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Review

Fuzzy Valence–Arousal Framework for Adaptive Cognitive Biases in Logistics Decision-Making

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Abstract

Background: Cognitive biases play a significant role in logistics decision-making, particularly in situations characterised by uncertainty, time pressure, and incomplete information. Previous research has examined the occurrence and consequences of individual biases, whilst the potential role of emotional states in their activation has received less attention. *Methods*: This research synthesises studies from the fields of psychology, behavioural science and logistics management to develop a theoretical framework based on the valence–arousal model of affect. The framework organises four selected cognitive biases along the dimensions of valence (from negative to positive) and arousal (from low to high). *Results*: It describes how patterns of bias activation may vary within a given decision-making context, depending on different combinations of these dimensions. A hypothetical logistics scenario illustrates the proposed fuzzy rules for bias activation, and a compromise derived from independently specified operational preferences. *Conclusions*: The proposed associations between affective states and cognitive biases, as well as presumed differences amongst marketing and logistics decision-makers, require empirical validation. The framework contributes to behavioural logistics research by identifying relationships for future studies to examine. It may serve as a guide in the design of decision-support tools and managerial practices that help to identify situations in which cognitive biases may influence logistics decisions.

Keywords: cognitive bias; logistics decision-making; supply chain management; valence–arousal model; fuzzy set theory; adaptive decision-making; decision support

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1. Introduction

Logistics plays a key role in the operation of industrial and service systems by coordinating the flow of materials, information, and resources within increasingly complex supply networks. Strategic, tactical, and operational logistics decisions are often made in uncertain environments, with incomplete information, and under significant time pressure. These circumstances rely heavily on intuitive judgment and heuristic thinking, which increases the likelihood of cognitive biases.

Cognitive biases are systematic deviations from rational judgment and decision-making that stem from the way individuals perceive, process, and interpret information [1,2]. In the fields of logistics and supply chain management, cognitive biases can contribute to forecasting errors, inventory distortions, misjudgments of risk, capacity planning problems, and suboptimal resource allocation [3]. Previous research has shown

that the occurrence and intensity of these biases are influenced not only by individual experiences, memory, and knowledge but also by the organisational and environmental context in which decisions are made [4]. Consequently, the occurrence and intensity of these same biases vary significantly across companies, organisational cultures, and decision-making situations.

Traditional research in the field of logistics has generally treated cognitive biases as factors that impair decision quality and reduce organisational performance. Accordingly, a significant portion of the literature focuses on identifying and measuring these biases and mitigating their negative effects. However, recent research in cognitive psychology and evolutionary decision theory has challenged the assumption that biases are exclusively irrational deviations. A growing body of evidence suggests that certain biases may also serve adaptive functions by facilitating rapid decision-making, reducing cognitive load, and supporting adaptation to uncertain and complex environments [5–7].

However, the logistics literature still lacks a comprehensive framework to explain why certain cognitive biases can have both beneficial and detrimental consequences, depending on the decision-making context. In particular, little attention has been paid to the emotional mechanisms that influence the activation of these biases. This represents a significant research gap, as emotions fundamentally shape attention, information processing, risk perception, and judgment—all of which are central elements of logistics decision-making.

The valence–arousal model [8–10] offers a promising approach to addressing this research gap. According to dimensional theories of emotion, affective experiences can be described along two fundamental dimensions: valence and arousal. Valence refers to the positive or negative nature of an emotion, while arousal denotes the degree of emotional activation or intensity [8,9]. These two dimensions are widely used in psychology and decision sciences to explain how emotional states influence cognitive processes and behaviour. However, the application of this approach to the study of cognitive biases arising in logistics decision-making has so far taken a back seat.

Furthermore, the relationships among emotional states, cognitive biases, and organisational expectations that arise during logistics decision-making are highly uncertain and subjective, making them difficult to describe with traditional, crisp categories [11]. Although fuzzy set theory [12] is widely used to address logistics and supply chain problems, its application to modelling the emotional background of cognitive biases has received little attention to date. At the same time, fuzzy representation is well-suited to mathematically describing the gradual transitions between valence–arousal states, as well as the uncertainty arising from differing perceptions among decision-makers. This makes it possible to interpret decision states not as discrete categories, but as ranges of acceptance that gradually transition into one another.

Therefore, the aim of this research is to develop a conceptual framework that interprets the cognitive biases arising during logistics decision-making using the valence–arousal approach and represents transitions between decision states using fuzzy sets. The proposed framework does not treat these biases solely as decision errors; it also examines how different emotional states may contribute to their adaptive activation. Fuzzy representation also allows for the modelling of the differing preferences of marketing and logistics decision-makers, as well as the acceptable decision zone that emerges between them, which forms the basis for strategic compromises. The study first reviews the characteristics of logistics decision-making and the most common cognitive biases, then presents the valence–arousal model and the role of fuzzy representation, and finally interprets the selected biases by integrating these two approaches. Finally, the study illustrates how hypothesised relationships between emotional valence, arousal, and the

four selected cognitive biases can be represented using fuzzy rules in a logistics decision-making context.

This study makes three main contributions. First, it links adaptive approaches to cognitive biases with research on logistics decision-making. Second, it introduces the valence–arousal model as a new interpretive framework for systematising cognitive biases that arise in the logistics context. Third, it uses fuzzy representation to place hypothesised associations between affective states and cognitive biases alongside independently specified operational preferences within a common conceptual framework. Their joint purpose is to make different aspects of decision-makers' evaluations transparent, without deriving operational preferences from the activation of emotional rules.

2. Theoretical Background

This study is based on a narrative, conceptual review of the literature on cognitive biases and affective processes. The literature review was conducted using Scopus, ScienceDirect, and Web of Science between March and October 2026, with search combinations including "cognitive biases" AND valence AND arousal AND "decision making", emotion AND ("confirmation bias" OR "optimism bias" OR "status quo bias" OR "loss aversion"), and ("fuzzy sets" OR "fuzzy logic") AND "decision making"; no predefined restriction based on publication year was applied. Sources were selected based on their relevance to the theoretical constructs, proposed relationships, and modelling approaches examined in the study. Table 1 presents the selected works that underpin the framework's psychological foundations, including research on specific biases, affective influences on judgment, and the description and measurement of affect. The related fuzzy methods and logistical applications are discussed separately in Section 2.4. The synthesis supports the development of the conceptual framework, and its conclusions are limited to the selected literature.

2.1. Cognitive Biases in Decision-Making

Cognitive biases are systematic deviations from the normative principles of rational judgment and decision-making that stem from the way individuals perceive, process, and interpret information [1]. Instead of engaging in exhaustive analysis in every situation, decision-makers often use mental shortcuts, known as heuristics, that simplify complex problems and enable rapid responses under uncertainty, information gaps, or time pressure [2].

Although these cognitive mechanisms often increase the efficiency of decision-making, they can also lead to predictable judgment errors and suboptimal decisions. Since the pioneering work of Kahneman and Tversky [13,14], cognitive biases have become a major area of research in psychology, economics, management, and operations research, revealing their impact on risk perception, forecasting, resource allocation, and strategic decision-making. Traditional approaches primarily viewed cognitive biases as sources of irrationality; however, more recent research suggests that certain biases may also serve an adaptive function in uncertain and dynamically changing environments. This shift in perspective is drawing increasing attention to the idea that cognitive biases should be examined not only as causes of decision-making errors, but also as mechanisms that support effective decision-making under real-world conditions.

