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Unpacking Psychological Antecedents of Low-Carbon Behavior: What Differentiates Champions, Skeptics, Talkers and Walkers across Young Adults?

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Abstract: This study explores low-carbon behavior (LCB), considering a number of psychological predictors deemed important according to the theory of planned behavior and the norm-activation model. Four distinct clusters were identified by conducting a cluster analysis of data collected from an online survey of young people in Croatia in 2022, revealing both consistent and inconsistent patterns of LCB. The study highlights the complexity of factors influencing LCB and utilizes a fuzzy-set qualitative comparative analysis to identify specific configurations of psychological variables that contribute to high and not-high levels of LCB within each cluster. The results validate the significance of established psychological determinants in explaining variations in low-carbon intentions and behaviors among young people, challenging the assumption of intention as the single best determinant of LCB and underscoring the presence of multiple causal complexities and equifinalities. Furthermore, the study demonstrates the asymmetric effects of different psychological conditions on high and not-high levels of LCB, suggesting that consistent and inconsistent LCBs cannot simply be viewed as opposite poles of the same continuum and that a variety of pathways can be explored to enhance carbon reduction activities.

Keywords: psychological predictors; theory of planned behavior; norm activation mode; multiple pathways; fuzzy set qualitative comparative analysis; young adults

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1. Introduction

Low-carbon behavior (LCB) primarily refers to the behaviors of individuals aimed at reducing their carbon footprint and minimizing harmful impacts on the environment [1]. It encompasses a wide range of daily activities, from choosing clean fuels or energy sources, purchasing local products or energy-efficient appliances, reducing waste generation, and practicing recycling [2], to influencing the behaviors of others in response to environmental concerns [3]. Psychological theories such as the Theory of Planned Behavior (TPB [4]) and the Norm Activation Model (NAM [5]) are commonly used to identify psychological predictors of targeted behaviors and explore their underlying causal relationships.

However, a previous study has reported the diversity of psychological traits and their heterogeneous effects on behavior [6]. Not all individuals who intend to engage in LCBs actually follow through, and as Martinsson and Lundqvist [7] stated, it is possible to adapt cleaner practices without becoming green. These findings suggest that there are multiple pathways to LCB. Ma et al. [8] discovered significant variations in energy consumption even among similar households within a region, underscoring the importance of examining subgroup differences within a population. While each individual exhibits unique and possibly contradictory behaviors, analyzing the diversity of actors and their behaviors can reveal previously unrecognized subgroups characterized by similar behaviors. By clustering the population into clusters based on their thoughts or behaviors, more effective communication can be established with the target population [9], which in turn influences the effectiveness of individual behavior change and policy interventions [10].

Young people, particularly students, are a promising group for behavior change as they develop a strong awareness of environmental degradation at a young age [11]. They have the potential to act as change agents within their local communities [12]. Given their critical role in facilitating a successful transition to low-carbon growth, there is a clear need for focused research that explores young people's involvement in everyday climate change activism [13]. However, limited empirical attention has been given to their psychological characteristics and the consistency of their LCBs. This gap may be due to the perception that they have limited income or resources, which may result in their exclusion from energy-related decision-making [1]. Nevertheless, young people are a crucial segment of the population that contributes to the momentum toward low-carbon living. They exhibit diversity, and identifying homogeneous subgroups among them can enhance our understanding of different "target groups", enabling psychologically informed interventions from government bodies, media, educational institutions, agencies, and other stakeholders interested in promoting sustainable behaviors.

Previous clustering studies have successfully identified diverse groups that promote pro-environmental or energy-saving behaviors within the general population, households, and countries facing high carbon emissions, severe energy problems, or those situated in the global North. However, they overlooked diverse activities in smaller countries. Croatia, as a member of the European Union, is experiencing a growth in consumption-based carbon emissions that outpaces its gross domestic product (GDP) [14], emphasizing the importance of individual behavior change. Although young people play a crucial role in driving the transition toward a low-carbon future, there has been limited research on clustering them based on their LCBs or intentions. This study aims to fill these gaps by (i) identifying distinct clusters of young adults who share similarities in their low-carbon intentions and self-reported behaviors, and (ii) uncovering the combinations of psychological factors that contribute to both high and not-high levels of LCB within each cluster of young adults.

This study utilizes *k*-means clustering to identify homogeneous subgroups within the data collected through an online survey in eight Croatian cities in 2022. In addition, it utilizes fuzzy-set qualitative comparative analysis (fsQCA) to address the second objective. fsQCA adopts a configurational approach to systematically examine causal conditions (in our case, psychological factors) across cases [15], assuming multiple causal complexity (i.e., different combinations of causal conditions lead to the outcome of interest), asymmetry (i.e., asymmetric configurations for the presence and absence of the outcome), and equifinality (i.e., multiple configurations lead to the same outcome) [16]. The method is based on Boolean algebra and algorithms that reduce all combinations of causal conditions until they reach a parsimonious solution [15]. Recently, both methods have gained popularity and have been used in studies on sustainable behavior (e.g., for clusters: [17,18], or for fsQCA: [19]). However, to the best of our knowledge, the determinants of the TPB or the NAM in LCB have not yet been considered from the perspective of multiple equifinalities and asymmetries that fsQCA enables. Schneider and Wagermann [20] pointed out that neglecting these aspects can lead to inconsistent results.

This study contributes to low-carbon research in several ways. First, it enhances our understanding of the complex causal structure underlying young adults' engagement in LCB, encompassing both consistent and paradoxical clusters. It demonstrates that high and not-high levels of LCB are multifaceted phenomena influenced by diverse configurations of sociopsychological conditions, rather than a single condition or combination as hypothesized in existing theories. Furthermore, it reveals novel findings regarding the asymmetric effects of these conditions on LCB, challenging the notion that irresponsible carbon behavior is merely the opposite of LCB. Ultimately, this study provides theoretical and empirical implications that broaden our current knowledge.

The next section explains the psychological factors that have been identified in previous research as important LCB determinants. Subsequently, attention is given to the methodology, with a particular emphasis on fsQCA. Section 4 reports the results and discusses the findings related to the previous research. Finally, the study concludes by summarizing the main findings and briefly discussing their implications for future LCB research.

