blue labels reduced acidity perceptions ($OR = 0.79, 95\% CI [0.67, 0.92]$). For wine body, a CLM without random effects was used due to instability in the mixed model. Red labels increased perceived body ($OR = 1.88, 95\% CI [1.61, 2.18]$), whereas blue and green labels reduced it. The color $\times$ saturation interaction, $LR \chi^2(3) = 21.91, p < 0.001$, showed that high-saturation red further strengthened full-body expectations ($OR = 1.36, 95\% CI [1.17, 1.59]$). While color $\times$ brightness interaction, $LR \chi^2(3) = 36.65, p < 0.001$, showed that high-brightness blue substantially decreased perceived body ($OR = 0.67, 95\% CI [0.58, 0.78]$).

Table 5 Likelihood ratio tests for ordinal dependent variables

Variable	Effect	LR χ^2	df	p
Sweetness	Color	6.86	3	0.076
	Saturation	2.92	1	0.088
	Brightness	0.35	1	0.557
	Color $\times$ Saturation	12.98	3	0.005
	Color $\times$ Brightness	8.33	3	0.040
	Saturation $\times$ Brightness	2.80	1	0.094
	Color $\times$ Saturation $\times$ Brightness	5.41	3	0.144
Acidity	Color	17.87	3	< 0.001
	Saturation	5.60	1	0.018
	Brightness	1.57	1	0.210

Wine body*	Color × Saturation	11.56	3	0.009
	Color × Brightness	9.04	3	0.029
	Saturation × Brightness	3.38	1	0.066
	Color × Saturation × Brightness	7.21	3	0.066
	Color	48.91	3	< 0.001
	Saturation	2.58	1	0.108
	Brightness	10.27	1	0.001
	Color × Saturation	21.91	3	< 0.001
	Color × Brightness	36.65	3	< 0.001
	Saturation × Brightness	9.94	1	0.002

*: Wine body model fitted using CLM (no random intercept) due to CLMM instability; three-way interaction excluded.

GLMMs for the nine binary attributes (flavor and complexity perceptions) indicated several targeted three-way color × saturation × brightness interactions (Table 6). Fruity expectations increased for high-saturation, high-brightness green labels and decreased for corresponding blue labels, $\chi^2(3) = 32.08, p < 0.001$. Similar higher-order interactions emerged for intensity, $\chi^2(3) = 54.20, p < 0.001$, with high-saturation, high-brightness red labels strengthening intense impressions, and for earthy notes, $\chi^2(3) = 40.25, p < 0.001$, with high-saturation, high-brightness blue labels amplifying earthy associations. Main effects of color were pronounced for intensity and subtlety: red labels strongly increased intensity ($\chi^2(3) = 115.12, p < 0.001$; OR = 2.72, 95% CI [2.25, 3.30]) and reduced subtlety (OR = 0.50, 95% CI [0.40, 0.61]), whereas green labels showed the opposite pattern (OR = 0.53 for intensity; OR = 2.11 for subtlety). Brightness reduced oak and intensity expectations (both $p < 0.001$), consistent with darker configurations cueing stronger, more oak-driven and more strong wines.

Table 6 Type III Wald χ^2 Tests for flavor and complexity variables

Variable	Effect	χ^2	df	<i>p</i>
Fruity	Color	16.89	3	< 0.001
	Saturation	1.09	1	0.296
	Brightness	0.03	1	0.860
	Color × Saturation	6.97	3	0.073
	Color × Brightness	9.53	3	0.023
	Saturation × Brightness	2.39	1	0.122

Floral	Color × Saturation × Brightness	32.08	3	< 0.001
	Color	6.17	3	0.104
	Saturation	3.56	1	0.059
	Brightness	9.68	1	0.002
	Color × Saturation	8.45	3	0.038
	Color × Brightness	9.49	3	0.023
	Saturation × Brightness	<0.01	1	0.944
Spice	Color × Saturation × Brightness	5.58	3	0.134
	Color	14.47	3	0.002
	Saturation	6.63	1	0.010
	Brightness	0.64	1	0.423
	Color × Saturation	17.86	3	< 0.001
	Color × Brightness	4.23	3	0.237
	Saturation × Brightness	0.03	1	0.866
Oak	Color × Saturation × Brightness	13.44	3	0.004
	Color	27.28	3	< 0.001
	Saturation	1.36	1	0.244
	Brightness	20.84	1	< 0.001
	Color × Saturation	13.61	3	0.003
	Color × Brightness	13.01	3	0.005
	Saturation × Brightness	7.98	1	0.005
Earthy	Color × Saturation × Brightness	12.96	3	0.005
	Color	3.86	3	0.277
	Saturation	7.75	1	0.005
	Brightness	0.06	1	0.808
	Color × Saturation	17.31	3	< 0.001
	Color × Brightness	25.16	3	< 0.001
	Saturation × Brightness	9.48	1	0.002
Intense	Color × Saturation × Brightness	40.25	3	< 0.001
	Color	115.12	3	< 0.001
	Saturation	12.09	1	< 0.001
	Brightness	43.47	1	< 0.001
	Color × Saturation	8.96	3	0.030
	Color × Brightness	29.53	3	< 0.001
	Saturation × Brightness	0.86	1	0.354
Subtle	Color × Saturation × Brightness	54.20	3	< 0.001
	Color	81.16	3	< 0.001
	Saturation	0.46	1	0.498
	Brightness	19.30	1	< 0.001
	Color × Saturation	7.03	3	0.071
	Color × Brightness	14.06	3	0.003
	Saturation × Brightness	9.15	1	0.002
Complex	Color × Saturation × Brightness	10.69	3	0.014
	Color	1.02	3	0.796

Simple	Saturation	2.96	1	0.085
	Brightness	6.95	1	0.008
	Color × Saturation	11.85	3	0.008
	Color × Brightness	7.65	3	0.054
	Saturation × Brightness	4.27	1	0.039
	Color × Saturation × Brightness	27.37	3	< 0.001
	Color	41.60	3	< 0.001
	Saturation	1.32	1	0.251
	Brightness	0.30	1	0.584
	Color × Saturation	0.35	3	0.950
	Color × Brightness	20.79	3	< 0.001
	Saturation × Brightness	2.22	1	0.136
	Color × Saturation × Brightness	31.84	3	< 0.001

Note: models fitted using GLMM with participant random effects where convergent; otherwise GLM used.

Purchase intention

For purchase intention, the LMM showed a main effect of color, $\chi^2(3) = 13.49$, $p = 0.004$, $\eta^2p = 0.01$. This was qualified by a strong color × brightness interaction, $\chi^2(3) = 70.11$, $p < 0.001$, $\eta^2p = 0.07$, and a three-way interaction significant, $\chi^2(3) = 15.57$, $p = 0.001$, $\eta^2p = 0.02$. The model explained 16.9% of the variance (marginal R^2) and 51.4% including random effects (conditional R^2 ; ICC = 0.415). Under low brightness, red labels elicited higher purchase intentions than the other colors, whereas high-brightness red lost this advantage (Table 7). A planned contrast supported a high-end for dark red labels, with low-brightness red yielding higher purchase intention than the remaining color-brightness combinations, $d = 0.73$, 95% CI [0.54, 0.92], $t(1423) = 7.51$, $p < 0.001$.

Consistency of effects across CPV dimensions

We observed that saturation was not irrelevant but functioned as an auxiliary configurational factor, particularly for social perception that showed a significant main effect ($p < 0.001$) and entered significantly into the three-way interactions for CPV and purchase intention, although with relatively small effect sizes ($\eta^2p = 0.02$ -0.03). For sensory perceptions, saturation occupied a key role, color × saturation interactions significantly strengthened expectations of sweetness, acidity and wine body ($p \leq 0.01$). By contrast, the color × brightness interaction was consistently significant (all p

< 0.001, $\eta^2_p = 0.07-0.10$), with the same pattern: dark red labels yielded the highest evaluations for CPV, purchase intention and partial sensory perception (Table 7-8). This stable configuration effect suggests a unified perceptual mechanism guiding wine label judgements.

Table 7 Post-hoc pairwise comparisons for the color $\times$ brightness interaction

Dimension	Brightness	Contrast	<i>d</i>	<i>SE</i>	95% CI	<i>P</i> *
Quality perception	High	Red - Blue	-0.46	0.117	[-0.69, -0.23]	< 0.001
	High	Red - Green	-0.70	0.134	[-0.97, -0.44]	< 0.001
	High	Red - Yellow	-0.37	0.117	[-0.60, -0.14]	0.001
	High	Blue - Green	-0.24	0.113	[-0.46, -0.02]	0.036
	High	Blue - Yellow	0.09	0.132	[-0.17, 0.35]	0.514
	High	Green - Yellow	0.33	0.118	[0.10, 0.56]	0.006
	Low	Red - Blue	0.97	0.119	[0.73, 1.20]	< 0.001
	Low	Red - Green	0.93	0.134	[0.67, 1.20]	< 0.001
	Low	Red - Yellow	0.96	0.114	[0.73, 1.18]	< 0.001
	Low	Blue - Green	-0.04	0.117	[-0.27, 0.19]	0.719
	Low	Blue - Yellow	-0.01	0.132	[-0.27, 0.25]	0.927
	Low	Green - Yellow	0.03	0.117	[-0.20, 0.26]	0.827
Emotional perception	High	Red - Blue	-0.48	0.116	[-0.80, -0.15]	< 0.001
	High	Red - Green	-0.61	0.132	[-0.87, -0.35]	< 0.001
	High	Red - Yellow	-0.39	0.115	[-0.62, -0.16]	0.001
	High	Blue - Green	-0.13	0.112	[-0.35, 0.09]	0.232
	High	Blue - Yellow	0.09	0.131	[-0.17, 0.35]	0.427
	High	Green - Yellow	0.22	0.116	[-0.01, 0.45]	0.033
	Low	Red - Blue	0.71	0.118	[0.48, 0.94]	< 0.001
	Low	Red - Green	0.65	0.133	[0.39, 0.91]	< 0.001
	Low	Red - Yellow	0.81	0.113	[0.59, 1.04]	< 0.001
	Low	Blue - Green	-0.07	0.115	[-0.27, 0.19]	0.523
	Low	Blue - Yellow	0.10	0.13	[-0.15, 0.36]	0.427
	Low	Green - Yellow	0.17	0.114	[-0.10, 0.43]	0.149
Social perception	High	Red - Blue	-0.60	0.147	[-0.89, -0.31]	< 0.001
	High	Red - Green	-0.86	0.182	[-1.22, -0.51]	< 0.001
	High	Red - Yellow	-0.35	0.144	[-0.64, -0.07]	0.014
	High	Blue - Green	-0.26	0.141	[-0.54, 0.01]	0.067
	High	Blue - Yellow	0.25	0.18	[-0.11, 0.60]	0.175
	High	Green - Yellow	0.51	0.148	[0.22, 0.80]	0.001
	Low	Red - Blue	1.18	0.149	[0.88, 1.47]	< 0.001
	Low	Red - Green	1.22	0.183	[0.86, 1.58]	< 0.001
	Low	Red - Yellow	1.12	0.142	[0.84, 1.40]	< 0.001

Purchase intention	Low	Blue - Green	0.04	0.144	[-0.25, 0.32]	0.790
	Low	Blue - Yellow	-0.06	0.18	[-0.41, 0.30]	0.763
	Low	Green - Yellow	-0.09	0.147	[-0.38, 0.20]	0.533
	High	Red - Blue	-0.54	0.115	[-0.77, -0.32]	< 0.001
	High	Red - Green	-0.53	0.131	[-0.79, -0.27]	< 0.001
	High	Red - Yellow	-0.34	0.116	[-0.57, -0.12]	0.003
	High	Blue - Green	0.01	0.111	[-0.20, 0.23]	0.901
	High	Blue - Yellow	0.20	0.13	[-0.05, 0.46]	0.122
	High	Green - Yellow	0.19	0.117	[-0.04, 0.42]	0.110
	Low	Red - Blue	0.71	0.117	[0.48, 0.94]	< 0.001
	Low	Red - Green	0.66	0.131	[0.41, 0.92]	< 0.001
	Low	Red - Yellow	0.825	0.112	[0.61, 1.05]	< 0.001
	Low	Blue - Green	-0.044	0.116	[-0.27, 0.18]	0.704
	Low	Blue - Yellow	0.117	0.129	[-0.14, 0.37]	0.364
	Low	Green - Yellow	0.161	0.115	[-0.06, 0.39]	0.161

*: p-values are Tukey-adjusted within each brightness $\times$ dimension family ($\alpha = 0.05$).

Table 8 Planned (a priori) contrasts: red $\times$ low brightness

Dependent variable	Cohen's <i>d</i>	<i>t</i>	df	<i>p</i>	95% CI	
Quality perception	0.69	7.49	1423	< 0.001	[0.48, 0.90]	
Emotional perception	0.77	8.35	1423	< 0.001	[0.56, 0.98]	
Social perception	0.66	7.14	1423	< 0.001	[0.45, 0.87]	
Purchase intention	0.73	7.51	1423	< 0.001	[0.54, 0.92]	
Dependent variable	Estimate	SE	95% CI	<i>p</i>	OR	OR 95% CI
Sweetness	0.44	0.18	[0.08, 0.81]	0.016	1.56	[1.09, 2.24]
Acidity	-0.54	0.19	[-0.90, -0.18]	0.004	0.58	[0.40, 0.84]
Wine body	0.91	0.18	[0.57, 1.26]	< 0.001	2.49	[1.76, 3.53]
Fruity	0.63	0.23	[0.19, 1.07]	0.005	1.88	[1.21, 2.92]
Floral	0.03	0.24	[-0.43, 0.50]	0.888	1.03	[0.65, 1.64]
Spice	-0.10	0.22	[-0.53, 0.34]	0.668	0.91	[0.59, 1.41]
Oak	-0.21	0.20	[-0.61, 0.19]	0.296	0.81	[0.54, 1.20]
Earthy	0.31	0.24	[-0.15, 0.78]	0.183	1.37	[0.86, 2.18]
Complex	-0.42	0.21	[-0.83, -0.01]	0.045	0.66	[0.44, 0.99]
Intense	1.41	0.22	[0.97, 1.84]	< 0.001	4.08	[2.65, 6.31]
Simple	-1.02	0.28	[-1.57, -0.47]	< 0.001	0.36	[0.21, 0.63]
Subtle	-0.74	0.26	[-1.24, -0.24]	0.004	0.48	[0.29, 0.79]

Note: planned contrast at low brightness: Red-mean(Blue, Green, Yellow). Estimates are on the model scale (continuous = mean difference; ordinal/binary = log-odds; OR = exp(Estimate)). *SE*, 95% CI, and *p* are based on a conservative aggregation of the three pairwise contrasts.

To assess robustness against individual differences, we re-estimated all models with gender, age, wine knowledge, consumption frequency and educational level as covariates. Wine knowledge and education showed positive main effects on CPV ratings and purchase intention (both $p < 0.01$), indicating that more knowledgeable and more highly educated respondents tended to evaluate the wines more favorably and expensively. The other covariates had only small and largely trivial effects.

When then tested whether these individual differences moderated the color $\times$ brightness pattern by adding three-way interactions. The color $\times$ brightness $\times$ wine knowledge and color $\times$ brightness $\times$ education interactions were not significant (both $p > 0.10$), and dark red advantage was virtually identical for novice and expert groups ($\Delta d = 0.03$). likewise, no consistent moderating effects emerged for gender, age, or consumption frequency. Together, these results indicate that the dark red advantage reflects a robust color-brightness schema that generalizes across expertise, usage habits and socio-educational background.

5.5.3 Interview results

Thematic analysis of 30 in-depth interviews identified five core themes aligned with the theoretical framework: (1) cross-domain learning through everyday experience; (2) consensus and heterogeneity in cultural schemas; (3) face-driven market anxieties; (4) schema convergence beyond knowledge level; and (5) critical consciousness and schema persistence. Full coding matrices and demographic distributions appear in Appendix C (Tables C2-C4).

Cross-domain learning through everyday experience, digital platforms as secondary
Most participants (83%; 25/30) traced color-attribute associations to everyday cross-domain analogies instead of wine-specific knowledge: fruit ripeness (e.g., strawberry $\rightarrow$ red $\rightarrow$ sweet/rich), beverage packaging (e.g., mineral water $\rightarrow$ blue $\rightarrow$

refreshing), and premium food packaging (e.g., dark fruit juice packaging → high-end positioning) (Table C5). Novices relied on fruit-ripeness analogies. Renee (F, 24, K = 1, novice): “I’m just relying on everyday experience, matching colors and flavors from daily life” (Quote C1). Callum (M, 25, K = 2.5, novice): “The colors you see on the market pretty much tell you what the taste will be” (Quote C2). Experts demonstrated the coexistence of everyday schemas and technical knowledge. Adelaide (F, 33, K = 6.5, expert): “Other colors come from packaging I see a lot, so the meanings carry across” (Quote C3).

Digital platforms functioned as secondary sources. Though 40% (12/30) consulted them, trustworthiness ratings were moderate ($M = 5.3/10$) (Table C5). Amira (F, 38, K = 4.25, advanced): “I’d give it about 5/10 for credibility; it felt more like advertising” (Quote C4). Dylan (M, 28, K = 3.25, intermediate): “A single video is maybe 3 or 4 out of 10; if lots say the same thing, it goes up” (Quote C5). Experts remained cautious. Adelaide: “You have to consider their commercial interests” (Quote C6).

Dark red as “high-end”, cultural consensus and heterogeneous boundaries

Most participants (27/30, 90%) mentioned dark red as more high-end than bright red, associating it with maturity (85%), formality (78%), aged complexity (70%), and gifting appropriateness (Table C6). Novices framed this as causal attribution. Zeth (M, 26, K = 3.5, intermediate): “Dark red feels noble; if it has inner quality, it doesn’t need loud colors” (Quote C7). Mason (M, 25, K = 1, novice): “Bright red looks like a soft drink for kids, whereas dark red feels like wine for adults” (Quote C8). Experts aligned this with ageing associations and strategic reading. Lucas (M, 33, K = 7, expert): “For banquets and formal events, dark red fits that atmosphere and gives a sense of substance” (Quote C9).

Several participants explicitly linked color preferences to Chinese dress codes and age norms. Lucy (F, 38, K = 5.5, advanced): “At weddings, the bride is in bright red, but the mother wears dark red; it fits her age and temperament” (Quote C10). Zeth: “Dark

red feels more respectful for elders or people of higher status” (Quote C11). However, two novice participants (7%) offered fully reversed interpretations. Elias (M, 18, K = 1, novice): “Bright red looks more high-end because the color is pure” (Quote C12). Lena (F, 20, K = 1.25, novice): “Dark red comes across as too old-fashioned; bright red has more of a premium vibe, take a Ferrari, bright red looks classier” (Quote C13). In follow-up probing, Elias described bright red as vital and motivating but dark red as lifeless and drained of energy, thereby inverting common cultural schemas. Lena saw dark red as conservative and traditional, and bright red as bold and demanding; for her, high-end design depends on using such saturated colors without slipping into vulgarity. Importantly, 83% (25/27) of those favoring dark red noted context-dependency: bright red suits casual gatherings, whereas dark red fits business settings and gifts to elders. Price expectations also differed: 5 of 27 participants (19%) spontaneously assumed dark red labels were more expensive than bright red. Lucy estimated dark red as 1-2 times pricier, while Elias expected a premium of 70-150 RMB (approximately 8.4-18.1 EUR).

Face-driven market anxiety and reliance on visual codes

All participants with gifting experience reported face-related anxiety centered on avoiding disrespect or incompetence signals. Anxiety intensity correlated negatively with knowledge ($r = -0.48, p < 0.01$), but forms varied (Table C7). Novices experienced acute anxiety. Mason: “I’m really afraid of losing face; people won’t sneer at and mock me” (Quote C14). Zeth: “I’d rather ask professionals which one will ‘carry face’ when I give it” (Quote C15). Experts framed gifting strategically. Julian (M, 38, K = 7, expert): “What I worry about most is wine quality; the label still matters, but it doesn’t really affect me” (Quote C16). Reliance on color cues in gifting peaked among intermediates (86%) compared to novices (70%) or experts (33%) (Table C8).

Schema convergence with reversed confidence

While 90% shared the “dark red = high-end” schema, reliance patterns differed. Confidence in color versus blind tasting showed up-side down: novices rated color

confidence high ($M = 7.4/10$) but tasting low ($M = 1.8/10$); experts reversed this (color: $M = 2.0$; tasting: $M = 7.7$) (Table C9). Mason: “Maybe 7 or 8 out of 10 for trusting the color; for blind tasting, I’m maybe 1” (Quote C17). Noah (M, 37, K = 6, expert): “For color, maybe 2 out of 10; for blind tasting, 7 or 8” (Quote C18). Similarly, endorsement of “color → attribute” belief declined with expertise: novices 80% (8/10), intermediates 71% (5/7), advanced 29% (2/7), experts 0% (0/6). Yet advanced and expert participants still used dark red strategically in gifting due to cultural recognizability. Schemas are widely shared; what differs is epistemic status and dependence degree.

Critical consciousness and schema persistence

Among participants, 60% (18/30) acknowledged color as marketing intent, 23% (7/30) believes color reflects quality, and 17% (5/30) with an ambivalent stance. Yet 89% (16/18) continued relying on color cues, 11% (2/18) reported partial reduction in reliance. Zeth: “Of course it’s marketing, but if the label looks good, I’d still quite like it” (Quote C19). Lucy: “A few disappointments don’t really change my use of color; I still look at it” (Quote C20). When color expectations failed (7 cases), 71% attributed failures to producers, 29% to personal taste, and none questioned the underlying schema. Adelaide: “The winery spent money in the wrong place; nice label, ordinary wine underneath” (Quote C21). Among novices, 60% expressed no motivation to deepen wine knowledge, citing color rules as sufficient (67%), high learning costs (50%), or low wine interest (33%). Clara (F, 23, K = 2, novice): “These color rules are enough; for gifting I just follow them” (Quote C22).

5.6. Discussion

5.6.1 Configurational color effects on perceived value (RQ1)

Our findings extend wine label color research beyond hue-centered models. Prior work

typically treats hue as the main driver of color effects, yet our data show that these effects depend on configurational meanings (Elliot & Maier, 2014). We observe a robust color $\times$ brightness interaction across all perceived value dimensions, while color $\times$ saturation and color $\times$ brightness $\times$ saturation effects are significant, but with small effect sizes. There is no single “red effect”, only specific red configurations have impact (Bortolotti, 2023). Brightness functions as a critical moderator. Low-brightness red activates expectations of “richness” and “complexity”, high-brightness red loses this advantage and can even create the opposite impression. Sensory meaning emerges from multidimensional combinations and cannot be inferred from hue in isolation. Cross-modal correspondences are thus not inherent property of hue but configurational property of joint hue-brightness conditions (Spence & Piqueras-Fiszman, 2016).

These results highlight limitations in experimental designs that compare pure hues. Such designs often conflate hue with brightness and saturation. When researchers report that “red labels enhance perceived quality”, this may reflect a specific low-brightness red instead of red as such. Wine labels also never consist of color alone: layout (Anagnostou et al., 2025), design (Lunardo & Rickard, 2019), shape (Lunardo & Livat, 2016), contrast (Capanna Piscè et al., 2022), award symbols (Mokrý et al., 2016), typography (Gmuer et al., 2015) and label material (Crichton-Fock et al., 2023) can all amplify or attenuate configurational properties.

Color psychology predicts that high saturation enhances arousal and attention (He & Lv, 2022). While saturation exerts significant, targeted effects in our data, the arousal mechanism does not appear to be the primary driver of overall perceived value. A plausible explanation is that, in the cognitive task of wine evaluation, consumers prioritize inferring status and quality over seeking mere arousal. They selectively attend to dimensions they treat as diagnostic of overall value and formal appropriateness (brightness), integrating saturation as a secondary cue for specific stylistic or sensory characteristics. This goal-directed selective attention suggests that color effects depend not only on stimulus attributes but also on the cognitive task and interpretive frame through which consumers approach the product. The mechanism behind the color $\times$

brightness interaction may be general, whereas the preferred direction is culturally specific. Western wine consumers likewise associate lower brightness with higher authenticity (Pelet et al., 2020), but the most preferred hue-brightness combinations are influenced by locally embedded meanings of color.

5.6.2 Expertise, reliance on color and face-related anxiety (RQ2)

The statistical results point to two sides of expertise. Color configuration effects are robust across knowledge levels: the color $\times$ brightness $\times$ knowledge interaction is non-significant, and novices and experts display almost identical preferences for low-brightness red. However, qualitative findings show that expertise shapes the degree and manner of reliance on color cues. This “schema-shared but reliance-differentiated” pattern refines existing views on expertise. Classical models emphasize changes in cognitive structures (Alba & Hutchinson, 1987), whereas our results suggest that expertise does not necessarily alter the cultural schema itself; instead, it modifies how individuals monitor, evaluate and strategically apply it. Both novices and experts “read” low-brightness reds as more high-end, but novices treat this as a factual property of wine, while experts frame it as a socially constructed convention that can be bracketed, differentiated or tactically used (Valentin et al., 2016).

This pattern is consistent with Bourdieu’s (1984) account of cultural capital. Underlying cultural schemas may be widely shared; what differs is the degree of reflexivity. Experts recognize the same associations as novices but maintain evaluative distance and treat them as conventions instead of inherent product qualities. They may draw on such cues in socially sensitive contexts such as gifting yet rely more on intrinsic attributes in private tasting. Cultural capital therefore operates less through rejecting mainstream schemas than through the ability to alternate between participation and distance depending on situational demands (Holt, 1998).

High reliance on color cues among intermediate consumers suggests a non-linear trajectory of expertise. Qualitative data indicate a “knowledge-rich but skill-poor”

transitional state: intermediate consumers are more aware than novices of the importance of sensory evaluation yet have not developed the sensory confidence of experts. They experience heightened uncertainty and lean more on external cues despite having more declarative knowledge. This pattern resembles a consumer-level “knowledge-skill gap”, whereby partial knowledge increases reliance on heuristics instead of reducing it (Raju et al., 1995). Increasing information without simultaneously building practical tasting skills may even reinforce dependence on packaging color cues (D’Alessandro & Pecotich, 2013).