2.2. Adaptive Perspectives on Cognitive Biases

The decision theory and psychological literature have traditionally interpreted cognitive biases as systematic errors in human information processing. According to this approach, biases represent deviations from the principles of normative rationality, as they

reduce the accuracy of judgment and the optimality of decisions. Over the past two decades, however, an alternative interpretive framework has emerged, according to which many cognitive biases are not simply the result of faulty functioning but rather evolved mechanisms that can confer an adaptive advantage under certain environmental conditions [2].

2.2.1. Ecological Rationality and the Adaptive Nature of Biases

According to the theory of ecological rationality, human decision-making mechanisms have adapted not to abstract logical norms, but to the statistical structure of the natural environment. Fawcett and colleagues [5] point out that many behaviours that appear irrational or biased under laboratory conditions may in fact be effective strategies in environments that are variable in time and space and highly uncertain.

According to the authors, the biases observed in human and animal decision-making often stem from simple heuristics that rely on past patterns in the environment to predict the future. Under such circumstances, perfect rationality does not necessarily imply optimal adaptation, as the costs of decision-making, information gaps, and time constraints often necessitate the use of rapid, approximate strategies.

The ecological rationality approach is particularly important for understanding why phenomena such as optimism, confirmation bias, or the overuse of pattern recognition have persisted from an evolutionary perspective. This is because these mechanisms often increase the chances of survival and adaptation, even if they lead to inaccurate conclusions in certain situations.

2.2.2. The Theory of Optimism and Error Management

One of the key explanations in evolutionary psychology for the development of cognitive biases is Error Management Theory, developed by Haselton and Nettle [6]. The theory's basic premise is that, when making decisions in an uncertain environment, different types of errors do not carry the same cost. If one type of error causes significantly greater losses than another, evolution may favour cognitive mechanisms that systematically bias perception and judgment toward the less costly error.

One of the best-known examples of this is the optimism bias. Excessive optimism can lead to an inaccurate perception of reality in certain situations, yet it also increases initiative, perseverance, and risk-taking. If the cost of failing to act on a potentially successful opportunity exceeds the cost of a failed attempt, then the optimism bias may be an adaptive strategy overall.

According to error management theory, many positive biases—such as optimistic expectations or overestimating one's own abilities—are the result of an evolutionary compromise that serves to manage uncertainty. The bias is therefore not a flaw in the system, but rather a functional characteristic of it.

2.2.3. The Social Functions of Confirmation Bias

Confirmation bias has traditionally been regarded as one of the most significant cognitive errors, as individuals tend to seek out and favour information that supports their preexisting views while ignoring evidence that contradicts them. Peters [7], however, argues that confirmation bias may have significant adaptive value in social contexts.

According to the author's "reality matching" model, confirmation bias does not merely result in a distorted representation of reality. Still, it can contribute to the social environment gradually adapting to an individual's beliefs and expectations. This mechanism is particularly evident in situations where beliefs concern other people or social relationships.

A positive self-image, for example, can promote self-confident behaviour, which elicits more favourable social feedback, thereby reinforcing the original belief. Similar mechanisms may also operate in leadership roles, in the context of group identities, or within organisational settings. Confirmation bias can thus, under certain circumstances, trigger self-fulfilling processes that result in more stable social relationships and more predictable interactions.

Peters' argument provides an important addition to evolutionary approaches, as it highlights that the adaptive value of distortions may stem not only from individual survival but also from their function within social systems.

2.2.4. An Integrated Evolutionary Interpretation

A common feature of these three approaches is that they interpret cognitive biases not as failures of rationality, but as functional adaptive mechanisms. Fawcett et al. [5] demonstrate, from an ecological rationality perspective, that biases result from adaptation to the statistical characteristics of the natural environment. Haselton and Nettle [6] offer an evolutionary explanation based on the varying costs of errors, while Peters [7] emphasises the social and self-organising functions of these biases.

From these perspectives, cognitive biases are not necessarily considered irrational. In many cases, they represent adaptive decision-making mechanisms that increase the likelihood of successful functioning for an individual or a group in uncertain, complex, and dynamically changing environments.

This perspective is particularly important in the study of logistics and supply chain decisions, where time pressure, information scarcity, and uncertainty are routinely present, and where biases can be interpreted not only as sources of error but also as potential adaptive mechanisms.

2.3. Comparative Overview of the Literature on Cognitive Biases and Valence–Arousal

Table 1 compares selected studies on cognitive biases, affective processes, and emotion measurement. The classification identifies each study's main focus, its treatment of cognitive and affective constructs, its methodological approach, and its relevance to the proposed framework.

Table 1. Summary of the references regarding cognitive biases and valence–arousal.

Author(s), (Year)	Research Area (Cognitive Biases)	Main Focus or Psychological Variables	Cognitive Biases or Heuristics	Affective Component (Valence, Arousal, Mood or Emotion)	Method and Relevance or Boundary
Anderson (2003) [15]	Decision avoidance	Status quo, deferral, omission and inaction; anticipated regret and emotion.	✓	✓	Integrative review; supports multiple cognitive and emotional mechanisms of avoidance.
Bradley & Lang (1994) [16]	Emotion measurement	Self-reported pleasure, arousal and dominance with the SAM instrument.	×	✓	Measurement comparison; possible route to operationalising affective inputs.
Buehler et al. (1994) [17]	Planning fallacy	Underestimation of task-completion times.	✓	×	Experimental research; relevant extension beyond the four selected biases.

Fischer et al. (2010) [18]	Confirmation bias	Decision mode, subjective confidence and confirmatory information processing.	✓	✓	Experiments; intuition is relevant, but a complete valence–arousal map is not tested.
Forgas (1995) [19]	Mood and judgement	Affect infusion under different information-processing strategies.	✓	✓	Theoretical review; explains context dependence in affective judgements.
Finucane et al. (2000) [20]	Affect heuristic	Affective evaluation in judgements of risk and benefit.	✓	✓	Experimental research; supports affective judgement, not the proposed four-rule map.
Hart et al. (2009) [21]	Confirmation bias	Selective exposure; defence and accuracy motives.	✓	✓	Meta-analysis; supports selective exposure, not a positive/low-arousal allocation.
Lerner et al. (2015) [22,23]	Emotion and decisions	Discrete emotions, appraisals and decision consequences.	✓	✓	Integrative review; explains why valence and arousal alone may be insufficient.
Lench & Ditto (2008) [23]	Optimism bias	Positive and negative events, base rates and automatic affective reactions.	✓	✓	Experiments; supports an affective route to optimism, not an exclusive quadrant.
Li et al. (2025) [24]	Overconfi-dence	Overestimation, overplacement and overprecision across tasks and time.	✓	×	Empirical studies; cautions against assuming uniform, stable bias tendencies.
Mandel et al. (2022) [25]	Bias blind spot	Self–other assessments of susceptibility to biases.	✓	×	Experiments; metacognitive and measurement context, not affect-quadrant evidence.
Rolls (2007) [26]	Affective neuroscience	Emotion, reward and punishment systems.	×	✓	Scholarly book; neurocognitive background rather than a logistics model.
Rozin et al. (2026) [27]	Sustainability beliefs	Perceived naturalness–sustainability causation and possible valence matching.	✓	✓	Survey studies; affective interpretation is proposed, not a four-bias test.
Russell (1980) [8]	Affect structure	Pleasure–displeasure and arousal as dimensions of affect.	×	✓	Circumplex model with affect-scaling evidence; coordinate-system foundation.
Russell (2003) [9]	Core affect	Valence, arousal and the construction of emotional experience.	×	✓	Theoretical synthesis; affective description does not uniquely identify a bias.
Samuelson & Zeckhauser (1988) [28]	Status quo bias	Preference for existing alternatives and resistance to change.	✓	×	Experiments and field-choice evidence; does not establish a negative/low-arousal rule.
Skagerlund et al. (2020) [29]	Affect and risk	Affect heuristic, risk perception and elicitation methods.	✓	✓	Empirical comparison; informs assessment and measurement choices.
Slovic et al. (2002) [30]	Affect heuristic	Affective impressions as inputs to judgement and choice.	✓	✓	Book chapter and research synthesis; conceptual foundation.
Slovic et al. (2007) [31]	Affect heuristic	Affective evaluation and risk–benefit judgements.	✓	✓	Journal synthesis; not automatically an independent replication of the 2002 source.

