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Original Research

Stakeholder bias and group decision dynamics: mitigating cognitive biases with an integrated consensus-building process

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Abstract: This study examines how stakeholder-driven preferential amplification affects outcomes in participatory group decision-making (DM) when allocation consequences have material significance. We structured development priorities for local value chains using the Analytic Network Process (ANP) and directly compared the pairwise judgments of value-chain representatives with those of other panel members to assess incentive alignment effects. Pre-consensus analysis revealed substantial divergence between stakeholder and non-stakeholder evaluations, indicating strong preferential positioning within the ANP structure under high-stakes conditions. We then implemented a structured Delphi-based iterative consensus refinement process and returned aggregated judgments (geometric means) to participants across two rounds to enable controlled reconsideration and revision. Post-iteration analysis shows a marked reduction in between-group divergence. Effect size assessment confirms moderation of extreme preferential positions rather than their complete elimination, consistent with the limited statistical power of small stakeholder subgroups. These findings demonstrate that participatory group DM frameworks remain essential for inclusive governance. However, when incentives are directly linked to allocation outcomes, decision architects should design balanced panel structures and incorporate structured consensus-feedback mechanisms to enhance robustness, transparency, and stability in ANP-based policy applications.

Keywords: Analytic network process, Biased judgments, Integrated consensus-building process, Group decision-making, Value chains

1. Introduction

Group decision-making (DM) is a cornerstone of many fields, including public policy and organizational management. While organizations depend on teams to generate and execute innovative ideas [1], these processes are not immune to biases. Such biases can compromise the quality and outcomes of the decisions made [2]. Developing methods to improve DM efficacy requires understanding the effects of biased judgments (BJs). Systematic mistakes in thinking, resulting from social pressures, emotional influences, or cognitive limitations, are the root cause of BJs [3]. Mental shortcuts and other cognitive biases can lead to incorrect conclusions [4]. Social pressures such as conformity and groupthink can exacerbate these biases [5], while emotional factors such as mood and personal feelings can skew judgment [6, 7]. Biased decisions in group DM have serious repercussions. They may cause group members to ignore relevant information or fail to assess alternatives objectively, resulting in suboptimal decisions

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[8]. For example, confirmation bias can lead groups to disregard contradictory evidence in favor of information that supports their preconceived notions [9]. Excessive reliance on preliminary estimates, even when inaccurate, can result from anchoring bias. Availability bias may lead to overestimating rare events, increasing risk aversion, while overconfidence bias can result in poor risk management [10]. Biases can restrict perspectives and hinder creativity, even though group DM is valued for its ability to generate diverse ideas [11]. Groupthink can lead to a narrow focus on traditional options, suppressing opposing viewpoints. BJs can impede implementation, causing delays or failures even when sound decisions are made [12]. Furthermore, biased decisions can raise ethical issues, particularly when influenced by vested interests or stereotypes, potentially resulting in discriminatory outcomes [13]. The PSI-theory (after the Greek letter Ψ, symbolizing the psyche and developed by Dietrich Dörner) categorizes decisions into two types: need-oriented and goal-oriented [14].

Because members may prioritize their own needs over objective standards, need-oriented judgments may diverge from the main goal of DM [15]. PSI theory posits that human judgments are influenced by need-oriented motivational states, whereby cognitive processing is shaped by goal-relevant pressures and situational incentives [14]. In high-stakes allocation environments, such need-oriented dynamics may manifest as preferential amplification rather than purely cognitive error [15]. In the present study, the behavior of Value Chain Development Agents (VCDAs) can be interpreted through this lens: when budget allocation is directly linked to evaluative outcomes, judgments may systematically reflect incentive-aligned prioritization. This theoretical framing suggests that the observed divergence is not necessarily irrational distortion, but rather contextually motivated positioning within a structured decision architecture. This raises questions about the reliability of expert judgments and the influence of emotions on DM. The paper aims to evaluate the impact of stakeholders on final decisions and whether those affected by the outcomes can serve as impartial judges. While prior research has extensively explored mathematical and fuzzy extensions of Analytic Hierarchy Process (AHP)/Analytic Network Process (ANP) to address uncertainty, comparatively less empirical attention has been paid to stakeholder-driven preferential amplification under real policy incentives and the moderating role of structured consensus refinement within such environments.

1.1 Literature review

It has long been acknowledged that group DM is a challenging but necessary process in social, political, and organizational contexts. Numerous academics have investigated how the variety of viewpoints involved in group decisions can result in more comprehensive and informed outcomes. Bringing together a range of perspectives and expertise, such as including multiple stakeholders in DM panels, is generally thought to improve the quality of decisions [16-19]. The active involvement of stakeholders in DM is widely seen as a necessity, not merely a benefit [20], as it helps to secure more dependable and socially acceptable results [21]. Although the development of remote group DM remains a topic of ongoing interest [22], this positive outlook is complicated by conflicts of interest. When a decision's outcome unfairly benefits one group while negatively impacting another, the process's legitimacy is undermined [23]. Under these conditions, the final decision may be a product of the influence of powerful or self-serving interests, rather than a neutral assessment of available choices. The impact of social, emotional, and cognitive biases on group decisions has drawn considerable scholarly attention in addition to structural factors. The most researched are probably cognitive biases, which are systematic departures from sound judgment. Confirmation bias, for instance, causes people to favor information that confirms their preconceived notions, which restricts critical thinking and receptivity to different viewpoints [8]. Even when the initial anchor is unimportant, anchoring bias causes an excessive dependence on the first pieces of information, which can distort later assessments [4]. Overconfidence bias causes people to overestimate their own knowledge or abilities, which frequently results in them dismissing opposing viewpoints and underestimating risks [10]. Availability bias can lead group members to overemphasize emotionally salient or easily remembered information, even when it does not accurately reflect the broader context [24]. Group DM is made even more difficult by social and emotional factors. For example, mood states can influence how people interpret information and form opinions. Negative moods promote more critical and analytical thinking, while positive moods may encourage more intuitive and hopeful DM [5]. Social factors such as groupthink – the propensity to value consensus over critical analysis – can stifle divergent viewpoints and strengthen prevailing narratives within the group [2, 25]. This not only increases the risk of poor decisions but also narrows the range of options considered. Furthermore, social loafing, a phenomenon in which people work less hard in groups than when working alone, can result in superficial analyses and decreased participation in the DM process [7]. Escalation of commitment is another significant social dynamic in which groups persist in funding an unsuccessful strategy because of past investments or a fear of acknowledging errors [7]. The accumulation of these biases has an impact on decisions' operational and ethical ramifications in addition to their quality. For example, discriminatory outcomes or the marginalization of minority voices can result from biased group judgments, particularly if stereotypes or prejudices are involved [13].

The process may serve vested interests rather than group objectives when powerful stakeholders have undue influence. Therefore, if some group members feel excluded or powerless during the process, even technically sound decisions may be poorly implemented [12]. This implies that the fairness and inclusivity of the process are just as significant as the outcome when evaluating the quality of a decision. Researchers have suggested a number of mitigation techniques to deal with these problems. Improving group DM starts with raising awareness and educating people about common biases. Training and workshops are crucial for helping group members recognize and mitigate their own cognitive biases [3]. To promote objectivity and thoroughness, structured DM methods such as scoring systems, decision matrices, and checklists have also been suggested. Groupthink and confirmation bias can be effectively countered by promoting dissent and diversity of opinion within the group. Broader participation and critical evaluation of ideas are made possible by tools such as brainstorming, the Delphi method, and nominal group techniques [26]. Additionally, bringing in outside experts can help the process become more objective. Consultants or external evaluators can provide objective assessments and challenge internal assumptions [27]. Technology is playing an increasingly significant role in reducing human bias, particularly through AI-based decision support systems. Large datasets can be objectively analyzed by these systems, which can also spot patterns that human judgment might miss. However, care must be taken because AI tools themselves may mirror the biases present in their training data [13, 28]. A more reflective and structured approach to team decision-making has also been recommended [11]. This entails intentional, planned conversations regarding group goals, DM procedures, and results. Teams can make more ethical and balanced decisions by using reflexivity to recognize possible biases, question assumptions, and alter their direction.

In summary, the literature highlights the dual nature of group DM: it offers the potential for superior outcomes through collaboration but also introduces a range of biases that can undermine both the process and the results. Therefore, a nuanced understanding of the psychological and social dynamics involved is essential for designing group DM processes that are effective, equitable, and credible. Raising awareness of biases and educating group members about their effects is crucial to reducing BJs [3]. A methodical framework for assessing information can be offered by structured DM procedures [2]. Groupthink and confirmation bias can be avoided by promoting dissenting viewpoints and a variety of perspectives [26]. The 1986 Challenger disaster serves as a reminder of how BJs within DM groups can result in disastrous outcomes [29]. NASA's leadership, influenced by confirmation bias, overconfidence, and groupthink, disregarded engineers' concerns about the O-rings' failure in low temperatures, prioritizing launch schedules over safety.

Team hierarchy significantly affects participation in DM processes, with lower-ranking members reporting limited opportunities to contribute. This structural dynamic, combined with pressures such as time constraints, can compromise the overall quality of group decisions [7]. Psychological biases also play a critical role in shaping risk assessment, particularly in investor decision contexts, where overconfidence, anchoring, and herd behavior have been identified as dominant influences [10]. Similarly, research in public policy settings highlights how groupthink and bounded rationality constrain critical evaluation, especially under leadership pressure and limited cognitive capacity [2]. Despite growing awareness of these distortions, effective mitigation mechanisms remain insufficiently developed. The need for targeted debiasing strategies, such as cognitive training and structured decision protocols, has therefore been emphasized [30]. Moreover, individual variability in susceptibility to bias suggests that uniform corrective approaches may not be universally effective [31]. The Delphi method has long been employed as a structured mechanism for consensus-building in complex decision environments characterized by expert subjectivity and uncertainty. Its core features – anonymity (or quasi-anonymity), iterative feedback, and controlled opinion revision – are specifically designed to mitigate extreme positions and reduce the impact of dominant stakeholders [32]. Related approaches, such as the Nominal Group Technique and hybrid consensus models, also aim to structure expert interaction rather than eliminate subjectivity. Within multi-criteria decision-making (MCDM) contexts, Delphi has frequently been integrated with AHP/ANP frameworks to improve the robustness and convergence of judgments [33].