Face-driven anxiety further clarifies why visible cues remain influential, particularly in Chinese gifting contexts (Gao & Ting-Toomey, 1998). Many participants experienced wine gifting as a face-sensitive situation in which a misjudged label could signal insufficient respect, taste or competence to both the recipient and the audience. Under this perceived social surveillance, color configurations and other visible codes function as protective devices opposed to mere aesthetic preferences (Goffman, 1967). Novice and intermediate participants lacking confidence in tasting skills often described dark red as a “safe” choice that would carry face with elders and superiors and avoided bright red for fear of appearing frivolous. Experts also attend to these visual codes but frame decisions in more strategic terms, focusing on matching color to the recipient’s status whilst being less preoccupied with personal embarrassment. Face-related anxiety therefore amplifies color-attribute schemas in high-stakes social situations by showing how objectified capital is mobilized to manage social risk when embodied capital is perceived as insufficient (Goffman, 1967; Bourdieu, 1986; Holt, 1998).

5.6.3 Social learning and the construction of color-attribute schemas

(RQ3)

Qualitative data illuminate the social-cognitive processes through which color-attribute associations are learned. Most participants traced color schemas to everyday, cross-category analogies instead of formal training or digital media. This pattern accords with

symbolic and social learning perspectives: consumers infer simple rules from recurrent visual regularities in the marketplace (Bandura & Walters, 1977). Everyday retail and consumption practices thus constitute an important field of symbolic learning (Holt, 1995). Repeated exposure to patterns such as “premium juices come in darker packages” or “bottled water comes in blue bottles” fosters a heuristic that “darker colors signal higher status”, which is later generalized to wine labels. Such cross-domain learning appears conservative, tending to reproduce existing market conventions as an alternative to inviting their critical evaluation.

Beyond this general “dark = high-end” heuristic, interviews revealed more fine-grained, shade-specific meanings for red in the Chinese context. Participants consistently distinguished between bright and dark red. Brighter reds were linked to youthfulness, playfulness and festive celebrations, echoing clothing conventions for weddings, birthdays and informal parties. Dark red was associated with maturity, seriousness and respect, paralleling dress norms for formal banquets or occasions involving seniors and superiors. Respondents often drew on these analogies when justifying label choices, describing bright red labels as “for younger people or casual gatherings” and dark red labels as “more suitable for business dinners or respectful gifts”. For Chinese consumers, the schema of red is therefore not a simple “red = auspicious” rule but a differentiated system in which brightness within red maps onto distinct social roles and relationship norms (Tang et al., 2015; Xu, 2024). This helps interpret our quantitative results: low-brightness reds are perceived as especially appropriate for high-stakes gifting and formal occasions, whereas bright red is associated with celebratory but less constrained situations. Everyday cross-domain learning transmits not only a generic status code for color but also internal distinctions within red that structure how shades are matched to social situations (Palmer & Schloss, 2010).

This mechanism helps explain why certain cultural schemas are both stable and shared across knowledge levels. Our findings align with Bourdieu’s (1990) notion of a “logic of practice”: schemas are internalized through repeated bodily engagement with the market environment instead of explicit rule learning. Consumers do not learn a formal

rule that darker labels equal higher quality; they gradually become accustomed to this association, which comes to be experienced as an objective property of wine. Digital platforms emerge as a secondary and more ambivalent source (Arnould & Thompson, 2005). Participants frequently expressed skepticism towards platform content, evaluated influencer credentials, searched for commercial motives and cross-checked across sources (Ding et al., 2025). These practices indicate a form of critical digital literacy: platforms provide information, but consumers filter and reinterpret it through their own experiential frames.

5.6.4 Schema stability, attribution and critical consciousness (RQ4)

Sixty percent of participants explicitly acknowledged that color is used as a marketing tool, yet 89% reported that they still rely on color cues in their own choices. This apparent tension is difficult to reconcile with simple rational-actor assumptions. We identify three mechanisms that help sustain the resilience of color schemas. First, attributions after expectation violations tend to protect the schema, yet not challenge it. When color-based expectations failed, 71% of participants blamed the wine producer and 29% their own tasting competence; none questioned the underlying rule. In attribution terms, they particularized the failure instead of generalizing it to the schema (Kelley, 1973), treating disappointing experiences as isolated exceptions and thus maintaining confidence in the color heuristic.

Wine label color schemas have a double function. They serve not only an inferential function (inferring value properties) (Piqueras-Fiszman & Spence, 2015) but also a communicative function (signaling meaning in social interaction) (Yang & Paladino, 2015). Several experts chose dark red labels for gifts not because they believed these wines were intrinsically superior, but because they assumed recipients would read dark red as more respectful and dignified. Color is thus used as common cultural knowledge. Even when consumers are skeptical about its diagnostic value, they continue to use it strategically as a shared symbol in face-sensitive situations (Goffman, 1967).

Long-term practice embeds color preferences in taste. Repeated exposure to color-product pairings becomes incorporated into what Bourdieu (1984) called habitus. Our interviews suggest that even when participants intellectually question the rule “darker = better”, they still derive aesthetic pleasure from labels that “look nice”. Visual enjoyment has emerged as a value in its own right, independent of its instrumental role in quality assessment. This embodied dimension introduces inertia: schemas persist in practice even when weakened at the level of explicit belief. Overall, revealing the constructed nature of color cues is unlikely, by itself, to eliminate their behavioral influence. Awareness does not automatically translate into resistance; consumers can act “as if” a schema was valid whilst simultaneously recognizing its conventional character.

This study has several limitations. We relied on designed Italian wine labels as stimuli, which may not capture the full complexity of Chinese labels (Chinese characters, traditional symbols, cultural material textures), and the online setting prevented control over screen calibration and ambient lighting, introducing potential variation in color perception. Brightness levels were calibrated through a pre-test, so alternative parameter choices might yield different patterns. We measured purchase intention and perceived value but not actual purchasing behavior or willingness to pay, so effect sizes may be weaker in real purchase situations. The survey sample was skewed towards urban, younger and highly educated respondents, and the 30 participants in Study 2 were recruited through purposive sampling; both features limit generalizability across city tiers, age cohorts and social groups. Expertise was assessed via self-report and interviews relied on retrospective accounts, which may be affected by social desirability and the Hawthorne effect. Saturation effects remain only partially understood and would benefit from process-tracing or neuroscience approaches. Our use of face theory, although supported by qualitative evidence, risks cultural essentialism, as Chinese consumers are heterogeneous and face concerns likely vary across generations and contexts. Finally, we examined static labels outside a competitive shelf environment

and did not model interactions with other label elements, which may condition color effects in retail settings.

Future work can deepen the analysis along several lines. Ecological and behavioral validity could be improved by using labels from domestic and imported wines already in circulation, testing color effects in physical stores or VR shelf simulations, and combining these with eye-tracking and incentive-compatible or field experiments that record actual purchases and willingness to pay. Research could extend beyond red wine to other alcoholic beverages and food categories to identify boundary conditions and category-specific expressions of the color-brightness interaction. More diverse samples, obtained through stratified quota sampling across city tiers, age groups and income levels, would allow geographical and generational heterogeneity to be mapped more systematically. To refine mechanism accounts, neurological measurement and experimental causal-chain designs could test mediating pathways. Contextual comparisons between gifting and self-consumption, and between public and private circumstances, would clarify the boundary conditions of face-related anxieties. Longitudinal and cross-cultural work in other Asian and Western markets could examine how color preferences evolve as markets develop and distinguish culturally specific from more general color-attribute associations, guarding against attributing the present findings too readily to “Chinese culture” as a single, homogeneous category.

5.7 Conclusion

This study examined how wine label color configurations, particularly the interaction between color and brightness, influence Chinese consumers’ perceived value. It linked consumer perceived value theory with other sociological theories to explain how, in face-sensitive contexts, consumers draw on cross-domain everyday experience to construct color-attribute associations and use them as heuristics to manage social risk. A mixed-design experiment combined with stratified qualitative interviews quantified

the robustness of the color $\times$ brightness interaction (with low-brightness red outperforming high-brightness red) across knowledge levels and traced the social learning of color meanings and the role of face-related anxiety. The findings provide label design guidelines for producers, importers and retailers targeting the Chinese market, especially for wines positioned for gifting.

5.8 References

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Chapter 6 The Contextual Paradox: Algorithmic Precision and the Privacy Value (Study 3)

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The candidate contributed to: conceptualization, methodology, software, validation, formal analysis, investigation, resources, and writing-original draft; Author Gianluca Antonucci: conceptualization, methodology, writing-review & editing, supervision, and project administration; Author Michelina Venditti: conceptualization, methodology, writing-review & editing, supervision, and project administration.

Contextual link to the dissertation

The previous two chapters examined how consumers evaluate products based on sensory and cultural signals; however, in hybrid marketing environments like Douyin (TikTok), the source of uncertainty shifts from the product to the platform's mechanism itself. This introduces the research to the contextual layer, where the “active agent” is

no longer the consumer searching for goods, but the algorithm pushing content to the consumer. This shift creates a new kind of uncertainty: the algorithmic black box.

This study, titled “The contextual paradox: algorithmic precision and the privacy value,” adopts a phenomenological approach to explore the lived experience of algorithmic recommendations. Grounded in EVT and the S-O-R Model. This chapter identifies a critical phenomenon: the “privacy value.” It reveals that diagnosticity is non-linear; when an algorithm becomes too diagnostic (too precise), it triggers fear and avoidance rather than trust. This finding exposes a trust deficit that visual cues alone cannot solve. This critical problem necessitates a systemic solution. Consequently, the final empirical chapter (Chapter 7) will test how ethical design can serve as a cognitive scaffold to repair this broken trust.

6.1 Abstract

TikTok (Douyin in China) is a trendy short video platform and e-commerce marketplace. This study investigates AI-Powered Personalized Recommendations (AI-PPRs) on China's TikTok, focusing on how they impact user engagement and purchasing decisions. Using the Expectancy-Value Theory (EVT) and the Stimulus-Organism-Response (S-O-R) model, we find that Douyin's proactive 'push' mechanism of AI-PPRs enhances user engagement by effortlessly integrating product discovery into the entertainment experience. Content-driven AI-PPRs align with user preferences, decrease search time, and increase satisfaction and purchase intentions through engaging short videos and live streaming. However, privacy concerns emerge when personalization is perceived as excessively intrusive, leading to negative emotions and avoidance behaviors. Recommendation timing and cultural context significantly influence receptiveness, with inappropriate timing (e.g., during holidays) causing negative reactions. Technical challenges, such as network issues during live streaming, negatively impact user experience and engagement. Content quality is crucial, and poor or irrelevant content leads to negative perceptions and disengagement. While Key Opinion Leaders (KOLs) face skepticism due to perceived commercialization, endorsements from trusted figures and authentic influencers are better received. Innovative payment methods, like 'Douyin Monthly Payment,' enhance financial flexibility and promote customer loyalty. This study highlights the need to balance personalization with privacy, emphasizing the importance of content quality and authenticity in influencer marketing. For businesses using AI-PPRs, maintaining this balance is essential for preserving trust and sustaining consumer engagement and loyalty.

6.2 Introduction

The convergence of technology and consumer culture has revolutionized e-commerce in China, ushering in a new era of online purchasing. Platforms like Douyin (TikTok in

China) have catalyzed a paradigm shift by merging commerce and entertainment, transforming consumer engagement (Sun & Chi, 2018; Wang et al., 2022). China's digital environment, where 97.7% of the 1.092 billion internet users actively consume short video content (CNNIC, 2024), provides a unique setting for exploring new consumer behaviors.

Douyin's success largely stems from its advanced use of AI-PPRs, which not only attract users but also significantly influence their purchasing habits (Jia & Stan, 2021; Su, 2023). This study aims to analyze the complex dynamics within the Douyin ecosystem, focusing on the mechanisms and motivations behind consumers' reactions to AI-PPRs, which are pervasive in the digital shopping experience.

To explore these complexities, this research is grounded in two theoretical frameworks: the Expectancy-Value Theory (EVT) (Eccles, 1983) and the Stimulus-Organism-Response (S-O-R) Model (Mehrabian & Russell, 1974). EVT explains how consumers perceive AI-PPRs and how expectations of accuracy, relevance, and effectiveness can increase engagement and purchase intentions. The S-O-R model offers a framework for understanding how cognitive and emotional reactions to AI-PPRs trigger actions, such as increased engagement or purchasing (Peng & Kim, 2014). This paradigm is particularly relevant to Douyin, where short video content strongly impacts customer responses. This study uses in-depth interviews with Douyin users to explore their experiences with AI-PPRs, integrating theoretical insights to examine the interaction between AI-PPRs and consumer behavior on short video e-commerce platforms.

6.3 Literature Review and Research Question

AI-PPR systems have significantly transformed how consumers engage with online platforms, becoming essential contributors to the e-commerce sector. Research indicates that AI-PPR systems enhance consumer satisfaction by fostering positive attitudes and experiences (Ho & Bodoff, 2014; Kang et al., 2016). These systems effectively reduce information overload and decrease search costs, making it easier for

consumers to find products that match their preferences (Adomavicius et al., 2018; Namjun et al., 2019). Moreover, by improving system quality, information quality, and service quality, AI-PPRs positively influence consumer satisfaction and purchase intentions (Qin et al., 2022). Through enhanced user experiences, these systems promote efficiency in e-commerce operations and increase consumer satisfaction (Dogan, 2023). The sophistication of AI-PPRs lies in their ability to offer highly personalized product recommendations based on past preferences. Advanced algorithms sift through vast data to generate tailored suggestions, improving engagement and satisfaction (Pazzani & Billsus, 2007; Wei et al., 2017) and further influencing and enhancing the online shopping experiences (Song 2023). Recent studies emphasize the revolutionary impact of AI on digital marketing, highlighting its role in enhancing consumer experiences and engagement (Raji et al., 2024).

On platforms like Douyin, AI-PPR systems integrate user preferences, video content, and live streaming interactions, offering a comprehensive approach that increases engagement and satisfaction (Yu et al., 2023; Yoon & Lee 2021). These systems have enhanced brand awareness, fostered positive attitudes, and boosted purchase intentions (Ameen et al., 2021; Yin & Qiu, 2021). Empathy also plays a mediating role, as AI-PPRs respond to customers' emotional and psychological needs (Yoon & Lee, 2021). Additionally, recommendation systems improve performance expectations, influencing both utility and hedonic motives while building perceived trust in the system (Cabrera-Sánchez et al., 2020; Yin & Qiu, 2021).

Another factor influencing consumer behavior is usage duration, known as 'user stickiness,' which positively mediates the relationship between short video content and customer loyalty (Ren et al., 2021; Yang & Lee, 2022). Consumers' interest and potential to purchase are reflected in their active participation and unique browsing patterns (Rosário & Raimundo, 2021). AI-PPRs also generate higher click-through rates, increasing ad effectiveness and reducing users' defensive judgments (Dong et al., 2024), reducing users' defensive judgments about AI-PPRs, and stimulating potential passive demands (Yin et al., 2024).

Aside from the core impact of AI-PPRs on consumers, their design and presentation methods are also crucial (Ko et al., 2022). In e-commerce, AI-PPRs have evolved from static recommendations (e.g., price comparisons or detailed descriptions) to dynamic formats like short videos and live streaming (Sun et al., 2019). These dynamic formats enhance consumer engagement by providing personalized recommendations, improving user experience, and increasing transaction rates (Shao, 2022). Their effectiveness in capturing user interest is notable (Zhang & Liu, 2022).

The timing and channels used for recommendations significantly influence purchasing preferences. Yoo and Kim (2014) emphasized the role of mental imagery in online product presentations, suggesting that well-timed AI-PPRs that align with users' mental imagery improve effectiveness. Yang et al. (2022) also found that timing, scene design, and interface design are critical to consumer engagement and decision-making in live e-commerce. Strategically scheduling recommendations during periods of high activity or significant events can strongly impact purchasing behaviors (Sun, 2023), with precise timing increasing relevance and effectiveness (Shang et al., 2023).

Live streaming offers a unique combination of immediacy and interactivity, which has proven to be a powerful tool for enhancing engagement (Sun et al., 2019; Xue et al., 2020). Its interactive nature, along with the vividness of information and trust-building, influences online purchasing intentions (Yeo et al., 2020). This has led to a rise in Key Opinion Leaders (KOLs) within these formats, reshaping influencer marketing by providing direct communication, better shopping experiences, and increased sales (Li et al., 2021). However, their performance metrics can sometimes harm brand owners (Niu et al., 2023).

Existing research suggests that real-time interaction can reduce perceived risks in online purchasing (Xiaojun et al., 2020). The streamer's expert description empowers consumers to comprehend more extensive and detailed product information (Wongkitrungrueng & Assarut, 2020), thereby potentially enhancing consumers' trust in products, raising the perceived value of streamers (Menezes et al., 2021). This, in turn, strengthens purchase intentions (Gruner et al., 2019; Zhao et al., 2018).

While existing studies have examined the impact of AI-PPRs on consumer behavior and their modes of expression, there is a lack of in-depth research on how these factors collectively influence consumer engagement, browsing behavior, and purchase intentions on platforms like Douyin. To fill this gap, we propose the research question: How do AI-PPR systems and their modes of expression affect Chinese consumers' engagement, browsing behavior, and purchase intentions on Douyin?

6.4 Theoretical Frameworks

This study builds upon the Expectancy-Value Theory (EVT) (Eccles, 1983; Eccles & Wigfield, 2002, 2020), which explains the motivational factors driving consumer behavior in online settings. The expectancy component refers to an individual's belief in their ability to succeed (Midgley et al., 1989; Simpkins et al., 2012). This belief is shaped by self-beliefs, task importance, abilities, cultural norms, experiences, and personal beliefs (Rosenzweig et al., 2019). In the context of short video e-commerce platforms like Douyin, consumers' perceptions, cultural backgrounds, and beliefs significantly impact their behavior.

The value dimension of EVT consists of four key components that influence expectancy: achievement value (importance to the individual), intrinsic value (interest or hedonism), utility value (usefulness of the activity), and relative cost (Wigfield et al., 2006). Initially, interest differentiates value, followed by utility and perceived benefits (Wigfield & Cambria, 2010). In AI-PPR interactions, all four dimensions play significant roles for Chinese online consumers, with utility and intrinsic value being particularly important (Liu et al., 2020). AI-PPRs deliver functional value, enhancing the intention to continue engaging with the platform (Ashraf et al., 2019). Perceived utility and intrinsic value moderate the relationship between AI-PPRs and purchase intentions (Yin & Qiu, 2021). While higher recognition and intrinsic values from AI interactions drive a greater willingness to purchase recommended products (Loureiro et al., 2024).

EVT underscores that the accuracy, relevance, and effectiveness of AI-PPRs are key variables influencing consumer purchase intentions. Chinese consumers report satisfaction when AI-PPRs align with their tastes, lifestyles, and expectations (Akram et al., 2021; Jin & Zhang, 2023). Expectancy disconfirmation can alter consumers' future expectations, affecting confidence, price perceptions, and equity considerations (Lin & Lekhawipat, 2016). Thus, accuracy, relevance, and effectiveness in AI-PPRs are crucial stimulus variables influencing consumers' purchase intentions.

Integrating EVT with the Stimulus-Organism-Response (S-O-R) model (Mehrabian & Russell, 1974) provides a comprehensive framework for understanding consumer behavior. The S-O-R model posits that external stimuli (S), such as AI-PPRs, affect an organism's internal state (O), leading to responses (R). This model has been used to study consumer attitudes towards social media and e-commerce platforms (Zhu et al., 2020; Li, 2019; Li et al., 2023; Lee & Chen, 2021), illustrating how stimuli like AI-PPRs can induce engagement through perceived interactive experiences (Asante et al., 2023). Research shows that e-service quality affects customers' psychological and behavioral engagement, supporting the S-O-R model's application in this context (Asante et al., 2023).

In this framework, stimuli are external environmental factors that attract attention through design or attributes, leading to psychological evaluations and behavioral responses (Asante et al., 2023). For Douyin users, AI-PPRs act as external stimuli where content, timing, and delivery method strongly influence cognitive engagement. Dynamic content like videos and live streams engages users by being vivid and interactive. Well-timed AI-PPRs, tailored to customers' current needs or lifestyle cycles, significantly affect their internal state, shaping perceptions and attitudes. The diverse dissemination methods of AI-PPRs, including in-app notifications, private messages, videos, and emails, directly impact users' emotional processes, evidenced by their positive and negative responses.

By integrating EVT with the S-O-R model, this study captures the complex interplay between external AI recommendations and internal motivational processes. EVT

elucidates how individuals' expectancies and values drive motivation and behavior (Eccles & Wigfield, 2002), mediating emotional and cognitive responses to AI-PPRs. This combined framework offers deeper insights into how AI-PPRs influence consumer engagement, browsing behavior, and purchase intentions on e-commerce platforms like Douyin.

6.5 Methodology

6.5.1 Research Approach

This study adopts a qualitative research design with a deductive approach to understand consumers' perceptions and experiences influenced by AI-PPRs on Douyin. Qualitative research is ideal for exploring the complex interactions that influence customers' involvement and decision-making, providing deeper insights into engagement with AI-PPRs (Hair Jr et al., 2019).

6.5.2 Data Collection

Telephone interviews were conducted with 36 participants, of whom 47% were male and 53% were female, aged between 17 and 64, all with prior purchasing experience on Douyin. Interviews ranged from 25 to 40 minutes, and participants were selected using purposive sampling methods (Palinkas et al., 2015).

6.5.3 Data Analysis

The interviews were semi-structured and conducted in Mandarin, recorded with participants' consent, and analyzed using NVivo 12 software. The interviews were transcribed and translated into English to facilitate this analysis.

Details on participant demographics (Table D1), recruitment methods, transcription and

coding procedures are provided in Appendix D.

6.6 Findings

To synthesize the insights gathered from our interviews, we developed a conceptual framework that encapsulates the multifaceted impact of AI-PPRs on consumer behavior. The Figure 3 visually represents these interconnected themes, providing a holistic view of how AI-PPRs influence user engagement, purchase intentions, and avoidance behaviors on Douyin.

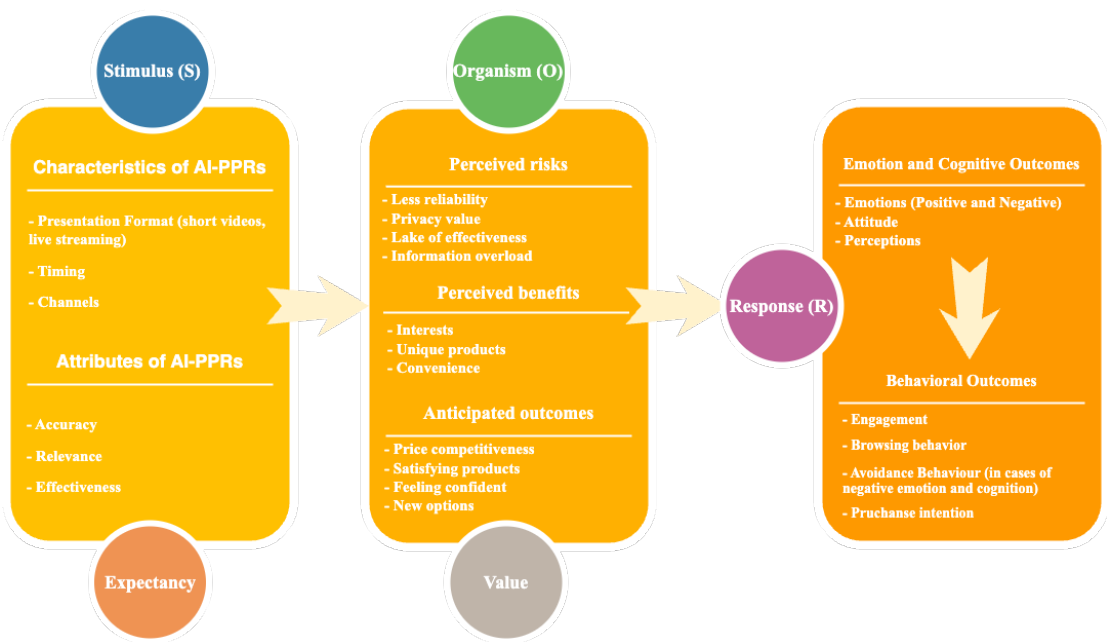


Figure 3 Conceptual Framework of the Impact of AI-PPRs on Consumer Behavior

6.6.1 Characteristics of AI-PPRs

Presentation Format

Our study found that participants preferred short video formats for AI-PPRs on Douyin. This format was perceived as more engaging and dynamic compared to text and images, allowing for a comprehensive presentation of product characteristics (Li, 2019). For

example, Michael expressed:

“Text and pictures can be all fancy, but videos are just more straight-up and feel more alive. Even if I’m really into something, I’ll check out the video (on the product description page) anyway. So, might as well just show me the video from the get-go.”

Timing

The timing of AI-PPRs significantly influenced participants’ receptiveness. Recommendations that matched immediate needs, such as when daily consumables were running low, were well received. AI-PPRs suggesting similar products or substitutes positively affected consumption behavior. Reflecting this, Andrew noted:

“Recommendations that pop up when I’m running low on essentials are super helpful. They remind me to restock without me having to think about it.”

However, recommendations during holidays were often met with negative emotions, as participants preferred to disconnect and enjoy the festive atmosphere. Reflecting this preference, Chloe stated:

“As for holidays, I almost never buy online. Seasonal products aren’t essentials, so they don’t tempt me. I prefer the traditional vibe of shopping on the streets during holidays like Christmas or Chinese New Year. Enjoying the atmosphere is more important to me.”

Channel

Participants expressed discomfort and mistrust towards unsolicited communication channels such as emails, text messages, and in-app notifications. This mistrust stemmed from the rise of telecommunications fraud, leading to the rejection of recommendations delivered through these less trusted channels. Highlighting this sentiment, Joseph

shared:

“I never check my email outside of work. To me, that’s junk mail territory. Messages? Even worse, they make me even more annoyed. In-app notifications are sort of okay, but I tend not to pay much attention to them either. Basically, anything that feels scammy gets on my nerves instantly, except for short video recommendations.”

