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PECULIARITIES OF MODELING THE IRRATIONAL BEHAVIOR OF CONSUMERS IN COMMODITY MARKETS

The paper systematizes determinants of irrational consumer decisions in commodity markets and proposes an operational coefficient of propensity to irrational behavior that integrates personality traits (emotional instability, introversion, conformity) with situational drivers (limited time and low awareness). We outline a hybrid measurement procedure combining surveys, digital analytics and neuromarketing signals, and show how the coefficient can be embedded into demand and marketing-response models for e-commerce.

Keywords: *consumer irrationality, commodity markets, cognitive biases, digital nudging, personality traits, neuromarketing.*

Introduction

Commodity markets increasingly operate under digital choice architectures where time pressure, information overload and social signals (ratings, recommendations, influencer content) shape purchasing decisions. In such environments, deviations from utility-maximization are systematic rather than random and may even improve short-run outcomes for firms through impulse demand and herding effects.

Recent marketing evidence consolidates how affect and self-control mechanisms drive impulse purchases across contexts (Iyer et al., 2020). Digital interfaces can further amplify these mechanisms through nudges and recommender systems (Weinmann et al., 2016; Jesse & Jannach, 2020), while social influence effects are especially salient in online environments (Bhukya & Paul, 2023).

For industrial firms and e-commerce platforms, the ability to quantify a consumer's propensity to irrational behavior is essential for demand forecasting, segmentation, and the design of ethically acceptable marketing interventions.

Although commodity markets are often associated with standardized products and relatively transparent pricing, real-world demand is shaped by information frictions, perceived quality signals, and situational constraints. Even when products are technically comparable, consumers face a cognitive task of translating dispersed signals (brand cues, reviews, delivery conditions, and promotional framing) into a purchase decision. Under uncertainty, this translation frequently relies on simplifications such as salience, anchoring, and social proof, which makes the same market conditions compatible with

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both rational and heuristic-driven choices. These effects become stronger in online settings, where the consumer's choice set is dynamically curated and where perceived scarcity, ratings, and time-limited offers can accelerate decisions and increase impulsive demand (Dabrowska et al., 2021).

From an industry perspective, quantifying these behavioral mechanisms is important not only for forecasting sales but also for reducing costly inefficiencies such as excessive returns, post-purchase regret, and churn. In high-competition e-commerce niches, small improvements in matching offers to behavioral segments can translate into measurable gains in conversion and customer satisfaction. Therefore, a model that connects psychological traits with external decision conditions provides an actionable bridge between behavioral economics and marketing practice.

Analysis of recent research and publications

Prospect theory and subsequent work on heuristics and biases explain why consumers systematically depart from expected-utility models, especially under risk and uncertainty (Kahneman & Tversky, 1979; Kahneman & Frederick, 2002).

Digital environments add new drivers: platform design can steer choices without changing prices or restricting options. The concept of digital nudging formalizes this phenomenon and highlights its managerial and ethical implications (Weinmann et al., 2016). Recommender systems represent a scalable nudge mechanism; a survey by Jesse and Jannach (2020) outlines typical nudging patterns and open research problems.

Empirical studies show that interface-related stimuli and app experience shape online purchase intentions and may strengthen non-deliberative responses (Chopdar & Balakrishnan, 2020). During the COVID-19 period, structural shifts toward e-commerce further increased the importance of digital touchpoints and changed consumer routines (Dabrowska et al., 2021).

A convenient way to interpret platform-driven irrationality is through the stimulus-organism-response (S-O-R) logic. Digital stimuli (interface design, recommendation ranking, ratings, and promotional cues) affect internal states such as arousal, perceived risk, and trust, which then shape observable responses including product choice and purchase timing. Empirical evidence from mobile commerce indicates that app-related cues and service experience can influence purchase intention through mediated psychological states (Chopdar & Balakrishnan, 2020). In this sense, the classical 'black box' of the consumer is not a passive container: it is continuously shaped by micro-interventions embedded in the digital environment.