1.2 Subjectivity and bias in AHP/ANP-based decision models and existing solutions in literature

AHP and ANP fundamentally rely on expert-driven pairwise comparisons. While this structure enables incorporation of domain expertise, it also introduces inherent subjectivity into the decision process. Numerous studies have acknowledged that pairwise judgments are susceptible to inconsistency, overconfidence, anchoring effects, and stakeholder-driven preference amplification [33]. In ANP models in particular, the feedback structure between clusters may further magnify preferential distortions when stakeholders hold vested interests in specific alternatives. Several methodological streams have emerged to address subjectivity and uncertainty in AHP/ANP-based models. One prominent approach involves Fuzzy AHP (FAHP) and Fuzzy ANP, where linguistic judgments are converted into fuzzy numbers to capture uncertainty and imprecision in expert evaluations. These models aim to represent vagueness rather than eliminate subjectivity [33]. Another stream integrates objective weighting techniques, such as entropy-based weighting, to counterbalance expert-driven inputs with data-driven measures. Hybrid frameworks combining ANP with Delphi, DM Trial and Evaluation Laboratory, or other structured consensus mechanisms have also been proposed to enhance convergence and reduce extreme dispersion in judgments [34]. Beyond MCDM, bias mitigation has been widely studied in fields such as behavioral economics, organizational DM, and artificial intelligence. Approaches include algorithmic debiasing, structured analytic techniques, and adversarial review mechanisms. Consensus-based moderation is one type of intervention within these broader mitigation strategies, emphasizing structured interaction and iterative reflection rather than algorithmic correction.

1.3 A theoretical model of bias reduction in stakeholder-based ANP

While previous studies have documented subjectivity, inconsistency, and preferential distortions in AHP/ANP-based evaluations, the mechanisms by which structured consensus processes may attenuate such distortions remain under-theorized. To clarify the expected effect of the Delphi-based iterative consensus process used in this study, we conceptualize bias reduction as operating through three interrelated mechanisms. First, stakeholder-aligned evaluations in resource allocation contexts may reflect incentive-amplified preference expression. When evaluators are directly connected to the alternatives under consideration, judgments may exhibit preferential intensification rather than neutral comparative assessment [17]. Such divergence can be motivational, strategic, or cognitively reinforced [17]. Second, structured feedback mechanisms such as controlled aggregation via geometric means, anonymous comparison of group responses, and iterative revision opportunities introduce reflective correction pressures [17]. Exposure to the distribution of peer evaluations can induce recalibration through informational updating rather than forced conformity. Third, iterative consensus frameworks reduce variance not by eliminating heterogeneity, but by moderating extreme positional divergence [31]. In this sense, bias mitigation should theoretically manifest as a reduction in effect size (magnitude of divergence), rather than complete disappearance of intergroup differences. Under this model, the Delphi-based Iterative Consensus-Building Process (ICBP) does not replace stakeholder input, nor does it assume purely cognitive error. Instead, it operationalizes structured reflection and controlled feedback to attenuate incentive-aligned preferential amplification within ANP-based group DM contexts. This theoretical framing provides an a priori justification for expecting moderated divergence following iterative consensus refinement.

1.4 From Delphi to a structured consensus-building process: a review of expert judgment methods

In many fields, from public health to business strategy, Consensus-Building Processes (CBPs) are a critical approach for resolving disputes and making informed decisions. By bringing stakeholders together to find mutually agreeable solutions, CBPs aim to mitigate the influence of prevailing voices and hierarchical power [32, 34]. A prime example of this is the Delphi method, which, through its use of anonymity, enhances openness and impartiality, thereby improving accuracy via statistical aggregation and dynamic correction mechanisms [35]. The Delphi method's strengths, such as its ability to combine qualitative and quantitative data [36], manage multiple criteria [33], and facilitate cooperation in remote or controversial settings [37], have made it a valuable tool in diverse applications, including supply chains [38], robotics [33], and academic medicine [39, 40], among others. Despite these advantages, conventional Delphi and similar methods primarily focus on achieving consensus, often without a specific mechanism to address the cognitive biases that can distort expert judgments. Biases originating from personal interests and stakeholder self-interest remain a significant challenge, especially in complex DM scenarios such as energy planning [41] and other professional domains where empirical validation is limited [42]. While CBPs aim to lower biases and improve strategic alignment by encouraging open, organized, and evidence-based decisions [43], they often lack a robust, structured framework to actively identify and correct these distortions.

In high-stakes public resource allocation contexts, the boundary between unconscious cognitive bias and strategic preference expression becomes blurred. When decision outcomes carry tangible regional consequences, stakeholders may systematically express preferences aligned with their institutional interests. Rather than isolating purely psychological bias, this study investigates the empirical manifestation of preferential distortion within an ANP-based group DM framework under real incentive conditions. Unlike fuzzy or entropy-based methods that mathematically model uncertainty, this study focuses on the behavioral dimension of preferential amplification under real-world incentive conditions. Specifically, it empirically examines how a structured Delphi-based iterative refinement process interacts with stakeholder-driven distortions within an operational ANP model. Therefore, this study contributes to the behavioral and governance dimension of subjectivity management in MCDM, rather than proposing a new mathematical uncertainty framework.

This paper addresses this gap by introducing an ICBP designed to systematically mitigate the influence of BJs. Through an empirical case study, we investigate whether the ICBP can effectively reduce the distortion in group DM outcomes caused by stakeholder self-interests. The study evaluates the ICBP's effectiveness in promoting more balanced and reliable judgments, particularly by examining how expert selection and preference weighting affect outcomes and whether aggregating individual opinions using geometric means leads to greater reliability. The consensus mechanism employed in this study is best understood as a structured, Delphi-based iterative refinement process tailored to the requirements of ANP pairwise comparisons. Rather than proposing a fundamentally new method, this study adapts established Delphi principles – iterative feedback, aggregation of judgments, and controlled revision – to the specific context of ANP-based provincial resource prioritization. By exploring these dynamics, our research aims to answer two key questions:

Do incentive-aligned preferential judgments distort group DM outcomes under high-stakes conditions?

Can a structured Delphi-based consensus refinement process moderate such preferential amplification?

2. Material and methods

The question of this study was whether incorporating the ICBP into the ANP method could be effective in modifying existing BJs. To answer this question, a research framework was designed. In the first phase, the priorities of the value chains for development were identified using the ANP method. In the second phase, by integrating the ICBP into the ANP method, the priorities were re-identified. Finally, the differences in the priorities of the criteria in the two phases were analyzed using the Kruskal-Wallis test.

2.1 Case study

To examine the effect of the ICBP on reducing BJs, it was necessary to design a group decision model in which the probability of BJs was high. For this purpose, in coordination with the Iranian Ministry of Industry, Mine, and Trade, a group decision model was developed using the ANP method to prioritize the development of wood value chains in Iran. More importantly, it was planned that the desired budget would be allocated to the alternative provinces based on the results of this research project. The Iranian Ministry of Industry, Mine, and Trade is carrying out development programs in various provinces across the country to identify value chains with different business trends and to develop plans for some of them. These plans aim to enable individuals or wood firms to join cooperative groups and share resources to reduce environmental risks [44]. Seven key hubs of the wood value chains in seven provinces were considered. Since the Ministry of Industry, Mine, and Trade was unable to perform all development projects, the experts were commissioned to determine the value chains' priorities. The priorities were given to three suitable value chains to be developed in the first four years, and the rest were scheduled for the following years. The results of this prioritization were important for stakeholders because the budget should be identified and allocated according to the study results. According to Ministry regulations, some members of the DM panel were VCDAs in every province. These individuals are responsible for making policy decisions and implementing changes within their provinces. One team works on each value chain, and team members are selected by the Iranian Ministry of Industry, Mine, and Trade. These teams are authorized to develop strategies for the growth period of their respective value chains. Given that the judgments of certain members of the DM panel could directly influence budget allocation priorities, the study examined whether traces of BJs were observable in this decision context. Furthermore, the research investigated whether any identified preferential distortions could be moderated through the structured consensus refinement process. VCDAs play a central role in planning and implementing development initiatives to strengthen and upgrade the value chain.

The most crucial feature is facilitating participation among the different partners throughout the entire value chain: enterprises, business services, private associations, non-governmental organizations, and local government. This project should be carried out in a staged and organized manner by different groups of experts. The VCDAs encourage and advance the execution of these policies by uniting the fitting partners and helping them to create shared goals. Mediating among value chain participants and building up linkages between the value chain and external partners is vital. The wood value chain under study consisted of six main primary activities and six supportive activities, which were identified across the value chain. All seven hubs of the wood value chains (Tehran, Qom, Guilan, Mazandaran, Hamedan, Khorasan, and East Azerbaijan) analyzed in this study had the sections shown in the model. Figure 1 illustrates the structural configuration of the studied wood value chains, distinguishing between primary value-adding activities and supporting institutional and infrastructural components. The upper section represents the sequential operational stages from forestry and raw material processing to final consumption and market distribution. The lower section identifies supporting actors and institutional entities, including governmental bodies, industry associations, and development agents, that influence value chain performance. Arrows indicate directional interactions and flow of value, while duplicated transport nodes highlight logistical interdependencies across stages. The figure provides the structural foundation upon which the subsequent ANP network model is constructed.

In this study, the ANP was used to prioritize alternatives. Analysis of judgments was performed using SuperDecisions software. ANP was selected because of the interactions and dependencies in the DM model. A DM model was developed to determine the priorities of wood value chains; this decision was once made using members of DM panel without their VCDAs, and again using only their VCDAs' judgments. Finally, pairwise comparison judgments were aggregated separately for each subgroup using the geometric mean, consistent with standard ANP procedures. The resulting priority weights and rankings were then compared to evaluate the magnitude of divergence between VCDA and non-VCDA evaluations. Figure 2 presents a streamlined overview of the research design structured into three macro-level stages: (1) baseline ANP evaluation, (2) Delphi-based iterative consensus refinement, and (3) post-refinement divergence assessment. The figure intentionally summarizes the logical structure of the study, while operational details such as geometric aggregation and the two revision iterations are described in the accompanying text to avoid redundancy. The study followed a three-stage operational structure corresponding to Figure 2. In Stage 1, participants completed independent pairwise comparisons, which were aggregated using the geometric mean. In Stage 2, aggregated results were fed back anonymously to panel members, followed by two structured revision iterations. In Stage 3, recalculated weights were compared between VCDA and non-VCDA subgroups, and divergence magnitude was assessed using nonparametric testing and effect size estimation.