6.6.2 Attributes of AI-PPRs

Accuracy and Relevance

Participants noted that Douyin’s AI-PPRs were highly accurate and relevant, matching their preferences and helping them discover products aligned with their needs and habits. This accuracy reduced search costs and alleviated information overload, enhancing user engagement (Adomavicius et al., 2018; Namjun et al., 2019). Reflecting this, Matthew stated:

“It is connected to my living habits or other aspects of life. Certain products are difficult for me to find ordinarily, but when I find them (AI-PPRs), they are really useful, and I will surely take them.”

And Benjamin remarked:

“Basically, they (AI-PPRs) are almost the same as the short videos I usually watch. The big data calculations are very accurate. It knows exactly what I want to buy.”

Effectiveness

The effectiveness of AI-PPRs was highlighted by participants who appreciated the reduced time spent searching for products and addressing information overload. Emphasizing this point, Andrew commented:

“Everyone is under a lot of work pressure nowadays. I just want to read fewer ads. I don’t have time to search (on conventional e-commerce platforms), so I prefer these AI-PPRs.”

6.6.3 Perceived Risks

Less Reliability and Lack of Effectiveness

Some participants expressed concerns about the reliability and effectiveness of certain AI-PPRs, especially when recommendations did not meet expectations. Low-quality or confusing video content led to frustration. This aligns with prior studies indicating that poor-quality recommendations can negatively impact user experience (Li et al., 2023).

Echoing these concerns, Christopher stated:

“It (AI-PPR) does come down to the quality of the video, right? Like, if there’s a 30-second video and 15 seconds of it are just nonsense, that can get pretty annoying.”

Privacy Value

Privacy concerns were a recurring theme. Participants felt uneasy when recommendations were too precise or invasive, leading to perceptions of being monitored or manipulated. This introduces the concept of ‘privacy value,’ where the accuracy of AI-PPRs intersects with user privacy concerns (Mou et al., 2021).

Emphasizing this discomfort, Anthony noted:

“Perhaps it’s a psychological sensation with a suspicion that I am being set up. Because I didn’t even realize I truly needed this item, so to get out of this crisis, I’ll ignore (the AI-PPRs).”

Sarah added:

“In the era of big data, we may believe that we are the masters of AI, but increasingly accurate recommendations make me feel that we humans are

more like pawns of AI and dominated by it. Hence, I frequently select ‘Not Interested’ in its recommendations to avoid it controlling my life too much.”

Information Overload

Excessive recommendations contributed to information overload, diminishing the user experience. Participants expressed frustration with the sheer volume of recommendations, which led to disengagement. Reflecting this frustration Joseph shared:

“The constant recommendations are really annoying, and now I don’t even feel like watching short videos anymore. It’s having a negative impact on me, like when I’m shopping and a sales assistant keeps trying to push products on me. It’s super frustrating!”

6.6.4 Perceived Benefits

Interests and Unique Products

Participants appreciated that AI-PPRs enhanced their interests and introduced them to unique products they might not have found otherwise. This aligns with Lim and Dubinsky’s (2004) emphasis on perceived benefits influencing user satisfaction. For example, Emily mentioned:

“Indeed, among these AI-PPRs, it may not be the product itself that causes me to spend more time on Douyin, but rather video-related features. For instance, the background music in the video may possess a pleasing mood, the protagonist in the video could be exceptionally attractive, and the video may effectively evoke a fascinating atmosphere, including love stories, charitable projects, expressions of patriotism, and high-level video aesthetic designs. I shall save these short videos as favorites.”

Convenience

The convenience of reduced search time and effort was a significant benefit. Participants valued the streamlined shopping experience provided by Douyin's AI-PPRs. This was highlighted by Daniel, who remarked:

“The area (Xinjiang) where I live is considered a ‘remote region’ in China, and a lot of sellers don’t offer free shipping. But the AI-PPRs for my region usually include free shipping, If I shop on other platforms, I have to spend time checking whether shipping is free or not, so it really saves me a lot of time.”

6.6.5 Anticipated Outcomes

Price Competitiveness

Participants recognized the price competitiveness of products recommended through AI-PPRs. Douyin's promotion mix of discounts and gifts increased perceived value. Highlighting this advantage, Brandon shared:

“The prices are low, which is Douyin's advantage. Also, there are various gifts and price reductions that all satisfy my demands. This promotion mix of discounts and gifts attracts me and is quite effective.”

Additionally, Douyin's introduction of ‘Douyin Monthly Payment,’ a payment option similar to a credit system, allowed users to make purchases first and settle payments at a later stage, enhancing financial flexibility and customer loyalty among younger consumers. Reflecting on this benefit, Alexander said:

“Douyin Monthly Payment can ease the monthly financial stress of young people like me who work hard in big cities. Moreover, it seems to have radically transformed my shopping habits. Douyin is now mostly just used for shopping.”

Satisfying Products and Feeling Confident

Accurate recommendations led to satisfaction with purchased products and increased confidence in shopping decisions. Emphasizing this positive impact, Jessica said:

“I am quite interested in jewellery, and I often watch videos about jewellery. Once, I was pushed to a live stream of jade jewellery, and I finally bought two items from that channel. I was very satisfied.”

New Options

Participants appreciated being introduced to new products through AI-PPRs, expanding their product choices and experiences. This excitement over discovering new products highlights the role of AI-PPRs in broadening consumer horizons and enhancing the shopping experience by offering novel options. Reflecting this excitement, Thomas expressed:

“Sometimes I see things I’ve never seen before, and I just really want to buy them and try them out.”

6.6.6 Emotion Outcomes

Positive emotion

Participants reported experiencing positive emotions and attitudes such as enjoyment, satisfaction, and emotional engagement when interacting with AI-PPRs that resonated with their interests and emotions. The narrative-driven and emotionally charged nature of Douyin’s content contributed to deeper user satisfaction, which is not fully captured by Dogan’s (2023) streamlined operational model for e-commerce platforms. Participants also felt a stronger connection to content that reflected their emotions, supporting the role of empathy in enhancing user engagement (Yoon & Lee, 2021; Bove, 2019). Emphasizing this connection, Olivia shared:

“Sometimes, I feel like AI-PPR is trying to transmit some feelings or

emotions to me. For some reason, these kinds of emotions are using my kindness to help someone get through difficult situations. I used to pay for this compassion. It doesn't have to be humans. Cats, dogs, and environmental concerns will also elicit my sympathies. I can also pay for those. That's not a big problem, but it made me think they need help more than anyone else."

Negative emotion

Conversely, participants also experienced negative emotions, particularly when AI-PPRs were overly intrusive, misaligned with their identities, or infringed on their privacy needs, leading to cognitive dissonance. This was evident with gender-specific or sensitive product recommendations, which triggered strong emotional backlash and avoidance behaviors. Reflecting this frustration, John expressed:

"I'm a guy. And sometimes the recommendations I get are all about makeup products, feminine hygiene stuff. It's so ridiculous."

Concerns about privacy and identity were also expressed by some participants. For instance, Andrew, shared his worries, stating:

"It's like the big data figured out I'm gay. Then it started recommending all these gay-related products. But I don't want people at work to know about my private life, so sometimes I'm scared to watch Douyin with friends. You never know when some gay-themed product might pop up, and this really worries me."

6.6.7 Cognitive Outcomes

Attitudes

The study examined participants' perceptions of Key Opinion Leaders (KOLs), distinguishing between authoritative figures with expertise and popular figures with

large online followings. While KOLs are often trusted to influence consumer decisions (He & Jin, 2022; Lee & Chen, 2021), participants expressed skepticism about the authenticity of their endorsements. Reflecting this skepticism, Anthony commented:

“If someone’s doing it, they must’ve been paid. Once they take money, it’s marketing, not a genuine recommendation anymore. I don’t trust so-called experts or authority figures because there’s always a profit motive behind it. It really puts me off, makes me feel like these experts are just ordinary folks after all.”

Despite this skepticism, exceptions existed for famous actors or singers, and well-known live streamers. Fan admiration led participants to accept recommendations from idols regardless of product relevance. Emphasizing this loyalty, Thomas said:

“I just like my idols, so I’m willing to buy their products. It’s like I don’t even care what the product is, just my love for them that makes me want to purchase.”

Well-known live streamers were perceived as more reliable due to transparency and quality control measures. Highlighting this perception, Hannah noted:

“Usually, these big streamers have their own quality control teams and can get stuff at lower prices, so I do watch their live streams.”

Perceptions

Participants reported negative perceptions associated with live streaming AI-PPRs due to technical issues such as network connectivity problems, limited mobile tariffs, and long loading times caused by large video sizes. Addressing these challenges, Benjamin remarked:

“Normally, it’s okay, but when my mobile data tariff is running out, my phone starts to throttle the speed, or when the network’s bad, that’s a real hassle. Everything just starts to lag terribly.”

Additionally, the quality of AI-PPR content significantly influenced cognitive engagement. Participants experienced negative perceptions when presented with fragmented, off-topic, or confusing video content. Such content reduced engagement. Highlighting this issue, Margaret added:

“Some videos are just so confusing, like half of it’s telling a story and the other half’s about the product. I don’t get the point of these kinds of recommendations. In the end, I don’t get the story or the product, and it just feels like a total waste of time.”

6.7 Discussion

This study comprehensively explores how AI-PPRs on Douyin influence consumer behavior through a complex interplay of characteristics, attributes, perceived risks and benefits, emotional and cognitive outcomes, and subsequent behavioral responses. By integrating the EVT and the S-O-R model, we offer deep insights into the mechanisms driving user engagement, purchase intentions, and avoidance behaviors.

6.7.1 Accurate and Relevant AI-PPRs Enhancing Satisfaction

Our findings corroborate earlier studies (Ho & Bodoff, 2014; Kang et al., 2016; Shin, 2020) which found that AI-PPRs can enhance customer satisfaction. In Douyin’s case, satisfaction was largely tied to AI-PPRs aligning with users’ habits and preferences, supporting the EVT’s premise that recommendations meeting user expectations lead to higher satisfaction (Wigfield et al., 2006). Participants acknowledged the precision of AI-PPRs in matching their preferences, reducing search costs and alleviating information overload, which enhances user engagement. Douyin’s AI-PPRs significantly reduce search costs, aligning with Namjun et al.’s (2019) and Adomavicius et al.’s (2018) findings that effective recommendations alleviate information overload and improve user engagement. This efficiency is especially effective on a platform like

Douyin, which focuses more on content engagement than product searches, a distinction noted by Qin et al. (2022). Douyin fosters a deeper connection between users and the platform by aligning product recommendations with content preferences, extending beyond simple product discovery (Pazzani & Billsus, 2007; Wei et al., 2017).

6.7.2 The Proactive ‘Push’ Mechanism Boosts Engagement

Douyin adopts a ‘push’ recommendation model, actively promoting products that align with users’ interests based on their short video consumption patterns. This proactive approach sets it apart from traditional ‘pull’ mechanisms in conventional e-commerce platforms, where recommendations are generated post-search (Pazzani & Billsus, 2007; Wei et al., 2017). The precision and relevance of these recommendations have significantly improved, minimizing user resistance. Participants reported increased engagement and browsing behavior due to this seamless integration of product discovery into the entertainment experience.

This proactive ‘push’ mechanism aligns with the EVT by meeting users’ expectations and enhancing satisfaction (Ho & Bodoff, 2014; Kang et al., 2016; Shin, 2020). The enhanced accuracy and relevance of AI-PPRs reduce search costs and information overload, fostering positive emotional responses and increased platform engagement.

6.7.3 Perceived Value and Pricing Drive Purchase Intentions

Our findings confirm the central role of perceived value, consistent with Lim and Dubinsky (2004). Participants highlighted anticipated outcomes and perceived benefits as central factors in their positive experiences with Douyin’s AI-PPRs. The combination of AI-PPRs and pricing advantages creates a perceived higher cost-performance ratio, demonstrating that AI-PPRs can enhance both value perception and consumer expectations, thus increasing satisfaction and purchase intentions (Wigfield et al., 2006).

Douyin's introduction of the 'Douyin Monthly Payment' has reshaped the relationship between users and the platform. This innovative payment option has enhanced financial flexibility and fostered long-term loyalty, particularly among younger consumers. This finding extends Ren et al.'s (2021) focus on system functions by demonstrating how integrating AI-PPRs with innovative payment systems enhances 'user stickiness' beyond traditional factors. Participants reported that this payment option not only eased financial stress but also transformed their shopping habits, indicating a deeper integration of the platform into their daily lives.

6.7.4 Narrative-Driven Content Elevates Experience

Participants reported that AI-PPRs with narrative-driven and emotionally charged content significantly enhanced their user experience. This heightened satisfaction is primarily observed in the viewing of suggested product-related videos and associated live streams. This finding is not fully captured by Dogan's (2023) streamlined operational model for e-commerce platforms, suggesting that factors beyond merely meeting customer expectations influence user satisfaction.

This aligns with Zulli and Zulli's (2022) findings that emotionally engaging content enhances user satisfaction and platform loyalty. The emotional connection fosters increased engagement and purchase intentions, supporting the S-O-R model where the organism's internal state influences behavioral responses (Mehrabian & Russell, 1974). However, it's important to note that negative evaluations of the e-commerce features do not necessarily result in dissatisfaction or disengagement with Douyin's short video content, as the purchasing activities and content consumption are independent.

6.7.5 'Privacy Value' Affect User Engagement

We propose a concept of 'privacy value' for AI-PPRs within the EVT framework. This term reflects consumers' concerns regarding the accuracy and intrusiveness of AI-PPRs.

Participants expressed discomfort and perceptions of danger when recommendations were overly precise or invasive, indicating that while diverse AI-PPRs can enhance user experience (Yoon & Lee, 2021; Yu et al., 2023), platforms need to ensure that this privacy value remains within a reliable range.

This finding supports Mou et al.'s (2021) assertion that privacy concerns can negatively impact customer satisfaction and purchase intentions. It challenges Yin and Qiu's (2021) claim that personalization invariably enhances customers' engagement and browsing habits. Our study reveals that excessive personalization without regard for privacy can lead to negative emotional responses and avoidance behaviors, affecting overall platform trust and engagement.

6.7.6 The Dual Role of Empathy in AI-PPRs

Our research highlights the dual role of empathy in AI-PPRs. While Yoon and Lee (2021) argue that empathy strengthens emotional connections, our findings reveal that excessive reliance on empathetic designs may reduce users' sense of control, leading to disengagement. Participants reported feeling manipulated or dominated by AI technology when recommendations leveraged their emotions excessively. Therefore, empathetic AI-PPRs must carefully balance emotional engagement with user autonomy to avoid unintended negative consequences.

6.7.7 Timing and Cultural Context Influence Receptiveness

The effectiveness of AI-PPRs is significantly influenced by timing and cultural context. While previous studies have focused on targeting, personalization, content creation, and ad optimization (Gao et al., 2023), our findings highlight that even relevant recommendations can be ill-received if delivered at inappropriate times, such as during holidays. For Chinese consumers, holidays are associated with relaxation and traditional shopping experiences. Participants preferred to disengage from online

purchasing during these periods.

This nuance indicates opportunities for AI-PPRs to align with cultural practices by offering specialized products that enhance, rather than detract from, the holiday experience. By accounting for these cultural factors, AI-PPR systems can optimize user receptiveness and prevent negative emotional responses that lead to disengagement.

6.7.8 Content Quality Shapes Cognitive Engagement

Our study demonstrates that the format of AI-PPRs, particularly short videos and live streaming, plays a critical role in cognitive attention. As noted by Ko et al. (2022), effective design and presentation of content significantly impact user preferences. Users favor video formats for their immediacy and dynamic nature, which allow for a comprehensive product presentation and foster greater engagement (Li, 2019).

However, poor-quality or confusing video recommendations can trigger negative emotional responses. Prior research, such as Li et al. (2023), has pointed out that overly tailored advertising recommendations may cause frustration among users. We expand on this by showing that fragmented, off-topic, or lengthy video content can shift users' emotional reactions from positive to negative. This suggests that AI-PPRs need to balance content quality and relevance to maintain positive cognitive engagement and prevent avoidance behaviors.

6.7.9 Trust and Authenticity in Communication and KOLs

Our findings align with concerns about the impact of fraud on consumer trust (Alhitmi et al., 2024). Participants reported that unsolicited messages, emails, and notifications instigate discomfort and annoyance, challenging Yeo et al.'s (2020) assertion regarding the trust-inducing capacity of interactivity. The mode and context of interactivity are crucial; unsolicited and intrusive communications may erode trust rather than build it.

This mistrust extends to AI-PPRs delivered outside the trusted short video channel, emphasizing the importance of trust and credibility in AI-PPR delivery methods.

KOL is defined as “the minority of people who have a considerable influence on consumers’ decision-making, attitude, and behavior” (He & Jin, 2022). Our study examined two groups: experts with field-specific knowledge (e.g., industry specialists) (Lee & Chen, 2021) and popular figures with large followings (e.g., entertainers, prominent live streamers) (Luo et al., 2021). While KOLs are generally expected to sway consumer behavior positively (Li et al., 2021), our results highlight the growing awareness among consumers of the commercialization behind endorsements. Participants perceived that KOLs might be driven by profit motives, which erodes trust in their recommendations. This skepticism reflects a broader trend where over-commercialization of influencer marketing compromises the authenticity and credibility of KOLs (Niu et al., 2023).

However, fan loyalty to idol personalities remains an exception, with fans willing to purchase products regardless of relevance, driven by emotional bonds rather than product necessity. Additionally, well-known live streamers maintain a higher degree of trust due to their perceived transparency and the economic value they offer (Yang et al., 2023). This suggests that product quality assurance, transparency, and perceived consumer benefits are key to sustaining trust in influencer marketing.

6.7.10 Technical Issues Impact User Engagement

Technical issues in live streaming, such as network connectivity problems, Internet data limitations, and long loading times, negatively impact user experience and perceptions. Participants reported frustration and decreased engagement due to these technical challenges. This finding underscores the importance of technical performance in delivering effective AI-PPRs.

Platforms must address these challenges by optimizing video content for smoother

streaming and providing data-efficient options. By enhancing the technical aspects, platforms can improve user satisfaction, prevent negative perceptions, and maintain engagement levels.

6.7.11 Emotional and Cognitive Outcomes Influence Behavioral

Responses

Building on the S-O-R model, our findings indicate that emotional and cognitive outcomes significantly influence behavioral responses. Positive emotions, such as enjoyment and satisfaction, foster increased engagement and willingness to purchase recommended products (Mehrabian & Russell, 1974). Participants who experienced positive emotional connections with content reported spending more time on the platform and exploring additional recommendations.

Conversely, negative emotions and perceptions led to avoidance behaviors. Participants reduced their usage of Douyin, especially in public settings, to prevent potential embarrassment or discomfort. Negative cognitive outcomes, such as skepticism towards KOLs and frustration with technical issues, diminished purchase intentions and engagement. This aligns with previous research suggesting that negative affective and cognitive responses can lead to withdrawal behaviors (Donovan et al., 1994).

6.8 Conclusion and Implications

Our research reveals that AI-PPRs on Douyin enhance user satisfaction and engagement by reducing search costs and aligning with browsing habits, particularly through the platform's proactive 'push' mechanism and engaging short video format (Ho & Bodoff, 2014; Kang et al., 2016; Shin, 2020). However, precise targeting raises 'privacy value' concerns, highlighting the tension between personalization and privacy (Yin & Qiu, 2021). Balancing personalization with privacy is essential to maintain user trust and

purchase intentions. Our findings extend the Stimulus-Organism-Response (S-O-R) model by demonstrating how AI-PPRs in dynamic formats engage users cognitively and emotionally, influencing satisfaction and purchase intentions (Asante et al., 2023; Dong et al., 2024). Negative reactions occur when recommendations conflict with personal identities or privacy expectations, leading to cognitive dissonance and decreased engagement. Regarding Key Opinion Leaders (KOLs), over-commercialization risks undermining authenticity and reducing trust in endorsements. However, live streamers and idol figures maintain influence due to perceived transparency and fan loyalty, underscoring authenticity's importance in influencer marketing (Niu et al., 2023).

For practitioners, balancing personalization with privacy is crucial. Transparency in data usage and giving users control over recommendations can maintain trust (Cabrera-Sánchez et al., 2020). Platforms like Douyin can enhance engagement by aligning AI-PPRs with users' viewing habits and leveraging emotionally resonant content (Yin & Qiu, 2021; Dong et al., 2024). Authenticity in influencer marketing is vital; brands should ensure transparent partnerships to sustain consumer engagement and loyalty (Yang et al., 2023).

6.9 Limitation and Future Research

Although this study examines Chinese consumers' perceptions of AI-PPRs on Douyin, it has limitations. First, cultural complexities may limit the global generalizability of the findings. Second, focusing solely on Douyin means differences in consumer behavior across other platforms were not explored. Third, the qualitative approach faced constraints in sample size and diversity; increasing these could enhance insights. Future research should compare cultures to understand how cultural factors influence perceptions and emotions. Longitudinal studies could track changes in consumer behavior over time. Additionally, investigating ethical issues like data privacy, bias, and transparency in recommendation systems is essential.

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Chapter 7 The Systemic Solution: AI Ethical Design as Cognitive Scaffolding (Study 4)

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The candidate contributed to: conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing-original draft, and visualization; Author Gianluca Antonucci: conceptualization, methodology, writing-review & editing, supervision, and project administration; Author Lea Iaia: conceptualization, methodology, writing-review & editing, supervision, and project administration. Author Marco Pironti: conceptualization, methodology, writing-review & editing, supervision, and project administration.

Contextual link to the dissertation

Chapter 6 identified a profound “Trust Crisis” in hybrid environments: consumers feel manipulated and surveilled by opaque algorithms. To resolve this tension, the thesis moves to its systemic layer. Mere optimization of sensory cues or cultural alignment is insufficient to address the structural anxiety identified in Chapter 6. A systemic intervention is required to restore the consumer’s sense of agency.

This study, titled “The systemic solution: AI ethical design as cognitive scaffolding,” investigates AI ethical design (transparency, fairness, privacy, and autonomy) as the

mechanism for trust reconstruction. Utilizing Dual-Process Theory, it tests the causal pathway from cognitive understanding to affective trust across multiple sequential mediation pathways. This chapter provides the systemic solution to the present research. It demonstrates that ethical features function as cognitive scaffolding, engaging System 2 processing to make the “black box” intelligible. By validating this mechanism, Chapter 7 completes the theoretical arc of the thesis: from seeing, to interpreting, to experiencing conflict, and finally to understanding and trusting. This sets the stage for the general discussion (Chapter 8), which will synthesize these four layers into a unified theory.

7.1 Abstract

This study examines how ethical design influences AI acceptance through cognitive and affective pathways. Using experimental data from 278 participants exposed to high versus low ethical AI designs, we uncover dual processing mechanisms: direct visceral responses and sequential cognitive-affective elaboration. Remarkably, all 16 sequential mediation paths were statistically significant, while simple mediations showed partial success. The equivalence of direct and sequential indirect effects implies that the processing of ethical AI features involves both intuitive and analytical systems. Different dimensions require distinct strategies: privacy needs cognitive scaffolding, autonomy triggers immediate responses, and fairness engages both routes. These findings establish ethical design as a central determinant of AI acceptance, requiring a complementary mediation model where cognitive understanding enables rather than competes with emotional engagement.

7.2 Introduction

Emerging technologies such as artificial intelligence (AI), Internet of Things (IoT), and blockchain are reshaping organizations and management (Schultz & Seele, 2023). Despite their benefits, these technologies raise ethical concerns and user acceptance issues. Technology design is often criticized for lacking ethical considerations (Häußermann & Lütge, 2022), resulting in privacy violations, data misuse, algorithmic bias, and diminished user autonomy (Wright et al., 2014). These issues impact both internal operations and external stakeholders, particularly end-user acceptance and intention (Pironti & Iaia, 2022).

While ethical design aims to embed ethical principles in technology development (Bruschi & Diomede, 2023), a critical gap remains: we lack understanding of the psychological mechanisms through which ethical features influence user behavior. Traditional technology acceptance models assume direct pathways from design features to user intentions. However, ethical AI features may engage distinct psychological

processes that remain unexplored.

The clarity of algorithmic decision-making in AI systems prompts fundamental questions regarding user information processing (Kim et al., 2021). When AI systems disclose their decision-making logic, data usage, and recommendation processes (i.e., algorithmic transparency), users need to understand this information through distinct psychological pathways. Current research, however, does not address whether people engage in both processes at the same time, react through immediate affective responses, or require cognitive comprehension before establishing trust (Zhou & Wu, 2024; Vorm & Combs, 2022).

This study addresses this gap by examining how ethical design in AI-powered recommendations influences user intentions through cognitive-affective mechanisms. In addition, this study challenges the conventional view that ethical features are secondary factors in technology acceptance. Instead, we empirically demonstrate that ethical design operates as a primary driver of user acceptance, but through a more complex pathway. Specifically, we reveal that users process ethical features through dual psychological pathways that must work in concert for acceptance to occur. Based on experimental data from 278 participants, we find that while both affective responses and cognitive understanding contribute to acceptance, only their sequential combination consistently reached statistical significance across all tested pathways. Compared to the partial effects of single pathways, this sequential mediation suggests that the processing of ethical AI features unfolds in a psychological trajectory that begins with awareness, continues with emotion, and culminates in action.

7.3 Literature review

Ethical design integrates ethical principles into technology development and implementation (Schultz & Seele, 2023), extending beyond functionality and efficiency to address social impact, user rights, and well-being (Tseng, 2023). Its relevance is heightened by the complexity, broad impact, and lack of transparency in emerging technologies (Häußermann & Lütge, 2022). While these technologies enable

innovation and faster decision-making (Pironti & Iaia, 2022), they also create challenges in acceptance and understanding, highlighting the importance of knowledge management and ethical considerations (Rhem, 2021). Ding et al. (2025) highlight dilemmas in AI-powered recommendations, such as data use, privacy, and user-centered design. Häußermann and Lütge (2022) stress the value of integrating diverse ethical principles into AI development. Although these studies provide a theoretical basis, most remain conceptual and lack empirical analysis of how ethical design affects user behavior. This gap is particularly problematic given that Martin and Freeman (2004) demonstrate technology and society are interdependent, with adoption of emerging technologies relying on ethical foundations including ethical climate, leadership ethics, and corporate social responsibility (Stahl & Eke, 2024).