2. Conceptual Framework of Low-Carbon Behavior

2.1. Low-Carbon Behavior

LCB encompasses the actions individuals take to minimize their carbon footprint and mitigate their detrimental impact on the environment [1,2,6]. In general, LCB comprises activities related to household energy consumption, personal transportation methods, and consumer product choices [6], such as purchasing eco-labeled or energy-efficient items, using locally sourced products, or engaging in recycling, composting, and waste reduction [2]. Moreover, Stern [3] provided compelling evidence that individuals, in addition to these consumption-related activities, can have a significant impact on carbon emissions as active citizens who share information, volunteer, advocate for public policies, and influence the awareness of others. Changes in individual behavior, thus, contribute significantly to reducing overall carbon emissions.

The scope and magnitude of LCBs vary depending on the nature of the low-carbon activities, actors, and contextual factors, reflecting the multitude of sociodemographic, economic, and psychological factors that determine, represent, or predict LCBs, often with conflicting results. Empirical evidence on the influence of sociodemographic factors is mixed, but often suggests that women tend to have higher intentions to LCB compared to men [21] and that younger individuals tend to have higher low-carbon intentions than older individuals [22,23]. More educated individuals with higher incomes residing in urban areas tend to have higher low-carbon intentions and behaviors [21,24], whereas homeownership status decreases their engagement in LCBs [24,25]. Evidence on the effects of psychological determinants on LCBs or intentions is also mixed in terms of their importance or causal interrelationships. A study by Thøgersen and Crompton [26] found that personal norms were a stronger predictor of pro-environmental behavior than attitudes or social norms, whereas a study by Bamber and Moser [22] found that consideration of future consequences may be the most significant LCB predictor.

The prevailing notion in carbon emission mitigation strategies is that individuals with more positive psychological attributes (higher positive attitudes, personal or social norms, and perceived behavioral control) have higher intentions and are more likely to engage in LCBs [27]. However, the finding that significant attitudinal changes are not always necessary to achieve environmental gains through behavioral change [28] suggests that effective carbon-reducing behaviors may result from multiple strategies characterized by attributing different importance to psychological determinants.

Individuals exhibit heterogeneity in their carbon-reducing activities, driven by specific norms, values, or attitudes. Therefore, understanding the average LCB predictors or determinants, while helpful, is not sufficient for providing incentives or behavioral changes for specific groups of individuals.

2.2. Theoretical Background

A wide range of psychological theories can be used to explain variations in LCBs [29]. Previous research has found that psychological factors exhibit relative stability, often represent unobservable factors or circumstances that trigger certain behaviors, and exert a significant influence on behavior independent of regulatory, technological, and contextual circumstances [6]. One of the most commonly used theoretical models, namely the TPB [4], assumes that behavior is preceded by behavioral intention, which in turn depends on attitudes, social norms, and perceived behavioral control. Another theoretical model, the NAM [5], assumes that behavior is directly influenced by moral and personal norms as well as concern for future consequences and personal responsibility to do something. Because human behavior cannot be determined unilaterally due to its complexity, combining the core constructs of the TPB (attitude, social norms, personal behavioral control, and intentions) with the constructs of the NAM (personal norms, awareness of consequences, attribution of responsibility, or subjective knowledge) increases pro-environmental behavior [30]. Their integration has been validated in home composting intentions [31], recycling behavior [32], and shopping behavior segmentation [33]. Based on these findings, this study suggests that LCB is preceded by a combination of psychological constructs from the TPB and the NAM, as shown in Figure 1.

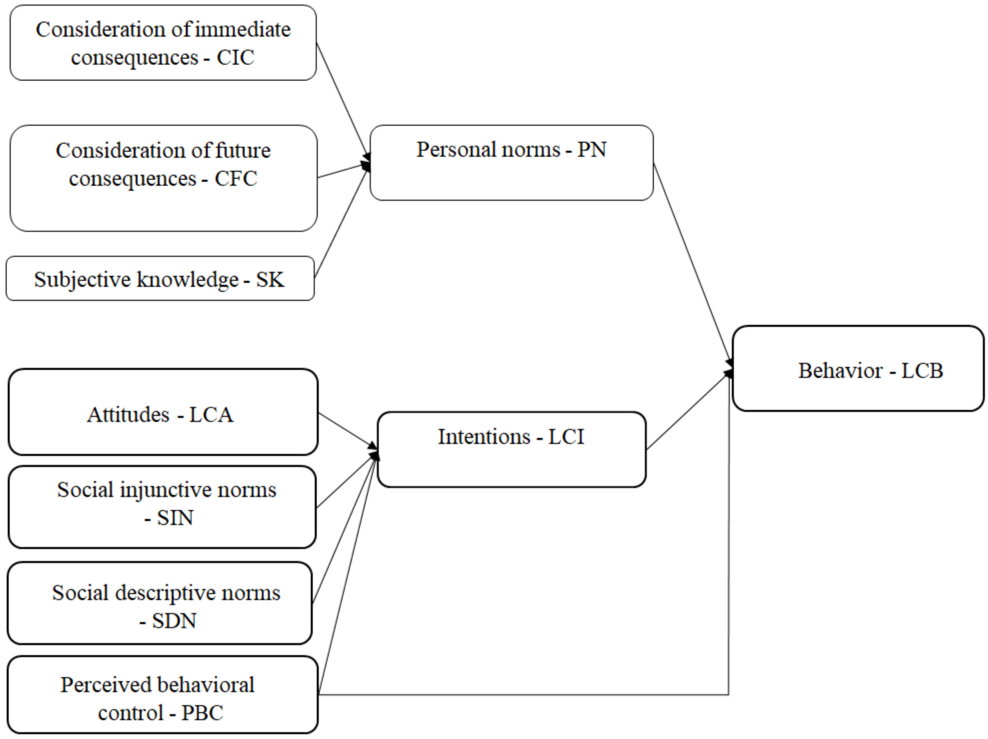

Figure 1. Conceptual underpinning of the TPB and NAM on low carbon behavior.

The integrated conceptual framework posits that personal norms [5] and intentions [4] can substantially enhance LCB. According to the NAM, LCB can be influenced by personal norms related to a sense of duty to reduce carbon emissions individually or to actively encourage others to do so. The higher the consideration of future or immediate consequences (awareness of the positive or negative consequences of LCB) and subjective knowledge of LCB, the higher the personal norm to perform or engage in low-carbon activities [29]. Behavioral intentions are considered another relevant and immediate antecedent of targeted behaviors [4], especially for planned or deliberation-based activities. Ultimately, the higher the attitudes, social norms (expectations of others or perceptions of what others do), or perceived control over behavior, the higher the intentions and, consequently, LCB.