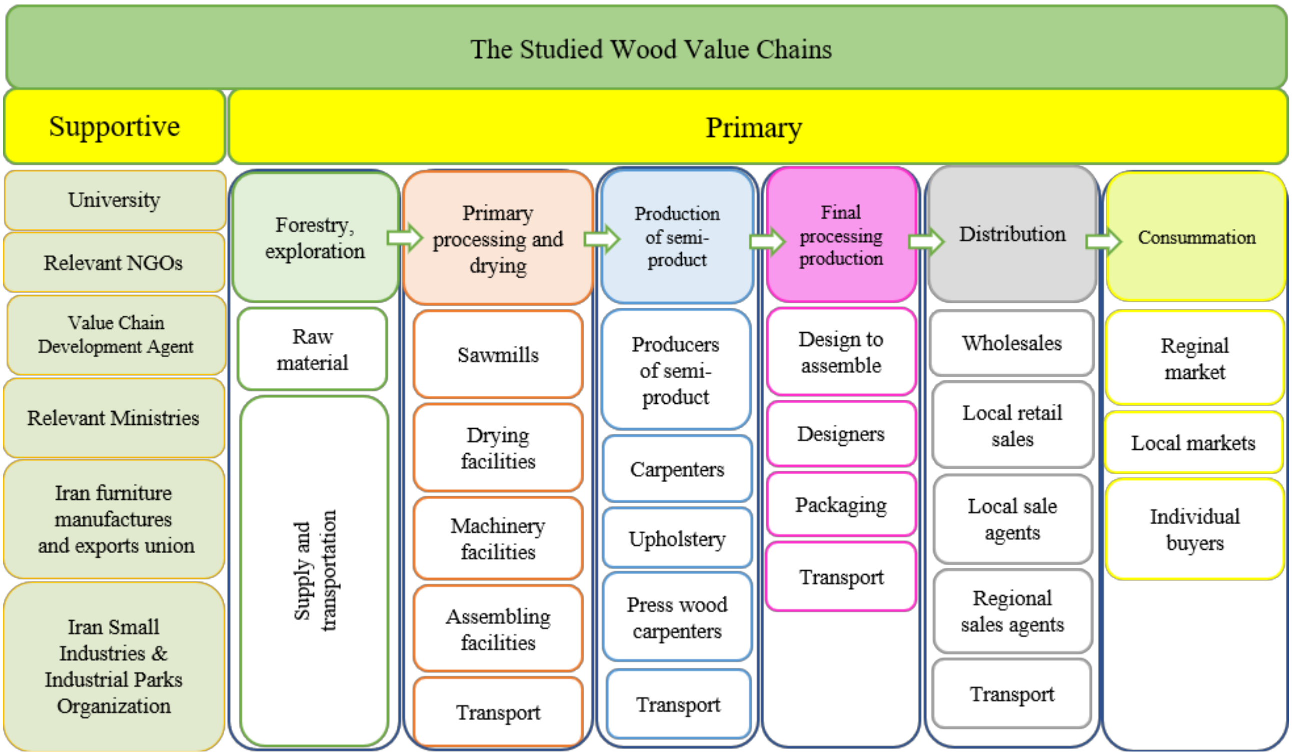

Figure 1. A model of the studied wood value chains

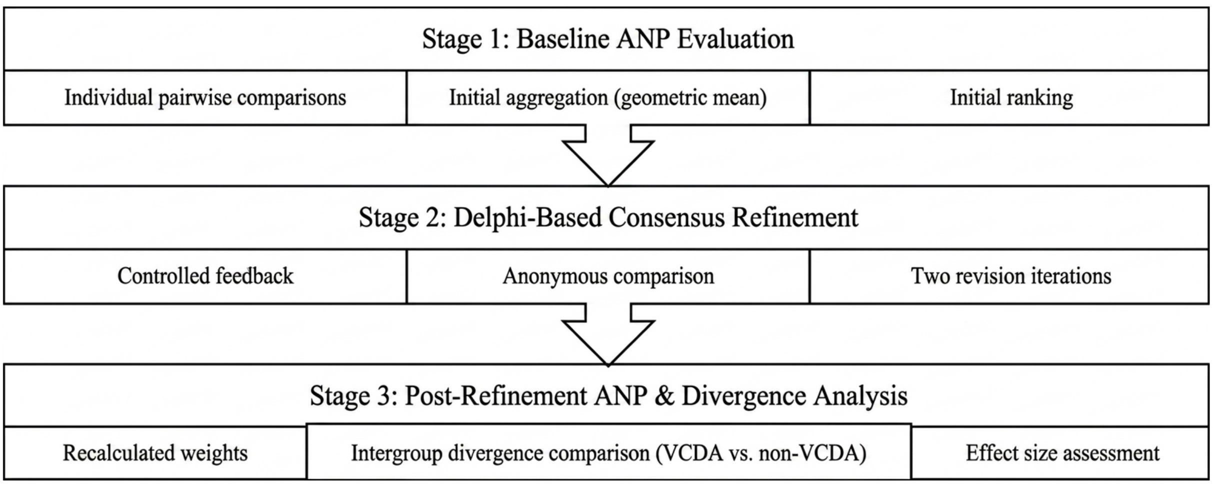

Figure 2. Integrated ANP–Delphi bias moderation framework

Initially, in the ANP phase, the criteria and sub-criteria were identified using a library study and the first questionnaire, which was designed as an open-ended questionnaire. Then, the decision model was developed. With the help of panel members, the criteria and sub-criteria were evaluated using the second questionnaire reflecting pairwise comparisons. Using the pairwise comparison questionnaire, the priorities of the alternatives were identified. By grouping the decision panel, the results of each VCDA team and the prioritization of the remaining panel members were compared. Afterward, in the ICBP phase, the results of the group DM were presented to the panel members, and they were asked to reconsider their judgments according to the collective perception or wisdom. A Kruskal-Wallis test using SPSS was employed to determine whether there was a statistically significant difference between the results obtained from incorporating the ICBP model and those obtained without it.

2.2 Selection of the criteria

To operationalize the study objectives, we systematically identified the criteria influencing value-chain development and the prioritization of research alternatives. We first conducted a structured review of academic literature, policy reports, and sectoral documents to extract relevant sub-criteria. After screening and consolidating overlapping elements, we organized the finalized sub-criteria under five primary dimensions: Market, Raw Material, Human Resources, Information and Knowledge, and Environmental Advantages. Table 1 presents the structured hierarchy of criteria and sub-criteria used in the ANP model. This table was distributed as an open questionnaire to all members of the DM panel (58 people). First, the purpose of the research was explained to the members of the decision panel. Then, they were asked to add more sub-criteria to this table if necessary. After removing overlapping sub-criteria that had been suggested multiple times, a complete table of all the proposed sub-criteria was prepared. The questionnaires were completed during face-to-face sessions. In the questionnaire prepared to determine the sub-criteria (the first questionnaire), the members of the DM panel were also asked about the dependent criteria.

Table 1. List of criteria and sub-criteria used in this research

Criteria	Code	Sub-criteria
Market	M1	Distribution channels
	M2	Market share
	M3	Marketing system
	M4	Market in Province
	M5	Market in neighbor countries
Raw material	R1	Variety of wood raw material
	R2	Variety of non-wood raw materials
	R3	Wood raw material prices
	R4	Non-wood raw material prices
Human resources	H1	Experienced human resources
	H2	Specialist human resources
Information and knowledge	I1	Innovation
	I2	Knowledge exchange
	I3	Research & Development
	I4	Efficiency
	I5	Flexibility
	I6	Technology development

	E1	Comparative advantage
	E2	Export facilities
Environmental advantages	E3	Financial resources
	E4	Government support
	E5	Existence of large factories

2.3 Model development

The researchers developed an ANP model using inputs from all members of the DM panel. The network model was represented in three steps: identifying criteria, grouping them into clusters, and determining interdependencies. Criteria were prioritized based on supermatrix analysis. Six components or clusters were established. With input from DM panel members and as shown in Figure 3, the influence of each model component on the others was determined, and alternatives for the case study were proposed. Figure 3 illustrates the ANP network structure developed for this study. We organized the decision problem into interconnected clusters representing the major dimensions: Market, Raw Material, Human Resources, Information and Knowledge, Environmental Advantages, and Alternatives. The directed arrows show the interdependencies and feedback relationships among clusters. Unlike a strictly hierarchical AHP structure, this configuration allows bidirectional influence between criteria, enabling the model to capture structural complexity and mutual reinforcement effects within the decision environment. The Alternatives cluster receives weighted influences from all criteria clusters, consistent with the supermatrix formulation underlying the ANP computational process.

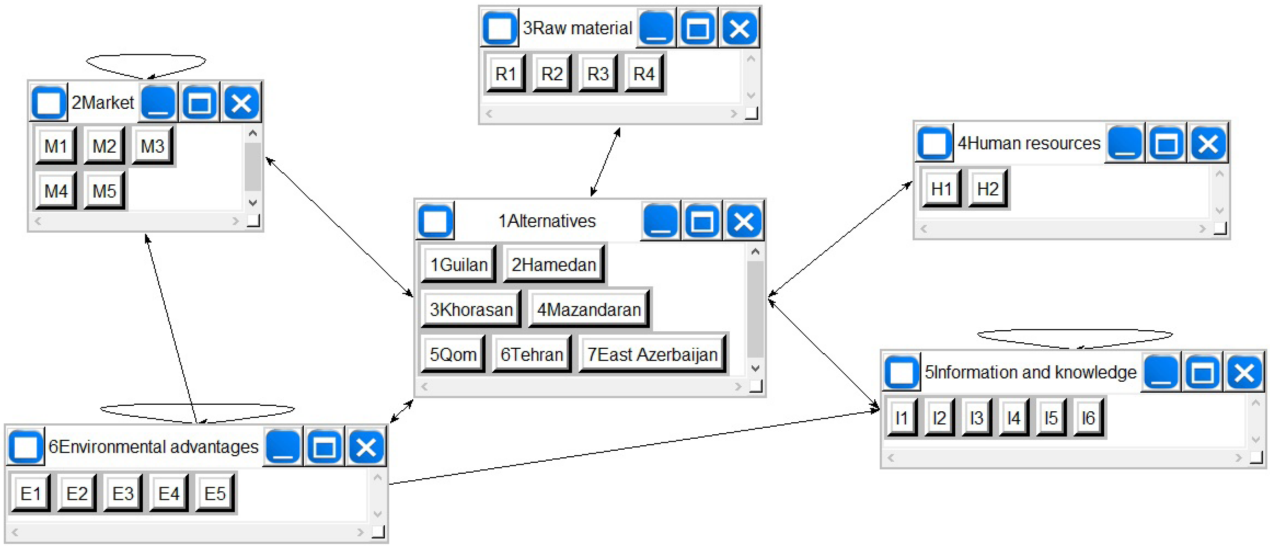

Figure 3. Diagram of the ANP model

2.4 DM panel

We employed purposive sampling to assemble a DM panel with substantial expertise in Iran's wood value-chain system. The panel comprised policymakers, academic experts, industry managers, and regional development authorities to ensure institutional and technical diversity in a high-stakes allocation context (Table 2). All participants possessed extensive professional experience relevant to value-chain development and contributed to validating and prioritizing criteria, sub-criteria, and alternatives. Data were collected through structured face-to-face interviews conducted by a member of the research team. The full panel participated in both baseline and post-refinement prioritization rounds. To examine stakeholder-aligned divergence, we compared the aggregated judgments of directly affected VCDA teams with those of the remaining panel members across all seven value-chain hubs. Given the heterogeneous expertise of participants, we applied geometric mean aggregation within groups, consistent with

ANP group decision procedures, to preserve proportional influence and prevent dominance by individual experts. This design enabled structural observation of divergence patterns without assigning subjective differential weights to panel members.