The traditional view of ethical design as an “add-on” to functional features is increasingly challenged by evidence suggesting its central role in technology acceptance (Chivukula et al., 2023). Ethical algorithm awareness refers to users’ cognitive understanding of algorithmic features in technology systems (Shin et al., 2022), AI systems encompassing transparency, fairness, privacy protection, and autonomy (Chang et al., 2018). These cognitive dimensions are critical because the opaque “black-box” nature of AI hinders informed decision-making (Eslami et al., 2015; Hargittai et al., 2020; Shin, 2021). Users must first comprehend algorithmic processes before they can form judgments about system acceptability. These issues highlight the importance of ethics in AI-powered recommendations. Recommendation algorithms should ensure fairness (avoiding bias and manipulation), transparency (clarifying recommendation logic), privacy protection (limiting data use to necessity and consent), and autonomy (allowing users control over recommendations). Research shows that violations of these ethical principles, such as group favoritism, price discrimination, or hidden processes, erode fairness and trust (Hargittai et al., 2020; Zhou et al., 2021), while non-consensual data use increases privacy concerns (Ding et al., 2025). Perceived manipulation further reduces usage intention (Bjørlo et al., 2021). However, existing research examines only the direct effects of algorithm awareness on user behavior, overlooking its potential mediating role between ethical design and outcomes. More

critically, few studies examine whether cognitive understanding alone suffices or whether it must be accompanied by other factors.

Additionally, beyond cognitive understanding, users' psychological responses are key predictors of technology acceptance and usage (Park et al., 2022). Gerli et al.'s (2022) framework identifies multiple affective dimensions, trust reflects users' emotional response to technology, credibility involves perceptions of professionalism, authority, and output quality, influencing attitudes and information-seeking behavior, likability captures positive emotions, like curiosity and open-mindedness, which promote adoption and learning, while resistance represents negative affective states including fear, annoyance, skepticism, hindering technology acceptance and skill development. In AI-powered recommendation systems, these affective responses may operate independently from or in conjunction with cognitive understanding (Ding et al., 2025). Trust (belief in system reliability and capability), for instance, is identified as a prerequisite for acceptance (Novozhilova et al., 2024), but whether trust emerges directly from design features or requires prior cognitive processing remains unexplored. This distinction is crucial because different ethical dimensions may engage cognitive and affective pathways differently.

Research on technology acceptance has mainly relied on models such as Technology Acceptance Model (TAM), which assume a direct relationship between system attributes and usage intentions (Kelly et al., 2023). Nonetheless, AI-powered systems pose distinct issues that conventional acceptance models struggle to address. In contrast to conventional technologies, where usefulness and ease of use primarily influence adoption, AI systems contain sophisticated ethical considerations necessitating related psychological processing mechanisms (Kelly et al., 2023; Mariani et al., 2022). Mariani et al. (2022) suggest that conventional TAM elements hardly encompass the comprehensive psychological dynamics of AI acceptance, especially where ethical considerations are critical. This limitation is especially salient when emerging technologies progressively integrate ethical issues into their fundamental functions.

Although extensive research on technology acceptance has been widely studied, few studies have systematically explored the influence of ethical design on user behavior in

the AI era (Mariani et al., 2022). Specifically, three critical gaps emerge from this literature review, first, conventional TAM models lack the distinct dual-processing requirements of ethical AI features. In contrast to conventional system attributes that users assess directly, ethical features may require cognitive interpretation before eliciting psychological responses. In addition, although it is recognized that both cognitive and affective aspects affect AI acceptance (Mariani et al., 2022), there is limited empirical evidence to clarify whether these processes occur concurrently or sequentially. Finally, ethical design impacts algorithm awareness (cognitive), which subsequently influences psychological responses (affective), and ultimately affects usage intention. This mediation relationship is untested. Understanding these mechanisms is not only critical for advancing theory, but also provides actionable guidance for practitioners designing AI systems that must balance transparency, fairness, and user trust.

7.4 Conceptual framework and research hypotheses

While the TAM has been instrumental in understanding technology adoption, it presents three primary limitations when applied to ethical AI systems. The TAM posits that system features are processed uniformly, considering all design elements as functionally equivalent stimuli that directly affect perceived usefulness or ease of use. Ethical features in AI systems function at various psychological levels, TAM's cognitive emphasis overlooks affective processes. Recent studies in human-AI interaction indicate that users' emotional responses, including trust, likability, and psychological resistance, are equally significant factors in technology acceptance (Gerli et al., 2022). Ethical AI features distinctly involve both analytical assessment and psychological responses, requiring a dual-pathway framework (Bravo & Ostos, 2023). And TAM supposes direct, unmediated connections between system attributes and behavioral results. Our framework points to ethical AI features that require sequential processing, wherein cognitive understanding (algorithm awareness) must scaffold affective responses before impacting usage intentions. This sequential mediation

signifies a significant shift from the TAM.

Based on dual-processing theory and recent research on AI recommendation acceptance (Li et al., 2025), we suggest that users engage with ethical AI features via two complementary mechanisms (Bravo & Ostos, 2023):

Cognitive Mechanism (Algorithm Awareness): Users' analytical comprehension of algorithmic features such as transparency, fairness, privacy, and autonomy. This illustrates System 2 processing, necessitating focused attention and cognitive resources to understand how the AI system works, its data utilization, and decision-making processes.

Affective Mechanism (Psychological Responses): Users exhibit emotional reactions to the AI system, including trust, credibility, likability, and psychological resistance. This includes both System 1 (automatic, intuitive) and System 2 (reflective) emotional processing, contingent upon the particular ethical dimension presented.

We propose that these mechanisms operate sequentially rather than independently. Algorithm awareness provides the cognitive scaffolding necessary for coherent psychological reactions, subsequently influencing usage intentions (Bhattacharjee, 2001). This sequential relationship demonstrates why simple exposure to ethical features may not affect behavior; users need to comprehend before they can engage emotionally.

Ethical design embeds principles such as transparency, fairness, and user control in technology development (Wright et al., 2014), shaping user perceptions of algorithmic systems. Ethically designed AI recommendations increase perceived transparency, fairness, privacy, and autonomy. Prior research links transparency to better system understanding (Vorm & Combs, 2022), ethical data use to fairness (Sun & Tang, 2021), data practices to privacy (Chang et al., 2018; Ding et al., 2025; Shin et al., 2022), and user-centric design to autonomy (Bjørlo et al., 2021). Therefore, we hypothesize:

H1: Ethical design in AI-powered personalized recommendation positively influences users' perceptions of algorithmic factors, such as transparency, fairness, privacy, and autonomy.

Technology adoption research identifies psychological factors changing user responses (Gerli et al., 2022). Ethical design can directly improve these responses by addressing user concerns and aligning with values, fostering trust and reducing resistance (Kelly et al., 2023). By clarifying algorithmic processes, ethical design increases trust (Novozhilova et al., 2024), credibility, likability, and reduces psychological resistance (Gerli et al., 2022; De Freitas et al., 2023). Thus, we hypothesize:

H2: Ethical design positively influences users' trust, credibility, and likability toward the AI-powered recommendation system, and reduces psychological resistance.

Previous research suggests that user perceptions of algorithmic features influence willingness to use AI systems (Vorm & Combs, 2022; Zhou et al., 2021). Algorithm awareness serves as a cognitive bridge between ethical design and usage intention (Zhou et al., 2021; Zhou & Wu, 2024), while psychological responses constitute an additional pathway. In AI marketing, such psychological responses play a critical role in technology adoption decisions (Mariani et al., 2022). Trust, credibility, and likability mediate the effect of ethical design on intention. Therefore, we hypothesize:

H3: Users' perceptions of algorithmic transparency, fairness, privacy, and autonomy mediate the impact of ethical design on usage intention.

H4: Users' trust, credibility, likability toward the system, and psychological resistance mediate the impact of ethical design on usage intention.

Research shows that user experience and technology acceptance are interrelated, with psychological factors affecting adoption outcomes (Partala & Saari, 2015). We propose a sequential mediation model: ethical design affects algorithm awareness, which then shapes psychological responses, and ultimately influences usage intention. This relationship remains underexplored in ethical design. Thus, we hypothesize:

H5: Users' algorithm awareness (transparency, fairness, privacy, autonomy) sequentially mediates the impact of ethical design on usage intention through psychological responses (trust, credibility, likability, psychological resistance).

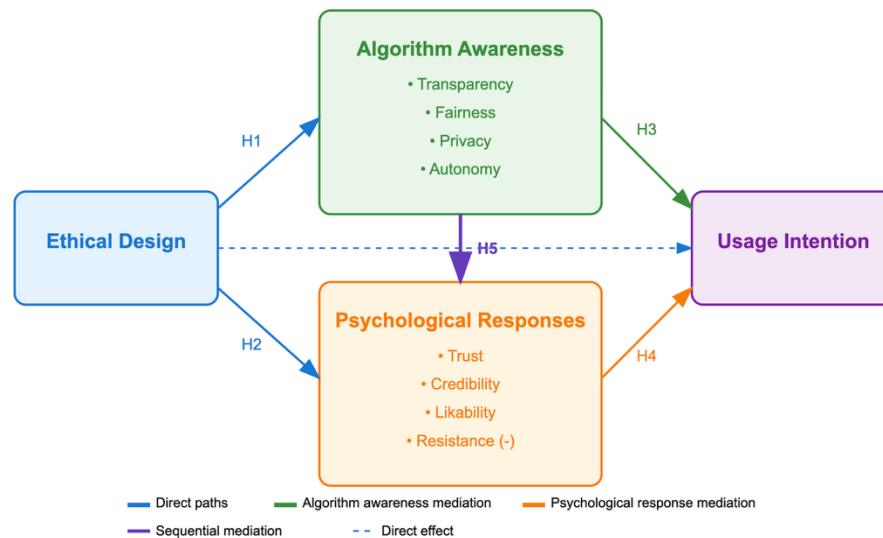


Figure 4 Conceptual Framework: Ethical Design's Effect on Consumer Usage Intentions

This conceptual framework and associated hypotheses guide our empirical investigation of how ethical design influences user intentions through both cognitive perceptions (algorithm awareness) and affective responses (psychological factors). This model responds to the requests for a more comprehensive understanding of AI acceptance (Mariani et al., 2022). This dual-pathway approach suggests that neither cognitive nor affective factors alone are sufficient for the acceptance of ethical AI, and it highlights sequential mediation as a central mechanism, indicating that the cognitive-affective sequence may not simply represent one possible pathway but could be particularly salient for certain ethical dimensions. This potential necessity of sequential processing has received limited attention in prior technology acceptance research. The framework, illustrated in Figure 4, specifies both direct and indirect relationships between ethical design and usage intention.

7.5 Methodology

7.5.1 Research Design

We used a between-subjects experimental design to test how ethical design in AI recommendation systems affects user intentions through algorithm awareness and psychological responses. Two experimental conditions were created, “high vs low ethical design,” differing in the presentation of recommendations to reflect varying levels of ethical consideration.

7.5.2 Participants

A total of 346 participants were recruited via an online panel and randomly assigned to two conditions. After data cleaning, the final sample comprised 278 participants (the high-ethics group ($N = 137$), low-ethics group ($N = 141$), retention rate: 80.3%). Responses were excluded if: (1) failed attention check questions and trap questions ($N = 32$), (2) had completion times within 3 minutes, suggesting insufficient effort ($N = 21$), (3) came from duplicate IP addresses ($N = 9$), and (4) had straightlining patterns (selecting the same response option across multiple questions) ($N = 6$).

The final sample included participants from China, Italy, South Korea, and the USA. The sample was 63.3% female, 36.0% male, and 0.7% preferred not to disclose gender. Age distribution was 66.9% (18-25), 21.2% (26-30), and 10.1% (31-40). Most participants (96.8%) had college-level education or higher; 76.3% held bachelor’s degrees. Nearly all (99.3%) had prior experience with AI-powered recommendation systems, and 48.9% described themselves as moderately familiar. Chi-square tests confirmed no significant demographic differences between groups (all $p > 0.05$), supporting successful randomization.

7.5.3 Stimulus Materials

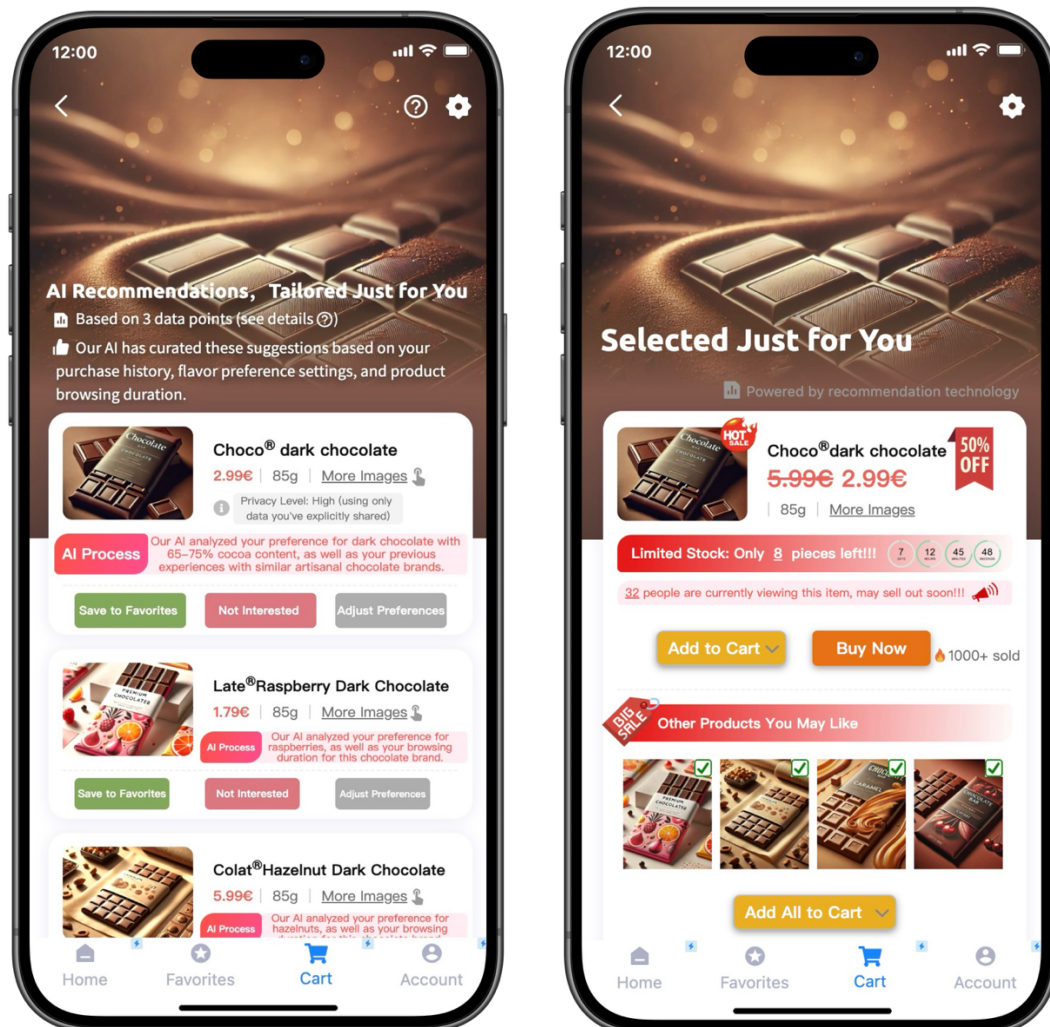
The ethical design of AI product recommendation interface was operationalized with two conditions, high-ethics and low-ethics design (see Figure 5). This approach follows established experimental paradigms in ethical technology research where design features are varied systematically rather than measured directly (Rader & Gray, 2015; Kizilcec, 2016). The manipulation involved altering four key ethical dimensions identified in existing literature: transparency, fairness, privacy protection, and user autonomy (Table 9). Both displayed the same chocolate bar product, but differed in the presentation of recommendations. We selected chocolate bars as they represent low-involvement products where recommendation algorithms are commonly used.

Table 9 Summary of design features of high/low-ethics versions

High-ethics condition featured:	Low-ethics condition featured:
— Clear transparency explaining AI-powered recommendations	— Hidden AI disclosure with minimal transparency
— Explicit data usage indicators showing exactly what information was used	— No data usage information
— Clear explanation of product recommendation logic	— Emphasis on urgency and scarcity triggers and social manipulation strategies
— Equal visual emphasis on recommended products and alternatives	— Unbalanced layout with overwhelming prominence given to recommended product
— User control options for adjusting preferences	— Vague personalization without explanation
— Privacy indicators showing limited data usage	— Limited user control options
— Clear and non-manipulative pricing	— Manipulative pricing with artificial discounts and countdown timers

Before the experiment, a pilot study involving 45 participants was conducted to validate the stimulus materials and ensure that the manipulation was perceived as intended. Participants were randomly assigned to view either the high-ethics or low-ethics version and then rated the ethical considerations of the design (“To what extent do you think this recommendation system was designed with ethical considerations?” 1 = not at all, 7 = extremely). The results indicated significant differences between conditions ($M_{\text{high}} = 5.82$, $SD = 1.14$; $M_{\text{low}} = 3.21$, $SD = 1.31$; $p < 0.001$), thereby supporting the validity of the manipulation applied. The ethical features presentation was slightly

adjusted to enhance clarity based on pilot feedback.



High-ethics version

Low-ethics version

Figure 5 High/low-ethics versions of the design

After viewing the recommendation interface, participants viewed a screen that explicitly revealed the data collection and algorithmic processes behind the recommendation. This follows the “algorithm explanation conditions intervention” methodology (Eslami et al., 2015; Rader et al., 2018), which enhances user understanding via explicit disclosures. This step simulated consumers’ true reactions upon learning the actual mechanisms behind AI-powered recommendations. The information matched each experimental condition and was used to assess the impact of this realization on participants’ perceptions, psychological responses, and usage

intentions.

7.5.4 Procedure

Participants first completed informed consent and demographic questions, then were randomly assigned to either the high-ethics or low-ethics condition. They viewed the product recommendation interface (20 seconds) → view the “Explanation conditions intervention” screen (15 seconds) → completed a questionnaire assessing algorithm awareness, psychological responses, and usage intention.

7.5.5 Measures

All constructs were measured with validated scales from prior literature.

Table 10 Details of the measurement process

Construct	Dimension	Item	Source	Cronbach's Alpha
Algorithm Awareness	Perceived Fairness	3	(Adanyin, 2024)	0.717
	Perceived Transparency	3	(Wang & Benbasat, 2016)	0.799
	Perceived Privacy	3	(Chang et al., 2018)	0.918
	Perceived Autonomy	3	(Raveendhran & Fast, 2021)	0.744
Psychological Responses	Ethical Trust	3	(Penney et al., 2021)	0.870
	Ethical Credibility	3	(Appelman & Sundar, 2016)	0.874
	Likability	3	(Bartneck et al., 2009)	0.907
	Ethical Threat to Freedom	4	(Dillard & Shen, 2005)	0.903
	Anger	1		
Behavioral Output	Usage Intention	3	(Penney et al., 2021)	0.888

We focus on usage intention, defined as the system-specific intention to use the focal AI recommender. We distinguish it from the broader behavioral intention, which reflects general adoption intentions toward algorithmic technologies, to avoid

conflating system-specific use decisions with domain-general tendencies. The continuance usage intention measure more precisely captures system-specific adoption likelihood, which aligns with our focus on AI recommendation acceptance (Bhattacharjee, 2001; Venkatesh et al., 2012). All measures used 7-point Likert scales (1 = Strongly Disagree, 7 = Strongly Agree) based on established scales. The questionnaire assessed the variables listed in Table 10. All scales demonstrated acceptable to excellent reliability, with alpha values ranging from 0.717 (fairness) to 0.918 (privacy). This confirmed that all scales had acceptable internal consistency (Cronbach's $\alpha > 0.70$).

7.6 Results

We first conducted descriptive and inferential analyses to examine differences in participants' perceptions between high-ethics and low-ethics conditions (H1 and H2). Descriptive results showed that participants in the high-ethics condition perceived the system as significantly more ethical than those in the low-ethics condition.

Table 11 Descriptive Statistics by Experimental Condition

Dimension	High-ethics		Low-ethics		Mean difference
	Mean	SD	Mean	SD	High - Low
Fairness	5.08	1.22	4.23	1.32	0.85
Transparency	5.75	0.97	4.83	1.16	0.92
Privacy	5.18	1.35	4.05	1.45	1.13
Autonomy	4.90	1.38	4.31	1.39	0.59
Trust	5.11	1.23	4.32	1.37	0.79
Credibility	5.33	1.15	4.39	1.40	0.94
Likability	5.39	1.16	4.41	1.39	0.98
Resistance	3.10	1.39	3.85	1.45	-0.75
Intention	5.39	1.05	4.49	1.36	0.90

The high-ethics group reported consistently higher scores on all positive dimensions (fairness, transparency, privacy, autonomy, trust, credibility, likability, and usage intention) compared to the low-ethics group. Conversely, psychological resistance was

significantly lower, indicating reduced psychological reactance toward the AI-powered recommendation system, as shown in Table 11.

Table 12 Mann-Whitney U Test Results and Effect Sizes

Dimension	W statistic	p-value	Effect size (r)	significance
Fairness	13240.0	< 0.001	0.322	*
Transparency	14451.5	< 0.001	0.431	*
Privacy	14185.5	< 0.001	0.406	*
Autonomy	11903.0	< 0.001	0.201	*
Trust	13390.5	< 0.001	0.335	*
Credibility	13845.5	< 0.001	0.376	*
Likability	14138.0	< 0.001	0.403	*
Resistance	6723.0	< 0.001	0.263	*
Intention	14302.5	< 0.001	0.418	*

Note: * indicates $p < 0.05$.

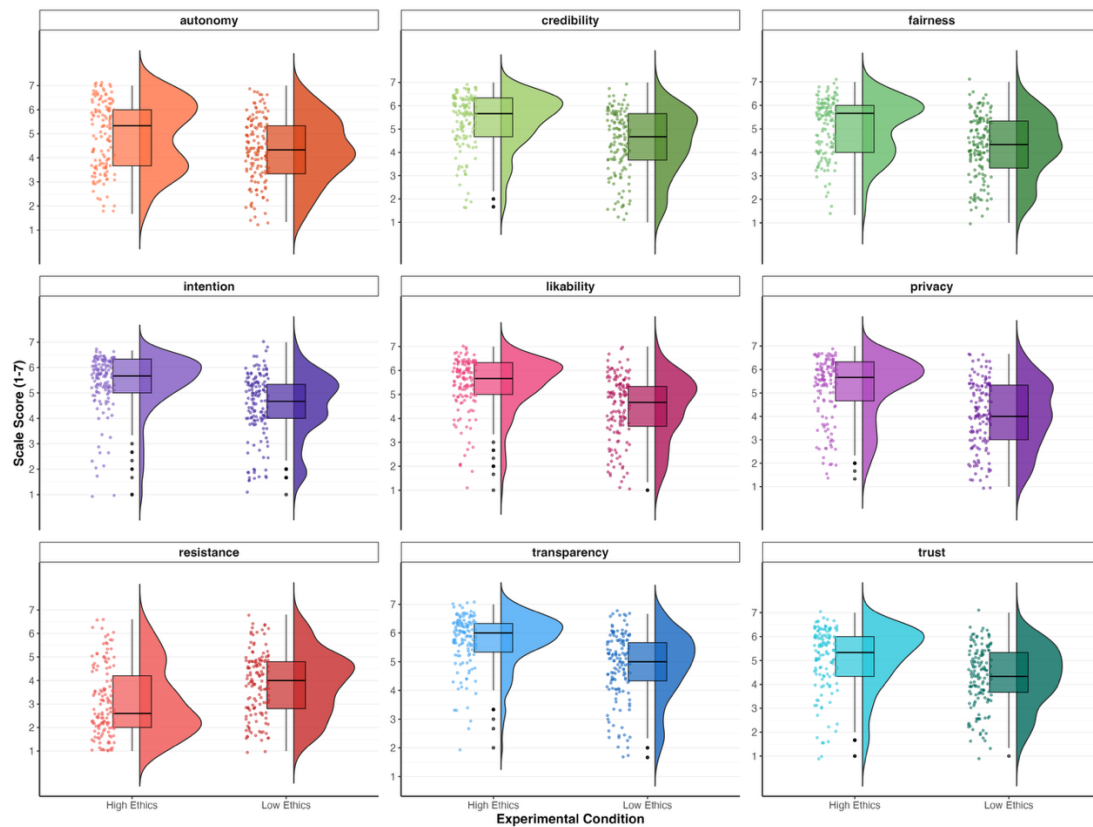


Figure 6 Distribution of dimensions by ethical design condition

Normality was assessed using the Shapiro-Wilk test, indicating non-normal distributions for all variables (all $p < 0.05$). Accordingly, the Mann-Whitney U test was

used as the primary inferential method, in line with standard practices (Fritz et al., 2012; Orcan, 2020), with independent-sample t-tests as a robustness check. Mann-Whitney U tests indicated significant differences between groups on all dimensions (all $p < 0.001$; Table 12). Participants in the high-ethics group reported higher scores on all positive outcomes and lower resistance. Score distributions are visualized in Figure 6.

The effect sizes (r) ranged from 0.201 (autonomy) to 0.431 (transparency), indicating medium effects. The largest effects were observed for transparency ($r = 0.431$), intention ($r = 0.418$), privacy ($r = 0.406$), and likability ($r = 0.403$). Fairness, trust, and credibility showed small to medium effects ($r = 0.322$ - 0.376), while autonomy and resistance demonstrated small effects ($r = 0.201$ and $r = 0.263$, respectively). Complementary t-tests yielded similar results, with Cohen's d values ranging from 0.429 (autonomy) to 0.857 (transparency), further supporting the observed effects. Collectively, these findings support H1 and H2, confirming that ethical design significantly enhances users' perceptions of algorithmic features and psychological responses.

We conducted a sequential mediation analysis using regression-based path estimation with bootstrap bias-corrected confidence intervals to test H3, H4, and H5 (Hayes & Little, 2018). The analysis included systematic covariate adjustment and extensive diagnostic assessment. Prior to testing the mediation hypotheses, six potential covariates were evaluated for inclusion based on multiple criteria, including theoretical importance, statistical significance, correlations, variance inflation factors (VIF), and R^2 contributions. The selection process resulted in the inclusion of five covariates: gender, age, education level, preference, and familiarity with AI systems. Gender was retained for theoretical importance and marginal statistical significance ($p = 0.063$). Age and education level were included for theoretical importance despite non-significant univariate associations. Preference and familiarity were included due to significant correlations with mediator ($r > 0.15$) and R^2 contributions (> 0.01). All included covariates showed acceptable (VIF < 1.22), indicating no multicollinearity.