Sokol-Hessner et al. (2009) [32]	Loss aversion	Emotion regulation, gain–loss choices and physiological arousal.	✓	✓	Experiments and skin-conductance measures; does not imply an invariant affect–bias link.
Staněk (2017) [33]	Sports betting	Home-team bias in real betting decisions.	✓	✓	Observational data and logit modelling; contextual bias example outside logistics.
Vogel et al. (2021) [10]	Prototype preferences	Category valence, typicality and evaluative preference.	✓	✓	Experiments; valence-specific context, not the original two-axis affect model.
Vosgerau (2010) [34]	Optimism and pessimism	Misattributed arousal and subjective probabilities.	✓	✓	Experiments; arousal may support optimism or pessimism depending on interpretation.
Wall et al. (2020) [35]	Framing and risky choice	Emotional valence of internal arguments under decision frames.	✓	✓	Empirical query-theory account; framing context rather than a general arousal model.

Note: ✓ indicates that the relevant construct is explicitly examined or theoretically discussed; × indicates that it is not an explicit focus of the study. An affective component may involve emotion, mood, valence, or arousal and does not necessarily imply direct measurement of any of these affective dimensions. The indicators describe thematic coverage and do not indicate the strength of evidence for the proposed quadrant assignments.

2.4. Fuzzy Sets and Application and Explanation of the COG

Fuzzy set theory represents gradual membership in a defined concept through values in the interval [0, 1] [36]. The meaning of a membership value depends on the set being defined [37]. In the present framework, emotional-profile membership describes compatibility with an affective configuration, whereas operational-preference membership describes the acceptability of a decision alternative. These meanings are kept separate throughout the model. A membership value is not, by itself, the probability of an event.

Earlier logistics research has examined cognitive biases in the choice between push and pull strategies and proposed fuzzy indicators based on operational characteristics [3,38]. Tatarczak and Gola [39] use fuzzy EW-AHP to determine criterion weights and fuzzy TOPSIS to rank potential partners in horizontal cooperation. Magableh et al. [40] use fuzzy PROMETHEE to prioritise strategies for managing supply chain nervousness. In that study, nervousness concerns instability in supply chain planning and operations and is distinct from an individual decision-maker's emotional arousal.

The present framework focuses on the explicit representation of affective assumptions and operational preferences within a common decision context. Its emotional component expresses the compatibility of valence–arousal inputs with four hypothesised cognitive-bias rules. Its operational component separately illustrates a compromise among independently specified preferences. No automatic mapping from the activation of emotional rules to operational preference parameters is specified. The contribution therefore concerns the conceptual organisation and transparent interpretation of these two perspectives; their effects on decision quality and practical coordination remain to be evaluated empirically.

Following the fuzzy-decision formulation of Bellman and Zadeh [41], common acceptability can be represented by an intersection of preference functions. The centre of gravity (COG) summarises the location of that intersection based on the entire membership profile. The appropriate defuzzification method depends on the intended application [42–44]. The operational-variable formulation, the positive-denominator

condition and the subsequent feasibility and acceptability checks are specified in Section 4.2.

3. The Valence–Arousal Dimension in the Field of Logistics

Numerous attempts have been made in the literature to systematise cognitive biases. Oliver Sibony [45] classifies decision-making biases into five main categories, each of which includes phenomena that may also arise during strategic decision-making in logistics. At the same time, existing classification systems focus primarily on the negative consequences of these biases, while paying little attention to the mechanisms that can simultaneously lead to both positive and negative decision-making outcomes. From this perspective, the concept of affective bias is particularly relevant; it refers to a systematic bias in judgment and decision-making that stems from an individual's positive or negative emotional reactions and that influences cognitive processing partly independently of the stimulus's objective characteristics [19,20,29,31].

Emotional valence is one of the most fundamental dimensions, expressing whether a stimulus or situation elicits a positive (pleasant) or negative (unpleasant) evaluation. The foundation of modern dimensional emotion theory was laid by James A. Russell's circumplex model [8], which organises emotions along two orthogonal dimensions: valence and arousal. Valence (emotional polarity) refers to whether an emotion is positive or negative. Arousal (level of activation) refers to the intensity of an emotion or its physiological activation [35].

This approach was further refined in Russell's [9] theory of core affect, which defined valence as a fundamental component of affective experience. Core affect is a neuropsychological baseline state that underlies every conscious emotional experience and serves as the foundation for the construction of more complex emotions. This approach provides a theoretical foundation for the general, context-transcending application of valence.

From a neurocognitive perspective, positive and negative valence are linked to distinct reward and punishment systems, which are discussed in detail by Edmund T. Rolls [26]. This supports the view that valence is not merely a subjective evaluation but also a structured processing dimension at the neural level.

In decision-theory research, valence plays a central role within the affect heuristic framework, developed by Paul Slovic and colleagues [30]. According to this approach, a global positive or negative feeling serves as a rapid, intuitive mechanism for judging that structures the perception of risk and reward. Valence is thus not merely an emotional quality but also a decision-making heuristic. Rozin et al. [27] found that respondents tended to view naturalness as promoting sustainability and proposed the shared positive valence of the two concepts as one possible explanation for this belief.

At the same time, integrative reviews [22] point out that, although valence is a fundamental dimension, discrete emotions (e.g., fear vs. anger) may have different decision-making consequences even when they share the same negative valence. This suggests that valence is a necessary but not always sufficient explanatory factor in modelling decision-making biases.

Valence describes whether a situation is evaluated as positive or negative, while arousal reflects the level of activation, urgency, or stress experienced by the decision-maker. Together, these dimensions provide a compact yet expressive representation of the psychological state in which logistics decisions are made.

3.1. Selection and Theoretical Justification of Cognitive Biases

Cognitive biases can influence individuals' judgements at various stages of decision-making, from the processing of information to the evaluation of possible outcomes.

Previous research has also highlighted that emotional states, decision certainty and affective reactions may play a role in shaping these processes. However, the relationships between emotions and cognitive biases cannot be regarded as uniform or deterministic, as individual decision-making mechanisms may respond differently to psychological and environmental conditions.