Table 2. List of DM panel members

Row	Position	Members	Age		Education	
			Min	Max	Min	Max
1	VCDA team of Tehran	5	35	49	BS	MS
2	VCDA team of Mazandaran	5	33	51	BS	MS
3	VCDA team of Hamedan	5	32	52	BS	MS
4	VCDA team of Khorasan	5	37	55	BS	MS
5	VCDA team of Guilan	5	29	53	BS	MS
6	VCDA team of East Azerbaijan	5	31	61	BS	MS
7	VCDA team of Qom	5	34	60	BS	MS
8	Directors of industrial value chain development in Iran Small Industries & Industrial Parks Organization	6	33	55	BS	PhD
9	University teacher with much experience in wood industry	11	37	58	BS	PhD
10	Board Members of Iran furniture manufactures and exports union	6	36	62	BS	MS
	Total:	58				

BS: Bachelor of Science; MS: Master of Science; PhD: Doctor of Philosophy.

2.5 Experiment report

Experts were deliberately selected to ensure adequate knowledge and professional experience for participation in the DM process. The list of seven provincial value-chain development agents, representing the seven hubs of the wood value chains, was obtained from the Iranian Ministry of Industry, Mine, and Trade. From each province, five experienced development agents participated (n = 5 per value chain). Due to logistical constraints, data were collected through structured individual interviews conducted by a single member of the research team to ensure procedural consistency. At the beginning of each session, the research objectives were clearly explained, and participants independently completed the pairwise comparison questionnaires required for the ANP model. The study followed a within-subject experimental design in which all panel members participated in two decision conditions: (1) an initial independent evaluation stage, and (2) a structured iterative consensus-refinement stage incorporating controlled feedback. In each province, the aggregated preferences of the development-agent subgroup were compared with those of the remaining panel members. This comparison was conducted in both stages to evaluate stakeholder-driven divergence and its potential moderation through structured iteration. The dependent variable was defined as the difference in alternative rankings between stakeholder and non-stakeholder groups across the two experimental stages.

2.6 Study context and incentive structure

Participants were informed that the prioritization results could inform future provincial budget allocation decisions. This created a high-stakes decision environment in which regional actors were aware of potential practical consequences. Such contextual conditions may activate strategic preference expression in addition to, or instead of, unconscious cognitive biases. The present study intentionally examines decision behavior under these real-world incentive conditions rather than in a laboratory-neutral setting. Therefore, findings should be interpreted within the context of stakeholder-incentivized group DM environments.

2.7 ANP

As illustrated in Figure 4, we implemented the ANP model through a structured four-step analytical sequence. In Step 1, we defined the decision problem and decomposed it into an interconnected network of clusters and elements. In Step 2, we conducted pairwise comparisons within and across clusters to evaluate relative importance and interdependencies, using Saaty's fundamental scale to derive local priority vectors (eigenvectors). In Step 3, we assembled these local priorities into a partitioned supermatrix that captures the influence relationships among clusters. In Step 4, we normalized and iterated the supermatrix to obtain the limit supermatrix, from which we derived the final global priority weights of criteria and alternatives. This sequence clarifies the computational logic of the ANP implementation and visually represents the procedural flow of the model.

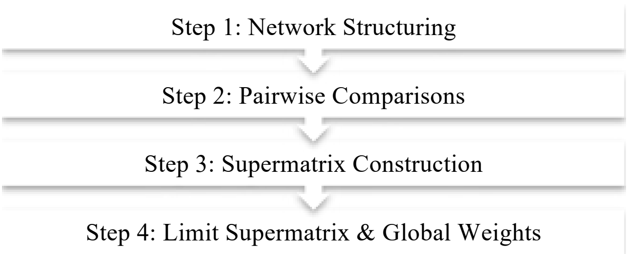

Figure 4. Steps to perform ANP method

The relative weights in ANP depend on the pairwise comparison of components at each level. These pairwise comparisons are based on their relative significance with respect to their control criteria, following the standard of AHP and measured using Saaty's 1-9 scale [45]. The score of a_{ij} in the pairwise matrix represents the relative priority of the component in row (i) over the component in row (j), i.e., aij = wi/wj. As for any criterion, pairwise comparisons are performed at two levels: the component and the cluster. If n components must be compared, the matrix is defined as follows:

$$A = \begin{bmatrix} \frac{W_1}{W_1} & \frac{W_1}{W_2} & \frac{W_1}{W_n} \\ \frac{W_2}{W_1} & \frac{W_2}{W_2} & \frac{W_2}{W_n} \\ \frac{W_n}{W_1} & \frac{W_n}{W_2} & \frac{W_n}{W_n} \end{bmatrix} = \begin{bmatrix} 1 & a_{12} & a_{1n} \\ a_{21} & 1 & a_{2n} \\ a_{n1} & a_{n2} & 1 \end{bmatrix} \tag{1}$$

After pairwise comparison, it is necessary to weight the vector (w) with $A_w = \lambda_{max}$w.

If λ_{max} is the largest eigenvalue of matrix A and w are the eigenvectors.

Inconsistency is also calculated as follows:

$$\mathrm{CI} = \frac{\lambda_{\max} - n}{n-1} \tag{2}$$

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RCI}} \tag{3}$$

If the CI was under 0.1, the judgment was considered reliable. When the inconsistency in the individual matrices was greater than 0.1, the decision panel members were asked to reconsider their judgments. At the last step, each matrix was normalized and the relative weights were determined. The relative weights are given by the right eigenvector (w) corresponding to the largest eigenvalue (λ_{max}), as:

$$A_w = \lambda_{\max} \cdot \mathrm{w} \tag{4}$$

To conduct the sensitivity analysis, the weights of the criteria were systematically varied, and the first resulting shift in the ranking of the alternatives was identified and reported. For this purpose, the judgments of all members of the decision panel were considered under two modes (with and without ICBP). The most critical criterion was defined as the one for which the smallest deviation from its current weight caused a change in the ranking of the alternatives. This procedure enabled a comparative evaluation of ranking stability across both modes and provided deeper insight into the robustness of the final prioritization results.

2.8 Delphi-based iterative consensus refinement process

The consensus refinement mechanism applied in this study follows the core principles of the Delphi method: structured iteration, controlled feedback, and opportunities for judgment revision. In each round, participants first provided independent pairwise comparisons. These individual judgments were then aggregated using the geometric mean and anonymously fed back to participants. In the next round, respondents were invited to reconsider and, if deemed appropriate, revise their evaluations in light of the summarized group response. Two iterative rounds were conducted to facilitate convergence while preserving independent judgment. The use of the geometric mean aligns with established ANP/AHP group DM procedures. Because ANP judgments are expressed on a ratio scale, aggregation must preserve multiplicative reciprocity within pairwise comparison matrices and maintain proportional relationships among preference intensities. The geometric mean satisfies these mathematical requirements, whereas arithmetic aggregation would distort relative intensities and potentially compromise consistency in the derived priority vectors. Beyond mathematical appropriateness, geometric aggregation provides methodological advantages in this research context. By moderating the influence of extreme evaluations while retaining proportional sensitivity to preference differences, it reduces the risk that isolated high-intensity judgments disproportionately affect the supermatrix structure. This feature is particularly important in subgroup comparisons between development agents and non-stakeholders, where preferential amplification may occur. Accordingly, the aggregation approach supports both Delphi-based consensus refinement and the study's objective of examining stakeholder-driven divergence under controlled iterative conditions.

Operationally, the procedure was carried out in three sequential stages. First, all panel members independently completed the ANP pairwise comparison matrices without exposure to other participants' evaluations, establishing a baseline of uninfluenced judgments. Second, individual responses were aggregated using the geometric mean, and the resulting group-level matrices were anonymously distributed as controlled feedback. Third, participants were invited to reassess and, if deemed appropriate, revise their evaluations in light of the summarized group response. This feedback–revision cycle was conducted twice. Thus, the overall process consisted of one initial independent evaluation stage followed by two structured refinement iterations. No face-to-face deliberation occurred at any point; all revisions were performed individually after controlled feedback, ensuring procedural consistency with Delphi principles. Figure 5 illustrates the structured iterative consensus refinement mechanism. The process begins with an initial independent judgment stage, followed by two feedback-revision cycles. In each iteration, subgroup judgments are aggregated using the geometric mean and redistributed anonymously to participants. The circular structure of the figure emphasizes iterative recalibration rather than linear convergence. The "two rounds" label refers specifically to the two controlled feedback loops conducted after the baseline evaluation.

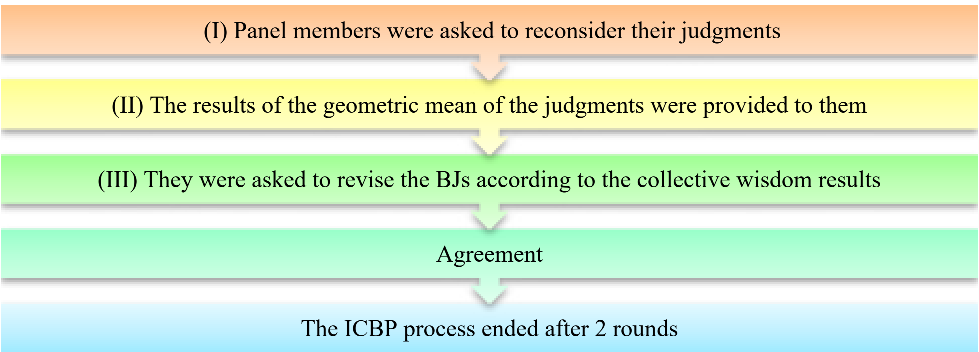

Figure 5. ICBP process

Note: "Two Rounds" refers to two feedback–revision iterations conducted after the initial independent judgment stage.

2.9 Conceptual positioning of the Delphi-based iterative consensus process

The consensus mechanism employed in this study should not be interpreted as a replacement for the classical Delphi method. Rather, it represents a structured operational configuration tailored for integration within an ANP-based resource allocation model. The distinctive feature of this configuration lies in its explicit embedding within a measurable multi-criteria weighting system, where iterative feedback is intended not only to achieve opinion convergence but also to monitor and moderate incentive-aligned preferential amplification. Unlike traditional Delphi applications that primarily seek convergence of expert judgments, the present framework evaluates how feedback iterations alter the structural distribution of weights across stakeholder-aligned alternatives. Thus, the contribution is not superiority over Delphi, but the integration of consensus refinement into a quantifiable ANP architecture capable of empirically observing moderation effects.