Integrating the TPB and the NAM can enhance understanding of the psychological factors influencing LCB by considering reasoning, personal values, and sense of duty. Profiling LCB with a broader set of variables allows for a better comprehension of the various pathways leading to LCB. These pathways involve different combinations of psychological factors that may contribute to both high and not-high levels of commitment to LCB. Although uncovering these combinations represents significant progress toward a deeper understanding of human behavior, it has so far remained at the margins of low-carbon research.

2.3. Previous Research

Clustering young adults by their LCB, intentions, or norms provides insight into the scope, size, and profile of mutually exclusive clusters and allows for more effective communication with each target group and, ultimately, more effective behavior change programs. Although evidence already exists for clustering participants based on their LCBs, our understanding of the various patterns of psychological determinants that contribute to LCBs is still limited. Table 1 provides a brief description of recent studies based on cluster analysis of carbon reduction behaviors across different populations (primarily individuals as residents, household occupants, or consumers).

Table 1. Relevant research on clustering of the population according to low-carbon behaviors.

Study	Criteria for Discrimination of Clusters	Participants	Clusters
Liu et al. [34]	Attitudes to climate change risk	Population survey, the UK	3 clusters: Skeptical, Concerned, Paradoxical
Kácha et al. [9]	Climate change beliefs and attitudes	Citizens of 22 European countries and Israel	4 clusters: Engaged (18%), Pessimistic (18%), Indifferent (42%), Doubtful (21%)
Amicarelli et al. [18]	Food waste perception, knowledge, and food waste generation	Citizens of Apulia region, Italy	3 clusters: Red (121), Green (92), Blue (110)
Fu [35]	Affective (feelings) and cognitive (knowledge) attitude on green travel	Citizens from Jiangsu Province, China	4 clusters: Negative/incongruent (26.6%), Positive/incongruent (33.3%), Positive/congruent (23.2%), Negative/congruent (26.6%)
Xu et al. [36]	Willingness of energy conservation and emissions reduction	University students in Wuhan, China	4 clusters: A, B, C, D differentiated along members' awareness, interest, and willingness
Liu et al. [37]	Household Energy conservation behaviors	Residential building occupants in Xi'an, China	4 clusters: Positives, Temperates, Conservatives, Introverts
Rastegari Kopaei et al. [31]	Home composting	Citizens of Isfahan, Iran	3 unlabeled clusters of home composters differentiated across the TPB and NAM factors
Tolppanen and Kang [38]	The effect of values on carbon footprints	University students from Joensuu, Finland	3 clusters: Self-transcendent, Conflicting values, Human-centered
Li et al. [39]	Four-dimensional carbon capability to reduce carbon emissions in their daily lives, learn low carbon knowledge and skills, change their lifestyle, influence others to change to a low-carbon lifestyle	Urban residents in Jiangsu Province, China	6 clusters: Balanced steady, Self-restraint, Fully backward, Comprehensive leading, Slightly cognitive, Restrain others cluster
Heidari et al. [17]	Separation of waste	Students of Ferdowsi University of Mashhad, Iran	3 clusters: Moderate recyclers (117), Low recyclers (165), High recyclers (138)
Wei et al. [1]	Environmental personality and low-carbon behavioral intention	Urban residents, China	4 clusters: Ecological residents with consistent traits, Non-ecological residents with gap traits, Non-ecological residents with consistent traits, Ecological residents with gap traits
Lavelle et al. [28]	Households pro-environmental behaviors	Residents, Ireland and Northern Ireland	4 clusters: Ever Greens (13.9%), Never Greens (34.1%), Aspiring Greens (46.5%), Accidental Greens (5.5%)
Tabi [27]	Energy use in heating, electricity, and transport activities	Residents, Hungary	4 clusters: Beginners (27.66%), Browns (36.22%), Energy savers (24.08%), Super greens (12.04%)
Vecchio and Annunziata [40]	Attitudes toward sustainable food	University students, Italy	3 clusters: Responsible food consumer, Inattentive food consumer, Potentially sustainable food consumer

Table 1 shows the variety of LCBs studied, ranging from recycling to general pro-environmental behaviors. These studies primarily rely on the TPB, the NAM, or the Value–Belief–Norm Theory [3,41] and reveal distinctly different psychological and sociodemographic characteristics of the identified clusters of participants.

Most studies focus on behaviors as the main criterion for clustering. Clusters are typically defined based on the intensity or frequency of behavioral variables [17,28,31,37]. For example, Heidari et al. [17] found that low recyclers were the most significant subgroup among students (n = 165, 39%), followed by high recyclers (n = 138, 32%), indicating that more than one-third of the student population could benefit from targeted interventions to improve recycling practices on campus.

Other studies focus on psychological factors such as beliefs, willingness, values, and attitudes, in addition to eco-personality or intentions [1,9,34,36,38,40]. For example, Tolpannen and Kang [38] studied carbon footprint and individuals' willingness to participate in pro-environmental actions among university students in Eastern Finland. These students were classified into three distinct groups based on their predominant value pairs. The self-transcendent group (n = 74) consisted of individuals with biospheric and altruistic values, the conflicting-values group (n = 37) included individuals with biospheric and hedonistic values, and the human-centered group (n = 96) included individuals with altruistic and hedonistic values. Not surprisingly, the self-transcendence group of students showed consistency in their pro-environmental behavior, having the lowest carbon footprint. Interestingly, a low carbon footprint was also confirmed among the group of students with conflicting values, for whom biospheric values outweighed the dominant hedonistic values. In addition, the same study provided evidence that even those students with low willingness to engage in pro-environmental actions can have a low carbon footprint similar to the self-transcendent group.

A few other studies also indicated the presence of consistent or inconsistent behaviors across a broader population. For example, Wei et al. [1] discovered substantial variability in young adults' LCB. They observed different subgroups, including individuals with negative eco-personality but high low-carbon intentions and those with positive eco-personality but low-carbon intentions. Previous studies have shown that psychological constructs discriminate well between groups of individuals engaged in low-carbon activities. Moreover, they demonstrated the presence of heterogeneity among subgroups in the effects of psychological factors on low-carbon behaviors (LCB). However, given the limited evidence on the consistency of young adults' carbon-reducing behaviors, the aim of this study is to explore the heterogeneity of university students' LCBs in terms of their psychological profiles. Exploring their psychological characteristics may shed new light on the existence of different pathways and opportunities for a variety of carbon-reduction strategies among young adults.

