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From intention to action: Modeling student lifestyle carbon emissions and reduction scenarios

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ABSTRACT

University students, as future decision-makers and practitioners, play a pivotal role in advancing carbon neutrality by 2060. Their awareness and behaviors are highly malleable during university education, with long-term impacts extending beyond campus boundaries. Using Peking University as a case study, this research quantifies the carbon footprint of students' lifestyles, develops a structural equation model (SEM) of low-carbon behavior mechanisms, and evaluates lifestyle-based emission reduction scenarios. Results show that food and transportation are the major contributors to students' carbon footprints, reflecting a paradox of "high support but low motivation" toward low-carbon practices. While changes in individual cognition are necessary, they yield limited mitigation benefits. Scenario simulations demonstrate that synergistic interventions from campuses, communities, and broader society can amplify emission reductions by up to 40 %, offering a scalable pathway for universities to pioneer behavior-driven decarbonization. This study thus provides both empirical evidence and a practical framework for building zero-carbon campuses and cultivating societal transitions toward sustainability.

1. Introduction

CO_2 is the principal greenhouse gas driving global warming, particularly through anthropogenic emissions. China is the world's largest emitter. In 2022, its carbon dioxide emissions reached 12.849 billion tonnes (IEA, 2022). The Chinese government has pledged to peak carbon emissions by 2030 and achieve carbon neutrality by 2060. Achieving these targets requires rapid and profound transformations across society (S. Zhang and Chen, 2022). Progress depends not only on supply-side reforms to the energy and industrial structure but also on unlocking demand-side mitigation potential (J. Zhang and Zheng, 2023). Because consumer behavior is tightly coupled with market supply and demand, producers will struggle to realize a genuine low-carbon transition without a broad societal shift toward low-carbon lifestyles (Pettifor et al., 2023). Within the "1+N" policy framework for the dual-carbon goals, China has designated the "Green and Low-Carbon National Action" as one of ten key initiatives, emphasizing ecological-civilization education and the promotion of green lifestyles to foster widespread participation and behavioral change at the societal level.

Universities will serve directly as implementers of this initiative. The contribution of university campuses to climate mitigation encompasses not only direct (Scope 1) emissions (Gu et al., 2019), but—more importantly—their influence on ideas, patterns of thought and behavior, and the low-carbon practices that students will carry into their future work and daily lives, which will directly shape society's future emissions (McCowan, 2023). Commitments to climate mitigation and adaptation in higher education can thus generate substantial societal impacts (Jiang and Kurnitski, 2023). Students are both direct participants in campus governance and "bridging actors" who can diffuse low-carbon knowledge and practices to wider communities (McCowan, 2020). However, existing campus carbon-neutral actions tend to focus on Scopes 1 and 2 (e.g., energy-efficiency retrofits and fuel switching), while systematic quantification and intervention design for Scope 3—particularly student consumption and behavior—remain limited. In particular, there is a lack of integrated research frameworks that couple modeling of behavioral mechanisms with scenario-based mitigation assessment. Evidence from multiple international universities indicates that Scope 3 often accounts for a large share, and that data quality and boundary definition are challenging, underscoring the need for fine-grained research centered on consumption and lifestyles (Helmers et al., 2021; Herth and Blok, 2023; Kiehle et al., 2023a).

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Therefore, this study is organized around three research questions: (1) Within the campus Scope 3 boundary, what are the magnitude and compositional characteristics of student lifestyle carbon emissions? (2) Under an integrated TPB–VBN–CADM framework, to what extent can students' low-carbon lifestyle intentions be translated into actual behaviors? If an intention–action deviation exists, what are the key drivers and constraints underlying it? (3) Under two intervention scenarios designed within the Avoid–Shift–Improve (ASI) framework, what mitigation potential can be achieved, and which intervention levers contribute most to the reductions?

Against this backdrop, we propose a consumption-side mitigation modeling pathway and take Peking University as a case study. We systematically quantify student lifestyle carbon footprints, construct a structural equation model (SEM) grounded in behavioral theories including VBN, TPB, and CADM, and then conduct ASI-based lifestyle scenario simulations to evaluate the mitigation potential of lifestyle changes, thereby offering a replicable pathway for lifestyle-oriented emission reductions. The contributions of this study are as follows: (1) Focusing on campus Scope 3 emissions, we prioritize the quantification and heterogeneity of student consumption- and lifestyle-related emissions, addressing the gap in campus research where student behavior–driven mitigation potentials are often insufficiently quantified. (2) The study's theoretical contribution lies in integrating TPB, VBN, and CADM within a single SEM to simultaneously capture three complementary mechanisms—deliberative planning, norm internalization, and habitual/contextual constraints—thus providing a mechanism-based explanation for the "high intention–low action" gap among students and identifying the key pathways through which intentions are formed and translated into practice. (3) Methodologically and in application, we embed the SEM-identified mechanisms into ASI-based scenario evaluation to form a closed-loop modeling workflow ("mechanism identification–intervention mapping–potential accounting"). We further translate key mechanisms into operational scenario parameters (e.g., participation/adoption rates, substitution intensity, and carbon-intensity improvement magnitude), enabling a computable mapping from individual behavioral changes to campus-scale Scope 3 mitigation outcomes and supporting reusable assessments. (4) We identify the marginally additive mitigation benefits of combined cognitive and contextual interventions. This finding has practical relevance for universities and education authorities seeking to advance a green transition in the national education system, and it also provides calibratable behavioral parameters for linking to larger-scale models, thereby improving the behavioral realism of consumption-side scenarios.