2.10 Questionnaire development

Questionnaires included (A) criteria and sub-criteria selection questionnaires, (B) criteria and sub-criteria prioritization questionnaires, and (C) an alternatives prioritization questionnaire. The first questionnaire was open-ended and included a list of criteria and sub-criteria. Questionnaires (B) and (C) were developed to include:

• Definition of relationships among elements and clusters

• Prioritization with influences among elements and clusters

A part of the questionnaire designed for pairwise comparisons is shown in Table 3. Participants were asked to compare the following elements of the market cluster according to their influence on A_1 of the alternatives cluster. Table 3 provides a sample excerpt from the pairwise comparison questionnaire used in the ANP evaluation. Participants compared two criteria relative to their influence on a specified alternative. Responses were recorded using Saaty's 1–9 scale, where qualitative verbal anchors correspond to quantitative intensity values. The structure ensures consistent elicitation of comparative judgments across all clusters.

Table 3. A part of the questionnaire used for comparison of alternatives

A: M_1 **B: M_2**									
Which is more important or has more influence?			○ A			○ B			
How much more?	☐ Equal	☐ Equal to moderate	☐ Moderate	☐ Moderate to strong	☐ Strong	☐ Strong to very strong	☐ Very strong	☐ Very strong to extreme	☐ Extreme

A Kruskal-Wallis test in SPSS was used to determine whether there is a statistically significant difference between the with and without ICBP modes. Given the ordinal nature of the ranking data and the unequal group sizes (VCDAs: $n = 5$; remaining members: $n = 53$), the Kruskal–Wallis test was employed to compare group differences. In addition to p-values, effect sizes were calculated using eta-squared (η^2), derived from the H statistic of the Kruskal–Wallis test:

$$\eta^2 = (H - k + 1)/(N - k) \tag{5}$$

Where H represents the Kruskal–Wallis statistic, k is the number of groups, and N is the total sample size. Reporting effect sizes allows interpretation of the magnitude of differences independent of statistical significance, which is particularly important given the small size of the VCDA subgroup ($n = 5$).

2.11 Ethical considerations

This study was conducted in coordination with the Iranian Ministry of Industry, Mine, and Trade as part of an officially sanctioned decision-support initiative. The research involved structured expert elicitation within participants' professional roles and did not include clinical human subjects, vulnerable populations, animal experimentation, medical or psychological intervention, or the collection of personally identifiable or sensitive data. Participation was fully voluntary. All participants were informed of the purpose and scope of the study before providing their judgments, and informed consent was obtained through voluntary completion of the structured evaluation process. Responses were recorded anonymously and analyzed only in aggregate to ensure that no individual participant could be identified. According to applicable institutional and national research ethics guidelines governing policy-oriented expert consultation studies, this type of minimal-risk research is exempt from formal Institutional Review Board approval. The exemption is based on the absence of identifiable personal data and the non-interventional nature of the study. Nevertheless, the research adhered strictly to recognized ethical principles, including voluntary participation, informed consent, confidentiality, and responsible data management throughout the research process. A preliminary version of this work was presented at a conference [46], where the consensus mechanism was described as a Delphi technique. The present manuscript substantially extends that earlier work through expanded empirical analysis, additional statistical evaluation (including effect size analysis), and deeper theoretical integration.

3. Results

3.1 Weights of criteria and sub-criteria

The results are presented in three stages: (1) baseline ANP model outputs, (2) stakeholder versus non-stakeholder comparisons, and (3) divergence moderation following the Delphi-based refinement process. The criteria weighting showed that Market and Raw materials, with weights of 0.348 and 0.273, respectively, had the highest weights. Following these, Human resources, Information and knowledge, and Environmental advantages, with weights of 0.141, 0.124, and 0.104, respectively, were next in priority. For the sub-criteria, Market in Province (M4), Market share (M2), and Distribution channels (M1) ranked first to third, with weights of 0.123, 0.107, and 0.092, respectively (Table 4).

3.2 The cluster and node interactions

The effect of each cluster on the other is shown in Table 5. Interpreting the priorities in the first column, Market (0.384) and Raw material (0.273) have the most impact on Alternatives.

Table 4. Weights of criteria and sub-criteria

Goal	Criteria	Global weight	Code	Sub-criteria	Global weight
Goal	Market	0.348	M1	Distribution channels	0.0925
			M2	Market share	0.1079
			M3	Marketing system	0.0771
			M4	Market in Province	0.1233
			M5	Market in neighbor countries	0.0463
	Raw material	0.273	R1	Variety of wood raw material	0.0485
			R2	Variety of non-wood raw materials	0.0363
			R3	Wood raw material prices	0.0848
			R4	Non-wood raw material prices	0.0485
	Human resources	0.149	H1	Experienced human resources	0.0264
			H2	Specialist human resources	0.0463
	Information and knowledge	0.124	I1	Innovation	0.0275
			I2	Knowledge exchange	0.0220
			I3	Research & Development	0.0259
			I4	Efficiency	0.0242
			I5	Flexibility	0.0171
			I6	Technology development	0.0281
	Environmental advantages	0.104	E1	Comparative advantage	0.0282
			E2	Export facilities	0.0194
			E3	Financial resources	0.0259
			E4	Government support	0.0241
			E5	Existence of large factories	0.0199

Table 5. The cluster matrix

	Alternatives	Market	Raw material	Human resources	Environmental advantages	Information and knowledge
Alternatives	0.000	0.451	1.000	1.000	0.621	0.401
Market	0.384	0.549	0.000	0.000	0.000	0.235
Raw material	0.273	0.000	0.000	0.000	0.000	0.000
Human resources	0.129	0.000	0.000	0.000	0.000	0.000
Environmental advantages	0.111	0.000	0.000	0.000	0.379	0.159
Information and knowledge	0.103	0.000	0.000	0.000	0.000	0.205

Table 6 shows the sub-criteria influence matrix. As shown, node interactions are present. For example, there are node interactions from M1, I1, E2, E2, and E3 to M3, I2, M5, E1, and I6, respectively. Cells with the number 1 indicate interdependent elements, while cells with the number 0 indicate their absence. Tables 4–6 establish the structural baseline of the ANP model prior to consensus refinement. These results confirm that the network relationships and derived weights produce a coherent initial prioritization structure. Importantly, this baseline serves as the reference point against which subsequent divergence moderation effects are evaluated. Without this structural stability, post-refinement comparisons would lack interpretive validity.

Table 6. Influence matrix

	A1	A2	A3	A4	A5	A6	A7	M1	M2	M3	M4	M5	R1	R2	R3	R4	H1	H2	I1	I2	I3	I4	I5	I6	E1	E2	E3	E4	E5
A1	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
A2	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
A3	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
A4	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
A5	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
A6	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
A7	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
M1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M2	1	1	1	1	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M3	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M4	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M5	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
R1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
R2	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
R3	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
R4	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
H1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
H2	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
I1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
I2	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
I3	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
I4	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
I5	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
I6	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
E1	1	1	1	1	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
E2	1	1	1	1	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
E3	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
E4	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
E5	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

3.3 ANP without ICBP

In all cases, the priorities obtained from overall judgments (n=53) without the relevant VCDAs and without the ICBP showed that Tehran was the top priority. After Tehran, Qom, Guilan, Mazandaran, Hamedan, Khorasan, and East Azerbaijan were preferred, respectively. Comparison of the overall and Tehran VCDAs' results showed that the order of value chain priorities was exactly the same. Figure 6 displays subgroup-specific priority weights in the baseline (without ICBP) condition. The vertical axis represents normalized ANP weights assigned to each provincial value chain, while the horizontal axis distinguishes between stakeholder and non-stakeholder groups. Divergence between bars indicates preferential amplification in stakeholder evaluations. The figure visually demonstrates that VCDAs consistently assign relatively higher weights to their own provinces compared to the aggregated non-VCDA panel.

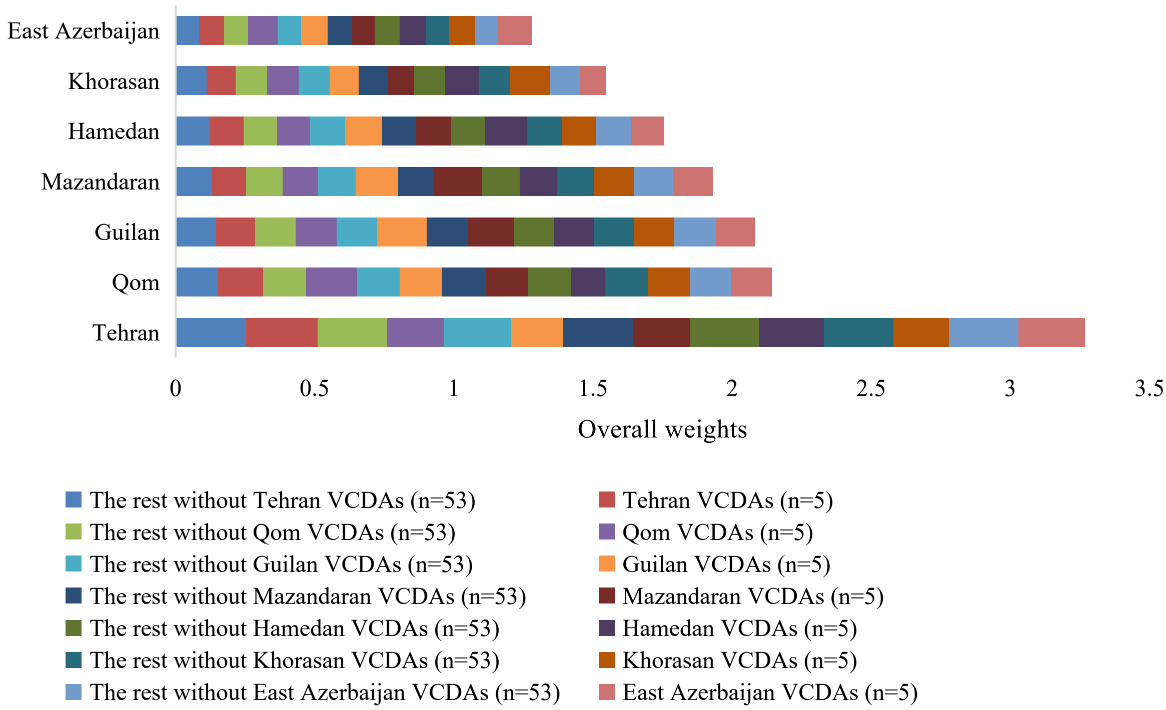

Figure 6. Comparison of the weights (without ICBP)

As shown in Table 7, value chain weights are different for each DM group. In all cases, VCDAs were considered a higher weight than the rest of the panel (n=53) for their value chains. Tehran VCDAs assigned the highest weight to the Tehran value chain. The Qom VCDAs gave the most weight to the Qom value chain after Tehran, and in their opinion, the Qom value chain was in the second place. After Tehran, Guilan VCDAs gave the highest weight to the Guilan value chain. Mazandaran VCDAs also considered the second rank for the Mazandaran value chain, and after Tehran, they assigned the highest weight to the Mazandaran value chain. Hamedan VCDAs also considered the second rank for the Hamedan value chain, and after Tehran, they assigned the highest weight to the Hamedan value chain. According to the rest of the panel without Khorasan VCDAs, the Khorasan value chain was ranked sixth by weight 0.113, while according to the Khorasan VCDAs, this value chain was ranked fourth by weight 0.144. According to the East Azerbaijan VCDAs, the Azerbaijan value chain was ranked fifth by weight 0.122 while, according to the rest cases, ranked seventh (Table 7).