This research focuses on four cognitive biases: confirmation bias, optimism bias, status quo bias, and loss aversion. The aim of this selection is not to provide a comprehensive classification of all biases occurring in logistical decision-making, but rather to illustrate four distinct decision-making mechanisms within the valence–arousal framework. The selected biases represent different aspects of information processing, future expectations, decisions relating to change, and risk assessment. These may all be relevant in logistical decision-making situations characterised by uncertainty, time pressure, incomplete information, or competing organisational objectives.

Confirmation bias refers to the tendency for decision-makers to favour information that is consistent with their existing beliefs and previous decisions. In their meta-analysis, Hart et al. [21] demonstrated that individuals generally tend to favour information that confirms their previous views, whilst the strength of this tendency is also influenced by motivational and decision-making circumstances, according to the experimental findings of Fischer et al. [18]. Both conscious and intuitive decision-making can enhance subsequent confirmation bias, in which subjective certainty about the correctness of the decision also plays a role. In logistics decision-making, this may manifest, for example, when the decision-maker favours information supporting a procurement or inventory management strategy previously deemed successful. Within the present framework, confirmation bias falls within the range of positive valence and low arousal, illustrating that in situations perceived as favourable and involving low emotional arousal, maintaining prior beliefs may be a possible decision-making tendency. However, this specific quadrant assignment is a theoretical assumption, the direct empirical validation of which requires further investigation.

Optimism bias can manifest itself in an overestimation of the probability of favourable future events occurring, or an underestimation of the probability of unfavourable events. According to the experimental findings of Lench and Ditto [23], individuals may make more favourable predictions about positive events even when the objective probabilities are the same, a phenomenon in which automatic affective reactions may play a role. Furthermore, Vosgerau's [34] research highlighted that the interpretation and misattribution of arousal can influence subjective probability estimates in both optimistic and pessimistic directions. In a logistics context, optimism bias may manifest, for example, in an overestimation of demand growth, excessive expectations regarding available capacity, or a more favourable assessment of the feasibility of meeting delivery deadlines. Assignment to the quadrant of positive valence and high arousal illustrates the hypothetical situation in which a positive emotional evaluation is associated with heightened arousal. However, the literature does not confirm that high arousal invariably results in an optimistic bias.

Status quo bias refers to a tendency to favour maintaining the current state of affairs or a previously chosen alternative, even in cases where other options might be more favourable. The classic study by Samuelson and Zeckhauser [28] demonstrated the significance of clinging to existing alternatives in decision-making. Anderson [15], in examining the psychological mechanisms of decision avoidance, pointed out that both cognitive and emotional factors can play a role in maintaining the status quo. In logistics decision-making situations, this may manifest, for example, in the maintenance of existing supplier relationships, transport arrangements or inventory management procedures, even when their performance is unsatisfactory. The present model assigns status quo bias

to the range of negative valence and low arousal, illustrating a hypothetical situation in which the decision-maker assesses the existing circumstances as unfavourable but does not experience a degree of urgency or emotional arousal that would prompt immediate change. This classification is primarily conceptual in nature, as the available literature does not directly support the view that status quo bias is most characteristic of this particular emotional configuration.

Loss aversion refers to the decision-making tendency whereby potential losses are given greater subjective weight than gains of a similar magnitude. Sokol-Hessner et al. [32] demonstrated that emotion regulation strategies can reduce loss aversion, and identified a link between physiological responses to losses and decision-making behaviour. This suggests that emotional processes may play a role in the subjective evaluation of losses. In a logistics context, loss aversion may, for example, influence decision-makers' evaluation of alternatives in the event of supply disruptions, capacity shortages or significant financial risks. Assignment to the quadrant of negative valence and high arousal illustrates a decision-making situation in which an unfavourable emotional evaluation is associated with heightened arousal and a focus on potential losses. At the same time, the relationship between emotional arousal and loss aversion cannot be regarded as unambiguous or consistently directional in all situations; therefore, this assignment also requires further empirical investigation.

The four selected biases therefore represent different decision-making mechanisms, which provide an opportunity to apply the valence–arousal framework in a concrete way. The classification presented does not assume that a given emotional state results exclusively in a specific cognitive bias, nor that the selected biases cannot occur in other emotional configurations. Valence and arousal are dimensions of the decision-maker's subjective emotional state, which are not in themselves identical to the objective operating conditions of the logistic system.

Accordingly, the four-quadrant model can be interpreted as a theoretical classification based on findings in the literature, but which is partly hypothetical. Its aim is not to prove the activation of individual biases, but to provide a structured presentation of possible relationships that may serve as a basis for subsequent empirical studies and decision-support applications. The inclusion of other biases relevant to logistics decision-making—such as anchoring, overconfidence, the availability heuristic or the planning fallacy—offers the possibility of further extending the framework. Buehler et al. [17] found that participants tended to underestimate the time needed to complete their own tasks. Li et al. [24] distinguished overestimation, overplacement, and overprecision and reported mixed evidence on the stability of overconfidence across tasks and over time.

3.2. Defining the Dimensions of Valence and Arousal in Logistics Contexts

Within this framework, valence denotes the pleasantness or unpleasantness of the decision-maker's subjective affective state when evaluating a logistics situation. Positive and negative valence therefore describe emotional experience rather than favourable or unfavourable system performance.

Arousal denotes the decision-maker's experienced level of activation, ranging from low to high. Routine operations, time pressure, demand changes, capacity constraints, and supply disruptions provide possible contexts for these experiences. However, a particular operational condition does not, by itself, establish a corresponding affective state. Valence and arousal are therefore treated as psychological inputs that require separate assessment, rather than being inferred directly from operational performance or external decision-making pressure.

Why is it important to examine the role of emotional valence and arousal in decision-making within the field of logistics?

- Emotional valence influences "judgments"—that is, whether we perceive something as a positive or negative event.
- The relationship between arousal and specific biases is a hypothesis to be examined within the model.

Within the proposed framework, valence and arousal provide dimensions for formulating hypotheses about possible affective influences on information processing and the evaluation of alternatives. Table 2 illustrates the selected affect–bias associations proposed for empirical investigation.

Table 2. Illustrative mapping of selected cognitive biases in the valence–arousal space. (Source: own compilation).

		Arousal	
		Low	High
Valence	Positive	**Confirmation bias**	**Optimism bias**
		In a situation perceived as favourable and calm, the decision-maker may confirm their previous expectations.	A positive emotional state combined with high arousal may lead to overly favourable expectations.
	Negative	**Status quo**	**Loss Aversion**
		In a situation perceived as unfavourable but not urgent, the desire to avoid change may come to the fore.	A negative emotional state and high arousal may heighten attention to potential losses.

The correlations presented are theoretical assumptions of the proposed conceptual framework, rather than empirically verified, exclusive associations. A given cognitive bias may manifest itself in several emotional configurations.