Regression diagnostic tests ($n = 48$ models) included tests for linearity (Ramsey RESET

test), independence (Durbin-Watson and Breusch-Godfrey tests), homoscedasticity (Breusch-Pagan and White tests), and normality (Shapiro-Wilk and Anderson-Darling tests). Diagnostics revealed that all fitted models exhibited non-normal residual distributions due to the use of Likert-scale data, heteroscedasticity in 29 models, autocorrelation patterns in 24 models, non-linearity in 21 models, and influential cases in 44 models (cook’s distance). Obviously, these findings suggested that standard OLS regression assumptions were not fully satisfied in our dataset. Given these violations, we relied on bootstrap methods, which offer robust inference without distributional assumptions. All bootstrap samples converged successfully, and we used the bias-corrected percentile method to determine confidence intervals (Hayes & Little, 2018) (see Figure 7).

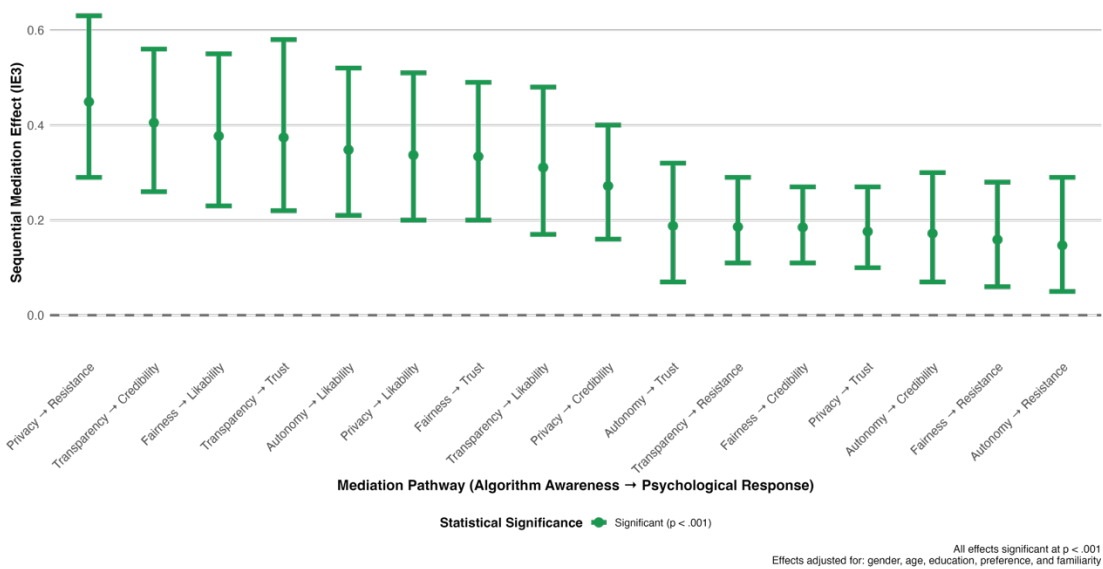


Figure 7 Bootstrap confidence intervals with 5,000 resamples

To further address these diagnostic issues and assess the robustness of our results, we applied heteroscedasticity-robust standard errors, M-estimators robust regression, non-parametric validation, and outlier sensitivity analysis. All 16 sequential mediation pathways were validated. For instance, HC3 heteroscedasticity-robust standard errors re-examined all the pathways’ coefficients, which remained significant (all $p < 0.001$), confirming effect robustness. M-estimator robust regression converged for all 16

pathways. Differences between bootstrap and robust estimates ranged from -17.5% to 31.6% (mean absolute difference of 13.6%), with 13 pathways below 20%. Distribution-free Spearman rank correlations validated all mediation pathway components without distributional assumptions (all $p < 0.001$). Overall, the pathway showing the largest difference was privacy $\rightarrow$ credibility (31.6% increase in robust regression). However, this represented a strengthening rather than weakening of the effect. The robust estimate (0.458) exceeded the bootstrap estimate (0.348). Mahalanobis distance identified 9 cases (3.24%) as potential outliers. Sensitivity analysis removing these outliers showed that sequential mediation effects became slightly stronger. Overall, the extensive robustness checks and bootstrap validation ensured reliable inference, well-suited to the characteristics of our data.

Table 13 Complete sequential mediation analysis results

M1 (Algorithm awareness)	M2 (Psychological responses)	IE1 (X → M1 → Y)				IE2 (X → M2 → Y)				IE3 (X → M1 → M2 → Y)				Direct Effect				Model R ²
		Effect	95% CI	p-value	Sig	Effect	95% CI	p-value	Sig	Effect	95% CI	p-value	Sig	Effect	SE	p-value	Sig	
Privacy	Likability	-0.029	[-0.13, 0.07]	0.549	ns	0.170	[-0.01, 0.37]	0.052	ns	0.337	[0.20, 0.51]	< .001	***	0.399	0.115	< .001	***	0.548
Transparency	Likability	-0.003	[-0.09, 0.08]	0.916	ns	0.326	[0.14, 0.53]	< .001	***	0.311	[0.17, 0.48]	< .001	***	0.243	0.110	0.027	*	0.598
Fairness	Likability	-0.068	[-0.15, 0.002]	0.058	ns	0.361	[0.15, 0.58]	< .001	***	0.377	[0.23, 0.55]	< .001	***	0.208	0.101	0.041	*	0.659
Privacy	Trust	0.132	[0.03, 0.26]	0.011	*	0.124	[-0.01, 0.29]	0.086	ns	0.176	[0.10, 0.27]	< .001	***	0.445	0.126	< .001	***	0.456
Privacy	Credibility	0.198	[0.07, 0.37]	0.002	**	0.148	[-0.01, 0.34]	0.061	ns	0.272	[0.16, 0.40]	< .001	***	0.259	0.114	0.024	*	0.573
Fairness	Trust	0.137	[0.01, 0.30]	0.036	*	0.236	[0.06, 0.45]	0.010	*	0.334	[0.20, 0.49]	< .001	***	0.171	0.110	0.122	ns	0.610
Transparency	Credibility	0.066	[-0.04, 0.19]	0.215	ns	0.255	[0.06, 0.48]	0.010	*	0.405	[0.26, 0.56]	< .001	***	0.152	0.103	0.140	ns	0.658
Fairness	Credibility	0.286	[0.15, 0.45]	< .001	***	0.083	[-0.04, 0.25]	0.210	ns	0.185	[0.11, 0.27]	< .001	***	0.324	0.124	0.009	**	0.495
Transparency	Trust	0.174	[0.01, 0.36]	0.030	*	0.026	[-0.09, 0.16]	0.706	ns	0.374	[0.22, 0.58]	< .001	***	0.304	0.115	0.009	**	0.560
Autonomy	Likability	0.200	[0.08, 0.35]	0.001	**	0.178	[0.03, 0.33]	0.018	*	0.348	[0.21, 0.52]	< .001	***	0.151	0.108	0.162	ns	0.620
Privacy	Resistance	0.099	[-0.02, 0.23]	0.098	ns	0.184	[0.03, 0.35]	0.019	*	0.449	[0.29, 0.63]	< .001	***	0.146	0.102	0.155	ns	0.660
Transparency	Resistance	0.362	[0.21, 0.54]	< .001	***	0.043	[-0.06, 0.16]	0.433	ns	0.186	[0.11, 0.29]	< .001	***	0.287	0.120	0.018	*	0.522
Fairness	Resistance	0.104	[0.03, 0.21]	< .001	***	0.245	[0.11, 0.40]	< .001	***	0.159	[0.06, 0.28]	< .001	***	0.370	0.110	< .001	***	0.570
Autonomy	Credibility	0.090	[0.02, 0.19]	0.001	**	0.373	[0.22, 0.54]	< .001	***	0.172	[0.07, 0.30]	< .001	***	0.242	0.106	0.023	*	0.617
Autonomy	Trust	0.074	[0.02, 0.16]	0.004	**	0.431	[0.27, 0.61]	< .001	***	0.188	[0.07, 0.32]	< .001	***	0.184	0.099	0.064	ns	0.668
Autonomy	Resistance	0.116	[0.02, 0.26]	0.013	*	0.090	[0.01, 0.20]	0.030	*	0.147	[0.05, 0.29]	< .001	***	0.525	0.122	< .001	***	0.457

Note: * p < 0.05; ** p < 0.01; *** p < 0.001; ns = not significant (p ≥ 0.05)

The mediation analysis (Table 13) provided mixed support for H3. Among the algorithm awareness mediation pathways (IE1: $X \rightarrow M1 \rightarrow Y$), the results provided partial support, that is 11 of 16 pathways (68.8%) showed significant effects based on bootstrap confidence intervals. The significant pathways ranged from 0.074 (autonomy $\rightarrow$ trust, $p = 0.004$) to 0.362 (transparency $\rightarrow$ resistance, $p < 0.001$). However, all five non-significant pathways showed either likability (3 pathways) or had p -value close to the threshold (2 pathways), including fairness $\rightarrow$ likability: $p = 0.058$, and privacy $\rightarrow$ resistance: $p = 0.098$. This suggests that algorithm awareness alone hardly generates positive psychological responses. The three likability pathways all showed negative coefficients (-0.029, -0.003, -0.068), indicating potential suppression effects. Transparency showed the strongest effect through resistance (0.362), but no effect through likability (-0.003, $p = 0.916$). This stark contrast reveals that understanding transparency reduces negative reactions but fails to create positive emotions. Robustness checks confirmed the stability of these effects.

For H4, 10 of 16 psychological response mediation pathways (IE2: $X \rightarrow M2 \rightarrow Y$) were significant (62.5%), ranging from 0.090 (autonomy $\rightarrow$ resistance, $p = 0.030$) to 0.431 (autonomy $\rightarrow$ trust, $p < 0.001$). Autonomy dominated the strongest effects, with autonomy $\rightarrow$ trust showing the largest coefficient (0.431). However, transparency $\rightarrow$ trust was essentially null (0.026, $p = 0.706$), suggesting that trust in the AI recommendation system requires more than transparency awareness, it needs the complete cognitive-affective sequence. Six non-significant pathways revealed systematic patterns: privacy and transparency hardly directly influence trust ($p = 0.086$ and $p = 0.706$), while fairness failed with credibility ($p = 0.210$). This indicates that ethical design features cannot skip the cognitive step to generate psychological responses.

The primary focus of our analysis was H5, which proposed sequential mediation through algorithm awareness to psychological responses (IE3: $X \rightarrow M1 \rightarrow M2 \rightarrow Y$). The results provided comprehensive support. All 16 tested sequential mediation pathways were significant ($p < 0.001$), with medium to large effects ranging from 0.147 (autonomy $\rightarrow$ resistance) to 0.449 (privacy $\rightarrow$ resistance) (Kenny & Judd, 2014).

This remarkable consistency was further validated through extensive robustness analysis. The 100% significance rate contrasts dramatically with the partial success of simple mediation (IE1: 68.8%; IE2: 62.5%). This reveals a fundamental psychological principle: ethical design features must be cognitively processed before generating emotional responses that drive behavior.

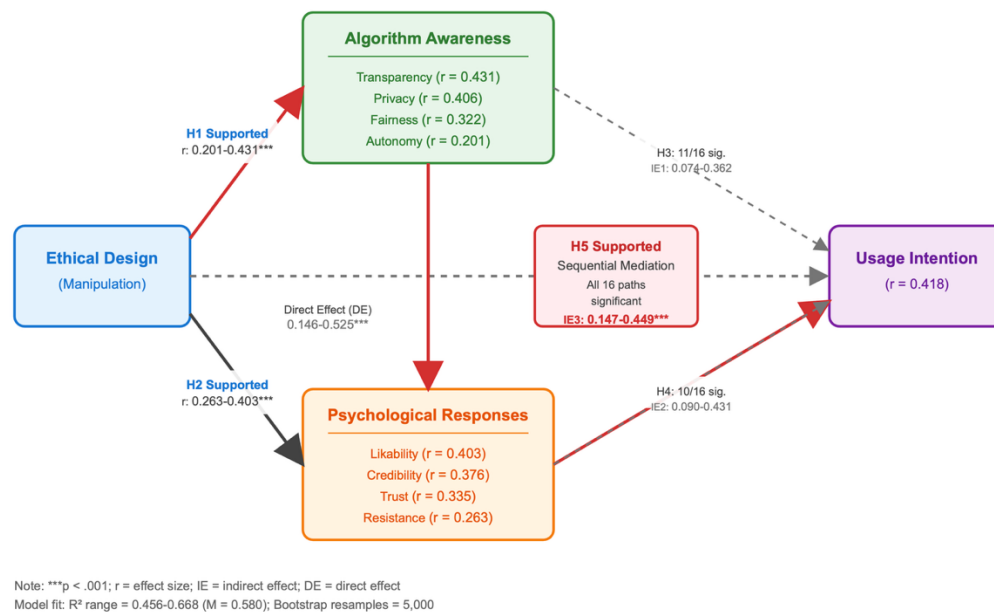


Figure 8 Sequential mediation model of ethical design's impact on usage intention

Furthermore, direct effect (DE) represents unmediated influence on usage intention. Eleven pathways (68.8%) showed significant direct effects, ranging from 0.208 (fairness $\rightarrow$ likability, $p = 0.041$) to 0.525 (autonomy $\rightarrow$ resistance, $p < 0.001$). The pattern of non-significant direct effects is revealing that fairness $\rightarrow$ trust ($p = 0.122$), transparency $\rightarrow$ credibility ($p = 0.140$), autonomy $\rightarrow$ likability ($p = 0.162$), privacy $\rightarrow$ resistance ($p = 0.155$), and autonomy $\rightarrow$ trust ($p = 0.064$). These pathways rely almost entirely on mediated processing, with minimal direct influence.

It is interesting to notice that average direct effect (0.276) precisely equals average sequential mediation (0.276). This mathematical coincidence masks profound heterogeneity. For example, in the dimension of immediate response, autonomy $\rightarrow$ resistance shows massive direct effect (0.525) versus moderate sequential mediation

(0.147). Users react viscerally to autonomy threats without needing cognitive processing elaboration. By Contrast, in the dimension of cognitive processing, privacy → resistance reverses this pattern (DE: 0.146, ns; IE3: 0.449). Privacy concerns require cognitive processing to generate resistance. Finally, in the dimension of dual processing, fairness pathways, such as fairness → likability (DE: 0.208, IE3: 0.377), show a balanced effect, engaging both automatic and controlled processing systems.

Models explained substantial variance (R^2 range: 0.456-0.668; $M = 0.580$). The highest R^2 occurred for autonomy → trust (0.668), while the lowest was for privacy → trust (0.456). This 0.212 range of differences indicates that some pathways are more predictable than others. Total effects were uniformly significant and strong ($M = 0.877$), confirming that ethical design reliably influences usage intention. In summary, the overall mediation structure is presented in Figure 8, highlighting the mechanisms established through our empirical analysis.

7.7 Discussion

This study advances the understanding of technology acceptance by empirically demonstrating that ethical design is no longer an overlooked factor but a central determinant of users' cognitive and affective engagement with AI-powered recommendation systems (Ding et al., 2025). Unlike traditional models that focus primarily on perceived usefulness or ease of use, the users' algorithm awareness and psychological responses serve as foundational mechanisms that both enable and constrain the formation of ethical perceptions toward AI technologies (Chang et al., 2018). Our study reveals that ethical design influences AI acceptance through two equally important but distinct mechanisms. The equivalence of average direct (0.276) and sequential indirect effects (0.276) suggests a core duality in how users process ethical features. The 100% significance rate for sequential mediation, contrasted with partial significance for simple mediation (IE1: 68.8%; IE2: 62.5%), indicates that the cognitive-affective sequence is not merely optional but appears to be a central pathway. This finding extends dual-processing theory to AI ethics: while System 1 (automatic)

and System 2 (controlled) can operate independently in traditional contexts, ethical AI features require their sequential integration (Warner et al., 2024). A different explanation is that the data pattern suggests a “cognitive scaffolding” effect (Sætra, 2025): algorithm awareness may provide a conceptual foundation necessary for psychological responses to form effectively. Without this foundation, emotional responses may lack coherence, resulting in non-significant effects. Consider transparency → trust: IE1 is significant (0.174, $p = 0.030$) but IE2 fails (0.026, $p = 0.706$). Users can understand transparency’s importance (cognitive) but cannot directly feel trust from transparency (emotional). Only when understanding leads to psychological response does trust emerge (IE3: 0.374, $p < 0.001$). This mechanism helps explain why the combination of big data, AI, and “nudging”, as discussed by Yeung (2017) and Sætra (2019), can be particularly effective: cognitive scaffolding provided by algorithm awareness enables psychological responses, making behavioral influence more robust. Moreover, consistent with the argument of Mariani et al. (2022), we emphasize that AI ethical design cannot be reduced to a single-dimensional process. Our data reveals three distinct processing modes: (1) Cognitive-dependent dimensions (Privacy, Transparency): These features show weak direct effects but strong sequential mediation. Privacy’s pattern is particularly striking, showing the weakest direct effect (0.146, ns) but strongest sequential effect (0.449). This suggests that the users cannot viscerally feel privacy violations until they cognitively understand them. Transparency similarly requires understanding before influencing behavior. (2) Affect-dominant dimensions (Autonomy): Autonomy triggers immediate visceral responses (strongest direct effects = 0.525) that actually diminish through cognitive processing. This counter-intuitive finding suggests that overthinking autonomy concerns reduces their emotional impact. (3) Balanced dimensions (Fairness): Fairness engages both processing systems effectively, showing significant effects across multiple pathways. Therefore, we propose a Complementary Mediation Model that reconceptualizes how ethical design achieves impact. Unlike traditional mediation, where direct effects represent “leftover” influence, our model suggests direct and indirect effects capture fundamentally different psychological processes that work in parallel. Direct effects

capture immediate, visceral responses to ethical features; sequential mediation captures the cognitive elaboration pathway; and total impact emerges from the interplay between these routes. This model explains why some features (autonomy) lose power through thinking while others (privacy) gain power only through understanding.

7.8 Conclusion

Our findings indicate that ethical AI features operate through an additional psychological architecture compared to traditional TAM variables. Our findings point to a distinct psychological constraint that qualifies the independence assumption in dual-process theory. Unlike typical dual-processing, in which System 1 (automatic) and System 2 (controlled) function independently (Frankish, 2010). Ethical AI elements necessitate a specific sequence: cognitive scaffolding precedes affective reaction because all 16 sequential pathways reached significance; however, simple cognitive and affective mediations were largely ineffective. This constraint exhibits varying manifestations across ethical dimensions. Therefore, we present this complementary mediation model, which explains how sequential indirect effects and direct effects reflect parallel psychological processes rather than competing ones. Their mathematical equivalency indicates contemporaneous operation rather than unexplained variance. Our findings re-conceptualize algorithm awareness from a direct variable in the TAM to a cognitive precondition that enables acceptance rather than directly causing it. The failure of transparency and privacy to foster trust through direct pathway, while succeeding through sequential mediation, indicates that understanding of algorithmic processes remains psychologically inactive until it is converted into affective responses. This cognitive-affective process requirement differentiates between ethical and functional design features, which explains why technically transparent systems frequently fail to gain user acceptability and why privacy policies rarely alter behavior despite increasing awareness (Rader et al., 2018).

This study also provides practical implications for practitioners. For privacy features, replace traditional policies with interactive data maps that display specific behavioral

data points at collection moments, using concrete tooltips rather than abstract categories. Transparency should avoid technical algorithmic explanations in favor of comparative statements and implement progressive disclosure from simple labels to specific recommendation criteria, to detailed breakdowns based on interaction depth. Autonomy features require surface-level placement with visible rejection controls and immediate preference adjustment options accessible from the main interface without menu navigation, revealing customization options contextually during use rather than through lengthy onboarding. Notably, failing to explain the importance of user control reduces psychological impact. Fairness implementation should combine immediate visual signals, including equal-sized product displays and randomized positioning, with an accessible dashboard showing recommendation distribution across categories, prices, and brands, supplemented by real-time metrics displayed during user scrolling. These design approaches recognize that effective ethical AI design must match interface elements to the specific psychological processing requirements of each ethical dimension.

Our experimental setting compressed months of user interaction into minutes, potentially overstating the importance of initial responses versus learned patterns. The recommendation context limits generalizability to commercial applications with low-stakes outcomes; these findings may not extend to high-consequence AI systems, including medical diagnosis, loan approval, hiring decisions, financial advisory services, or safety-critical applications, where processing patterns likely involve heightened cognitive scrutiny and risk assessment. Individual differences remain unexplored beyond cultural variations, age, educational attainment, technical expertise, and prior AI experience may significantly alter the cognitive dependency and visceral processing patterns we observed. Future research should examine whether domain expertise moderates these effects across different professional contexts, how processing patterns evolve through repeated long-term interactions, whether high-stakes decision environments activate alternative psychological pathways, the effectiveness of ethical design interventions across diverse demographic groups, longitudinal studies tracking cognitive-affective pattern stability, neural and physiological measures to validate dual-

processing mechanisms, and real-world deployment studies to confirm laboratory findings in naturalistic settings.

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Chapter 8 General Discussion

8.1 Synthesis of the diagnostic framework in hybrid marketing environments

This doctoral dissertation investigates the contemporary marketing landscape, where the dissolution of boundaries between physical and digital touchpoints has created a highly interwoven “Hybrid Marketing Environment.” Within this ecosystem, consumers do not act as linear decision-makers restricted to single channels. Instead of merely touching products offline or browsing information online, they engage in a continuous multimodal interaction stream.

This research addresses a fundamental academic question: within a hybrid marketing ecosystem fraught with multiple forms of uncertainty (physical, social, and algorithmic), how do consumers process heterogeneous sensory and algorithmic cues to construct trust and reach decisions? Across four studies, this thesis constructs and validates the “Consumer Information Diagnosticity Framework in Hybrid Marketing Environment.”

The core premise of this framework posits that uncertainty reduction remains the fundamental challenge for consumers in both physical and digital domains. However, uncertainty implies a hierarchically evolving psychological construct distinct from a unidimensional variable. It progresses from foundational perceptual uncertainty to social uncertainty, and finally to systemic uncertainty. Resolving these distinct layers requires specific diagnostic cues, the effectiveness of which depends on their accessibility and diagnostic relevance within the cognitive processing system.

This research elucidates the complete psychological trajectory of consumer trust formation:

- Physiological Resource Allocation (Study 1: Brightness-modulated cognitive load).
- Cultural Schema Activation (Study 2: Color configuration reducing social risk).
- Algorithmic Recommendation Experience (Study 3: The privacy concern of recommendation accuracy).

- Cognitive Scaffolding (Study 4: Ethical design sequentially mediating systemic trust).

This process is hierarchically nested; the processing outcome of each layer functions as the input condition for the subsequent layer. This chapter will expound upon the theoretical contributions, practical implications, and limitations of this integrated framework.

8.2 Integrated synthesis of findings

The four studies presented in this dissertation converge to illuminate a single, overarching phenomenon: the hierarchical processing of diagnostic signals in hybrid marketing environments. To synthesize these findings, we propose the Consumer Information Diagnosticity Framework (CIDF) (see Figure 1). This framework conceptualizes the consumer as an active navigator of uncertainty who employs different diagnostic tools depending on the layer of the environment.

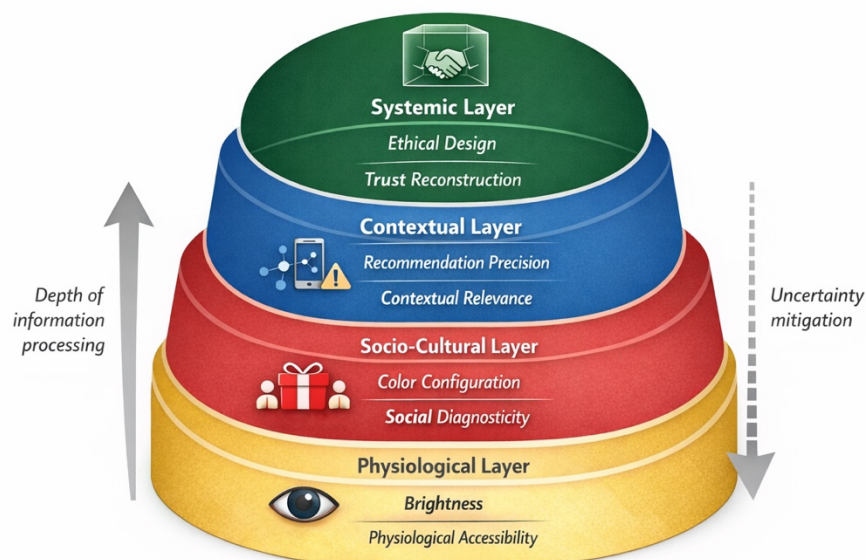


Figure 9 The Consumer Information Diagnosticity Framework (CIDF): Hierarchical mechanisms of uncertainty mitigation across physical and digital marketing environments.

Layer 1 Perceptual Layer: Physiological accessibility and the front-loading of cognitive resources

The foundational component of the hybrid marketing environment involves consumer visual contact with product packaging, marking the physical genesis of trust establishment. Study 1 elucidates the temporal mechanism of visual processing by integrating eye-tracking with time-resolved pupillometry.

The extant visual marketing literature predominantly characterizes “brightness” as merely an aesthetic property or a salience enhancer. These studies posit that the primary function of brightness is to capture attention or increase detection probability via low-level visual contrast. However, this conventional perspective obscures the fundamental distinction between “being seen” and “being processed.” Findings from Study 1 demonstrate that high-brightness labels induce a front-loading of cognitive resources during the early encoding stage. This manifests as increased pupil dilation amplitude within early and mid-term temporal windows, accompanied by a marked reduction in cognitive effort during the late evaluation stage. This provides evidence that brightness enables consumers to extract more intense diagnostic information within constrained temporal bounds. Crucially, the mechanism of brightness pertains to processing intensity distinct from processing breadth. Results indicate an increase in mean fixation duration, whereas fixation count exhibits no significant variance. These findings demarcate “salience” from “accessibility.” The former accounts for mere visibility (being seen), while the latter addresses comprehension (being processed).