The literature on digital nudging with recommender systems further highlights that algorithms can steer attention and preferences without changing prices, by altering defaults, salience, and informational context. Such nudges may be welfare-improving when they reduce search costs, but they can also amplify imitation and impulsivity, especially for consumers with higher vulnerability to social influence or time pressure (Jesse & Jannach, 2020). This observation motivates the need for a formal parameter capturing individual propensity toward heuristic decision-making, which can then be incorporated into demand modeling and marketing optimization.

Algorithmic feedback loops are a specific modern channel through which irrationality can be amplified. Recommendation systems learn from clicks and purchases, but these signals are themselves influenced by salience, defaults, and social proof. Over time, such systems can create reinforcing loops in which early random advantages become persistent popularity, thereby strengthening herding effects and reducing diversity of exposure. For consumers with hig K_i^Q the combination of time pressure and algorithmic curation may effectively substitute deliberation with platform-driven heuristics. This implies that the coefficient can be used to study not only individual choice, but also the dynamics of preference formation in digital environments (Jesse & Jannach, 2020).

Social influence remains a core mechanism of irrationality, from informational cascades to conformity-driven consumption. A recent hybrid systematic review synthesizes how social influence operates across consumer decision stages and identifies measurement challenges (Bhukya & Paul, 2023). In live-streaming commerce, time pressure and social presence can intensify impulse buying by compressing deliberation windows (Liu et al., 2023).

Behavioral heterogeneity also interacts with equilibrium outcomes in markets where consumer choices are strategically interdependent. When consumers observe others' actions (ratings, purchase counters, popularity signals), imitation can generate multiple self-reinforcing market states,

including informational cascades and lock-in effects. In such settings, equilibrium concepts from game theory clarify how non-standard preferences and partial information affect stability and welfare. For example, Berge-type equilibria capture situations in which agents may sacrifice individual payoff to support others, while refinements describe existence and computation in realistic environments (Courtois et al., 2017). Within reflexive approaches, consumer imitation and reflexive control can be interpreted as mechanisms that shift equilibrium selection under uncertainty. Therefore, incorporating K_i^Q into demand models is not merely a behavioral add-on: it is a way to parameterize equilibrium-relevant deviations that shape aggregate market dynamics and strategic outcomes for firms (Mazhara & Kapustyan, 2019).

At the individual level, personality traits such as emotional instability (neuroticism) moderate online trust formation and repeated buying, indicating stable heterogeneity in susceptibility to persuasive cues (Lim et al., 2021). Neuromarketing and consumer neuroscience provide complementary measurement tools, linking attention and affect to marketing stimuli at a physiological level (Plassmann et al., 2015; Wei & Zhang, 2022).

In the Ukrainian research tradition, reflexive approaches emphasize imitation, herd behavior and reflexive control in marketing activities (Shumilo, 2017; Shumilo, 2022). Game-theoretic refinements such as Berge equilibrium illustrate that non-selfish (seemingly irrational) behavior may be consistent within alternative optimality concepts (Courtois et al., 2017).

Purpose of the article

The purpose of the paper is to substantiate a theoretical framework for measuring consumers' propensity to irrational behavior in commodity markets by integrating psychological and situational factors into a single normalized coefficient, and to outline directions for its empirical calibration and further development.

Research results

We distinguish two factor groups that provoke irrational purchase decisions: 1) external factors—limited decision time and low awareness/experience; 2) individual factors—emotional instability, introversion and conformity. Then, from the selected factors, it is possible to form a general coefficient of propensity for irrational behavior $K_i^Q \in [0;1]$, where: en_i^Q — level of emotional instability of consumer i; in_i^Q — level of introversion of consumer i; kn_i^Q — level of conformity of consumer i; d_i^Q — level of awareness/experience of consumer i; v_i^Q — assessment by consumer i of the time allotted for decision-making.

The obtained numerical values of the listed factors are normalized into parameters, including individual characteristics of the consumer en_i^Q, $in_i^Q, kn_i^Q \in [0;1]$, which is equivalent to each other in terms of weight in terms of influence on manifestations of imitation in consumer behavior; external factors, which are also comparable to each other and relate to the assessment of the probability of a reward prediction error (risk) $d_i^Q, v_i^Q \in [0;1]$.