3. Materials and Methods

3.1. Data and Demographic Statistics

Data were collected from 800 student respondents in the eight largest Croatian cities (Osijek, Varazdin, Zagreb, Pula, Rijeka, Zadar, Split, and Dubrovnik) through an online survey conducted in 2022. Participants were informed about the study's purpose, GDPR data protection, and their voluntary participation. Their data were anonymized, except for three respondents who refused consent. A total of 797 valid questionnaires were approved by the ethics committee or the dean of the respective college.

Table 2 contains the descriptive statistics of the sample. The majority of the respondents (50.7%) were in the age group between 21 and 25 years, and only 7.9% were older than 25 years. They lived mostly in urban areas (64%), and they estimated their financial situation (52.9%) to be in line with the Croatian average.

Focusing on university students, this paper sacrifices some degree of representativeness and the ability to extrapolate the findings to the broader population within Croatia or across different countries. Nevertheless, we assume that university students represent a heterogeneous yet reasonably accurate cross-section of young people in Croatia. Indeed, this demographic, especially students, holds promise as a group for effecting behavior change due to their heightened awareness of environmental issues from a young age, as discussed in Skovdal and Benwell [11]. Since they possess the potential to serve as catalysts for change in a low-carbon future, we agree with Walker [13], who highlighted the need for targeted research on young people's engagement in everyday climate actions.

Table 2. Sociodemographic features of the sample.

Criterion	Characteristic	Frequencies (in %)	Criterion	Characteristic	Frequencies (in %)
Gender	Male	30.5	Living area	Urban	64.0
	Female	69.0		Rural	36.0
	Other	0.5	Region of residence	Pannonian HR	31.6
Age	<21	41.4		North HR	3.1
	21–25	50.7		Zagreb	6.8
	25–35	7.9		Adriatic HR	58.5
Financial situation	Below	37.5			
	In average	52.9			
	Above	9.5			

Note: Financial situation is compared with the Croatian average. HR refers to Croatia.

3.2. Instrument Design

The structured questionnaire used in the survey captures respondents' attitudes, opinions, and beliefs on various topics related to LCB, along with their sociodemographic characteristics. After a preliminary analysis, the initial set of 40 variables used in this study was reduced to 35 variables. All measured variables were assessed using a 5-point Likert scale, utilizing scales and indicators validated in previous studies. Subjective knowledge of environmental problems and solutions [42], personal norms against LCB [21], and consideration of future or immediate outcomes [43] were measured with four, five, and three items, respectively. These scales were conceptually and contextually adapted to the LCB domain. In Figure 1, we propose that these exogenous latent variables serve as significant predictors of young people's personal attitudes toward LCB. Intention to engage in LCB was measured with two items, while attitudes, injunctive and descriptive social norms, and perceived behavioral control were initially measured with three items each, following the approach of de Leeuw et al. [44] in scale design.

Initially, the LCB scale comprised 20 items. To account for the complexity and dimensionality urged by Stern [3], a principal component analysis was employed for reduction. The scale proved suitable for explanatory factor analysis, with a Kaiser-Meyer-Olkin measure of sampling adequacy of 0.822, surpassing the recommended threshold of 0.60. Bartlett's test of sphericity was also significant ($\chi^2(190) = 2224.37$, $p < 0.01$). Applying varimax rotation and retaining the components with eigenvalues of at least 1, five factors were extracted. This study focuses primarily on the first component, labeled 'LCB", which accounts for 21.61% of the variance.

3.3. Method

The disclosure of the data structure is usually achieved by using clustering methods. These methods involve the formation of homogeneous clusters based on the similarities between the variables included in the model. There are several clustering methods to choose from, but the *k*-means algorithm is the most commonly employed due to its flexibility, comprehensiveness, and effectiveness [45]. The *k*-means algorithm is a partitioned, centroid-based, nonhierarchical, and iterative algorithm designed for clustering data and identifying distinct patterns within a medium or large number of cases, such as the young individuals in our study. For more information on *k*-means clustering, refer to Blömer et al. [46]. In this paper, standardized variables were employed to ensure equal contributions to the distance or similarity between cases, with squared Euclidean distance serving as a measure of divergence. Given the method's sensitivity to outliers and the order of the cases, an initial screening of the data was conducted, revealing several outliers. However, as their impact on the final solution was minimal, they were retained in the sample. The order of the cases in the file mirrored the chronological sequence in which the completed questionnaires were collected.

Before applying the k-means algorithm to estimate the initial values, a hierarchical cluster analysis utilizing Ward's method was performed. The Ward's method is a widely used approach for assessing dissimilarity or similarity between two clusters, employing squared Euclidean distance. It aims to minimize the sum of squared differences within clusters formed at each step, demonstrating robustness in the presence of outliers. This method is particularly useful for generating compact, homogeneous clusters of approximately equal sizes, providing a strong foundation for the subsequent application of the k-means clustering algorithm (for details, see [45,46]). Moreover, to evaluate the statistical significance of differences in cluster means, a one-way analysis of variance (ANOVA) was conducted, followed by a post hoc Bonferroni test. Additionally, a cross-tabulation analysis was performed to investigate demographic differences between the groups.

As a complex phenomenon, LCB is influenced by various causal conditions. Exploring these conditions is crucial, as they can combine in different ways to produce the outcome [47]. We employed the fsQCA method to study the impact of seven causal conditions (explanatory variables) on the outcome (dependent variable), examining all possible combinations. The method starts with calibration, a process that involves three steps: calculating the mean for each construct, identifying three fuzzy conversion metrics—full membership, cross-over point, and full nonmembership, and then converting each variable's metrics (the set in fsQCA terminology) into measures of membership in the fuzzy set [47]. Following Ragin [15,47] and considering the nature of our research data, we used the direct method to calibrate the causal conditions and outcomes, determining the membership degrees by identifying three anchor points. For the desired outcome of interest, we assigned a score of 4 for full inclusion, 2 for full exclusion, and 3 for the cross-over point. Considering the transitional nature of young adults in Croatia toward LCB, which is not yet prevalent, this scoring system follows the recommendations of Pappas and Woodside [16] and has been utilized previously in the social sciences [48]. Hence, anchors 4 and 2 represent the frequent and rare engagement of young adults in low-carbon activities, respectively. For consistency and to maintain an analogous scale (4 = mostly agree; 2 = mostly disagree) across all measures, the same calibration approach was applied to all causal conditions.