3.4 ANP with ICBP

Tehran ranked first, followed by Qom, Guilan, Mazandaran, Hamedan, Khorasan, and East Azerbaijan as second through seventh, respectively. Although some differences in value chain rankings remained, these differences were smaller than those observed without using the ICBP. Figure 7 presents subgroup priority weights following the Delphi-based consensus refinement process. Compared to Figure 6, the dispersion between stakeholder and non-stakeholder evaluations is visibly reduced. While the rank order remains largely stable, weight intensities converge toward more proportionate distributions. The figure supports the interpretation that structured feedback moderates preferential amplification without eliminating heterogeneity.

Table 7. Weights and ranks (without ICBP)

	Tehran	**Qom**	**Guilan**	**Mazandaran**	**Hamedan**	**Khorasan**	**East Azerbaijan**
The rest without Tehran VCDAs (n=53)	0.252	0.151	0.145	0.132	0.124	0.111	0.085
Ranks	1	2	3	4	5	6	7
Tehran VCDAs (n=5)	**0.26**	0.164	0.14	0.122	0.12	0.105	0.089
Ranks	**1***	2	3	4	5	6	7
The rest without Qom VCDAs (n=53)	0.248	0.154	0.147	0.13	0.121	0.113	0.087
Ranks	1	2	3	4	5	6	7
Qom VCDAs (n=5)	0.203	**0.184**	0.146	0.129	0.119	0.114	0.105
Ranks	1	**2***	3	4	5	6	7
The rest without Guilan VCDAs (n=53)	0.244	0.152	0.147	0.134	0.126	0.111	0.086
Ranks	1	2	3	4	5	6	7
Guilan VCDAs (n=5)	0.186	0.154	**0.177**	0.152	0.133	0.104	0.094
Ranks	1	3	**2***	4	5	6	7
The rest without Mazandaran VCDAs (n=53)	0.251	0.155	0.149	0.131	0.122	0.104	0.088
Ranks	1	2	3	4	5	6	7
Mazandaran VCDAs (n=5)	0.206	0.154	0.167	**0.172**	0.123	0.0959	0.082
Ranks	1	4	3	**2***	5	6	7
The rest without Hamedan VCDAs (n=53)	0.246	0.153	0.142	0.134	0.123	0.112	0.09
Ranks	1	2	3	4	5	6	7
Hamedan VCDAs (n=5)	0.233	0.124	0.143	0.136	**0.153**	0.119	0.092
Ranks	1	5	3	4	**2***	6	7
The rest without Khorasan VCDAs (n=53)	0.249	0.151	0.144	0.132	0.125	0.113	0.086
Ranks	1	2	3	4	5	6	7
Khorasan VCDAs (n=5)	0.201	0.152	0.1457	0.142	0.123	**0.144**	0.092
Ranks	1	2	3	5	6	**4***	7
The rest without East Azerbaijan VCDAs (n=53)	0.25	0.149	0.148	0.141	0.124	0.106	0.082
Ranks	1	2	3	4	5	6	7
East Azerbaijan VCDAs (n=5)	0.238	0.144	0.141	0.142	0.118	0.095	**0.122**
Ranks	1	2	4	3	6	7	**5***

* Indicates ranking assigned by VCDAs to its own province

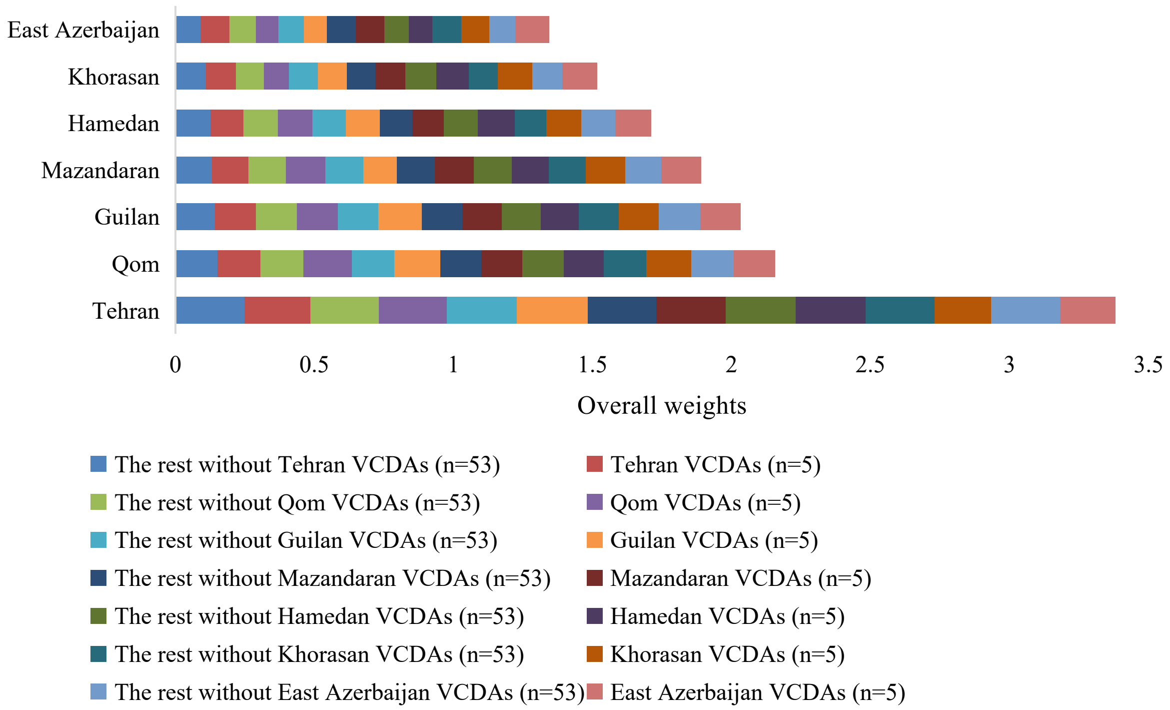

Figure 7. Comparison of the weights (with ICBP)

Tehran VCDAs assigned the highest weight to the Tehran value chain. The Qom VCDAs gave the most weight to the Qom value chain after Tehran, and in their opinion, the Qom value chain was in second place. After Tehran, Guilan VCDAs gave the highest weight to the Qom value chain, and in their opinion, Guilan value chain was in third place. Mazandaran VCDAs also considered the fourth rank for the Mazandaran value chain, and after Tehran, Qom, and Guilan, they assigned the highest weight to the Mazandaran value chain. Hamedan VCDAs ranked their own value chain fourth, placing it behind Tehran, Qom, and Guilan, to which they assigned greater weights. According to the rest of the panel without Khorasan VCDAs, the Khorasan value chain was ranked sixth by weight 0.105, while according to the Khorasan VCDAs, this value chain was ranked fifth by weight 0.127. According to the East Azerbaijan VCDAs, the East Azerbaijan value chain was ranked fifth by weight 0.129 while according to the rest of the panel, ranked seventh (Table 8).

In Tables 7 and 8, cells corresponding to each VCDAs' evaluation of its own province are highlighted to facilitate identification of stakeholder-aligned preferential positioning. Comparison of the pre- and post-refinement results shows that while the overall ranking structure remains broadly stable, stakeholder-specific weight intensities are moderated following the consensus refinement process. This pattern suggests that the Delphi-based iterative mechanism does not fundamentally restructure priorities; rather, it tempers preferential amplification and promotes more proportionate weight distributions without eliminating stakeholder heterogeneity. Table 9 subsequently provides a consolidated view of these divergence shifts across conditions. As shown in Table 9, rating differences with the ICBP were less than those without the ICBP.

As illustrated in Table 9, ranking divergence between stakeholder subgroups decreases systematically following the consensus refinement process. The reduction in rating gaps suggests that structured, iterative feedback induces evaluative recalibration rather than forced convergence. Importantly, divergence is moderated, not eliminated, indicating attenuation of preferential amplification while preserving heterogeneity among stakeholders. From a practical standpoint, this pattern supports the use of structured consensus loops in high-stakes ANP applications where complete neutrality is neither expected nor realistic.

3.5 Sensitivity analysis

The percentage change in criteria weight that caused the first change in the ranking of alternatives is shown in Table 4. The absolute-any critical criterion is the most critical, as it requires the smallest change in weight to alter the ranking of alternatives. Therefore, the absolute-top critical criterion was Market. A 15% decrease from 34.8 changed the ranking between Qom and Guilan. Most changes in the ranking of alternatives occurred between Qom and Guilan. Weight changes in Market, Raw material, Human resources, and Information and knowledge caused shifts in the ranks of Qom and Guilan. No shifts were observed in the Tehran rank (Table 10). Most of the shifts were due to changes in the weight of Market and Raw materials.

Table 8. Weights and ranks (with ICBP)

	Tehran	Qom	Guilan	Mazandaran	Hamedan	Khorasan	East Azerbaijan
The rest without Tehran VCDAs (n=53)	0.249	0.151	0.142	0.132	0.125	0.11	0.091
Ranks	1	2	3	4	5	6	7
Tehran VCDAs (n=5)	**0.236**	0.155	0.147	0.131	0.12	0.109	0.103
Ranks	**1***	2	3	4	5	6	7
The rest without Qom VCDAs (n=53)	0.246	0.154	0.147	0.135	0.124	0.099	0.095
Ranks	1	2	3	4	5	6	7
Qom VCDAs (n=5)	0.245	**0.175**	0.149	0.141	0.123	0.091	0.082
Ranks	1	**2***	3	4	5	6	7
The rest without Guilan VCDAs (n=53)	0.251	0.153	0.145	0.136	0.121	0.103	0.091
Ranks	1	2	3	4	5	6	7
Guilan VCDAs (n=5)	0.256	0.164	**0.157**	0.122	0.123	0.104	0.082
Ranks	1	2	**3***	5	4	6	7
The rest without Mazandaran VCDAs (n=53)	0.246	0.147	0.145	0.137	0.116	0.104	0.105
Ranks	1	2	3	4	5	6	7
Mazandaran VCDAs (n=5)	0.25	0.149	0.141	**0.139**	0.113	0.107	0.102
Ranks	1	2	3	**4***	5	6	7
The rest without Hamedan VCDAs (n=53)	0.252	0.149	0.141	0.136	0.123	0.111	0.088
Ranks	1	2	3	4	5	6	7
Hamedan VCDAs (n=5)	0.251	0.144	0.137	0.131	**0.136**	0.117	0.084
Ranks	1	2	3	5	**4***	6	7
The rest without Khorasan VCDAs (n=53)	0.249	0.151	0.144	0.133	0.112	0.105	0.106
Ranks	1	2	3	4	5	6	7
Khorasan VCDAs (n=5)	0.202	0.1634	0.144	0.142	0.124	**0.127**	0.101
Ranks	1	2	3	4	6	**5***	7
The rest without East Azerbaijan VCDAs (n=53)	0.249	0.153	0.148	0.129	0.122	0.107	0.092
Ranks	1	2	3	4	5	6	7
East Azerbaijan VCDAs (n=5)	0.198	0.148	0.145	0.142	0.124	0.122	**0.129**
Ranks	1	2	3	4	6	7	**5***