The parameters, which consist of the individual characteristics of the consumer and external factors, form the general coefficient of imitation of the consumer $K_i^Q \in [0;1]$, which is calculated according to the following formula (1):

$$K_i^Q = 0,5\left(\frac{1}{3}en_i^Q + \frac{1}{3}in_i^Q + \frac{1}{3}kn_i^Q\right) + 0,5\left(\frac{1}{2}d_i^Q + \frac{1}{2}v_i^Q\right)$$

The first term captures personality-based vulnerability to imitation and impulsivity, while the second term captures context-induced cognitive load and reward-prediction error risk. Equal weights within each group are used as a transparent baseline; in applied settings they can be calibrated using historical conversion data or experimental designs.

(a) Survey module: a representative sample of potential buyers completes a structured questionnaire; psychometric tools such as the 16PF (Cattell et al., 1970) can be mapped to. (b) Digital analytics module: behavior traces (session duration, bounce, search queries, ad reactions, cart abandonment) proxy time pressure and awareness, supporting and estimation. (c) Neuromarketing module: eye-tracking and EEG/fMRI signals can validate attention and affect and help de-bias self-reports (Plassmann et al., 2015; Bazzani et al., 2020).

In practice, the five inputs of the propensity coefficient can be obtained via a hybrid measurement strategy. The personality-related components (emotional instability, introversion, conformity) can be proxied using psychometric instruments (e.g., 16PF-based scales) and then mapped to [0; 1] by min-max normalization within the target sample. External components can be measured both subjectively and

behaviorally: awareness/experience can be approximated by self-reported category familiarity and by digital traces (prior page views, repeat visits, search depth), while perceived time pressure can be measured by a short questionnaire item and validated against session-level indicators such as dwell time and checkout latency. Using both subjective and behavioral proxies reduces common-method bias and increases robustness to measurement error.

To support extrapolation from the surveyed group to the relevant market population, the sample should be stratified by key observable characteristics (age, gender, region, and purchase purpose) and aligned with available platform analytics. When only a limited survey budget is feasible, a two-stage design may be used: a small psychometric subsample to calibrate the mapping from questionnaire scales to normalized factors, followed by a larger behavioral sample where external factors are inferred from digital signals. Reliability checks (internal consistency of scales and stability of normalized scores across subgroups) help ensure that the coefficient reflects stable tendencies rather than noise.

While psychometric surveys and digital analytics provide scalable inputs, neuromarketing tools can serve as an objective benchmark for validating time pressure, emotional arousal, and attentional patterns. For instance, EEG-based protocols can detect changes in cognitive load and affective reactions to marketing stimuli, helping to refine the mapping from observed behavior to normalized parameters (Bazzani et al., 2020). However, because neuromarketing studies are costly and logistically demanding, a pragmatic approach is to use them selectively: small laboratory samples may be employed to calibrate the effect sizes of specific nudges or interface elements, and the calibrated relationships can then be transferred to larger digital datasets. This triangulation improves construct validity without requiring continuous neuromarketing measurement.

The coefficient can be used as a multiplicative or mixture parameter in purchase probability models. For example, for product A, the expected conversion among a population with share Q of irrational-prone consumers can be estimated by weighting rational and irrational choice rules, where K_i^Q shifts sensitivity to social proof, scarcity messages and recommendation exposure.

A simple way to integrate the propensity coefficient into a purchase model is to interpret it as a mixture weight between a rational component and a heuristic component.

The operational coefficient is valuable only if it improves predictive or explanatory performance. Therefore, firms can validate the approach using out-of-sample prediction (e.g., comparing log-loss or AUC with and without K_i^Q), as well as field experiments. In A/B tests, segments with higher predicted K_i^Q should exhibit stronger sensitivity to nudges such as limited-time offers, social proof badges, or simplified choice sets. Such validation not only supports the model empirically, but also helps identify which marketing interventions are likely to be effective without increasing customer dissatisfaction.