Different emotional states may be associated with different patterns of cognitive bias. Based on this, a dimension can be defined in Table 2 along valence and arousal in decision-making within the industry:

- Within the proposed framework, positive valence combined with high arousal is hypothesised to be associated with excessive risk-taking and optimism.
- In cases of positive valence + low arousal, heuristics and simple decisions emerge; that is, people in a calm, positive state tend to rely on information that reinforces their own beliefs—as can be observed, such as in the case of confirmation bias.
- Negative valence combined with high arousal is typically accompanied by anger, stress, and fear. Loss aversion manifests in such situations: individuals' fear of loss and anxiety about risk. Loss aversion typically manifests in crisis situations that disrupt supply chains.
- Negative valence + low arousal is a "pessimistic" bias in which individuals stick to their previous statements and ideas and avoid making new decisions—a pattern typically identified as status quo bias.

Table 2 summarises the illustrative relationships proposed within this framework. Confirmation bias is associated with positive valence and low arousal, whilst loss aversion is associated with negative valence and high arousal. Optimism bias and status quo bias are associated with the positive–high and negative–low configurations, respectively. These classifications are theoretical assumptions that require empirical testing. They do

not imply that valence and arousal unambiguously determine the occurrence of a given bias, nor that any of the selected biases is exclusively linked to a single affective configuration. Based on our experience in logistics, these classifications can provide a useful theoretical basis for exploring potential links between emotional states and cognitive biases in the field of logistics decision-making.

3.3. Behavioural Implications for Logistical Decision-Making

The valence–arousal framework allows us to reinterpret logistics decisions as the result of psychologically conditioned processes. Instead of assuming purely rational evaluation, the model suggests that decision-makers apply different implicit weighting schemes depending on their emotional state.

Within the proposed framework, affective configurations provide a basis for formulating hypotheses concerning information processing and the evaluation of decision-making alternatives. Within the proposed framework, positive valence combined with low arousal is hypothesised to be associated with confirmation bias, expressed as a preference for information that supports existing beliefs.

Within the proposed framework, negative valence combined with high arousal is hypothesised to be associated with loss aversion, which manifests as a greater subjective weighting of potential losses than of equivalent gains. These statements do not establish causal relationships, nor do they allow us to infer any of these biases solely from emotional states. The interpretation of these findings also requires consideration of discrete emotions, individual differences, and the decision-making context.

3.4. Mapping the Valence–Arousal Space and Cognitive Biases

The proposed framework organises four illustrative hypotheses about cognitive biases within a two-dimensional valence–arousal space (Table 2). The four regions represent the following illustrative relationships. The quadrants describe the decision-maker's subjective affective state:

- Positive valence—low arousal level: This region describes a pleasant, low-arousal emotional state that a decision-maker might experience during routine operations.

Decision-makers tend to rely on existing knowledge and beliefs, favouring information consistent with prior assumptions. Confirmation bias illustrates a possible tendency to favour information that supports existing beliefs or decisions whilst in a pleasant, low-arousal state.

- Positive valence, high arousal: This region describes a pleasant, high-arousal emotional state that a decision-maker might experience when considering growth or market opportunities. Decision-makers may exhibit an optimism bias, characterised by underestimating the time required and overestimating the system's capabilities. The optimism bias illustrates a hypothetical tendency to overestimate favourable outcomes or underestimate unfavourable outcomes whilst in a pleasant, highly aroused state.
- Negative valence, low arousal: This region describes an unpleasant, low-arousal emotional state that a decision-maker might experience when feeling dissatisfied with existing operations, where decision-makers avoid change and maintain existing strategies despite suboptimal performance. Status quo bias illustrates a possible preference for maintaining an existing alternative in an unpleasant, low-arousal state.
- Negative valence, high arousal: This region describes an unpleasant, high-arousal emotional state that a decision-maker might experience during a supply disruption or a perceived crisis. Loss aversion illustrates a hypothetical tendency to attach

greater subjective weight to potential losses than to equivalent gains whilst in an unpleasant, highly aroused state.

Stable operations, growth pressure, capacity constraints and supply disruptions are possible contexts that may elicit affective responses. These circumstances do not, by themselves, determine a particular valence–arousal configuration, and different decision-makers may respond differently to the same situation. The proposed quadrant assignments are non-exclusive theoretical hypotheses that require empirical testing; they neither establish the dominance of a particular bias nor exclude its occurrence in other affective configurations.

3.5. Formal Representation of Bias Activation

The relationship between normalized valence v, arousal a, and the four rule activation degrees is represented by a vector-valued mapping f. For each input pair (v,a), the output vector $b(v,a)$ contains the activation degrees of the confirmation-bias (CB), optimism-bias (OB), status quo-bias (SQ), and loss-aversion (LA) rules, in this order.

Each component expresses the degree to which the affective input satisfies the antecedent conditions of the corresponding hypothesized rule. These values are neither observed bias intensities nor probabilities, and their sum is not required to equal one.

The vector-valued mapping (1) has four components, which are defined explicitly by Equations (4)–(6). Valence is normalised to $[-1, 1]$, arousal to $[0, 1]$, and the four activations are obtained from the specified membership degrees using the minimum t-norm.

$$f(v,a) = \left(b_{CB}(v,a), b_{OB}(v,a), b_{SQ}(v,a), b_{LA}(v,a)\right) \tag{1}$$

Let $v \in [-1, 1]$ denote normalised self-reported emotional valence, where −1, 0, and 1 represent maximally negative, neutral, and maximally positive valence, respectively. Let $a \in [0, 1]$ denote normalised arousal, from minimal to maximal activation. The two input linguistic variables are negative/positive valence and low/high arousal. For the baseline specification, the corresponding membership functions are

$$\mu_{V+}(v) = \frac{v+1}{2}, \qquad \mu_{V-}(v) = \frac{1-v}{2}, \quad -1 \le v \le 1 \tag{2}$$

$$\mu_{A+}(a) = a, \qquad \mu_{A-}(a) = 1-a, \quad 0 \le a \le 1 \tag{3}$$

All four membership values lie in [0, 1]. These linear shoulder functions deliberately overlap, avoiding a discontinuous assignment at the axes. Their breakpoints and slopes are modeling assumptions, not parameters inferred from psychological observations. The fuzzy conjunction is the minimum t-norm. For the four bias rules, the firing strengths are

$$b_{\mathrm{CB}} = \min\{\mu_{V+}(v), \mu_{A-}(a)\}, \qquad b_{\mathrm{OB}} = \min\{\mu_{V+}(v), \mu_{A+}(a)\}, \tag{4}$$

$$b_{\mathrm{SQ}} = \min\{\mu_{V-}(v), \mu_{A-}(a)\}, \qquad b_{\mathrm{LA}} = \min\{\mu_{V-}(v), \mu_{A+}(a)\}. \tag{5}$$

The rule base comprises four hypothesised associations:

R1: IF valence is positive AND arousal is low, THEN assign the rule's firing strength to the confirmation bias label (CB).

R2: IF valence is positive AND arousal is high, THEN assign the rule's firing strength to the optimism bias label (OB).

R3: IF valence is negative AND arousal is low, THEN assign the rule's firing strength to the status quo bias label (SQ).

R4: IF valence is negative AND arousal is high, THEN assign the rule's firing strength to the loss aversion label (LA).

Each b_i is a fuzzy rule activation degree, not an observed bias intensity or a probability that *a* bias occurs. The rule activations form the output vector

$$b^T(v,a) = \left(b_{\mathrm{CB}}, b_{\mathrm{OB}}, b_{\mathrm{SQ}}, b_{\mathrm{LA}}\right) \quad (6)$$

For descriptive classification only, the most strongly supported rule can be identified as $B^*(v,a) \in arg\,max_{i\in\{CB,OB,SQ,LA\}} b_i(v,a)$. Ties are retained as multiple supported rules rather than resolved arbitrarily. In practice, the valence and arousal inputs would require a documented measurement instrument and normalisation protocol.