Drawing upon Information Richness Theory (Daft & Lengel, 1983) and the Adaptive Strategy Selection Framework (Payne et al., 1993), this research validates that the diagnostic value of visual cues lies in reducing the physiological cost of information extraction, distinct from merely attracting attention.

Layer 2 Cultural Layer: Configurational cues and the activation of social schemas

As visual information traverses from the retina to the cerebral cortex, physiological signals undergo transformation into social symbols imbued with specific meaning. Study 2 elevates the analytical perspective from micro-physiological mechanisms to

macro-sociocultural dimensions. It investigates how consumers utilize color cues to mitigate “Social Risk” within the specific cultural context of China. At this layer, the prevailing uncertainty concerns social propriety: “Is this product appropriate for the social occasion?” Study 2 extends the analysis from unidimensional visual variables to configurational effects. Within the context of Chinese wine consumption, the interaction of hue $\times$ brightness $\times$ saturation significantly influences all dimensions of perceived value (quality, emotional, social, sensory) and purchase intention. A core finding indicates that low-brightness red labels (dark red) significantly outperform other color configurations across all conditions, whereas high-brightness red forfeits this advantage. Qualitative interviews reveal that the psychological mechanism underlying this effect stems from cross-domain analogical learning, distinct from specific wine knowledge. Consumers construct color-value mapping schemas via daily experiences, such as the correlation between dark red pigmentation and fruit ripeness or color conventions in premium packaging. Crucially, “Face anxiety” amplifies reliance on color cues within gift-giving scenarios. Intermediate consumers constitute a cohort: they possess sufficient cognitive capacity to recognize social risks yet lack the sensory confidence required for intrinsic cue evaluation. Consequently, they employ dark red configurations to circumvent the risk of losing face. These findings extend the applicability of Cue Utilization Theory (Olson & Jacoby, 1972). Traditional theory emphasizes the substitution of extrinsic cues for intrinsic ones to infer quality. However, this study demonstrates that the diagnosticity of extrinsic cues functions as a signal of social appropriateness, extending beyond mere quality inference. The value of color configuration lies in mitigating social uncertainty as opposed to product uncertainty.

Layer 3 Contextual Layer: The nonlinear diagnosticity of algorithmic accuracy

As the research perspective shifts from static packaging to dynamic digital platforms, the object of consumer interaction undergoes a qualitative transformation: the passive product gives way to the active algorithmic system. Study 3, grounded in phenomenological interviews, unveils the core “Privacy-Convenience Paradox” within the hybrid marketing environment.

At this layer, an agency transfer occurs. Within algorithm-driven digital environments, the algorithm ascends to the position of an active recommender. Synthesizing Expectancy-Value Theory (Eccles, 1983) and the Stimulus-Organism-Responses Model (Mehrabian & Russell, 1974), this study introduces the concept of the privacy value. When recommendation accuracy surpasses the range of user expectancy, users experience existential anxiety, defined here as the fear of compromised privacy boundaries. This anxiety triggers defensive avoidance behaviors, such as deliberately selecting “not interested” to obfuscate the algorithmic system. Crucially, this paradox unveils the nonlinear nature of diagnosticity. The diagnostic value of a signal exhibits diminishing marginal utility or explicitly negative effects after crossing a specific threshold. Within the algorithmic domain, excessive manipulation inference precipitates an inversion of diagnosticity from positive to negative.

Layer 4 Systemic Layer: Cognitive scaffolding and the sequential mediation of trust

Addressing the algorithmic trust crisis identified in Study 3, Study 4 investigates systemic solutions by examining how AI ethical design functions as a high-order diagnostic signal to reconstruct trust. Study 4 validates the causal mechanism of ethical design via experimental methodology. The central finding indicates that the mechanism of ethical design features (transparency, fairness, privacy, autonomy) does not influence behavioral intention directly. Instead, it operates through a dual-stage process: first facilitating cognitive understanding, which subsequently fosters emotional trust. The traditional Technology Acceptance Model (Davis, 1989) posits that perceived usefulness and ease of use drive adoption intention directly, thereby overlooking the cognitive-affective relationship. In contrast, this study conceptualizes cognitive scaffolding as follows: ethical design provides cognitive support to transform “black box” algorithms into comprehensible systems, thereby activating System 2 (analytical processing). Only after users resolve cognitive ambiguity via System 2 does System 1 (intuitive processing) generate a sense of security and emotional trust. The objective of ethical design is distinct from transforming users into algorithm experts. Instead, it aims to provide the cognitive support necessary to transition users from a state of “unknown

yet anxious” to “apparently understood and reassured.”

In summary, the theoretical novelty of this framework resides in elucidating that physical visual cues and digital algorithmic features function fundamentally as homologous diagnostic signals employed by consumers to mitigate uncertainty. Their processing adheres to shared psychological principles yet exhibits adaptive variation across contextual hierarchies.

Specifically:

Universality: The evaluation of all diagnostic cues rests upon the trade-off between accessibility and relevance (Feldman & Lynch, 1988). Brightness enhances accessibility without altering relevance. Color configuration influences both dimensions simultaneously. Algorithmic accuracy impacts relevance yet potentially diminishes accessibility. Ethical design functions to enhance relevance by restoring accessibility.

Divergence: Physical cues precipitate low construal levels (concrete), whereas algorithmic recommendations induce high construal levels (abstract).

Contextuality: Diagnosticity constitutes a context-dependent psychological evaluation distinct from a static attribute. The identical cue (e.g., red) activates a “maturity/stability” schema under low-brightness conditions but a “vitality/frivolity” schema under high-brightness conditions. Similarly, moderate recommendation accuracy mitigates uncertainty, whereas excessive precision provokes manipulation anxiety.

8.3 Theoretical contributions

Construction of an integrated perspective: a unified diagnosticity framework

Scholarly inquiry in marketing frequently exhibits a distinct bifurcation: sensory marketing scholars predominantly examine the influence of physical product attributes, such as packaging, color, and form, on consumers, whereas digital marketing and information systems scholars focus on interface design and algorithmic acceptance in virtual environments. These two domains traditionally employ disparate theoretical

paradigms and measurement instruments. This study bridges these domains by employing Information Diagnosticity Theory as the foundational logic. By constructing the “Consumer Information Diagnosticity Framework in Hybrid Marketing Environment,” this research extends the classical framework of Feldman and Lynch (1988) from static product attribute evaluation to dynamic, multimodal human-machine interaction systems. This integrated perspective postulates that consumer decision-making in hybrid environments constitutes a continuous, cross-modal diagnostic process.

Redefining “salience”: from visual to epistemic salience

This research expands and reconstructs the connotation of salience, a core concept in marketing. Traditional attention models (Itti & Koch, 2000) focus primarily on visual salience, referring to the prominence of stimuli based on physical features. Through the progression of four studies, this dissertation proposes a multidimensional taxonomy of salience, enriching this theoretical construct:

- Physiological Salience: Determined by physical attributes such as brightness; it directly influences cognitive resource allocation and encoding efficiency at the physiological level (Study 1).
- Cultural Salience: Determined by specific color configurations (e.g., red under low brightness); it activates social norms and “Face” schemas within specific cultural contexts (Study 2).
- Epistemic Salience: Determined by ethical design; it refers to the visibility and explainability of system logic (Study 4).

These definitions constitute a significant supplementation to AI marketing theory. They indicate that in the algorithmic era, making products visually “visible” to consumers is insufficient. It is imperative to make the operational logic behind the system “cognitively visible.” This logical visibility functions as a prerequisite for establishing high-order trust, marking a profound paradigm shift in salience research from the sensory level to the cognitive level.

Configurational theory in sensory marketing: transcending single-dimensional

In sensory marketing, particularly within consumer color psychology, mainstream paradigms often focus on the main effects of Hue (e.g., green induces organic, red induces attractiveness). Study 2 introduces the configurational perspective from complexity theory, validating that marketing effects derive from specific combinations of hue, brightness, and saturation distinct from the cumulative effect of single attributes. Research findings indicate that dark red possesses high perceived value and face-saving functions in the Chinese market because low brightness and high saturation jointly regulate the cultural semantics of red. This finding refutes the coarse cultural stereotype in the existing literature that red symbolizes luck in Chinese culture. It demonstrates that the diagnosticity of sensory cues relies heavily on the Gestalt of attributes.

The cognitive scaffolding mechanism in HCI: an extension of dual-process theory

In the domains of AI trust and technology acceptance, existing models (e.g., TAM, UTAUT) frequently postulate that external variables directly influence usage intention or that they influence attitude and behavior in parallel. Study 4 utilizes a sequential mediation model to revise the application of dual-process theory within the context of AI ethics. Study 4 reveals that when confronting complex, opaque intelligent systems, the intuitive emotional system (System 1) remains “muted” or “apprehensive” unless the analytical cognitive system (System 2) intervenes first to provide explanation and logical support. The principle established here is that it must be trust before understanding. Ethical design functions operate initially as cognitive scaffolding to assist users in constructing a rational cognitive model of the system. Only subsequent to this cognitive grounding can the system induce emotional trust and a sense of security. This finding establishes the primacy of cognitive understanding in AI ethical acceptance and provides a theoretical explanation for the frequent failure of purely “emotional design” in resolving algorithmic trust crises.

Deep integration of cultural psychology and information processing: the decision weight of face theory

This research integrates the face theory into the information processing model, positing it as a critical variable for explaining consumer risk-averse behavior in hybrid marketing environments. Study 2 and Study 3 collectively illuminate that “Face” constitutes a critical risk variable in marketing environments, distinct from a purely sociological concept. In the context of physical goods, face anxiety impels consumers to select high-diagnostic colors (e.g., dark red) as social insurance to mitigate the risk of negative interpersonal evaluation. Yet the digital context, face anxiety transforms into a fear of “digital Face” leakage (i.e., privacy data, backend profiling), driving consumers to exhibit defensive and avoidance behaviors toward excessively precise algorithms. The theoretical contribution lies in revealing how cultural schemas function as moderating variables, altering the weight allocation consumers assign to diagnostic cues.

8.4 Managerial implications

The theoretical framework developed in this study offers direct guidance for marketing practice. Stakeholder groups categorize the following managerial implications.

Implications for visual designers: extends the window for deep processing during average browsing sessions. For labels with complex information, designers should employ high brightness to support detailed information extraction. Conversely, for high-aesthetic products, low brightness is preferable to trigger the consumer’s compensatory processing in back-loading. On the other hand, E-commerce platforms can dynamically adjust image brightness in real-time based on user browsing velocity. Study 2 reveals that hue alone is not the key to favorability. The critical factor lies in the configuration of hue, brightness, and saturation. For the gift market or high-end series, designers should adopt a low-brightness dark red configuration. This configuration activates the “maturity, stability, and luxury” cultural schema and effectively circumvents face-related risks. For younger consumers in daily drinking scenarios, high-brightness configurations may be attempted to convey “vitality and fashion.” However, the suitability for gift-giving requires cautious assessment. Firms

are advised to establish a “configuration-schema activation” database to record association test results of different configurations among target populations, thereby forming a data-driven design decision process.

Implications for marketers: Study 3 concerning “privacy value” discovers that consumers prioritize recommendation precision and relevance, yet reject “infinite precision.” Platforms should avoid the pursuit of absolute prediction. In practice, marketers can set diverse interventions to recommend varied content types. This strategy maintains relevance while mitigating the anxiety of “being spied on” by the algorithm. Marketers should annotate recommendations with brief logical explanations. Defining the boundaries of information sources prevents the triggering of defensive reactions. Recommendation systems should provide a “recommendation intensity adjustment” feature. Pushing commercial recommendations during holidays often induces negative emotions. Algorithms should integrate calendar data (e.g., Spring Festival) and user context signals (e.g., location in a public environment) to reduce commercial recommendation frequency during specific periods, switching instead to entertainment or cultural content.

Implications for platform designers: The most critical managerial implication from Study 4 is that ethical design constitutes a necessity for trust reconstruction. Different dimensions of ethical issues require specific strategies. Transparency should be implemented in layers. Instead of displaying all algorithmic logic at once, platforms should provide a multitier explanation structure (e.g., simple, medium, and detailed), allowing users to select the level of detail. Utilizing visualizations as opposed to dense text reduces the threshold for understanding. Privacy protection design should clearly state the usage and constraints of consumer privacy, activating user cognitive evaluation, which subsequently fosters emotional trust. Platforms should provide a one-click option to delete specific data types (e.g., Delete all interest tags) to enhance the perception of autonomy immediately. For fairness design, systems should provide diversity assurance mechanisms. Reserving a diversity quota in recommendation lists

to display content of varying prices and sources prevents the user perception of “algorithmic discrimination.” Furthermore, autonomy design should include interfaces that explicitly maintain an “Opt-out” option at all times. Allowing users to disable personalized recommendations and switch to a generic recommendation mode is crucial. Results show that autonomy support exerts the strongest direct effect because it directly triggers a sense of control at the emotional level.

8.5 Final conclusion

Through four progressive studies, this dissertation establishes an integrated theoretical framework for assessing consumer information diagnosticity in the hybrid marketing environment. The research sheds light on the fact that consumer decision-making is a hierarchical process of uncertainty reduction. Furthermore, the efficacy of diagnostic cues depends upon their accessibility and relevance at specific hierarchies.

By integrating physical product design and digital algorithmic design into a unified framework, this study demonstrates that although they exhibit distinct manifestations, both adhere to shared psychological principles: the adaptive optimization of information processing. However, the findings also expose the complexity inherent in diagnosticity theory. Diagnosticity constitutes a context-dependent, dynamically evolving, and nonlinear psychological evaluation. This characteristic admonishes the industry that while pursuing precision marketing, it is imperative to respect consumer cognitive boundaries and ethical requirements.

Ultimately, this dissertation’s core message is that within the hybrid marketing ecosystem, trust is a constructed outcome of successful information diagnosis. This research redefines “salience” not as a mere visual property, but as a multi-dimensional construct evolving from visual salience (physiological) to cultural salience (social) and finally to epistemic salience (systemic). We conclude that while sensory cues like brightness and color can lower the threshold for entry, only the cognitive scaffolding provided by ethical design can sustain long-term consumer relationships in the algorithmic era. The transition from the algorithmic “black box” to the ethical “glass

box” is thus established not just as a moral preference, but as a functional prerequisite for uncertainty reduction.

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Appendices

Appendix A: Supplementary Materials for Chapter 4 (Study 1)

Appendix B: Supplementary Materials for Chapter 5 (Study 2 - quantitative part)

Appendix C: Supplementary Materials for Chapter 5 (Study 2 - qualitative part)

Appendix D: Supplementary Materials for Chapter 6 (Study 3)

Appendix E: Other Supporting Documents

Appendix A: Supplementary Materials for Chapter 4 (Study 1)

Table A1: Eye-Movement Analysis - Detailed Statistical Results

Full details of the linear mixed-effects models for eye-movement outcomes, including fixed effects, random effects, and model diagnostics.

Section	Model/Block	Term / Contrast	Estimate	SE	df	95% CI low	95% CI high	p	Notes
A1. LMM (mean fixation duration)	Fixed effects (REML)	(Intercept)	322.027	7.685	31.095	306	338	< 0.001	
A1. LMM (mean fixation duration)	Fixed effects (REML)	brightness: high vs low	14.75	7.313	30.358			0.0526	
A1. LMM (mean fixation duration)	Fixed effects (REML)	trial_order_z	-4.381	3.307	470.374			0.1858	
A1. LMM (mean fixation duration)	Random effects (SD/Var)	participant intercept SD	34.61						Var=1197.7
A1. LMM (mean fixation duration)	Random effects (SD/Var)	residual SD	85.12						Var=7245.6
A1. LMM (mean fixation duration)	Robustness checks	brightness + saturation + hue	14.8	7.071	30.091			0.026	Adding covariates

Section	Model/Block	Term / Contrast	Estimate	SE	df	95% CI low	95% CI high	p	Notes
A1. LMM (mean fixation duration)	Robustness checks	1-99% Winsorization	13.3	6.052	30.358			0.028	Outlier handling
A1. LMM (mean fixation duration)	Robustness checks	Parametric bootstrap	14.75			1.8	27.6		95% CI, n=2000
A1. LMM (mean fixation duration)	Robustness checks	Leave-one-subject-out	11-18						Range across subjects
A1. LMM (mean fixation duration)	Model comparison	LRT vs null	14.75					0.024	Likelihood ratio test
A2. GLMM (fixation count)	Fixed effects (ML)	(Intercept)	0.0316	0.0305	30.82			0.31	log(count)
A2. GLMM (fixation count)	Fixed effects (ML)	brightness: high vs low	-0.0475	0.0264	30.42			0.072	log(count)
A2. GLMM (fixation count)	Fixed effects (ML)	trial_order_z	-0.0354	0.0119	466.6			0.003	log(count)
A2. GLMM (fixation count)	Poisson rate ratio	high vs low	0.954					0.072	exp(coef)
A2. GLMM (fixation count)	Random effects (SD/Var)	participant intercept SD	0.137						Var=0.0188
A2. GLMM (fixation count)	Random effects (SD/Var)	residual dispersion							Poisson: fixed at 1
A3. LMM (first fixation time)	Fixed effects (REML)	(Intercept)	410.8	11.58	30.85	387.1	434.5	< 0.001	
A3. LMM (first fixation time)	Fixed effects (REML)	brightness: high vs low	-10.02	8.104	30.53			0.224	
A3. LMM (first fixation time)	Fixed effects (REML)	trial_order_z	-6.591	3.731	463.4			0.077	

Section	Model/Block	Term / Contrast	Estimate	SE	df	95% CI low	95% CI high	p	Notes
A3. LMM (first fixation time)	Random effects (SD/Var)	participant intercept SD	51.89						Var=2692.5
A3. LMM (first fixation time)	Random effects (SD/Var)	residual SD	96.31						Var=9275.6
A3. LMM (first fixation time)	Robustness checks	brightness + saturation + hue	-9.71	7.789	30.23			0.224	
A3. LMM (first fixation time)	Robustness checks	1-99% Winsorization	-9.88	7.634	30.53			0.202	
A3. LMM (first fixation time)	Robustness checks	Log transformation	-10.3	9.124	30.57			0.264	log(FFT)
General notes	Eye-tracking setup	Sampling rate	1000						Hz
General notes	Eye-tracking setup	Calibration accuracy	<0.5						degrees
General notes	Data quality	Trials excluded	127						<5% total
General notes	Data quality	Participants excluded	0						All 32 retained

Table A2: Pupillometry LMM - Type III ANOVA Results

Analysis of variance results for the linear mixed-effects model of pupil diameter changes.

Effect	SumSq	MeanSq	NumDF	DenDF	F	p	p_report
brightness	1607	1607	1	32.6	14.5719	0.0005718	0.00057180
time window	1150323	575161	2	22111.4	5216.2477		< 0.001
saturation	79	79	1	22109.6	0.7165	0.3973128	0.39731280

Effect	SumSq	MeanSq	NumDF	DenDF	F	p	p_report
hue	1382	461	3	22107.9	4.1765	0.0057813	0.00578130
brightness: time window	79579	39790	2	22124.2	360.8586		< 0.001

Table A3: Pupillometry LMM - Fixed Effects

Fixed effects estimates, standard errors, and significance tests for the pupillometry model.

Term	Estimate	SE	df	t	p
(Intercept)	-20.94	0.8822	38.37	-23.737	< 0.001
brightness high	6.013	0.6694	58.99	8.983	< 0.001
time window middle	14.29	0.34	22100	42.038	< 0.001
time window late	25.53	0.2982	22100	85.626	< 0.001
saturation high	0.1195	0.1411	22100	0.846	0.39731
hue green	0.4271	0.2181	22100	1.958	0.0502
hue blue	0.5995	0.2181	22100	2.748	0.0060
hue yellow	1.302	0.2177	22100	5.981	< 0.001
brightness high: time window middle	-2.238	0.1989	22100	-11.254	< 0.001
brightness high: time window late	-9.194	0.1743	22100	-52.753	< 0.001

Table A4: Pupillometry LMM - Random Effects Structure

Random effects variance components and correlations.

Group	Effect	Variance	SD	Corr
Participant ID	(Intercept)	21.957	4.686	
Participant ID	brightness high	9.715	3.117	-0.54
Residual		110.263	10.501	

Table A5: Estimated Marginal Means by Time Window

Brightness contrasts and effect sizes for early, middle, and late time windows.

time window	contrast	estimate_pct	SE_pct	df	lowerCL_pct	upperCL_pct	p_value	p_fdr	N	mean_diff	sd_diff	dz
early	low - high	-6.013338	0.669377	inf	-7.325293	-4.701383	< 0.001	< 0.001	32	6.026880	4.387196	1.374
middle	low - high	-3.774049	0.624739	inf	-4.998514	-2.549584	< 0.001	< 0.001	32	3.780235	4.592391	0.823
late	low - high	3.179841	0.579823	inf	2.043408	4.316274	< 0.001	< 0.001	32	-3.088990	3.272360	-0.944

Table A6: Two One-Sided Tests (TOST) Results

Equivalence testing results for middle and late time window effects.

time window	estimate_pct	n	low_eq	high_eq	tost_p1	tost_p2
middle	-3.774049	32	-3	3	0.888	< 0.001
late	3.179841	32	-3	3	< 0.001	0.621

Note: Both middle and late effects exceeded the $\pm 3\%$ smallest effect size of interest (SESOI), indicating meaningful effects beyond the equivalence bounds.

Table A7: Hue Pairwise Comparisons (FDR-Adjusted Tukey)

FDR-adjusted Tukey pairwise comparison results for hue effects in middle and late time windows, as referenced in the main text.

contrast	estimate	SE	df	asympt.LCL	asympt.UCL	z.ratio	p.value	p_fdr
red - green	0.427058	0.218105	inf	-0.133260	0.987375	1.958	0.2041	0.2449
red - blue	0.599468	0.218137	inf	0.039068	1.159869	2.748	0.0305	0.0458
red - yellow	1.302156	0.217716	inf	0.742837	1.861475	5.981	< 0.001	< 0.001
green - blue	0.172411	0.218235	inf	-0.388241	0.733063	0.790	0.8590	0.8590
green - yellow	0.875098	0.217761	inf	0.315664	1.434533	4.019	0.0003	0.0010
yellow - blue	-0.702687	0.217761	inf	-1.262266	-0.143108	-3.227	0.0073	0.0146

Table A8: Post-hoc pairwise comparisons for brightness differences (low - high) by time window and hue (FDR-adjusted)

Results are averaged over saturation levels. Degrees-of-freedom method: asymptotic.

time_window	color	contrast	estimate	SE	asympt.LCL	asympt.UCL	z.ratio	p.value	p_fdr
early	red	low - high	-4.41	0.932	-6.23	-2.580	-4.728	< 0.001	< 0.001
middle	red	low - high	-3.74	0.802	-5.31	-2.164	-4.657	< 0.001	< 0.001
late	red	low - high	3.54	0.655	2.26	4.825	5.404	< 0.001	< 0.001
early	green	low - high	-6.88	0.934	-8.72	-5.053	-7.369	< 0.001	< 0.001
middle	green	low - high	-3.80	0.804	-5.37	-2.223	-4.725	< 0.001	< 0.001

time_window	color	contrast	estimate	SE	asympt.LCL	asympt.UCL	z.ratio	p.value	p_fdr
late	green	low - high	3.17	0.655	1.89	4.459	4.846	< 0.001	< 0.001
early	blue	low - high	-3.03	0.934	-4.86	-1.197	-3.241	0.0012	0.0013
middle	blue	low - high	-2.09	0.803	-3.66	-0.515	-2.602	0.0093	0.0092
late	blue	low - high	2.35	0.655	1.07	3.639	3.592	< 0.001	< 0.001
early	yellow	low - high	-9.69	0.933	-11.51	-7.856	-10.380	< 0.001	< 0.001
middle	yellow	low - high	-5.49	0.802	-7.06	-3.916	-6.840	< 0.001	< 0.001
late	yellow	low - high	3.70	0.654	2.42	4.980	5.653	< 0.001	< 0.001

Appendix B: Supplementary Materials for Chapter 5 (Study 2 - quantitative part)

Material preparation

We employed a within-subjects $4 \times 2 \times 2$ design: Hue (warm: red, yellow; cool: blue, green) $\times$ Saturation (high, low) $\times$ Brightness (high, low), yielding 16 conditions. Each participant viewed one image per condition (16 trials). Labels were designed to resemble realistic Italian wine labels while minimizing non-color confounds. Each label displayed a fictional white brand logo, product name, vintage, origin, alcohol content, net volume and allergen declaration. All text used a uniform sans-serif typeface with consistent size and placement (Joshi et al., 2024). Minimalist graphic backgrounds while avoiding imagery known to bias attention, such as castles or award stickers (Tang et al., 2015; Mokry et al., 2016). Label layout followed a vertical hierarchy (logo at the top, product and origin in the center, regulatory details at the bottom). The design adhered to the current European Union regulations, including Regulation (EU) No 1308/2013, Commission Delegated Regulation (EU) 2019/33, Regulation (EU) No 2021/2117, and Italy's Legislative Decree No 61/2010. These regulations mandate that wine labels must include specific elements: the product name, designation of origin, alcohol content, net quantity, allergen declaration, and country of origin. Color attributes were manipulated in Pixelmator Pro 3.0. Saturation was set to +70% (high) or -20% (low) to produce vivid versus muted colors without greyscale reduction. Very low saturation would render the color greyish, alter expectations of the intended hue and affect perception (Cutler et al., 2024). Brightness was set to +70% (high) or -70% (low) to generate luminous versus dark tones, ensuring clear contrasts while preserving hue recognisability (see Figure B1).

A pilot pretest was conducted to ensure that the 16 label images differed as intended in hue, saturation, and brightness. A separate sample of 40 participants ($M_{\text{age}} = 22.8$ years,

50% female) viewed each label in random order. For each image, participants viewed all 16 labels and indicated the dominant color category for each image and whether saturation and brightness were “high” or “low” as intended. The results confirmed that the manipulations were clearly distinguishable, we therefore set the low-saturation level at -20% .