The baseline specification assigns equal weights within the personality block and within the external block. In applied settings, firms may adjust these weights based on empirical evidence or domain knowledge. One option is to estimate weights by regressing observed impulsive or imitative actions on the normalized factors and then rescaling coefficients to sum to one within each block. Another option is to use factor analysis or Bayesian updating to reflect uncertainty about the contribution of each component. Importantly, reporting a sensitivity analysis (e.g., how segment membership or predicted purchase probability changes under alternative weight sets) strengthens the credibility of the model and helps avoid overfitting to a specific sample.

A central methodological challenge is that behavioral indicators used to proxy awareness or time pressure may be endogenous: consumers who are already inclined to buy may spend less time searching, and highly engaged users may appear 'more aware' because of intention rather than experience. To mitigate this risk, the measurement pipeline can incorporate pre-treatment indicators (historical behavior before exposure to a campaign), use panel data to separate stable traits from situational shocks, and validate propensity estimates against independent survey items. Where feasible, instrumental strategies (e.g., exogenous variation in delivery time, interface layout, or promotion timing) can help identify causal effects of external factors.

Firms can (i) segment users by predicted K_i^Q and adapt communication intensity; (ii) test time-limited offers with explicit ethical constraints for high-K segments; (iii) monitor how platform changes (recommendations, ranking, social proof)

affect K_i^Q-driven demand dynamics, especially in e-commerce and marketplaces (Jesse & Jannach, 2020; Weinmann et al., 2016).

Although the discussion often emphasizes household consumers, similar mechanisms operate in industrial procurement, where buyers face complex specifications, tight deadlines, and reputational risk. Procurement committees may rely on simplified vendor reputations, peer benchmarking, and conformity to industry standards, especially when evaluation is costly or information is incomplete. In these environments, 'irrationality' often appears as risk-avoidant imitation and preference for familiar suppliers rather than strict cost minimization. Extending the measurement pipeline to organizational buyers may involve surveying decision teams and combining responses with tender and purchasing histories. This extension strengthens the practical relevance of the framework for industrial markets and enterprise marketing.

Because the proposed framework can be used to design influence strategies, it is important to distinguish between supportive nudges and manipulative practices. A responsible application should aim to reduce decision friction, increase transparency of product information, and avoid exploiting vulnerable segments. From a compliance perspective, firms should ensure lawful data collection, informed consent for psychometric surveys, and privacy-preserving processing of behavioral traces. In addition, monitoring fairness outcomes is advisable, since segmentation by behavioral vulnerability may unintentionally target specific demographic groups more intensively.

Understanding irrationality is also relevant for consumer protection and market regulation. Platforms increasingly face scrutiny regarding 'dark patterns' and manipulative choice architectures. A quantitative propensity framework can be used not only to increase conversion, but also to design safer environments: for segments with high K_i^Q, firms may provide clearer information, cooling-off prompts, or default settings that reduce regret and returns. Such an approach aligns commercial objectives with consumer welfare, potentially improving long-term trust and reducing reputational risk in industrial and digital markets.

Consider an online retailer introducing product A in a competitive category. Using a short survey and early-session analytics, the firm estimates K_i^Q distributions across visitors. For a high-propensity segment, the retailer emphasizes simplified bundles, highlights verified reviews, and reduces the number of competing options shown on the first screen. For a low-propensity segment, the retailer provides detailed comparison tables and transparent delivery-cost decomposition. In a controlled A/B test, the model predicts that the high-propensity segment will respond more to salience and social proof, while the low-propensity segment will respond more to attribute-based information. This segmented design illustrates how the coefficient can guide both experimentation and personalization strategies.

Future work may extend the framework in three main ways. First, K_i^Q can be modeled dynamically, allowing propensity to evolve with learning, repeated purchases, and changing market conditions. Second, social influence can be embedded explicitly via network effects and contagion processes, which are especially relevant for platform markets and influencer-driven demand. Third, cross-market and cross-cultural validation would clarify the stability of factor weights and the generalizability of psychometric mappings. These extensions would strengthen both theoretical grounding and practical applicability of the model for industrial and digital markets.

Conclusions

Modeling irrational consumer behavior belongs to the class of complex socio-economic modeling problems because preferences and decision rules may change both deterministically and chaotically under marketing stimuli and social interaction.