Calibration is followed by an analysis of necessity and sufficiency. Necessity considers whether a condition is present (or mainly present) when the outcome occurs, but it alone is not sufficient to produce the outcome. Necessity is measured by the consistency value, ranging from 0 to 1. A value above 0.9 indicates that the condition is generally necessary for the outcome [20,47]. Sufficiency is tested by examining whether an outcome occurs when a condition or combination of conditions is present. A sufficient causal condition (or combination of causal conditions) is sufficient, but not necessary (due to multiple causal paths), for an outcome to occur. To assess sufficiency, a truth table is constructed. It contains all logically possible configurations (i.e., combinations of conditions) and their consistency scores. A consistency score is a percentage of cases of a given configuration in which the outcome is obtained. Due to the large number of combinations, reduction is applied. A consistency value above 0.75 or 0.8 is generally accepted [20]. The final statistically significant configurations (referred to as recipes, causal pathways, or solutions) were obtained by further narrowing down the selected configurations based on p-values from the Wald test with a significance level of 0.05. Following Baumgartner [49], this study focuses on parsimonious solutions because of their accuracy, reliability, and explanatory power. The coverage score, which includes both raw coverage and unique coverage, is examined to determine the relative empirical importance of a given solution as a whole and each configuration in explaining the outcome, respectively [20,47]. The row coverage refers to the proportion of all cases that can be explained by a single configuration, while the unique coverage measures the degree of coverage that is unique to a particular configuration. The latter should be greater than zero [20]. The intensity of the association between the configuration(s) and the outcome is measured by consistency. The recommended value for solution consistency is above 0.75 [20,50].

The software SPSS 23 and Stata 17 [51] were used to perform *k*-means clustering and fsQCA, respectively.

4. Results with Discussion

4.1. Typological Profiling of Young People LCBs

We used *k*-means cluster analysis to group young individuals based on LCB, intentions, and perceived behavior control, aiming to understand and predict diverse pathways to high and not-high levels of LCB. Following Hair et al.'s [52] recommendation, we computed multiple cluster solutions and selected the optimal option by statistical judgment. The dendrogram indicated a potential range of three to five clusters, leading us to conduct *k*-means clustering for each option. After evaluation, we found that four clusters exhibited the most pronounced differences, resulting in statistically significant, stable, and meaningful clusters. This conclusion was further supported by the ANOVA and Bonferroni test results. The presence of a small number of clusters suggests less behavioral heterogeneity among young adults, sharing similar routines, attitudes, motivations, and perceptions of control, in line with previous studies (see Table 1). While all sociopsychological TPB constructs were found to be statistically significant, the analysis revealed that LCB, followed by intentions, played a more significant role in clustering than perceived behavioral control. Consequently, the labeling of each cluster is based on LCB, while the cluster descriptions are derived from the selected clustering criteria and the personal characteristics of the respondents as presented in Table 3.

Table 3. Demographic and sociopsychological characteristics of respondents between clusters.

Demographics	Cluster 1 Low-Carbon Champions (n = 213; 27.7%)	Cluster 2 Low-Carbon Skeptics (n = 112; 14.6%)	Cluster 3 Low-Carbon Talkers-Mostly (n = 201; 37.8%)	Cluster 4 Low-Carbon Walkers-Mostly (n = 153; 19.9%)	χ^2 (df) [p-Value]
Gender:					
Male (n = 39)	16.7%	21.5%	37.8%	24.0%	33,295 (6) [0.208]
Female (n = 173)	32.5%	11.3%	38.0%	18.2%	
Other (n = 3)	33.3%	33.3%	33.3%	0.0%	
Age:					
<21 (n = 68)	21.7%	18.8%	37.3%	22.3%	17,532 (6) [0.151]
21–25 (n = 122)	31.0%	12.5%	38.7%	17.8%	
>25 (n = 23)	37.1%	6.5%	35.5%	21.0%	
		Region of residence:			
Panonian (n = 82)	32.9%	8.0%	43.4%	15.7%	36,560 (9) [0.218]
North (n = 8)	32.0%	4.0%	56.0%	8.0%	
Zagreb (n = 19)	35.2%	9.3%	37.0%	18.5%	
Adriatic (n = 104)	23.6%	19.5%	33.8%	23.1%	

Note: all p-values < 0.01. The strength of associations is given in square brackets.

Gender, age, and region of residence were found to have statistically significant differences among clusters at a 99% significance level. However, it is worth noting that these variables are only weakly correlated with cluster membership. On the other hand, other demographic variables such as living area (χ^2 = 1.869 (3), p = 0.600), place of residence (urban/rural, χ^2 = 8.701 (12), p = 0.720), house size (χ^2 = 5.687 (6), p = 0.459), finances (χ^2 = 15.274 (12), p = 0.227), and income (χ^2 = 5.816 (6), p = 0.444) did not show significant differences at a 95% significance level. As a result, these variables were not considered in explaining cluster membership.

The first cluster consists of 213 young people, accounting for 27.70% of the entire sample, who demonstrate a high level of LCB. Therefore, this cluster is labeled "Low-Carbon Champions". The members of this cluster exhibit a consistent inclination toward LCB and believe in their role as agents of change. They possess a good awareness of environmental issues such as global warming, climate change, energy conservation, and efficient energy use. They incorporate various aspects of LCB into their daily behavior and feel empowered to shape the future. A significant proportion of respondents in this cluster reside in the capital, highlighting the role of large cities in fostering low-carbon communities, promoting low-carbon awareness, developing infrastructure, and implementing environmentally focused solutions for genuine LCB (see [53]). Nearly one-third of all female respondents belong to this cluster, whereas only 16% of the male respondents are part of it, indicating a gender disparity. This aligns with previous studies suggesting that women are more prone to LCB [54]. However, it is important to consider this gender effect in relation to other factors, as noted by Fitzgerald [19]. Notably, the proportion of respondents in this cluster increases with age within the cohort of young people, suggesting that older young individuals are more inclined to adopt LCB. However, this conclusion cannot be generalized to all age groups, as recent literature shows that older individuals may not exhibit the same inclination toward LCB [55] or that there may be a nonlinear relationship between age and LCB [56]. It is worth noting that the literature on LCB also reports insignificant effects of age and gender [57].

Cluster 2 consists of 112 young people, representing 14.6% of the sample. This cluster has the smallest number of individuals and is labeled "Low-Carbon Skeptics". It exhibits the lowest scores on LCB and psychological determinants such as intentions and perceived behavioral control. It comprises the smallest proportion of surveyed women, the oldest respondents (aged 25–35), and the fewest individuals residing in the Pannonian region, the northern part of Croatia, or the capital. In contrast, it has the highest proportion of young people living on the Adriatic coast, specifically in Zadar, Split, and Dubrovnik. This observation supports the notion that LC transition can be viewed as a geographic process [58]. Individuals in this cluster express greater concern for their current situation than about the future. They tend to believe that the future is not worth contemplating and show indifference to the consequences of their own and others' nonecological behavior. Consequently, young people in this cluster are rarely engaged in low-carbon activities. Their almost ignorant behavior can partially be attributed to their belief that individual contributions cannot effectively mitigate global warming and climate change.