In this framework, the activation of bias is treated not as binary but as context-dependent, allowing for gradual transitions between different behavioural systems. Although each region of the valence-activation space may be associated with a distinct distortion, overlapping effects may also occur between neighbouring regions, reflecting the continuous nature of emotional states.

The framework can be illustrated using hypothetical inputs, whereas its practical application requires empirical measurement of valence and arousal and independent behavioral assessment of the relevant cognitive biases.

3.6. Contributions of the Framework

The framework makes explicit two distinct aspects of logistics decision-making: assumptions about potentially relevant cognitive biases and the operational preferences expressed by different decision-makers. The emotional component supports formulating questions about potential biases associated with affective states, while the operational component provides a transparent representation of the preferences underlying an illustrative compromise.

Their combined role is to support a structured examination of differing evaluations within the same decision context. The framework does not derive operational preferences from emotional states, and its effects on decision quality or organisational coordination remain to be evaluated empirically.

By linking emotional conditions to cognitive biases, the framework facilitates an understanding of decision-making in logistics systems and provides a basis for more realistic modelling of human-influenced processes.

4. Application of the Proposed Framework

This section illustrates two components of the proposed framework in a logistics decision-making context: the calculation of fuzzy rule activation degrees from valence and arousal inputs, and the identification of a compromise between separately specified operational preferences. The numerical values and membership parameters are assumed for illustration. The example demonstrates the mathematical formulation; empirical testing of the occurrence and effects of bias on decision outcomes remains a task for future research.

4.1. Interdepartmental Decision Alignment in the Valence–Arousal Space

Logistics decisions are rarely made by a single decision-maker. Typically, multiple organisational functions are involved in shaping strategic decisions, each representing different goals, priorities, and evaluation criteria. One of the most characteristic examples of this is the collaboration between marketing and logistics, where customer-oriented objectives often clash with operational constraints and resource capacities.

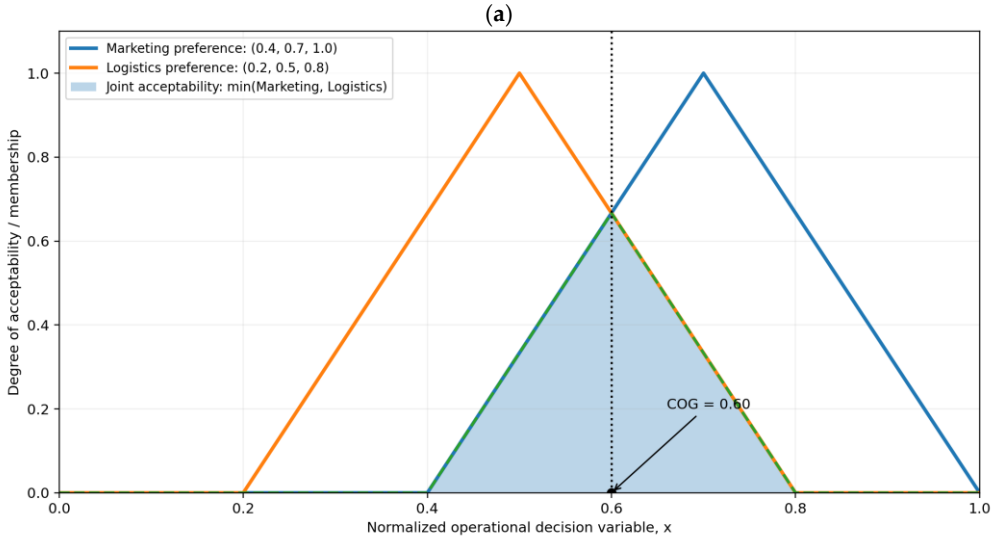
In the illustrative scenario, the marketing decision-maker is assumed to experience positive valence and high arousal when considering anticipated market opportunities, whereas the logistics decision-maker is assumed to experience negative valence and high arousal in response to perceived capacity constraints. These profiles are hypothetical

inputs selected for demonstration and do not imply that members of either organisational function generally share a particular emotional state. Different individuals, or the same individual in another situation, may respond differently to similar operating conditions.

Figure 1a illustrates these assumed emotional profiles in relation to the hypothesised cognitive-bias rules. Figure 1b separately illustrates a compromise between independently specified operational preferences. Together, the two panels distinguish the possible affective background of an evaluation from the operational preferences expressed in the same decision context.



(**a**)



(**b**)

Figure 1. (**a**) Illustrative function-specific emotional-state profiles and candidate cognitive-bias rules in the valence–arousal space. Dashed ellipses denote hypothetical fuzzy-profile contours; no bias diagnosis is implied. (**b**). Triangular marketing and logistics operational-preference functions, their minimum intersection (shaded), and the calculated centroid x_COG = 0.60. All parameters are illustrative.

4.2. Function-Specific Fuzzy Emotional States and Organisational Decision Alignment

Fuzzy representation allows decision states in the valence–arousal space to be represented not as single points but as ranges that form a gradual transition. This accurately reflects the characteristics of logistics decision-making, where marketing and logistics preferences rarely diverge sharply but rather overlap to varying degrees. Fuzzy membership functions, therefore, not only serve to mathematically handle uncertainty but also provide a means of visually representing the transitions between the decision preferences of the two disciplines.

The acceptable decision zone can be interpreted as the intersection of the fuzzy sets, denoting the range where both the market expectations defined by marketing and the operational constraints of logistics are met to an appropriate degree. Within this range, neither discipline's preferences dominate to an extreme degree.

The use of fuzzy sets in this research is not presented as a standalone decision-support method but rather as a mathematical representation of the gradual transitions between valence–arousal states and the associated cognitive biases. This enables a unified interpretation of the relationships between emotional states, cognitive biases, and organisational decision-making preferences.

The proposed framework combines two complementary perspectives for evaluating shared logistical decisions. The emotional component represents valence–arousal inputs and their compatibility with the four hypothesised cognitive bias rules. Its role is to draw attention to potentially relevant biases that would require an independent behavioural assessment. The operational component separately represents the acceptability of decision alternatives from the perspective of the organisational functions involved, and illustrates a compromise between their stated preferences.

4.2.1. Function-Specific Emotional-State Profiles and Candidate Biases

Marketing and logistics decision-makers may evaluate the same strategic situation differently. For example, anticipated growth may be associated with positive valence and high arousal for marketing, whereas concerns about capacity and disruption may be associated with negative valence and high arousal for logistics. Under the illustrative four-rule classification in Section 3.5, these states are compatible with optimism-bias and loss-aversion rules. The quadrant associations are hypotheses, not exclusive psychological relationships.

For organizational function $j \in \{M,L\}$, a two-dimensional fuzzy emotional-state profile can be represented by the following Gaussian membership surface:

$$\mu_{\mathrm{j}}(v,a) \;=\; exp\{-½[((v-c_{\mathrm{v,j}})/\sigma_{\mathrm{v,j}})^2 \;+\; ((a-c_{\mathrm{a,j}})/\sigma_{\mathrm{a,j}})^2]\} \tag{7}$$

Here $c_{v,j}$ and $c_{a,j}$ denote the center of the function-specific valence–arousal profile; $\sigma_{v,j} > 0$ and $\sigma_{a,j} > 0$ control its spread. These centers refer to emotional states, not to the preferred operational decision value introduced below. The ellipses in Figure 1a are schematic contours of such profiles; their positions and widths are hypothetical.