* Indicates ranking assigned by VCDAs to its own province

Table 9. Ranking difference

Value chain	Tehran	Qom	Guilan	Mazandaran	Hamedan	Khorasan	East Azerbaijan
Ranks of the rest without VCDAs (without ICBP)	1	2	3	4	5	6	7
Rank of VCDAs for their value chain (without ICBP)	1	2	2	2	2	4	5
Ratings difference	0	0	1	2	3	2	2
Ranks of the rest without VCDAs (with ICBP)	1	2	3	4	5	6	7
Rank of VCDAs for their value chain (with ICBP)	1	2	3	4	4	5	5
Ratings difference	0	0	0	0	1	1	2

Table 10. Sensitivity analysis in two modes with and without ICBP

Criteria	Market		Raw material		Human resources		Information and knowledge		Environmental advantages	
Ai-Aj	Without ICBP	With ICBP	Without ICBP	With ICBP	Without ICBP	With ICBP	Without ICBP	With ICBP	Without ICBP	With ICBP
Tehran-Qom	n/a*	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Tehran- Guilan	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Tehran- Mazandaran	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Tehran- Hamedan	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Tehran- Khorasan	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Tehran- East Azerbaijan	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Qom- Guilan	-15%	-17%	+21%	+23%	+26%	+22%	-28%	-22%	n/a	n/a
Qom- Mazandaran	-24%	-20%	n/a	n/a	n/a	n/a	-25%	-21%	n/a	n/a
Qom- Hamedan	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Qom- Khorasan	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Qom- East Azerbaijan	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Guilan- Mazandaran	+24%	+21%	-21%	-22%	n/a	n/a	n/a	n/a	n/a	n/a
Guilan- Hamedan	n/a	n/a	+29%	+24%	n/a	n/a	n/a	n/a	n/a	n/a
Guilan- Khorasan	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Guilan- East Azerbaijan	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Mazandaran- Hamedan	+16%	+19%	-25%	-28%	n/a	n/a	n/a	n/a	n/a	n/a
Mazandaran- Khorasan	+22%	+22%	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Mazandaran- East Azerbaijan	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Hamedan- Khorasan	n/a	n/a	n/a	n/a	-27%	-26%	n/a	n/a	n/a	n/a
Hamedan- East Azerbaijan	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Khorasan- East Azerbaijan	+19%	+17%	-21%	-18%	n/a	n/a	n/a	n/a	n/a	n/a

* n/a: no value available

3.6 Statistical test results

To assess intergroup divergence between the VCDA subgroup (n = 5) and the remaining panel members (n = 53), we applied the Kruskal–Wallis test separately under baseline conditions (without ICBP) and after structured consensus refinement (with ICBP). In addition to statistical significance (p-values), we calculated eta-squared (η^2) based on the H statistic to quantify effect magnitude. Because the Kruskal–Wallis test evaluates rank-based group differences, η^2 provides a more informative estimate of practical divergence beyond binary significance decisions. As shown in Table 11, statistically significant intergroup differences ($\alpha = 0.05$) were observed in five provinces: Guilan, Mazandaran, Hamedan, Khorasan, and East Azerbaijan. No significant differences were detected for Tehran and Qom. Notably, effect size analysis shows that divergence magnitude was negligible in Tehran ($\eta^2 = 0.000$) and small in Qom ($\eta^2 = 0.045$), while all five significant provinces exhibited large effect sizes (η^2 ranging from 0.531 to 0.633). These values indicate substantial preferential divergence between the VCDA subgroup and the broader expert panel under baseline conditions. Large η^2 values (≈ 0.58–0.63) suggest that a considerable proportion of variance in rank allocations was attributable to subgroup membership, confirming strong alignment-based amplification prior to refinement.

Table 11. Difference of results without ICBP

Province	H (Chi-square)	df	p-value	Eta²	Effect Magnitude
Tehran	0.192	1	.661	0.000	Negligible
Qom	3.523	1	.061	0.045	Small
Guilan	34.337	1	.000	0.595	Large
Mazandaran	36.433	1	.000	0.633	Large
Hamedan	33.454	1	.000	0.580	Large
Khorasan	36.433	1	.000	0.633	Large
East Azerbaijan	30.738	1	.000	0.531	Large

Test Statistics: 95% Confidence Interval

Table 12. Difference of results with ICBP

Province	H (Chi-square)	df	p-value	Eta²	Effect Magnitude
Tehran	0.293	1	.588	0.000	Negligible
Qom	3.119	1	.077	0.038	Small
Guilan	0.884	1	.347	0.000	Negligible
Mazandaran	1.362	1	.243	0.006	Very Small
Hamedan	9.206	1	.002	0.147	Large
Khorasan	11.121	1	.001	0.181	Large
East Azerbaijan	14.247	1	.000	0.237	Large

Test Statistics: 95% Confidence Interval

Following implementation of the ICBP, divergence patterns changed substantially (Table 12). Intergroup differences were no longer statistically significant for Tehran, Qom, Guilan, and Mazandaran. Significant differences remained for Hamedan, Khorasan, and East Azerbaijan. However, the crucial insight comes from effect size comparisons. Post-refinement η^2 values decreased markedly across most provinces. Guilan's large baseline effect (η^2 = 0.595) was reduced to negligible levels (η^2 = 0.000). Mazandaran declined from 0.633 to 0.006, representing near-complete attenuation. Hamedan, Khorasan, and East Azerbaijan retained statistically significant differences, yet their effect sizes declined substantially (e.g., from 0.580 to 0.147 in Hamedan). These reductions indicate moderation of divergence magnitude rather than complete elimination.

A direct comparison of η^2 values across conditions demonstrates substantial proportional reductions in divergence magnitude. For example:

- Guilan: 100% reduction (0.595 → 0.000)
- Mazandaran: 99% reduction (0.633 → 0.006)
- Hamedan: 75% reduction (0.580 → 0.147)
- Khorasan: 71% reduction (0.633 → 0.181)
- East Azerbaijan: 55% reduction (0.531 → 0.237)

These findings confirm that ICBP moderated preferential divergence by attenuating extreme subgroup differences. Nevertheless, divergence was not uniformly eliminated. Given the relatively small size of the VCDA subgroup (n = 5), the statistical power of the Kruskal–Wallis test is limited. Consequently, non-significant p-values in the post-refinement condition should not be interpreted as proof of complete convergence. Instead, they indicate insufficient statistical evidence to reject the null hypothesis at conventional thresholds. Effect size analysis therefore provides a more informative measure of practical impact. Across provinces, divergence magnitude shifted from predominantly large effects in the baseline condition to small, very small, or reduced large effects following refinement. To provide a summary indicator of moderation intensity, Table 13 presents aggregated divergence metrics across provinces.

Table 13. Divergence reduction metrics

Metric	Pre	Post	% Reduction
Mean η^2	0.431	0.087	79.8%
Mean Gap	0.31	0.19	38.7%

The substantial decline in mean η^2 confirms that structured iterative refinement attenuated subgroup divergence in a practically meaningful way. Accordingly, the results indicate that ICBP substantially moderated intergroup divergence, although residual differences remained in selected provinces.

4. Discussion

The results demonstrate that value chain weights varied among members of the DM panel. In several instances, the VCDA subgroups (n = 53) assigned higher weights to their respective wood value chains. Notably, when VCDA members evaluated value chains outside their direct interest, their rankings aligned closely with those of the remaining panel members, suggesting comparatively less biased judgment in non-stakeholder contexts. Interpreting these findings through PSI theory provides additional conceptual clarity. Rather than viewing stakeholder divergence solely as cognitive bias, we find that the observed patterns align with need-oriented judgment formation under incentive conditions. When evaluation outcomes carry material consequences, motivational pressures may systematically shape pairwise comparisons. Within this framework, the Delphi-based refinement process should not be interpreted as eliminating bias. Rather, it functions as a structured regulatory mechanism that moderates incentive-aligned amplification. Importantly, the objective of the Delphi-based refinement in this study was not merely opinion convergence. In stakeholder-driven public policy contexts, convergence alone does not necessarily indicate a reduction in incentive-sensitive distortions. Instead, the iterative consensus loop functioned as a structural moderation mechanism within the ANP weighting system, enabling measurement of inter-group divergence through effect size comparisons before and after feedback rounds. Thus, the framework addresses the regulation of incentive-sensitive weighting distortions rather than simple harmonization of expert opinions.

The inclusion of effect size analysis substantially refines interpretation of the statistical outcomes. Although several post-refinement comparisons were no longer statistically significant at α = 0.05, eta-squared values show that the magnitude of divergence was reduced rather than fully eliminated. Given the limited statistical power associated with the small VCDA subgroup (n = 5), non-significant p-values should not be viewed as definitive evidence of convergence. Instead, the proportional reduction in effect sizes across provinces supports the interpretation that the ICBP functioned as a moderating governance mechanism rather than a bias-eradication tool. This distinction is both statistically and conceptually important. Substantively, the market criterion emerged as the most critical factor influencing value chain development. The findings indicate that development priorities are strongly associated with access to major wood markets and the overall market environment. Value chain development was consistently prioritized in areas proximate to major urban population centers. In particular, Tehran, given its role as the capital and a major consumption hub, represents a structurally advantageous market where distribution channels have long been established. Consequently, Tehran's wood value chain was prioritized for development, even by stakeholders from other regions. Tehran's superiority as an alternative was sufficiently pronounced that potential BJs did not alter its rank position.

The relative convergence observed in Tehran suggests that when an alternative has widely recognized structural advantages, stakeholder-aligned amplification is less pronounced. This contrast reinforces the interpretation that divergence in other provinces is incentive-sensitive rather than structurally inevitable. Sensitivity analysis further supports this conclusion: changes in criteria weights did not affect Tehran's ranking, while other value chains showed greater sensitivity, with at least one rank shift occurring under modified weight conditions. Before the implementation of the ICBP, BJs significantly influenced rankings in five provincial value chains (Guilan, Mazandaran, Hamedan, Khorasan, and East Azerbaijan). After incorporating the ICBP, statistically significant differences remained in only three cases (Hamedan, Khorasan, and East Azerbaijan). These results demonstrate the practical effectiveness of the ICBP in moderating potential bias. The ICBP adjusts criteria weights through structured feedback, reducing extreme preference amplification. However, although effective, the process did not fully eliminate BJs.