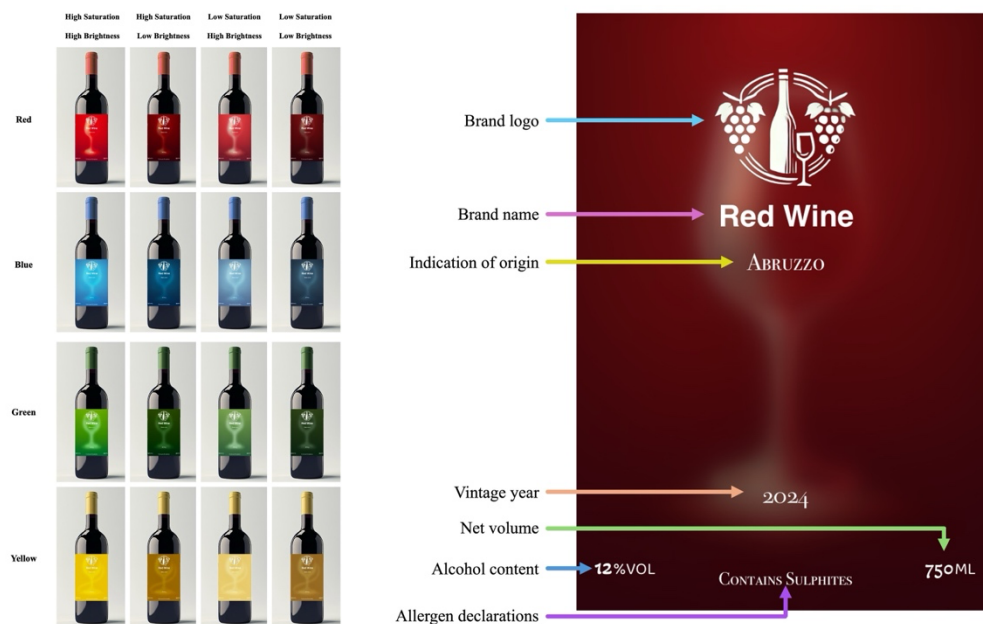


Figure B1. Sample Wine-Label

Survey design

Drawing on CPV theory, this study uses a questionnaire to examine how wine label hue, saturation and brightness influence consumers’ perceptions and judgements across four dimensions of perceived value: quality, emotion, society and sensation. The questionnaire covered the following constructs and item sources (all on a 7-point Likert scale, 1 = strongly disagree, 7 = strongly agree). All attitudinal items used a 7-point scale, except for the multinomial/ordered response options in the sensory dimension. Internal consistency for the overall scale was Cronbach’s $\alpha = 0.89$. The sensory dimensions used multiple-choice formats (see Table B1 for details):

Table B1. Full list of questionnaire items

Constructs	Full items	Reference	Option details or scale reliability
Subjective wine knowledge	I don't understand much about wine. (reverse) I am confident in my knowledge of wine. Among my friends, I am the wine expert. I know less about wine than others do. (reverse)	Lunardo et al. (2021)	Cronbach's $\alpha = 0.89$
Wine drinking frequency	How often do you consume wine?	Cornil et al. (2017)	Never; Less than twice a year; 2-5 times a year; About once every two months; About once a month; About once every two weeks; About once a week; More than once a week
Sweetness perception	How would you describe the sweetness level of this wine based on the wine picture?	Noble et al. (1987)	Dry (no sweetness); Semi-dry (very low sweetness); Semi-sweet (low sweetness); Sweet; Not sure
Acidity perception	What level of acidity do you expect this wine to have based on the wine picture?	Noble et al. (1987)	Very Low Acidity; Low Acidity; Medium Acidity; High Acidity; Very High Acidity; Not sure
Wine body perception	How full or light would you expect the body of this wine to be, based on the wine picture?	Noble et al. (1987)	Full-bodied; Rich; Medium; Light; Very light; Not sure
Flavor perception	Based on the wine picture, which of the following flavors do you expect this wine to have?	Noble et al. (1987)	Fruity Flavors; Herbal & Floral Flavors; Spice Flavors (e.g., pepper, cinnamon, cloves, etc.); Oak Flavors (e.g., Vanilla, Toast, Smoke, Chocolate, coffee, etc.); Earthy Flavors (e.g., soil, forest floor, stone, etc.); Others; Not perceived
Intense perception	Based on the wine picture, how complex do you expect the flavor of this wine to be?	Noble et al. (1987)	Intense; Complex; Subtle; Simple; Others; Not sure

Quality perception	The likelihood that wine is reliable is very high. The wine you have just seen is of high quality.	Yoo et al. (2000)	Spearman-Brown = 0.76
Emotional perception	I would like this wine. This wine would arouse positive feelings in me.	Sweeney and Soutar (2001)	Spearman-Brown = 0.81
Social perception	This wine improves the way I am perceived by others. This wine gives its owner social approval.	Pestar Bizjak et al. (2020)	Spearman-Brown = 0.90
Purchase intention	I would like to buy this bottle of wine. I intend to purchase this bottle of wine.	Yoo & Donthu (2001)	Spearman-Brown = 0.88
Demographic questions	What is your gender? Which age range do you belong to? What is your highest education level?		Male; Female; Others; Prefer not to say Under 18; 18 - 25 yrs; 26 - 35 yrs; 36 - 45 yrs; 46 - 55 yrs; 56 and above Primary school or below; Junior high school; High school; Junior college; bachelor's degree; master's degree or above

For the dimension of sensory perception design, we conceptualized sensory perception as comprising three components, which are aroma perception, palate perception, and wine body perception, and developed items accordingly:

- 1) Aroma Perception: Items were derived from the standardized “Aroma Wheel” by Noble et al. (1987), which provides a comprehensive framework for describing wine aromas.
- 2) Palate Perception: Design focused on sweetness and acidity, fundamental elements of the wine-tasting experience, as emphasized by Koone et al. (2014).
- 3) Wine Body Perception: Following Niimi et al. (2017) wine body was included as

a critical factor in overall flavor perception and purchasing decisions. Tannin-related items were excluded to avoid confusion, given the complex interplay between wine body, astringency, and tannin perception, influenced by grape variety, production methods, and barrel ageing.

To mitigate participant fatigue, we used a mixed design. Within-subjects, each participant completed four repeated measurements in their assigned version, with the combination of color, saturation and brightness varying across the four trials. Questionnaire version (1-4) served as a between-subjects counterbalancing factor. A pseudo-randomized scheme was used to balance stimulus combinations and presentation order across participants and to control for order and combination confounds. The parameter settings and display order were as follows:

- 1) Version 1: (1) red - high saturation - high brightness; (2) blue - low saturation - high brightness; (3) green - high saturation - low brightness; (4) yellow - low saturation - low brightness.
- 2) Version 2: (1) blue - high saturation - low brightness; (2) green - low saturation - low brightness; (3) yellow - high saturation - high brightness; (4) red - low saturation - high brightness.
- 3) Version 3: (1) green - high saturation - high brightness; (2) yellow - low saturation - high brightness; (3) red - high saturation - low brightness; (4) blue - low saturation - low brightness.
- 4) Version 4: (1) yellow - high saturation - low brightness; (2) red - low saturation - low brightness; (3) blue - high saturation - high brightness; (4) green - low saturation - high brightness.

We compared key socio-demographic variables (gender, age, and educational level, wine drink frequency) across the four questionnaire versions. Chi-square tests and one-way ANOVAs indicated no significant differences between versions (all $p > 0.10$), suggesting that the samples can be regarded as equivalent in terms of basic demographics.

Translation and cross-cultural equivalence procedures, we adopted the procedure as follows:

- 1) Forward translation (English into Chinese): Two bilingual authors with marketing/psychometric backgrounds independently translated the English items into Chinese. A project team member reconciled the two versions into a consensus draft.
- 2) Back translation (Chinese into English): A bilingual translator, independent of the forward translators, translated the Chinese draft back into English.
- 3) Comparison and reconciliation: The forward and back-translated versions were compared item by item with the original English items. The research team held a meeting to check semantic consistency and conceptual equivalence and to agree on amendments.
- 4) Cultural and comprehensibility review: An international student who spoke Chinese as a second language, had studied in China, and was familiar with everyday consumption contexts reviewed the items for clarity and cultural relevance. His feedback was used to identify linguistic ambiguities and potential cultural misinterpretations.
- 5) Pre-testing: A small sample ($N = 10$) evaluated readability and comprehensibility. Wording was refined where necessary without altering item content.
- 6) Finalization: The final Chinese version was produced and used in the main survey.

Participants

A paid online service (wenjuanxing.com) recruited 510 participants for the four questionnaire versions. Participants were anonymized and screened using the following exclusion criteria:

- 1) Age: Participants under 18 were excluded ($N = 3$).
- 2) Attention Checks: Responses failing trap questions or logic checks were removed ($N = 23$).

- 3) Response Quality: Illogical or low-quality responses, such as failing reverse-coded items or completing the survey in under 3 minutes, were excluded (N = 31).
- 4) Duplicates: Submissions from identical IP addresses were eliminated (N = 18).

After data cleaning, 435 valid responses were retained, distributed as follows: Version 1 (113), Version 2 (97), Version 3 (104), and Version 4 (121), achieving an 85.3% retention rate.

All participants were informed that they would complete the survey on their own smartphone or computer. They were told that all data would be anonymized and reported only in aggregated form. Participation was allowed only after they had read the online information sheet and provided informed consent. As compensation, participants received a randomly drawn monetary reward between 2-20 RMB (approximately 0.24-2.42 EUR).

Procedure

To minimize visual bias caused by different equipment, all online subjects are required to follow the same guidelines before answering the questions. The detailed specifications of the screen display settings used during the survey are provided below. These settings were standardized to ensure consistent display quality across different devices and participants, thereby minimizing variability in respondents' visual perception of the experimental images.

"To ensure the accuracy of this experiment, please follow the steps below to adjust your device settings before starting to answer the questions:

1) Turn off Night Mode/Eye Care Mode:

- Mobile/Tablet Users:

o iOS (Apple) Devices: Go to "Settings" > "Display & Brightness" and turn off the "Night Shift" feature.

o Android Devices: Pull down the quick settings menu and turn off "Eye Care Mode" or "Night Mode."

- Computer Users:

- o Windows: Turn off “Night Mode” or any third-party eye care software.*
 - o Mac: Go to “System Preferences” > “Displays” > “Night Shift” and turn it off.*
 - 2) Adjust Screen Brightness: Set your screen brightness to 50% to 70% for the best visual experience.*
 - 3) Use Standard Display Mode: If your device has multiple display modes, please select the “Standard Mode” or “Default Mode.”*
 - 4) Choose an Appropriate Viewing Environment: Perform the experiment in a well-lit and evenly illuminated indoor environment, avoiding strong sunlight or overly dim settings.*
- After submitting the survey, you can restore your previous display settings by following the same steps.*
- Thank you again for your cooperation!”*

Data processing procedures

Data from 435 participants (1,740 observations) were analyzed using R (R version 4.4.2). Given the nested data structure, we employed mixed-effects models to account for individual variability and repeated measurements.

We analyzed one continuous block of outcomes (quality perception, emotional perception, social perception, and purchase intention), three ordinal outcomes (Sweetness, Acidity, Wine body), and nine binary outcomes (Fruity, Floral, Spice, Oak, Earthy, Intense, Subtle, Complex, Simple). For all models, predictors included Hue (Red, Blue, Green, Yellow), Saturation (High, Low), Brightness (High, Low), and their interactions (up to three-way; Wine body used two-way interactions for model stability). “Not sure” responses in ordinal outcomes were excluded a priori. Random effects comprised nested random intercepts, capturing between-participant variation and within-participant variation across experimental versions.

For continuous variables, we fitted linear mixed-effects models (LMMs) using the lme4 package. Models were fitted using restricted maximum likelihood (REML). Significance of fixed effects was assessed using Type III tests with Kenward-Roger approximation for degrees of freedom (Kuznetsova et al., 2017).

For ordinal variables, we used cumulative link models with a logit (proportional-odds) link. When the mixed-effects model (CLMM; participant random intercept) did not yield a stable variance-covariance matrix, we fit a fixed-effects CLM (two-way interactions for Wine body) to ensure identifiability.

For binary variables, we used logistic mixed-effects models (GLMM; logit link, participant random intercept). If a model was singular or failed to converge, we reported the corresponding logistic GLM.

Significant interactions were decomposed with estimated marginal means using the emmeans package (Lenth, 2016); exploratory pairwise comparisons used Tukey's HSD to control the family-wise error rate. Our a priori planned contrast, applied uniformly to all outcomes, compared Red with the mean of other colors under low brightness on each model's linear predictor scale, that is, identity for continuous, logit/cumulative-logit for ordinal and binary. We report two-tailed 95% CIs and p values ($\alpha = 0.05$), Cohen's d with 95% CIs for continuous outcomes based on the model residual SD, and odds ratios with 95% CIs for ordinal and binary outcomes.

Appendix C: Supplementary Materials for Chapter 5 (Study 2 - qualitative part)

We utilized theory-driven purposive stratified sampling. Based on respondents' wine knowledge (K) and reported consumption patterns in the survey, the 30 interviewees were allocated to theoretically relevant strata (novice, intermediate, advanced, expert) in order to capture contrast in cultural capital configuration and forms of reliance on cues (see Table C1.).

Table C1. grouped by wine knowledge (K)

Categories	N	Inclusion Criteria	Theoretical Purpose
Expert (high knowledge)	6	$K > 5.5$, possession of professional experience, specialized training, or wine industry practitioner	Expert comparison, strategic employment
Advanced (mid-high)	7	$4 < K \leq 5.5$, recurrent consumption	Transitional domains, learning continuum
Intermediate (mid-low)	7	$2.5 < K \leq 4$, sporadic consumption	Integration of a hybrid dependency paradigm
Novice (entry-level)	10	$K \leq 2.5$, annual consumption of low occurrences	Reliance on extraneous informational sources.

The final sample ($N = 30$) comprised 18 females and 12 males, aged 18-42 years ($M = 29.23$, $SD = 6.20$). 17 held a bachelor's degree and thirteen a master's degree or above. Participants were located in Shanghai (8), Guangzhou (7), Shenzhen (5), Beijing (4), Xi'an (2), Suzhou (2), Zhengzhou (1), and Dalian (1). Group means for wine knowledge confirmed the intended differentiation (novice group: $M = 1.68$, $SD = 0.60$; intermediate group: $M = 3.32$, $SD = 0.47$; advanced group: $M = 4.89$, $SD = 0.50$; expert group: $M = 6.67$, $SD = 0.41$). With regard to gifting practice, 12 participants reported frequent gifting (≥ 6 times/year), 8 mainly gifted during major festivals, and 10 gifted only occasionally. Interviewees were recruited from the survey sample via snowball sampling procedures. All interviews were conducted via online calls, lasted

between 70 and 90 minutes, were audio-recorded with informed consent, and were processed under strict anonymization. Participants received a reward of 50 RMB (approximately 6.10 EUR) after the interview. The details of the sample are summarized in Table C2.

Table C2. profile of all interviewee's information

No.	Pseudonym	Gender	Age	Educational level (Background)	City	Occupation	K
1	Aria	Female	36	Master (Fashion marketing)	Beijing	Freelance	4.5
2	Lara	Female	28	Master (Public management)	Beijing	Internet company employee	2.75
3	Chloe	Female	30	PhD (Sociology)	Beijing	Short video blogger	2
4	Maya	Female	32	Bachelor (Business English)	Dalian	Marketing specialist	5
5	Noah	Male	37	Bachelor (Software engineering)	Beijing	IT programmer	6
6	Adelaide	Female	33	Master (Mass communication)	Zhengzhou	Marketing manager	6.5
7	Callum	Male	25	Bachelor (Sport dance)	Shanghai	New media operation	2.5
8	Zeth	Male	26	Bachelor (Electronic information)	Shanghai	IT programmer	3.5
9	Siena	Female	23	Bachelor (Accounting)	Shanghai	Cashier	2.5
10	Elodie	Female	25	Master (Finance)	Shanghai	Bank employee	2.75
11	Lena	Female	20	Bachelor (Industrial engineering)	Shanghai	Student	1.25
12	Mason	Male	25	Bachelor (Business management)	Guangzhou	Salesperson	1
13	Lucy	Female	38	Master (Aquaculture)	Shanghai	Legal worker	5.5
14	Amira	Female	38	Master (Pharmaceutical technology)	Shanghai	Fulltime housewife	4.25
15	Evan	Male	42	PhD (Life sciences)	Shenzhen	Food research and development specialist	5

16	Theo	Male	33	Master (Viticulture and winemaking)	Guangzhou	Salesperson	5.5
17	Julian	Male	38	Master (Viticulture and winemaking)	Guangzhou	Wine brand ambassador	7
18	Iris	Female	29	Master (Viticulture and winemaking)	Guangzhou	Salesperson	6.5
19	Reid	Male	30	Master (Viticulture and winemaking)	Xi'an	Winemaker	7
20	Hazel	Female	37	Bachelor (Statistics)	Guangzhou	Salesperson	4
21	Tessa	Female	26	Bachelor (Logistics management)	Shenzhen	Salesperson	3.75
22	Clara	Female	23	Bachelor (Logistics management)	Shenzhen	Salesperson	2
23	Elise	Female	22	Bachelor (Design)	Shenzhen	Unemployed	1.5
24	Owen	Male	28	Master (Education)	Shenzhen	School teacher	2
25	Lucas	Male	33	Bachelor (wine marketing)	Guangzhou	Wine teacher	7
26	Celia	Female	30	Bachelor (Law)	Guangzhou	School teacher	3.25
27	Dylan	Male	24	Bachelor (Chinese language and literature)	Shanghai	Company employee	3.25
28	Elias	Male	18	Bachelor (psychology)	Xi'an	Student	1
29	Freya	Female	24	Bachelor (Tourism management)	Suzhou	Tour Guide	4.5
30	Renee	Female	24	Bachelor (E-commerce)	Suzhou	E-commerce operation	1

A semi-structured interview guide was organized into five core modules: (1) Background (5-10 min): consumption context, frequency, and self-assessed knowledge; (2) Sources of color associations (15-20 min): presenting red, blue, green, and yellow label stimuli, followed by open-ended probing on “where do these ideas come from?”; (3) Brightness semantics (20-30 min): comparison of bright red and dark red samples, including “Which one seems more high-end, and why?” and “What does this color mean in Chinese culture?”; (4) Anxiety and decision making (20-25 minutes): simulated gift-giving scenarios, asking “What would you be concerned about?” and “How would you make your decision?” and (5) Critical Reflection (5 minutes): “To what extent does the color indicate quality rather than just marketing?” and “Have you

ever had an experience where the wine did not match the expectations created by its color or packaging?”. All questions were open-ended and detailed narratives were encouraged. The interviewer used exploratory follow-up questioning techniques (“Can you give some specific examples?” and “Why is it important to you?”) and refrained from correcting or evaluating participants’ views. All interviews were audio-recorded and transcribed into verbatim transcripts, including salient pauses and intonation. Transcription was conducted using an online service (iflyrec.com); the first author cross-checked 10 transcripts (33%) and found an error rate below 2%. Key quotations from the original Mandarin transcripts were translated into English for presentation in the article.

Subsequently, we applied a hybrid coding approach (Fereday & Muir-Cochrane, 2006), integrating deductive and inductive themes. Deductive coding was guided by integrated theoretical frameworks. Drawing on Cultural capital theory (Bourdieu, 1984), we distinguished embodied capital (tasting competence) from objectified capital (reliance on label cues) to capture different forms of capital accumulation. Consumer Culture Theory (Arnould & Thompson, 2005) guided the identification of cultural schemas in color-attribute associations and the culturally specific meanings attached to red in the Chinese context. Social Learning Theory (Bandura & Walters, 1977) informed the coding of learning sources, including experiential learning, offline interpersonal interaction, and digital or platform-mediated learning, thereby addressing the under-specified mechanisms of capital acquisition in Bourdieu’s account. Face Theory (Goffman, 1967; Gao & Ting-Toomey, 1998; Qian et al., 2007) was used to locate face-saving concerns and marketplace anxieties as culturally embedded perceptions of social risk. Critical Consciousness Theory (Carducci, 2006) informed codes on participants’ awareness of commercial manipulation and their resistance strategies. These frameworks were operationalized into six deductive coding dimensions: (1) source of learning (experiential, interpersonal/social interaction, digital/media-based, other); (2) cultural meanings (dark red, bright red, high-end, festive); (3) anxieties (face-related risk, choice pressure); (4) level of dependence (high, medium, low); (5) level of critical

awareness (acceptance, questioning, ambivalence), and (6) capital accumulation barriers (see Table C3). On the other hand, inductive coding was then employed to identify unanticipated themes, such as “everyday analogies” (e.g. associations with fruit color or beverage packaging), “age-color matching rule”, “heterogeneous counter-viewpoints”, and “emotional dependence discourse” (see Table C4). NVivo 15 was used to support data management and coding. A thematic frequency matrix was generated, and representative quotations were extracted to facilitate cross-case comparison between novice and expert participants. We tracked the emergence of new codes during the coding process. By around the 23rd interview, no substantively new concepts were identified, and subsequent interviews mainly elaborated and refined existing themes. On this basis, we considered that conceptual saturation had been reached and that the final sample of 30 interviews was adequate for the study aims. Initial thematic summaries were shared with six interviewees (20%) for respondent validation; all confirmed that the interpretations were accurate. Lastly, triangulation was conducted by comparing the interview findings with the survey results from Study 1 to access cross-method consistency.

Table C3. details of deductive codes

Theory-code	Sub-code	Operational definition (theory-based)
Learning mechanisms <i>Theoretical foundation:</i> <i>Social Learning Theory</i> <i>(Bandura & Walters, 1977)</i>	Observational learning: digital platforms	Learning perceived wine-selection rules by observing video, KOLs, livestreaming or bloggers on digital platforms.
	Observational learning: social circle	Learning through observing how friends, family members, or colleagues choose wine.
	Vicarious learning: others' experience	Indirect learning from others' reported successful or failed purchase experiences.
	Direct experience: tasting	Building embodied knowledge through personal tasting experiences.
	Direct experience: consumption outcomes	Learning from positive or negative post-purchase outcomes of one's own choices (online platform reviews).
	Symbolic-mediated learning: traditional media	Acquiring structured wine knowledge from books, television, magazines, or professional media.

	Symbolic-mediated learning: everyday analogy	Transferring lay theories from other product domains to wine (e.g., luxury product analogies).
	Implicit cultural transmission	Absorbing color codes unconsciously through everyday cultural exposure; source cannot be clearly identified.
Cultural Schema Content	Color-quality association	Color is taken to signal or reflect the objective quality of the wine.
<i>Theoretical foundation:</i>		
<i>Consumer Culture Theory (CCT; Arnould & Thompson, 2005)</i>	Color-price expectation	Color informs expectations of an appropriate or justified price level.
	Color-maturity association	Color is linked to grape or wine maturity and perceived ripeness.
	Color-class marker	Color operates as a marker of social class, refinement, or sophistication.
	Color-occasion fit	Different colors are considered suitable for different social occasions or rituals.
	Color-emotion/atmosphere	Color evokes specific emotions or symbolic atmospheres (e.g. festivity, luck, warmth).
	Color-origin/style cue	Color is read as indicating specific origins, grape varieties, or winemaking styles.
Marketplace Anxiety Types	Face-loss anxiety	Anxiety about choosing the “wrong” wine and losing face or feeling embarrassed in front of others.
<i>Theoretical foundation:</i>		
<i>Face Theory (Goffman, 1967; Gao & Ting-Toomey, 1998)</i>	Social evaluation anxiety	Concern that others may negatively judge one’s taste, aesthetic judgement, competence, or refinement.
	Decision uncertainty anxiety	Anxiety arising from low confidence in one’s own judgement and fear of making a wrong choice.
	Economic loss anxiety	Worry about paying a high price for a wine that turns out to be disappointing.
	Relational risk anxiety	Fear that an inappropriate wine choice may harm interpersonal or business relationships.
	Identity threat anxiety	Concern that one’s wine choice may expose low cultural capital or a lower social position.
	No/low anxiety	Explicit indication of little or no anxiety in wine selection situations.
Capital Reliance	Full reliance on objectified capital	Decisions depend entirely on external symbols (e.g. color, packaging, price,

<i>Theoretical foundation:</i> <i>Cultural Capital</i> <i>(Bourdieu, 1984)</i>		awards), with no use of embodied judgement.
	Predominant reliance on objectified capital	Primarily guided by external cues, with occasional use of personal sensory evaluation.
	Balanced use	Objectified and embodied capital are used to a comparable extent.
	Verification use of objectified capital	Embodied capital is primary; external cues are used only to confirm an existing judgement.
	Strategic use of objectified capital	External symbols are selectively used in specific social contexts (e.g. gifting, business), while personal consumption relies less on them.
	Minimal reliance on objectified capital	Wine choices are guided almost entirely by embodied knowledge and sensory assessment.
	Resistance to objectified capital	Explicitly questioning or rejecting the validity of external symbols as reliable indicators.
Critical Consciousness Levels <i>Theoretical foundation:</i> <i>Critical Consciousness</i> <i>(Carducci, 2006)</i>	Naive consciousness	Treats color codes as direct, objective reflections of quality; no awareness of their marketing construction.
	Pragmatic consciousness	Aware that color codes are marketing devices but accepts them as convenient heuristics.
	Critical but compliant	Recognizes the manipulative or constructed nature of color codes but continues to rely on them in practice.
	Cynical consciousness	Holds a strongly critical view of market manipulation and feels powerless to escape these marketing game.
	Active resistance	Deliberately avoids color codes and seeks alternative bases for judgement (e.g. tasting, expert advice).
	Expectation-experience discrepancy	Has experienced a mismatch between color-based expectations and actual wine quality, prompting reflection on color codes.
Capital Accumulation Barriers <i>Theoretical foundation:</i> <i>Cultural Capital</i> <i>(Bourdieu, 1984)</i>	Structural barrier: time	Lack of available time to attend tastings or systematic wine education.
	Structural barrier: economic	Insufficient financial resources to pay for courses or purchase higher-quality wines for practice.