Let $b_k(v,a)$ denote the firing strength of fuzzy bias rule k as defined in Section 3.5. A function-specific compatibility score is

$$R_{j,k} = \frac{\int_{-1}^{1}\int_{0}^{1}\mu_j\,(v,a)\,b_k(v,a)\,da\,dv}{\int_{-1}^{1}\int_{0}^{1}\mu_j\,(v,a)\,da\,dv} \tag{8}$$

$$k \;=\; arg\,max_{\mathrm{k}}\,R_{\mathrm{j,k}} \tag{9}$$

The scores summarize the compatibility of a fuzzy emotional-state profile with the stipulated rules; they are neither probabilities nor measured occurrences of cognitive

biases. A candidate bias should be independently assessed using behavioral evidence before a debiasing intervention is selected.

To demonstrate computational reproducibility, two illustrative Gaussian emotional-state profiles were considered. For marketing, the parameters are $c_{v,M} = 0.6$, $c_{a,M} = 0.8$, $\sigma_{v,M} = 0.25$, and $\sigma_{a,M} = 0.15$. For logistics, they are $c_{v,L} = -0.6$, $c_{a,L} = 0.8$, $\sigma_{v,L} = 0.25$, and $\sigma_{a,L} = 0.15$. These values are assumed for illustration and have not been empirically calibrated.

At the marketing profile centre $(v, a) = (0.6, 0.8)$, the membership degrees are $\mu_V + (\mathrm{v}) = 0.8$, $\mu_V - (\mathrm{v}) = 0.2$, $\mu_A + (\mathrm{a}) = 0.8$, and $\mu_A - (\mathrm{a}) = 0.2$. The minimum t-norm yields the pointwise rule-activation vector

$$\mathrm{b}_M = (0.2, 0.8, 0.2, 0.2) \tag{10}$$

At the logistics centre $(-0.6, 0.8)$, the corresponding vector is

$$\mathbf{b}_L = (0.2, 0.2, 0.2, 0.8) \tag{11}$$

Numerical integration over the full bounded valence–arousal domain (Table 3), using Equation (8), yields the following profile-level compatibility scores.

Table 3. Numerical integration over the full bounded valence–arousal domain.

Cognitive-Bias Rule	Marketing	Logistics
Confirmation bias (CB)	0.2270	0.1527
Optimism bias (OB)	0.7110	0.2146
Status quo bias (SQ)	0.1527	0.2270
Loss aversion (LA)	0.2146	0.7110

The highest compatibility scores are obtained for optimism bias in the marketing profile and for loss aversion in the logistics profile. These are consequences of the stipulated membership functions and parameters, not empirical evidence that either bias actually occurs. Scores are not probabilities and need not sum to one.

The Gaussian spreads were varied individually by ±20%, keeping the profile centres and all other parameters fixed. The tested values were $\sigma_{\mathrm{v}} = 0.20, 0.25, 0.30$ and $\sigma_{\mathrm{a}} = 0.12, 0.15, 0.18$. Table 4 summarises the highest compatibility scores calculated using Equation (8).

Table 4. Highest rule-compatibility scores under individual Gaussian spread changes.

Profile	Highest Rule	Baseline Score	Score Range After ±20% Changes
Marketing	OB	0.7110	0.6960–0.7240
Logistics	LA	0.7110	0.6960–0.7240

OB (optimism bias) remained the highest-scoring rule for marketing, and LA (loss aversion) for logistics, in all tested cases. This indicates local stability of rule selection within the specified parameter changes.

4.2.2. Operational Preference Functions and the Common Decision Zone

A separate normalized operational decision variable $x \in [0, 1]$ represents, for example, the proposed magnitude of a customer-service-level increase. Each organizational function j has a triangular acceptability function with parameters $l_j < c_j < r_j$:

$$\mu_{\mathrm{j}}(x; l_{\mathrm{j}}, c_{\mathrm{j}}, r_{\mathrm{j}}) = max\{0, min[(x - l_{\mathrm{j}})/(c_{\mathrm{j}} - l_{\mathrm{j}}), (r_{\mathrm{j}} - x)/(r_{\mathrm{j}} - c_{\mathrm{j}})]\} \tag{12}$$

The parameter c_j is the most preferred operational decision value from function j's perspective, where its acceptability reaches 1. The parameters l_j and r_j are the lower and upper limits of nonzero acceptability; the distances $c_j - l_j$ and $r_j - c_j$ describe how rapidly acceptability declines on either side. For instance, $c_M = 0.7$ represents a marketing preference for a relatively large service-level increase, whereas $c_L = 0.5$ represents a more moderate logistics preference. These values are illustrative assumptions, not elicited empirical preferences (illustrative assumption).

For the example, use $(l_M, c_M, r_M) = (0.4, 0.7, 1.0)$ and $(l_L, c_L, r_L) = (0.2, 0.5, 0.8)$. The common acceptable decision set is obtained through minimum intersection:

$$\mu_D(x) = min\{\mu_M(x), \mu_L(x)\} \quad (13)$$

Its area S and center of gravity (COG) are defined by

$$S = \int_0^1 \mu_D(x)\, dx \qquad x_COG = \frac{\int_0^1 x\, \mu_D(x)\, dx}{S} \quad (S > 0) \quad (14)$$

For these symmetric illustrative functions, $S = 0.13333$ and $x_COG = 0.60$. The COG is a mathematical compromise of the expressed preference functions; it is not generally the arithmetic mean of their centres and does not itself identify a cognitive bias. If $S = 0$, no positive common acceptance exists and the COG is undefined.

Figure 1 is a two-panel figure: panel (a) identifies potentially different bias-related profiles, while panel (b) illustrates a compromise over an operational decision variable. No direct causal or computational mapping from the bias-compatibility scores $R_{j,k}$ to the preference parameters (l_j, c_j, r_j) is assumed.

The COG is used here to summarise the entire common acceptability profile via its centroid (Table 5). In this symmetric example, the common membership function has a single maximum at $x = 0.600$; therefore, the COG, MoM and FoM all yield a result of 0.600. This agreement does not prove the superiority of any single method. The choice of defuzzification method depends on the application and the intended interpretation of the output [42,43].

Table 5. Defuzzification results for the illustrative common acceptability function.

Method	Result	Interpretation
Centre of Gravity (COG)	x* = 0.600	Centroid of the entire common acceptability profile.
Mean of Maxima (MoM)	x* = 0.600	Mean of the decision values at which common acceptability reaches its maximum.
First of Maxima (FoM)	x* = 0.600	Smallest decision value at which common acceptability reaches its maximum.

Note. Here, x* denotes the representative operational decision value obtained using the specified defuzzification method.

Varying the preference spread width by ±20% changes the common acceptance area and, for unequal changes, its centroid (Table 6). The marketing-left and logistics-right spreads varied, while the preferred values and outer endpoints remained fixed.