Accordingly, careful composition of the DM panel remains essential. Professional competence and relative impartiality of members are critical considerations. Panelists who stand to gain or lose materially from the decision outcomes should have lower influence weights, as their judgments may introduce distortions sufficient to alter final rankings. In situations where stakeholder participation is unavoidable, as is often the case in public policy ,bias-moderation techniques such as the ICBP become particularly valuable. Consistent with prior research, the ICBP enhances consensus formation, improves evaluation reliability [47], supports the development of better solutions, and facilitates agreement on complex decision questions [48].

The structured consensus process observed in this study did not completely eliminate preferential distortions; instead, it moderated extreme positions through iterative feedback and collective transparency. This finding suggests that Delphi-based mechanisms function primarily as governance instruments capable of regulating stakeholder-driven amplification within complex group DM systems. The empirical pattern shows a shift from large, highly pronounced divergence to smaller, more contained discrepancies after iterative feedback. This distinction is critical: the consensus mechanism serves as a regulatory moderator rather than a complete neutralizer of preferential influence.

The primary contribution of this study is not the introduction of a new consensus methodology, but the empirical examination of how a Delphi-based iterative refinement process interacts with stakeholder-driven preferential distortions in an ANP-based governmental resource allocation context under real incentive conditions. The findings show that when decision outcomes create differential advantages or disadvantages for panel members, BJs are likely to arise and influence relative rankings. At the same time, the iterative consensus procedure can meaningfully mitigate though not entirely eliminate this divergence.

Importantly, the findings should not be interpreted solely as evidence of unconscious cognitive bias. Given the real allocation consequences embedded in the decision context, observed preferential weighting may reflect strategic stakeholder behavior consistent with institutional advocacy roles. In this respect, the study complements rather than replaces existing methodological approaches such as FAHP or entropy-based weighting. While those methods primarily model uncertainty mathematically, the present results highlight the critical role of structured interaction in moderating stakeholder-driven amplification under incentive conditions. Participatory DM remains a cornerstone of inclusive governance. However, inclusivity alone does not guarantee neutrality. The findings indicate that participatory group DM frameworks benefit substantially from intentional panel design and iterative moderation processes, particularly when decisions carry material consequences. In real policy environments, complete neutrality is rarely attainable; decision makers typically operate within institutional, regional, or sectoral incentive structures. Therefore, the practical objective is not to eliminate interests but to govern interest-driven inputs. Structured feedback mechanisms, such as Delphi-based refinement, provide procedural safeguards that enhance decision stability while preserving legitimate stakeholder representation. This interpretation aligns with broader research on structured consensus building in MCDM environments, where iterative feedback aims to improve convergence without suppressing valid diversity of expert opinion [33]. Despite its methodological rigor, the study has several limitations. First, the empirical analysis focuses on wood value chains within a single national context, which may limit generalizability across sectors or institutional settings. Second, although the within-subject design strengthens internal validity, the fixed panel composition may introduce familiarity effects across iterative rounds. Third, BJs were operationalized through subgroup divergence in rankings; while analytically tractable, this measure may not capture the full behavioral complexity of strategic bias. Future research could extend the framework across sectors, incorporate behavioral experiments, or employ longitudinal panel designs to examine the stability and transferability of the observed moderation effects.

From a theoretical standpoint, the study contributes to decision science in three principal ways. First, it empirically integrates the ANP with a structured Delphi-based refinement mechanism to examine stakeholder-driven divergence in multi-criteria contexts. Second, it advances understanding of preferential amplification by demonstrating how subgroup incentives can reshape relative priority structures within network-based models. Third, it provides methodological clarification regarding the role of geometric aggregation in preserving proportional integrity while moderating dominance effects in group decision environments. Collectively, these contributions extend the literature on bias moderation in complex, interdependent decision systems. From a managerial and policy perspective, the findings highlight the importance of structured feedback mechanisms when stakeholder incentives are distributed asymmetrically. In public policy and multi-regional investment prioritization contexts, decision panels may unintentionally amplify localized interests. The controlled implementation of iterative refinement procedures can reduce disproportionate influence without suppressing legitimate preference heterogeneity. Organizations employing ANP or similar multi-criteria frameworks may enhance the fairness, transparency, and robustness of strategic allocation decisions by embedding structured consensus-feedback cycles within their decision architecture. To synthesize the empirical evidence from the three-stage analysis, the main research questions and their corresponding evidence-based answers are summarized in Table 14. This summary integrates the statistical findings and the observed behavioral patterns of stakeholders, providing a concise validation of the study's hypotheses regarding the presence of BJs and the moderating role of the ICBP framework.

Table 14. Research findings

Question 1	Do BJs originating from personal interests distort group DM outcomes?
Answer 1	Yes. Our empirical findings unequivocally demonstrate that stakeholders' biased judgments, particularly those influenced by self-interest, have a significant and measurable impact on the final group DM outcomes. The initial judgments exhibited a clear divergence, which subsequently distorted the overall priorities set for the value chains.
Question 2	Can the ICBP effectively mitigate these biases?
Answer 2	Yes. The ICBP proved to be an effective and robust framework for moderating biased judgments. The iterative, feedback-driven process enabled participants to re-evaluate their initial positions, leading to a demonstrable reduction in the level of bias. While the process did not entirely eliminate all biases, it successfully guided the group toward a more objective and reliable consensus.

5. Conclusion

The present study investigated stakeholder-driven preferential divergence within an ANP-based group DM framework operating under real-world incentive conditions. Instead of attributing divergence solely to cognitive error, the analysis conceptualized it as potentially incentive-amplified preference expression and examined whether a structured Delphi-based iterative consensus refinement process could moderate this amplification. The findings indicate that embedding controlled feedback loops within ANP systems systematically reduces the magnitude of divergence while preserving legitimate heterogeneity among participants. The results therefore support a moderation interpretation – attenuation of preferential amplification – rather than full convergence or neutrality. From a policy design perspective, these findings are directly relevant to ministries, regional development authorities, public budget committees, and corporate boards engaged in high-stakes resource allocation. In participatory governance contexts, decision-makers often hold legitimate, interest-aligned positions. Attempting to eliminate such actors or to identify fully "neutral" judges is neither realistic nor desirable. Instead, this study demonstrates that institutional design can incorporate structured consensus-refinement architectures to regulate extreme divergence while maintaining representation. In this sense, iterative feedback mechanisms serve as procedural stabilizers that enhance robustness without suppressing stakeholder input. Methodologically, the contribution extends beyond the specific context of the wood value chain. While ANP and Delphi processes are each well established, their structured integration within a measurable divergence-moderation architecture provides a transferable decision-support configuration. Any multi-stakeholder domain involving network-based prioritization – such as infrastructure investment, industrial policy design, sustainability governance, public procurement, or strategic corporate portfolio selection – may benefit from embedding iterative consensus loops within ANP evaluations. The framework is therefore generalizable as a bias-moderation architecture for complex decision environments characterized by incentive-aligned evaluation dynamics.

Importantly, the results should not be interpreted as evidence of purely unconscious cognitive bias. Because participants were informed that outcomes could influence allocation decisions, the observed divergence likely reflects a combination of strategic positioning, motivational alignment, and cognitive reinforcement processes. Examining behavior under real incentive exposure enhances ecological validity, even if it complicates causal isolation. Future experimental replications under consequence-neutral laboratory conditions could help disentangle strategic and cognitive components more precisely. Looking forward, the framework opens several pathways for scalable enhancement. One promising direction involves hybrid AI-assisted extensions capable of detecting anomalous weighting patterns, modeling divergence trajectories across iterations, or dynamically recalibrating aggregation thresholds under varying incentive intensities. A simulation-based extension, for example, could model divergence scaling as stakeholder group size increases or as incentive asymmetry intensifies, thereby stress-testing consensus-loop efficiency under higher systemic complexity. Such simulations would allow evaluation of how the moderation architecture performs in multi-sector, cross-regional, or multinational allocation settings beyond the wood industry case. The broader implication of this work is that bias mitigation in participatory group DM does not require replacing stakeholders or suppressing interest-based perspectives. Instead, structured procedural engineering using transparent aggregation, controlled feedback, and iterative recalibration can make divergence management an operational and testable part of decision-system design. By translating abstract discussions of bias into a measurable consensus-embedded ANP configuration, this study advances applied decision sciences toward more resilient, incentive-aware decision architectures.

A scalable extension of the present framework could be explored through simulation-based modeling of stakeholder divergence under varying structural conditions. For instance, a hypothetical multi-sector allocation scenario could model increasing stakeholder group sizes (e.g., 10, 30, 100 evaluators) and varying incentive intensity parameters to examine how divergence magnitude changes across iterative consensus rounds. Such a simulation could track effect size trajectories, convergence speed, and the stability of final rankings under progressively complex network structures. By stress-testing the ANP–Delphi refinement architecture in simulated high-density stakeholder environments, researchers could evaluate the scalability and robustness of the moderation mechanism beyond sector-specific applications. This would enable assessment of performance thresholds and procedural efficiency in larger governmental, multinational, or cross-sector decision contexts.

Abbreviations

AHP: Analytic Hierarchy Process
ANP: Analytic Network Process
BJs: Biased Judgments
BS: Bachelor of Science
DM: Decision-Making
FAHP: Fuzzy Analytical Hierarchy Process
MS: Master of Science
PSI: The Greek letter Ψ
SPSS: Statistical package for social science
ICBP: Integrated Consensus-Building Process
VCDAs: Value Chain Development Agents

Authors' contribution

Omid Hossein Zadeh: Conceptualization, methodology, software, formal analysis, investigation, writing – original draft, visualization. Marzieh Hajjarian: Conceptualization, methodology, investigation, writing – review & editing. Mohammad Reza Abdi: Investigation, writing – review & editing, conceptualization.

Conflicts of interest

The authors state that they have no financial interests or personal relationships that could have affected the work in this paper.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Ethics statement

This study was conducted in accordance with ethical standards and the principles of the Declaration of Helsinki. Participation in the research was entirely voluntary, and all participants provided informed consent prior to completing the questionnaire. Participants were fully informed about the purpose of the study and how the results would be used. No sensitive personal data were collected, and participants' anonymity and confidentiality were strictly maintained throughout the research process. Ethical approval was not required according to the policies of our institution for this type of minimal-risk, survey-based research.

Institutional review board statement

Ethical review and approval were waived for this study because it did not involve human or animal subjects, nor the collection of personal or sensitive data.

Declaration of generative AI

During the preparation of this manuscript, the authors used AI-powered tools for grammar and spelling checks. The authors reviewed, edited, and take full responsibility for the final content.

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