Structural barrier: geographical	Limited access to wine-related events, shops, or knowledgeable venues due to location.
Social capital barrier	Lack of social networks that provide guidance, invitations, or shared expertise in wine.
Psychological barrier: low self-efficacy	Belief that one cannot understand or master wine knowledge.
Psychological barrier: fear of failure	Fear of making mistakes or being ridiculed when trying to learn.
Motivational barrier: satisfied with codes	Perception that existing simple rules (e.g. color codes) are sufficient; no perceived need for deeper learning.
Motivational barrier: low interest	Limited intrinsic interest in wine, reducing motivation to build embodied capital.
Positive learning intention	Explicit desire to develop embodied cultural capital and move beyond surface cues.

Table C4. details of inductive codes

Theme	Operational definition	Reason for coding
Dark red as a shared premium schema	A widely shared interpretive schema in which dark red labels are read as signaling higher status, sophistication, and premium quality.	A strong convergence is observed, most of participants explicitly describe dark red as “high-end”, “elegant”, “serious”, or similar.
Bright red as “wedding-banquet wine” and low-tier cue	Bright red labels are specifically associated with mass-market, low-quality, or generic wedding-banquet wines, generating a devaluation of this color in non-wedding contexts.	Many participants link bright red directly to wedding-banquet wine or “cheap banquet alcohol”.
Everyday analogy learning	Participants learn color rules by analogy with everyday product categories (e.g. juice, soft drinks, snacks), transferring the “darker = higher quality, high value” logic to wine.	Most of participants use cross-category analogies to justify their wine color expectations.
Age-coded color norms	Color norms are structured by age-related cultural rules, where different shades of red are	Some participants explicitly describe age- or role-specific color prescriptions.

	considered appropriate for different generations or roles.	
Ambivalent trust in social media platform (Xiaohongshu, Douyin/TikTok, bilibili, WeChat, Weibo)	Users rely on social media as a reference yet report only moderate trust, indicating simultaneous dependence on and skepticism towards digital advice.	Many participants more or less express ambivalent trust (neither full endorsement nor full rejection).
Heterogeneous counter-readings	Minority interpretations that invert or challenge the dominant color meanings (e.g. bright red as vitality, dark red as ominous).	Minority positions introduced counter-arguments and offered reasons that were analytically significant for interpreting the data
Emotional dependence discourse	Participants use explicitly emotional, relational, or loyalty-based language to justify continued reliance on color codes, beyond instrumental reasoning.	Some participants frame color in terms of attachment, fondness, or emotional tolerance rather than mere usefulness.
Expert strategic distancing	Self-identified experts or experienced drinkers describe color codes as tools used strategically (e.g. for gifting, signaling) while maintaining cognitive and emotional distance from these codes.	Expert participants explicitly distinguish between their “real” evaluation criteria and their tactical use of color codes for others.
Schema convergence beyond knowledge level	Novices and experts share similar core schemas (e.g. “dark red = premium, high-end”) while differing in degree and mode of reliance (novices depend heavily and confidently on color; experts minimally).	Cross-group comparison shows aligned meanings but divergent dependency.

Table C5. Distribution of learning sources (N = 30)

Learning mechanisms	Freq.	%	Theoretical reference
Symbolic mediation: everyday analogies	25/30	83%	Symbolic modelling (Bandura & Walters, 1977)
Observational learning: digital platforms	12/30	40%	Mediated symbolic modelling; digital cultural intermediaries
Direct experience: accumulation through tasting	9/30	30%	Embodied cultural capital (Bourdieu, 1984)
Observational learning: social circle	6/30	20%	Vicarious learning (Bandura & Walters,

			1977)
Implicit cultural transmission: cultural osmosis	5/30	17%	Habitus and enculturation (Bourdieu, 1977)

Table C6. Consider dark red more high-end (N = 27)

Positive association of dark red	Freq.	%	Negative association of bright red	Freq.	%
High-end/status-fit	24/27	89%	Festive but not suitable for business event	25/27	93%
Mature/steady	23/27	85%	Cheap/superficial	20/27	74%
Formal/gifting/business appropriate	21/27	78%	Young/novice	17/27	63%
Aged/more complex taste	19/27	70%	Resembling drinks rather than wine	13/27	48%
Reserved/sophisticated/elegant	14/27	52%			

Table C7. Market anxiety types among gifters (N = 30)

Type of anxiety	Freq.	%	Forms of anxiety
Face-threat anxiety	17/30	57%	Afraid of losing face
Social evaluation anxiety	8/30	27%	Might look unprofessional/lacking taste
Decision uncertainty	13/30	43%	Do not understand how to choose/conflicted
Relationship-risk anxiety	10/30	33%	Influences the recipient's perception of gifter
Economic risk anxiety	8/30	27%	If it's expensive but bad taste, it's a waste
Identity-threat anxiety	10/30	33%	Afraid of looking low/unsophisticated

Table C8. Anxiety gradients by knowledge level (self-rated, 1-10)

Knowledge group	Anxiety M (SD)	Explicit "face" language	Reliance on color cues*
Expert (N = 6)	2.33 (1.11)	1/6 (17%)	2/6 (33%)
Advanced (N = 7)	4.71 (1.39)	4/7 (57%)	2/7 (29%)
Intermediate (N = 7)	7.00 (1.31)	5/7 (71%)	6/7 (86%)
Novice (N = 10)	5.70 (2.37)	7/10 (70%)	7/10 (70%)

*: Proportion mentioning label color as a key decision cue in gifting.

Table C9. Confidence inversion: an asymmetry between color and competence

Knowledge level	Confidence in color cue M (SD)	Confidence in blind tasting M (SD)	ΔM
Expert (N = 6)	M = 2.00 (0.82)	M = 7.67 (1.49)	-5.67
Advanced (N = 7)	M = 4.43 (0.90)	M = 4.14 (1.96)	0.02
Intermediate (N = 7)	M = 6.14 (1.25)	M = 4.00 (1.41)	2.14

Qualitative Data: Complete Interview Quotes

This appendix provides the full verbatim transcripts of interview quotes cited in Section 4.2. Each quote is presented with participant demographics and the complete original statement to support transparency and replicability.

Quote C1 - Renee (F, 24, K = 1, novice):

“Yellow makes me think of pineapple, quite sour and a bit bitter. Blue reminds me of minerals water, slight sweetness. I’m just relying on my everyday experience, matching colors and flavors from things in daily life.”

Quote C2 - Callum (M, 25, K = 2.5, novice):

“I go with my feelings and past experiences. It comes from the packaging of other drinks, like juice drinks, beer. The colors you see on the market pretty much tell you what the taste will be.”

Quote C3 - Adelaide (F, 33, K = 6.5, expert):

“It’s based on my usual impressions of wine labels and how red works in everyday life. Red, for me, stands for red wine, usually lighter (body). Other colors come from other kinds of packaging I see a lot drinks, foods, so the meanings carry across.”

Quote C4 - Amira (F, 38, K = 4.25, advanced):

“I use Xiaohongshu [...]. I saw a post about visiting an Italian winery

and introducing some wines. I'd give it about 5/10 for credibility. It felt more like a travel influencer with some advertising involved, and not particularly professional."

Quote C5 - Dylan (M, 28, K = 3.25, intermediate):

"I use Xiaohongshu and Douyin, but only when I want to look something up, like a wine course. A single video on its own is maybe 3 or 4 out of 10. If lots of different videos say the same thing, then it goes up to scores."

Quote C6 - Adelaide (F, 33, K = 6.5, expert):

"It depends on whether the blogger has proper qualifications, but you also have to consider their commercial interests."

Quote C7 - Zeth (M, 26, K = 3.5, intermediate):

"Bright colors feel cheap to me, because they're just there to grab attention. Dark red feels more noble. The cheaper it is, the more it wants to be seen. If it has 'inner quality', it doesn't need loud colors. Dark red has a more complex flavor and a more mature wine body."

Quote C8 - Mason (M, 25, K = 1, novice):

"Dark red feels more high-end. Light (color) cheap. From what I usually see, bright red looks like a soft drink, like grape drinks for kids, whereas dark red feels like wine for adults."

Quote C9 - Lucas (M, 33, K = 7, expert):

“Dark red suggests ageing and higher value. It’s easier to link it to the actual color of the wine. [...] For high-end occasions in China (such as) banquets, formal events, and dark red fits that atmosphere and gives a sense of substance. Bright red (by contrast) feels a bit frivolous, not very suitable for business settings, and not very valuable.”

Quote C10 - Lucy (F, 38, K = 5.5, advanced):

“Dark red doesn’t really have a specific meaning in Chinese culture as such, but it feels more like a color for middle-aged women, like in cheongsams. It’s a color they prefer. [...] At weddings, the bride is definitely in bright red, but the bride’s mother will usually be in dark red, which fits her age and temperament.”

Quote C11 - Zeth (M, 26, K = 3.5, intermediate):

“Dark red gives a sense of respect, especially towards older people. I feel it reflects their clothing taste, so dark red feels more respectful for elders or people of higher status.”

Quote C12 - Elias (M, 18, K = 1, novice):

“Bright red looks more high-end to me because the color is pure. Perhaps the dark one is more expensive, like ¥70-150 more, because a stronger taste feels like it should cost more. For me, ‘high-end’ is mainly about looking good, whereas higher price comes from stronger flavor or higher alcohol.”

Quote C13 - Lena (F, 20, K = 1.25, novice):

“From my perspective, dark red just comes across as too old-fashioned, you know? I reckon bright red has more of a premium vibe. I mean, take a Ferrari, do you think dark red looks classier or bright red? Definitely bright red”

Quote C14 - Mason (M, 25, K = 1, novice):

“I basically wouldn’t give a bright red one in any situation [...]. Even if it tastes good and costs more, it feels like giving something I wouldn’t drink myself. I’m really afraid of losing face. Giving a gift should make the other person happy; this bright red one breaks that basic logic. [...] gift has to look good and people won’t sneer at and mock me”

Quote C15 - Zeth (M, 26, K = 3.5, intermediate):

“Dark red gives a sense of respect, especially for older people. With gifting, I worry a lot; it has to be appropriate. If you choose wrong, people may think you’re impolite or disrespectful. I’m very afraid of losing face, especially in front of leaders or elders. I’d rather [...] ask professionals [...] which one will ‘carry face’ when I give it.”

Quote C16 - Julian (M, 38, K = 7, expert):

“I’d choose dark red because it’s steadier; it signals something that matches the recipient’s identity, age and position. With Chinese culture, that’s important. What I worry about most is wine quality. I rarely think they’ll see it as low-grade, it doesn’t really affect me. The label still matters, maybe [...] they’re disappointed, but it’s fine.”

Quote C17 - Mason (M, 25, K = 1, novice):

“I’d say maybe 7 or 8 out of 10 for trusting the color. For blind tasting, I’m a right nobody, maybe 1 (out of 10).”

Quote C18 - Noah (M, 37, K = 6, expert):

“For color, maybe 2 out of 10, it doesn’t really tell you much. For blind tasting, 7 or 8 (out of 10). I trust my nose and palate more.”

Quote C19 - Zeth (M, 26, K = 3.5, intermediate):

“Of course, it’s marketing [...] but if the label looks good, even if the taste isn’t amazing, I’d still quite like it. When you like how it looks, you’re more tolerant. So I still go by the color.”

Quote C20 - Lucy (F, 38, K = 5.5, advanced):

“A few disappointments or fails don’t really change my use of color. I still look at it.”

Quote C21 - Adelaide (F, 33, K = 6.5, expert):

“In that case the winery spent money in the wrong place. It’s just a mask, nice label, ordinary wine underneath.”

Quote C22 - Clara (F, 23, K = 2, novice):



“These color rules are enough. For gifting I just follow them.”

Appendix D: Supplementary Materials for Chapter 6 (Study 3)

Participant Demographics

Table D1 provides a detailed breakdown of participants, including the participants' names (To protect the privacy of the interviewees, all names have been anonymized. Each participant has been assigned a pseudonym based on gender, as per ethical guidelines), gender, age, living area, educational level, and relevant purchasing experience on Douyin.

Table D1. Participant demographics

No.	Pseudonym	Gender	Ages	Living area	Educational level	Year of use
1	Emily	F	33	Beijing	Master's degree	3
2	Michael	M	21	Zhejiang	Bachelor's degree	6
3	James	M	31	Jiangxi	Bachelor's degree	2
4	David	M	28	Shaanxi	High school	4
5	Daniel	M	20	Xinjiang	Bachelor's degree	6
6	Andrew	M	30	Hebei	Bachelor's degree	7
7	Margaret	F	64	Shaanxi	High school	6
8	Robert	M	32	Taiwan	Bachelor's degree	6
9	William	M	31	Guangdong	Bachelor's degree	7
10	John	M	39	South Korea	High school	5
11	Christopher	M	26	Shanxi	Bachelor's degree	6
12	Sophia	F	26	Beijing	Master's degree	4
13	Matthew	M	23	Shaanxi	Bachelor's degree	5
14	Olivia	F	28	Heilongjiang	PhD	2

15	Joseph	M	36	Fujian	Bachelor's degree	4
16	Emma	F	29	Hubei	Master's degree	6
17	Jessica	F	26	Xinjiang	Bachelor's degree	5
18	Benjamin	M	33	Shanghai	Bachelor's degree	4
19	Laura	F	37	Guangxi	Master's degree	7
20	Sarah	F	32	Shanghai	Master's degree	1
21	Alexander	M	24	Jiangxi	Bachelor's degree	4
22	Rebecca	F	33	Shandong	Bachelor's degree	5
23	Hannah	F	28	Henan	Bachelor's degree	4
24	Thomas	M	34	Italy	High school	5
25	Grace	F	28	Anhui	Bachelor's degree	7
26	Chloe	F	20	Anhui	High school	2
27	Elizabeth	F	33	Hongkong	High school	3
28	Mia	F	18	Hunan	High school	3
29	Abigail	F	18	Fujian	High school	5
30	Ryan	M	27	Guizhou	Master's degree	6
31	Brandon	M	21	UK	Bachelor's degree	3
32	Ella	F	17	Jiangsu	High school	1
33	Victoria	F	32	Canada	Master's degree	6
34	Anthony	M	33	Jiangsu	Master's degree	2
35	Samantha	F	36	Shandong	Bachelor's degree	6
36	Lily	F	19	Yunnan	High school	7

Recruitment Methods

Participants for this study were recruited using purposive sampling techniques, specifically targeting individuals who had prior purchasing experience on the Douyin platform. Recruitment was conducted through the following steps:

Firstly, invitations were distributed via popular Chinese social media platforms, including WeChat, QQ, Xiaohongshu. Posts outlined the purpose of the study and the inclusion criteria, which required participants to be active users of Douyin and have made at least one purchase through the platform. Secondly, all the respondents expressing interest in the study were asked when and what they last bought on the Douyin e-commerce platform to ensure they met the criteria for participation. And whether they have their own ideas about Douyin online shopping that they want to express and communicate. Thirdly, screening the participants, all the eligible participants must have made at least one purchase on Douyin within the past 12 months. They needed to be fluent in Mandarin Chinese, as interviews were conducted in Mandarin Chinese. Lastly, eligible participants were contacted via WeChat phone call to schedule their interviews. Each participant was informed about the study's purpose, procedures, and objectives, along with assurances regarding the confidentiality of their data. Verbal consent was obtained to record the audio of the interview. Additionally, participants were notified that they would receive 50 *yuan* as compensation for their time upon completion of the interview.

Transcription

After conducting the interviews, all recordings were transcribed verbatim in Mandarin Chinese. The transcription process aimed to capture not only the spoken words but also their emotional inflections to preserve the context of participants' responses. Transcriptions were carefully reviewed by the research team to ensure accuracy.

Coding procedures

All translated interview transcripts were cross-checked twice against the audio recordings to ensure accuracy and to prevent any omissions or errors in the transcription

and translation process. Following this, the text was pre-processed, including formatting adjustments and removing irrelevant content for optimal analysis. The data were then imported into NVivo 12 software for coding. A line-by-line coding process was employed, with the text content assigned to relevant coding categories according to predefined coding rules. Since a deductive approach was used, several broad categories based on the EVT and S-O-R model were established at the outset.

Throughout the analysis, we refined the categories by splitting those with differences, merging similar ones, and identifying key phenomena and issues reflected in the study. The results were then compared and aligned with the theoretical framework, and category creation continued until no new concepts could be further subdivided. After the coding process was complete, we re-examined the categories, splitting or merging them again where necessary by comparing them with the data source to ensure the reliability and validity of the findings.

First of all, drawing from the pre-established theoretical framework of EVT, we developed two dimensions: expectancy and value. Then, within the S-O-R model, we focused specifically on the “Organism” (O) aspect. In the context of this study, the S-O-R model posits that consumers exhibit physiological and psychological reactions in response to the stimulation of AI-PPRs. In other words, whether consumers’ final purchasing behavior is driven by AI-PPR stimulation largely depends on the physiological and psychological judgments formed in the “Organism” component. One key objective of employing qualitative research in this study was to better understand the process and mechanism behind these physiological and psychological factors.

We identified 5 initial categories to form the basic framework for our analysis. These categories were constructed based on a thorough understanding of relevant theories and a well-defined research direction. After analyzing the collected text data, we conducted an initial classification according to the 5 categories, which were then subdivided into 16 secondary categories. For each text fragment, we carefully evaluated its content and classified it into the most appropriate category.

Building on the 16 secondary categories, we conducted further reviews and comparisons of the specific content within each category, gradually uncovering differences among them. This led to the creation of 67 third-level classifications. For content with similar characteristics and themes, we integrated it into existing secondary subcategories once again, allowing us to better represent the richness and complexity of the text data.

Throughout the analysis, we continuously reflected and adjusted, carefully reviewing each classification and merging decisions to ensure logical consistency and rationale.

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Instructor Name	Prof. Michelina Venditti	Expected Presentation Date	2026-04-01

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b) **Digital Pay-Per-Uses of Academic Course Content and Materials (e-coursepacks, electronic reserves, learning management systems, academic institution intranets).** For uses in e-coursepacks, posts in electronic reserves, posts in learning management systems, or posts on academic institution intranets, the following additional terms apply:

i) The pay-per-uses subject to this Section 14(b) include:

A) **Posting e-reserves, course management systems, e-coursepacks for text-based content**, which grants authorizations to import requested material in electronic format, and allows electronic access to this material to members of a designated college or university class, under the direction of an instructor designated by the college or university, accessible only under appropriate electronic controls (e.g., password);

B) **Posting e-reserves, course management systems, e-coursepacks for material consisting of photographs or other still images not embedded in text**, which grants not only the authorizations described in Section 14(b)(i)(A) above, but also the following authorization: to include the requested material in course materials for use consistent with Section 14(b)(i)(A) above, including any necessary resizing, reformatting or modification of the resolution of such requested material (provided that such modification does not alter the underlying editorial content or meaning of the requested material, and provided that the resulting modified content is used solely within the scope of, and in a manner consistent with, the particular authorization described in the Order Confirmation and the Terms), but not including any other form of manipulation, alteration or editing of the requested material;

C) **Posting e-reserves, course management systems, e-coursepacks or other academic distribution for audiovisual content**, which grants not only the authorizations described in Section 14(b)(i)(A) above, but also the following authorizations: (i) to include the requested material in course materials for use consistent with Section 14(b)(i)(A) above; (ii) to display and perform the requested material to such members of such class in the physical classroom or remotely by means of streaming media or other video formats; and (iii) to "clip" or reformat the requested material for purposes of time or content management or ease of delivery, provided that such "clipping" or reformatting does not alter the underlying editorial content or meaning of the requested material and that the resulting material is used solely within the scope of, and in a manner consistent with, the particular authorization described in the Order Confirmation and the Terms. Unless expressly set forth in the relevant Order Confirmation, the License does not authorize any other form of manipulation, alteration or editing of the requested material.

ii) Unless expressly set forth in the relevant Order Confirmation, no License granted shall in any way: (i) include any right by User to create a substantively non-identical copy of the Work or to edit or in any other way modify the Work (except by means of deleting material immediately preceding or following the entire portion of the Work copied or, in the case of Works subject to Sections 14(b)(1)(B) or (C) above, as described in such Sections) (ii) permit "publishing ventures" where any particular course materials would be systematically marketed at multiple institutions.

iii) Subject to any further limitations determined in the Rightsholder Terms (and notwithstanding any apparent contradiction in the Order Confirmation arising from data provided by User), any use authorized under the electronic course content pay-per-use service is limited as follows:

A) any License granted shall apply to only one class (bearing a unique identifier as assigned by the institution, and thereby including all sections or other subparts of the class) at one institution;

B) use is limited to not more than 25% of the text of a book or of the items in a published collection of essays, poems or articles;

C) use is limited to not more than the greater of (a) 25% of the text of an issue of a journal or other periodical or (b) two articles from such an issue;

D) no User may sell or distribute any particular materials, whether photocopied or electronic, at more than one institution of learning;

E) electronic access to material which is the subject of an electronic-use permission must be limited by means of electronic password, student identification or other control permitting access solely to students and instructors in the class;

F) User must ensure (through use of an electronic cover page or other appropriate means) that any person, upon gaining electronic access to the material, which is the subject of a permission, shall see:

- a proper copyright notice, identifying the Rightsholder in whose name CCC has granted permission,

- o a statement to the effect that such copy was made pursuant to permission,
- o a statement identifying the class to which the material applies and notifying the reader that the material has been made available electronically solely for use in the class, and
- o a statement to the effect that the material may not be further distributed to any person outside the class, whether by copying or by transmission and whether electronically or in paper form, and User must also ensure that such cover page or other means will print out in the event that the person accessing the material chooses to print out the material or any part thereof.

G) any permission granted shall expire at the end of the class and, absent some other form of authorization, User is thereupon required to delete the applicable material from any electronic storage or to block electronic access to the applicable material.

iv) Uses of separate portions of a Work, even if they are to be included in the same course material or the same university or college class, require separate permissions under the electronic course content pay-per-use Service. Unless otherwise provided in the Order Confirmation, any grant of rights to User is limited to use completed no later than the end of the academic term (or analogous period) as to which any particular permission is granted.

v) Books and Records; Right to Audit. As to each permission granted under the electronic course content Service, User shall maintain for at least four full calendar years books and records sufficient for CCC to determine the numbers of copies made by User under such permission. CCC and any representatives it may designate shall have the right to audit such books and records at any time during User's ordinary business hours, upon two days' prior notice. If any such audit shall determine that User shall have underpaid for, or underreported, any electronic copies used by three percent (3%) or more, then User shall bear all the costs of any such audit; otherwise, CCC shall bear the costs of any such audit. Any amount determined by such audit to have been underpaid by User shall immediately be paid to CCC by User, together with interest thereon at the rate of 10% per annum from the date such amount was originally due. The provisions of this paragraph shall survive the termination of this license for any reason.

c) ***Pay-Per-Use Permissions for Certain Reproductions (Academic photocopies for library reserves and interlibrary loan reporting) (Non-academic internal/external business uses and commercial document delivery).*** The License expressly excludes the uses listed in Section (c)(i)-(v) below (which must be subject to separate license from the applicable Rightsholder) for: academic photocopies for library reserves and interlibrary loan reporting; and non-academic internal/external business uses and commercial document delivery.

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- iii) reproduction of an entire Work (cover-to-cover copying) except where the Work is a single article;
- iv) reproduction for resale to anyone other than a specific customer of User;
- v) republication in any different form. Please obtain authorizations for these uses through other CCC services or directly from the rightsholder.

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d) ***Electronic Reproductions in Online Environments (Non-Academic-email, intranet, internet and extranet).*** For "electronic reproductions", which generally includes e-mail use (including instant messaging or other electronic transmission to a defined group of recipients) or posting on an intranet, extranet or Intranet site (including any display or performance incidental thereto), the following additional terms apply:

- i) Unless otherwise set forth in the Order Confirmation, the License is limited to use completed within 30 days for any use on the Internet, 60 days for any use on an intranet or extranet and one year for any other use, all as measured from the "republishing date" as identified in the Order Confirmation, if any, and otherwise from the date of the Order Confirmation.
- ii) User may not make or permit any alterations to the Work, unless expressly set forth in the Order Confirmation (after request by User and approval by Rightsholder); provided, however, that a Work consisting of photographs or other still images not embedded in text may, if necessary, be resized, reformatted or have its resolution modified without additional express permission, and a Work consisting of audiovisual content may, if necessary, be "clipped" or reformatted for purposes of time or content management or ease of delivery (provided that any such resizing, reformatting, resolution modification or "clipping" does not alter the underlying editorial content or

meaning of the Work used, and that the resulting material is used solely within the scope of, and in a manner consistent with, the particular License described in the Order Confirmation and the Terms.

15) Miscellaneous.

a) User acknowledges that CCC may, from time to time, make changes or additions to the Service or to the Terms, and that Rightsholder may make changes or additions to the Rightsholder Terms. Such updated Terms will replace the prior terms and conditions in the order workflow and shall be effective as to any subsequent Licenses but shall not apply to Licenses already granted and paid for under a prior set of terms.

b) Use of User-related information collected through the Service is governed by CCC's privacy policy, available online at www.copyright.com/about/privacy-policy/.

c) The License is personal to User. Therefore, User may not assign or transfer to any other person (whether a natural person or an organization of any kind) the License or any rights granted thereunder; provided, however, that, where applicable, User may assign such License in its entirety on written notice to CCC in the event of a transfer of all or substantially all of User's rights in any new material which includes the Work(s) licensed under this Service.

d) No amendment or waiver of any Terms is binding unless set forth in writing and signed by the appropriate parties, including, where applicable, the Rightsholder. The Rightsholder and CCC hereby object to any terms contained in any writing prepared by or on behalf of the User or its principals, employees, agents or affiliates and purporting to govern or otherwise relate to the License described in the Order Confirmation, which terms are in any way inconsistent with any Terms set forth in the Order Confirmation, and/or in CCC's standard operating procedures, whether such writing is prepared prior to, simultaneously with or subsequent to the Order Confirmation, and whether such writing appears on a copy of the Order Confirmation or in a separate instrument.

e) The License described in the Order Confirmation shall be governed by and construed under the law of the State of New York, USA, without regard to the principles thereof of conflicts of law. Any case, controversy, suit, action, or proceeding arising out of, in connection with, or related to such License shall be brought, at CCC's sole discretion, in any federal or state court located in the County of New York, State of New York, USA, or in any federal or state court whose geographical jurisdiction covers the location of the Rightsholder set forth in the Order Confirmation. The parties expressly submit to the personal jurisdiction and venue of each such federal or state court.

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