Specifically, the baseline widths $c_M - l_M = 0.30$ and $r_L - c_L = 0.30$ were changed to 0.24 or 0.36. Table 6 shows selected combinations.

Table 6. Effect of selected preference-spread changes on the common acceptance area and centroid.

Marketing Spread Change	Logistics Spread Change	S	x_{COG}
Baseline	Baseline	0.13333	0.60000
−20%	−20%	0.08167	0.60000
+20%	+20%	0.18778	0.60000
−20%	+20%	0.13333	0.64667
+20%	−20%	0.13333	0.55333

The common region remained positive in all tested cases. Equal percentage changes preserved the centroid at 0.60000, while unequal changes shifted it. The overlap area changed nonlinearly. These results describe the local sensitivity of the illustrative model.

The framework comprises two complementary but mathematically independent fuzzy representations. The first describes compatibility between hypothetical emotional-state profiles and cognitive-bias rules in the valence–arousal space. The second represents acceptability of operational alternatives from the marketing and logistics perspectives. Their intersection defines a common acceptable decision region, and centroid defuzzification provides a representative compromise. No causal or computational mapping from bias compatibility scores to operational preference parameters is assumed. The contribution is therefore a conceptual combination of behavioural and operational perspectives, not a fully integrated behavioural–operational optimisation model. Any direct linkage would require further assumptions and empirical validation.

5. Discussion and Conclusions

The aim of this research was to develop a conceptual framework that integrates the adaptive approach to cognitive biases, the valence–arousal emotion model, and fuzzy set theory into the analysis of logistics decision-making. The proposed model is based on the assumption that logistics decisions are not solely determined by objective parameters but are also significantly influenced by decision-makers' emotional states and cognitive biases. The use of fuzzy representation allows these effects to be represented not as discrete categories, but as decision ranges exhibiting gradual transitions.

5.1. Theoretical Propositions

The study advances three main theoretical propositions.

Firstly, in logistics decision-making, certain cognitive biases may be linked to decision-makers' subjective affective states. The proposed framework organises these potential links along the dimensions of valence and arousal. The four-quadrant classification is an illustrative, non-exhaustive hypothesis that has not been empirically validated.

Secondly, differences between affective states and cognitive biases may influence how organisational actors evaluate the same decision-making situation. The marketing and logistics profiles used in the hypothetical example illustrate this possibility. They represent neither the empirically established characteristics of organisational functions nor the emotional origins of inter-departmental conflicts.

Thirdly, fuzzy sets provide complementary representations of the affect–bias relationships featured in the hypothesis and the independently defined operational preferences. Where the operational preference functions overlap, their intersection defines the region of mutual acceptability under the specified assumptions. The current model does not specify any causal or computational relationship between the activation of emotional rules and the parameters of operational preferences.

5.2. Theoretical Contributions

This research contributes to the expansion of the literature in three ways.

First, it integrates evolutionary and adaptive approaches to cognitive biases into the study of logistics decision-making. While previous research has focused primarily on the negative consequences of biases, this study highlights that certain biases can also play an adaptive role under specific circumstances.

Second, the study applies the valence–arousal model as a unified psychological framework for analysing logistics decision-making. This allows various cognitive biases to be organised around a common emotional background, thereby reducing the conceptual fragmentation in the literature.

Third, the study places a fuzzy representation of hypothesised associations between affective states and cognitive biases alongside a separate representation of operational preferences. Their shared conceptual purpose is to clarify different aspects of evaluation within the same logistics decision context. The emotional component directs attention to potentially relevant biases, whereas the operational component illustrates a compromise among independently specified preferences. The study does not specify how emotional rule activation would change those preferences; developing and empirically testing such a relationship remains a task for future research.

5.3. Potential Managerial Applications

The proposed framework identifies potential applications in managerial reflection and coordination. These applications have not yet been evaluated in a real-world logistics decision-making context.

The valence–arousal component may help to structure discussions regarding possible links between subjective affective states and selected cognitive biases. Identifying an actual cognitive bias would require an independent behavioural assessment.

During the coordination of marketing and logistics, the separately elicited operational preference functions could be used to map the acceptability of alternative decisions and identify a common region of acceptability where they overlap. The centroid would provide a possible summary of this region, whilst operational feasibility and stakeholder acceptance would require separate assessment.

Following empirical calibration and validation, the framework could provide guidance for developing future decision-support tools. Any potential benefits in terms of decision quality, organisational coordination or conflict reduction remain hypotheses awaiting testing.

5.4. Limitations and Future Research Directions

This study is primarily conceptual in nature; therefore, its aim is not to develop a new decision-making algorithm, but rather to present an integrated theoretical framework. The fuzzy representation illustrates the transitions between decision states; however, the parameterisation of the fuzzy membership functions in this study is not empirically based.

Future empirical research could use the valence and arousal scales of the Self-Assessment Manikin [16] to obtain separate pictorial self-reports of subjective pleasantness and activation. In a scenario-based study, ratings could be collected immediately after participants read the logistics decision scenario and before they make their decision. The scoring direction would be specified in advance, with higher recoded scores indicating more positive valence and greater arousal. Ratings would then be linearly rescaled using the fixed endpoints of the administered scales to the model input ranges of [−1, 1] for valence and [0, 1] for arousal. This transformation would define the inputs without, by itself, validating the membership functions or the proposed affect–bias associations [25].

The four cognitive biases would require independent behavioural assessment through tasks that examine selective information search, outcome estimates relative to appropriate benchmarks, preferences for an existing alternative, and choices involving matched gains and losses. These behavioural measures could then be compared with the emotional component's rule activations to evaluate the proposed hypotheses.

The quadrants assigned to marketing and logistics, as well as the emotional profiles associated with them, should be regarded as hypotheses rather than empirically verified patterns. The membership functions and preference parameters are merely illustrative modelling assumptions; thus, the calculated COG (centre of gravity) represents a hypothetical mathematical compromise whose practical feasibility must be examined separately. Future research would benefit from combining empirical measurements of valence and arousal with an independent, behaviour-based assessment of cognitive biases, and from examining the sensitivity of the results to parameter choices and defuzzification methods.

5.5. Conclusions

This study proposes a new conceptual framework for interpreting cognitive biases in logistics decision-making. Using hypothetical inputs, the model integrates the adaptive approach to cognitive biases, the valence–arousal model of emotions, and fuzzy set theory to provide a conceptual basis for examining the psychological and organisational underpinnings of decision-making behaviour. Further empirical measurement of valence, arousal, and decision-making behaviour in logistics settings is needed to evaluate the proposed relationships and the framework's practical applicability.

The proposed framework regards subjective affective states as potentially relevant to logistics decision-making and formulates hypotheses regarding their relationship with selected cognitive biases. It demonstrates how these hypotheses and the independently defined operational preferences can be represented through complementary fuzzy components. Numerical examples illustrate the computational implications of the specified assumptions. Whether the proposed affect–bias relationships correspond to observed behaviour, and whether taking them into account alongside operational preferences improves decision outcomes, remain questions for future empirical research.

The framework presented not only offers a new theoretical interpretation of the behavioural factors in logistics decision-making but can also lay the groundwork for the development of future decision-support systems that integrate objective operational metrics, emotional states, and a fuzzy representation of decision uncertainty. This could contribute to increasing the soundness and flexibility of strategic decisions made in complex logistics systems.

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