The members of these two clusters demonstrate consistent behavior aligned with their low-carbon intentions and perceived levels of behavioral control. However, the following two clusters exhibit a certain degree of inconsistent or even paradoxical behavior, which has also been observed in the literature on sustainable behavior [1,18,48].

The third cluster, referred to as the "Low-Carbon Talkers-Mostly", is the most populous and consists of 291 young people (37.8% of the total sample). It is characterized by an equal distribution of males and females across all age groups. Interestingly, this cluster includes the largest proportion of female and male respondents, as well as respondents from all age groups. Similarly, it encompasses the highest proportion of respondents based on their region of residence. Although members of this cluster have higher levels of intention of engaging in LCB and believe in their ability to influence their own behavior and the environment, paradoxically, they fail to translate their intentions into actual LCB. They rarely engage in low-carbon activities, underscoring the fact that intentions do not always match behavior. The mismatch between low-carbon intentions, perceived behavioral control, and LCBs can be attributed to situational factors, such as social norms, limited knowledge, availability of low-carbon opportunities, products, and services, as well as economic and energy costs, which act as barriers and prevent them from adopting LCB. This observation aligns with previous literature examining the relationship between low-carbon consumption behavior and intentions among Chinese college students [54], ecological personality and LCB among Chinese urban residents [1], and food waste awareness and behavior among Italian college students [18].

The fourth cluster, labeled "Low-Carbon Walkers-Mostly", consists of 153 young people (19.9% of the sample) who exhibit limited intentions and doubt their ability to effect change as individuals. Yet, they sometimes engage in low-carbon practices. This paradoxical behavior can be attributed to their great distrust in the efficacy of individual actions in influencing the environment. They believe that LCB alone cannot significantly reduce harmful emissions or mitigate climate change. Therefore, the occasional adoption of low-carbon practices may stem from other motivations requiring further investigation. Previous research has highlighted economic factors [18,59] and motivational or situational factors [1] as potential drivers of the gap between low-carbon consciousness and behavior. However, in the context of this study, further research is needed to explore this phenomenon in greater depth.

Cluster analysis confirmed the necessity of categorizing individuals' behavior. To determine the specific configuration of psychological variables contributing to high or not-high levels of LCB within each cluster, fsQCA was employed. This is especially important for understanding the causal configurations that lead to paradoxical behavior, as there is limited knowledge in this area [48].

4.2. Toward Configurational Understanding of Low-Carbon Behavior

4.2.1. Results

fsQCA was performed to analyze the various configurations of the seven causal conditions depicted in Figure 1 in relation to the outcome variable (LCB). In line with standard fsQCA conventions, the uppercase and lowercase letters in Table A1 (Appendix A) and 4 indicate the presence or absence of conditions in each configuration, resulting in a total of 27 (128) configurations.

Necessity and sufficiency analysis: The fsQCA was conducted using the converted fuzzy score data. The analysis began by examining the necessity and sufficiency conditions to determine if any conditions were necessary and/or sufficient for the outcome. The results are presented in Table A1 (Appendix A). Perceived behavioral control and personal norms emerged as the most important single necessary conditions, surpassing social descriptive norms and a consideration of future environmental consequences at a threshold of 0.9 for both high and not-high LCB. However, these conditions alone were not sufficient to determine LCB. This finding aligns with previous research on the TPB, highlighting that LCB is shaped by a complex interplay of multiple determinants. The sufficiency analysis revealed that no single condition was sufficient for high LCB in all clusters and across the entire sample, except for Cluster 1, where subjective low-carbon knowledge played this role. In contrast, sufficiency conditions were primarily associated with not-high LCB, particularly in Clusters 2 and 3, where very low levels of LCB were observed (refer to Panel 1, Table A1, Appendix A).

Configuration analysis: The results presented above indicate the importance of examining the causal relationship between high and not-high LCB and their determinants from a configurational perspective. Therefore, a truth table was constructed for both high and not-high LCB, which was then reduced to include only sufficient configurations with a consistency level greater than 0.8 at a significance level of 0.05. The findings of this analysis are reported in Table 4.

Clusters 1 and 4, which consist of respondents demonstrating higher levels of LCB, are the only clusters that exhibit empirically relevant configurations specifically associated with high LCB. These configurations, four and five for Clusters 1 and 4, together explain about 89% and 26% of high LCB, respectively. Their combined solution consistencies are about 0.78 and 0.97, respectively, suggesting a strong association with high LCB. However, the recipes from Cluster 1 accounted for a much larger portion of the outcome.

In Cluster 1, the first causal configuration (SDN*PBC*CFC*PN) has a raw coverage rate of 82.5% and a unique coverage rate of 10.6%, indicating that young people engage in low-carbon activities when they strongly embrace social descriptive norms, personal norms, perceived behavioral control, and consideration of future environmental consequences. This configuration accounts for the majority of young people with high LCB (82.5%) and demonstrates an appropriate consistency level of 0.779, meaning that approximately 78% of cases with this configuration exhibit consistently high LCB.

Table 4. fsQCA results for each cluster and the whole sample.