The paper proposes to treat irrationality as a measurable propensity shaped by two interacting factor groups: external (time deficit, low awareness/experience) and individual (emotional instability, introversion, conformity).

The main scientific contribution is the formulation of an operational coefficient K_i^Q in [0;1] that aggregates these factors in a transparent, group-balanced structure and can be directly embedded into applied demand and marketing-response models.

The methodological contribution is the proposed hybrid measurement pipeline that combines 1) psychometric survey data; 2) digital analytics of consumer behavior; 3) neuromarketing signals for validation and reduction of respondent bias.

For practitioners, the results provide an actionable way to a) quantify the share and intensity of

irrational-prone demand; b) design and evaluate marketing interventions (scarcity, social proof, recommendations) with controlled risk; c) improve customer satisfaction by aligning communication with the actual decision-making mode of the target segments.

Addressed recommendations: industrial producers and e-commerce retailers should integrate K_i^Q — based segmentation into CRM and advertising systems; market analysts should incorporate K_i^Q as a latent variable when forecasting demand shocks; and policymakers should consider transparency requirements for digital nudges to mitigate manipulative practices for vulnerable segments.

Scientific novelty is expressed in the integrated operationalization of personality-driven and context-driven determinants of irrationality within one coefficient and in the explicit linkage of that coefficient to measurable digital traces and neuromarketing indicators.

Limitations include the baseline equal-weight assumption, the cost of neuromarketing tools, and potential cultural specificity of psychometric mappings. Further research should 1) calibrate weights using longitudinal transaction data; 2) test the model across product categories and regions; 3) extend the framework to dynamic settings where K_i^Q evolves under learning and repeated exposure.

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ОСОБЛИВОСТІ МОДЕЛЮВАННЯ ІРРАЦІОНАЛЬНОЇ ПОВЕДІНКИ СПОЖИВАЧІВ НА ТОВАРНИХ РИНКАХ

У статті досліджено особливості моделювання ірраціональної поведінки споживачів на товарних ринках у контексті цифровізації та посилення ролі рекомендаційних алгоритмів, соціальних мереж і механізмів «цифрового підштовхування». Визначено, що відхилення від раціональності не зводяться до помилок: вони можуть генерувати як індивідуальні виграші, так і системні ефекти (зростання попиту, хвильові продажі, нестійкість очікувань). Уточнено, що ключовими тригерами ірраціональних рішень є поєднання зовнішніх умов (дефіцит часу, низька поінформованість/досвід) та індивідуальних властивостей (емоційна нестійкість, інтроверсія, конформність), які посилюють евристичні судження, наслідування та імпульсивність. Запропоновано узагальнювальний коефіцієнт схильності споживача до ірраціональної поведінки, нормований у межах [0;1], що агрегує зазначені фактори з рівними вагами в межах двох груп: особистісної та ситуаційної. Обґрунтовано практичний спосіб оцінювання складових коефіцієнта через такі комплементарні канали даних: 1) опитування цільової аудиторії (зокрема психометричні шкали на кшталт 16PF); 2) цифрова аналітика (пошукові запити, поведінка на сайті, реакції на рекламу, соціальні сигнали); 3) нейромаркетингові інструменти (eye-tracking, EEG тощо) для валідації емоційної реакції та уваги. Такий підхід зменшує суб'єктивність самооцінок, дозволяє сегментувати попит за рівнем схильності до ірраціональних рішень і формувати більш точні маркетингові сценарії. Практичне значення результатів полягає в можливості інтегрувати коефіцієнт у моделі ймовірності купівлі, оцінювати ефект дефіциту часу та інформаційного перевантаження, налаштовувати рекомендаційні механізми й комунікації для різних сегментів споживачів. Перспективи подальших досліджень пов'язані з емпіричною перевіркою параметрів на великих масивах даних, побудовою динамічних моделей адаптації уподобань, а також оцінюванням соціальних наслідків застосування інструментів впливу на ірраціональну поведінку.

Ключові слова: ірраціональна поведінка, товарні ринки, когнітивні упередження, цифрове підштовхування, риси особистості, нейромаркетинг.