	Number of Set	Final Reduction Set	Raw Coverage	Unique Coverage	Solution Consistency
		Cluster 1: Low-carbon Champions			
High	1	SDN*PBC*CFC*PN	0.825	0.106	0.779
	2	PBC*sk*CFC*cik*PN	0.562	0.020	0.868
	3	SIN*PBC*CFC*PN	0.653	0.008	0.861
	4	SIN*SDN*PBC*PN	0.664	0.032	0.860
	Statistics	Total Coverage = 0.888; Solution Consistency = 0.777			
Not-high		No Sets Identified as True			
		Cluster 2: Low-carbon Skeptics			
High		No Sets Identified as True			
Not-high	1	sin*sdn*pbc*sk*cfc*cic*pn	0.170	0.035	0.993
	2	sin*sdn*PBC*sk*cfc*CIC*pn	0.151	0.020	0.994
	3	SIN*sdn*pbc*sk*CFC*cic*PN	0.149	0.042	0.990
	Statistics	Total Coverage = 0.158; Solution Consistency = 0.988			
		Cluster 3: Low-carbon Talkers-Mostly			
High		No Sets Identified as True			
Not-high	1	sin*sdn*PBC*sk*CFC*CIC*pn	0.070	0.005	0.988
	2	sin*PBC*sk*CFC*cic*PN	0.506	0.088	0.990
	3	sin*SDN*PBC*sk*CFC*PN	0.474	0.045	0.983
	4	SDN*PBC*CFC*cic*PN	0.558	0.148	0.951
	Statistics	Total Coverage = 0.679; Solution Consistency = 0.953			
		Cluster 4: Low-carbon Walkers-Mostly			
High	1	SIN*SDN*PBC*SK*CFC*CIC	0.245	0.065	0.965
	2	sin*sdn*SK*CFC*CIC*pn	0.198	0.001	0.986
	3	sin*PBC*SK*CFC*cic*PN	0.138	0.004	0.984
	4	sin*sdn*SK*cfc*cic*PN	0.171	0.000	0.983
	5	PBC*SK*CFC*CIC*pn	0.163	0.004	0.994
	Statistics	Total Coverage = 0.259; Solution Consistency = 0.970			
Not-high	1	SIN*sdn*pbc*sk*CFC*cic*pn	0.261	0.011	0.930
	2	sin*pbc*sk*cfc*cic*PN	0.460	0.039	0.928
	3	SIN*SDN*PBC*sk*CFC*cic	0.453	0.002	0.867
	4	SDN*sk*CFC*cic*PN	0.577	0.065	0.854
	Statistics	Total Coverage = 0.577; Solution Consistency = 0.857			
		Whole sample: Young adults in Croatia			
High		No Sets Identified as True			
Not-high	1	sin*sk	0.714	0.140	0.853
	2	sin*cfc	0.188	0.001	0.874
	3	pbc*cfc	0.119	0.000	0.929
	4	sk*cfc	0.159	0.009	0.856
	5	pbc*cic	0.289	0.012	0.937
	6	sdm*pn	0.248	0.000	0.899
	7	sin*cic	0.353	0.006	0.865
	8	sdn*CIC	0.266	0.000	0.884
	9	sk*CIC	0.351	0.034	0.834
	10	sdn*CFC	0.456	0.027	0.850
	11	CFC*pn	0.224	0.007	0.884
	Statistics	Total Coverage = 0.799; Solution Consistency = 0.806			

Note: Capital letters indicate set membership, while lowercase letters indicate not being in a set. Symbols used for psychological features are: SIN = social injunctive norms; SDN = descriptive normative beliefs; PBC = perceived behavioral control; SK = subjective knowledge; CFC = consideration of future consequences; CIC = consideration of immediate consequences; PN = personal norms.

The second configuration (PBC*sk*CFC*cik*PN) accounts for 56.2% of high LCB among young people but is exclusive to only 2% of the sample cases. It displays a high consistency level of 0.87. The same interpretation applies to the other configurations. The second configuration represents young people with strong perceived behavioral control, personal norms, and consideration of future environmental consequences, but they lack low-carbon knowledge or have insufficient knowledge, and they do not consider immediate environmental consequences. Although this configuration provides an alternative causal path for the outcome, it holds less empirical importance due to its lower unique coverage. Thus, the first configuration for Cluster 1, with the highest unique coverage, along with the first configuration for Cluster 4, emerges as the dominant causal path.

As expected, there is no causal pathway leading to high LCB in Clusters 2 and 3. Young adults in these clusters are rarely involved in low-carbon activities. When it comes to not-high LCB in Cluster 2, the total coverage is low, and it is primarily the absence or insufficient level of psychological traits that contributes thereto. For instance, the first configuration for Cluster 2 (sin*sdn*pbc*sk*cfc*cic*pn) supports this observation. Even when there is a combination of subjective injunctive norms, consideration of future consequences, and personal norms, as in the third pathway for the same cluster (SIN*sdn*pbc*sk*CFC*cic*PN), this is not sufficient to generate not-high LCB. Rather, the absence of social descriptive norms, perceived behavioral control, subjective knowledge, and consideration of immediate consequences, in combination with other factors, lead to not-high LCB.

Configuration four (SDN*PBC*CFC*cic*PN) emerges as the dominant one for Cluster 3, accounting for 55.8% of all cases with not-high LCB and 14.8% of the sample cases individually. It exhibits a high consistency level of 0.951, indicating that the presence of social descriptive norms, perceived behavioral control, consideration of future consequences, and personal norms, combined with the absence of immediate consequence considerations, predicts not-high LCB among individuals in Cluster 3.

The results for the whole sample indicate that there is no specific configuration of psychological conditions that leads to high LCB. However, various combinations of these two psychological characteristics can contribute to not-high LCBs. These findings are somewhat expected, given that the median LCB is 2.67 and the mode is 3 (signifying occasional engagement in low-carbon activities).

4.2.2. Discussion

In general, the results challenge the theoretical underpinnings of linear causality of personal norms or intentions as the best immediate antecedents of LCB. Instead, high LCB emerges from a combination of psychological causal conditions (such as personal norms, perceived behavioral control, etc.) in sufficient configurations, supporting the causal complexity hypothesis. This study specifically revealed that personal norms and perceived behavioral control play a dominant role in a cluster of young people (Cluster 1) who more frequently behave in a low-carbon way. However, these factors alone are not sufficient to guarantee high LCB. Additionally, they are not necessary components in the configurations that lead to high LCB in Cluster 4. Instead, other psychological characteristics must be present to varying degrees to promote high LCB. In other words, only specific configurations of psychological causal conditions can accurately predict both high and not-high LCB.

Interestingly, a consideration of immediate environmental consequences and subjective knowledge does not appear to be as significant in explaining and predicting LCB among young adults who already engage relatively frequently in low-carbon activities. These conditions appear in only one configuration, specifically in the form of their absence or inadequacy (as seen in the second set for Cluster 1 in Table 4). This deviates from previous research that emphasized the importance of subjective knowledge. However, for individuals who exhibit LCB only occasionally (Cluster 4), both conditions seem to play an important role in conjunction with other factors.

Furthermore, the results indicate that both high and not-high levels of LCB can be achieved through multiple causal pathways, which reinforces the notions of equifinality and multiple causal complexity. Moreover, when comparing the causal configurations for high and not-high LCB, it becomes evident that the presence or absence of the same psychological traits can either promote or suppress LCB, depending on their specific combination. This supports the concept of multiple asymmetries. This study highlights that LCB is generally more intricate than suggested by previous studies that utilized structural equation modeling to examine the net effects of TPB determinants on the outcome of interest. Asymmetry may contribute to the explanation of the inconsistent findings observed in the literature, as noted by Schneider and Wagermann [20].

It appears that there is only one dominant recipe with multiple variants that may potentially be overlooked due to their very low unique coverage scores among young people in Cluster 4. Although such configurations may be treated as variants of the dominant configuration due to substitutable conditions, they should not be disregarded entirely and may still hold value for researchers. Indeed, Breuer et al. [60] argued that lower coverage may indicate a rarer causal combination, while Grofman and Schneider [61] noted that even with lower coverage, a configuration may still be theoretically and/or empirically informative, making it a valuable starting point for further research. While this recipe aligns with the TPB in terms of high LCB being achievable through the presence of psychological causal conditions, further research is warranted for this cluster, particularly because the total coverage score of 0.259 suggests that there may be other causal conditions not accounted for by the model. Interestingly, the presence of low-carbon knowledge and considerations of future consequences proved to be significant factors for Cluster 4, as they are present in each configuration. Although high LCB is the main focus of policy interest, the low total coverage score for Cluster 2 (15.8%) also indicates the need for further research. The combinations of the TPB determinants were found to have lower explanatory power for not-high LCB.

To assess the robustness of the findings, several sensitivity analyses were conducted following Skaaning [62]. First, fsQCA was performed with different calibrations using the upper quartile (95%), median (50%), and lower quartile (25%) of the original variable values. Additionally, different consistency thresholds for sufficient conditions (0.75) were utilized. The findings of these analyses remained consistent with those reported here.

5. Conclusions

Human behavior displays diverse patterns shaped by a combination of psychological characteristics and contextual factors such as climate change and policy incentives, leading to distinct profiles of LCB. Based on data collected through an online survey in Croatia in 2022 and using the *k*-means algorithm, this paper clustered young people into four clusters, which demonstrated both consistent and inconsistent behavior regarding LCB, aligning with previous research on sustainable behaviors. The findings highlight the complexity of factors influencing LCB and suggest the need for determining the specific configuration of psychological variables that contribute to high or not-high levels of LCB within each cluster. To that end, fsQCA was employed for each cluster. Empirically relevant configurations for high LCB were observed exclusively in Clusters 1 and 4, consistent with expectations, as respondents in these clusters demonstrated higher levels of LCB.

This study contributes to the growing body of evidence based on alternative approaches to carbon reduction behaviors by emphasizing the diversity of actors and the psychological antecedents of their LCBs. The results have several theoretical and practical implications, particularly regarding high LCB. First, fsQCA expands research on the TPB by considering alternative configurations of sociopsychological conditions driving high and not-high LCB, shedding light on the complex causal structure of LCB, and confirming equifinality and conjunctural causality. Second, this study emphasizes the importance of accounting for asymmetry in understanding LCB, challenging previous linear approaches. Third, policymakers should recognize the need for multiple configurations in different clusters and consider the crucial role of specific conditions in promoting LCB. Fourth, targeted measures tailored to specific populations should be developed based on the fine-grained differences and variations identified in the study. For example, the education sector may develop programs that emphasize the significance of pro-environmental efforts and encourage students to engage in open debates about their psychological or sociodemographic preconditions. It can incorporate various pedagogical approaches that emphasize the development of environmental attitudes, intentions, or values, such as real-world sustainability projects, hackathons, community service, etc. Universities can adapt their infrastructure and culture to resonate with specific subgroup profiles or enhance tools for assessing and monitoring changes in students' attitudes and behaviors over time. Finally, the study highlights the value of acknowledging paradoxical behaviors, which provide insights into the complexity of individual low-carbon choices and actions.

Although this study focused on Croatia, which is a limitation, the findings may also be relevant to countries with similar social, economic, or geographic circumstances, particularly those with high carbon emissions relative to their GDP growth rate. However, it is important to note that the study solely focused on young people, representing only one age cohort, and that LCB represents a mixture of individual private and public consumption patterns, which also imposes some limitations on the generalizability of the results. Nevertheless, further research may focus on comparing different age groups to provide insights into how LCB pathways evolve across the lifespan. In addition, cross-cultural comparisons would be valuable in identifying commonalities and variations in LCB segmentations in various settings.

Factors such as education, urban versus rural settings, and socioeconomic status can also influence the characterization of the clusters. Therefore, further investigation of consistent and paradoxical LCB, with the addition of contextual variables, would be beneficial for developing strategies and practical guidance to enhance LCBs.

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Data Availability Statement: The data that support the findings of this study are available from the corresponding author, Djula Borozan, upon reasonable request.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Necessity and sufficiency analysis results.

Symbols	Cluster 1		Cluster 2		Cluster 3		Cluster 4		Whole Sample	
	Nec.	Suffic.	Nec.	Suffic.	Nec.	Suffic.	Nec.	Suffic.	Nec.	Suffic.
Panel 1: High LCB										
LCB	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
SIN	0.709	0.858	0.580	0.198	0.787	0.314	0.586	0.723	0.692	0.607
SDN	0.906	0.764	0.548	0.117	0.943	0.204	0.672	0.609	0.843	0.469
PBC	0.988	0.752	0.904	0.106	1.000	0.170	0.827	0.698	0.946	0.438
SK	0.552	0.950	0.780	0.243	0.743	0.477	0.442	0.876	0.557	0.719
CFC	0.927	0.727	0.880	0.065	0.982	0.167	0.883	0.496	0.921	0.378
CIC	0.329	0.893	0.754	0.118	0.611	0.315	0.521	0.710	0.440	0.507
PN	0.968	0.731	0.907	0.097	0.984	0.168	0.809	0.546	0.927	0.410
Panel 2: Not-high LCB										
LCB	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
SIN	0.862	0.421	0.213	0.995	0.440	0.981	0.589	0.723	0.480	0.711
SDN	0.949	0.322	0.294	0.987	0.749	0.915	0.725	0.687	0.679	0.668
PBC	1.000	0.304	0.510	0.995	0.937	0.905	0.752	0.665	0.823	0.678
SK	0.703	0.484	0.201	1.000	0.274	0.987	0.383	0.771	0.324	0.745
CFC	0.968	0.303	0.791	0.970	0.906	0.876	0.944	0.560	0.896	0.664
CIC	0.384	0.417	0.386	0.983	0.329	0.968	0.435	0.620	0.368	0.763
PN	0.977	0.295	0.545	0.978	0.913	0.883	0.865	0.612	0.829	0.658

Note: for a description of symbols used see Table 3. Nec. = necessity; suffic. = sufficiency.

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