2. Literature review and research hypothesis

2.1. Carbon-neutral campus planning and action

The concept of a "low carbon campus" can be traced back to the 1977 Tbilisi Declaration. In the 1990s, frameworks advanced by the United Nations and non-governmental organizations further brought higher education institutions (HEIs) into the sustainable development agenda (Calder and Clugston, 2003; Chung C Y et al., 2014; Clugston and Calder, 1999; Wright, 2002). These declarations catalyzed greener campus governance and operations, yet lacked binding and accountability provisions at the institutional level; on the educational side, few efforts formed a closed loop linking measurable learning outcomes to quantified mitigation contributions (Capstick et al., 2014; Dubois et al., 2019). Research indicates that incorporating behavior change and educational interventions into the governance toolbox can yield mitigation potentials comparable to conventional technological pathways (Bray and Cridge, 2013; Cordero et al., 2020). In recent years, the international community has begun to systematically strengthen education's role in climate action: UNESCO's Greening Education Partnership (GEP) promotes a whole-of-system approach that couples climate education with school governance, curricula, and community engagement. In parallel, the Sustainable Development Solutions Network (SDSN), together with the ClimateWorks Foundation and Monash University, released the Net Zero on Campus guide and an online toolkit, providing HEIs with roadmaps and community-of-practice guidance on emissions reduction across energy, mobility, facilities, waste, and procurement (Mallow S et al., 2020). On finance and taxation, the UK's Public Sector Decarbonization Scheme (PSDS) and the United States' Inflation Reduction Act Direct Pay (Elective Pay) mechanism provide grants and cashable clean-energy tax incentives, respectively, to nonprofits such as universities, accelerating campus electrification and renewable-energy deployment (Barlow and Boff, 2024; Singh, 2024).

Universities today shoulder growing social responsibility and influence, playing a pivotal role in shaping students' future low-carbon behaviors (Anderson, 2012). Globally, campus energy-saving and emissions-reduction practices in the United States and Europe have become more institutionalized and standardized. In the U.S., more than 1000 institutions are registered users of the STARS Reporting Tool to rate emissions performance with transparency and systematization, enabling international benchmarking (STARS, 2020). In Europe, De Montfort University (UK) and Leuphana University (Germany) have both inventoried their campus carbon footprints and are working toward operational carbon-neutral campuses (Opel et al., 2017; Ozawa-Meida et al., 2013). Although differences in boundary setting and methodological choices persist across HEIs, greater disclosure and comparability are lowering information barriers to like-for-like assessment. In China, a number of universities are exploring campus emissions research, but the focus remains largely on Scope 1 and Scope 2 emissions and their corresponding solutions (Li et al., 2015; Liu et al., 2017; Zheng et al., 2021).

China has recently advanced on both the top-level institutional front and within the education system. The Interim Regulations on the Administration of Carbon Emissions Trading were promulgated and took effect on May 1, 2024, establishing the legal basis and regulatory framework for the national carbon market. In 2023, the Interim Measures for the Administration of Voluntary Greenhouse Gas Emissions Trading (trial) provided the supervisory framework for the relaunch of CCERs, further improving both compliance and voluntary market mechanisms and creating potential mitigation drivers for HEIs (Lee and Lee, 2021). On the education side, the Ministry of Education issued the Implementation Plan for Building a National Education System for Green and Low-Carbon Development, calling for the systematic integration of green and low-carbon principles into campus construction, curricula, and governance (L. Liu and Gao, 2020).

Overall, top-down mechanisms provide price and rule signals that drive structural mitigation on the energy and infrastructure sides; however, they are limited in capturing the preferences, habits, and contexts of micro-level actors and thus cannot by themselves unlock Scope 3 behavior change (B. Yang, 2025). Bottom-up interventions in education and campus communities can reshape preferences, habits, and contextual constraints in high-impact domains such as diet and mobility, offering low-cost and replicable advantages; yet without institutional and infrastructural support, such mitigation effects are difficult to sustain (Jabeen et al., 2023). Therefore, university mitigation should couple these two dimensions by using carbon markets, standards, and information disclosure to create external constraints and incentives, while simultaneously operationalizing the translation from cognition and intention to actual behavior through curriculum design, organized activities, and infrastructure retrofits. Doing so can help establish a linkage between subjective well-being and sustainability, and build measurable and accountable behavioral decarbonization pathways (Lengyel et al., 2019).

2.2. Low-carbon behavioral influences

Changes in pro-environmental behavior constitute one of the most cost-effective pathways to a low-carbon and sustainable society; their benefits lie not only in short-term energy savings but also in the durable shaping of life-cycle behavior patterns. A substantial body of research shows that behavioral factors can reduce total heating energy use by about 30 % and cooling energy use by about 50 % (Steemers and Yun, 2009). In the higher-education context considered here, students' value orientations, knowledge structures, and socialization processes are highly malleable, and their behavioral choices exert significant spillover effects on future societal emissions. In this paper, we define low-carbon consumption behavior as energy-use behavior undertaken with the aim of reducing CO_2 emissions—such as purchasing and consuming energy-efficient products, using green energy and energy-saving facilities, operating energy-consuming equipment in low-carbon ways, and related practices that generate positive changes in ecosystems and the environment (Stern, 2000).

To address the three core questions—"why one is willing to act," "whether one is able to act," and "whether one can persist"—mainstream behavioral theories provide complementary explanatory frameworks. The value–belief–norm (VBN) theory emphasizes the sequential role of values and ascription of responsibility in pro-environmental behavior, making it well suited to explain the moral driver of "ought to act," but it depicts situational constraints and enactment capability less fully (Raghu and Rodrigues, 2022). By contrast, the theory of planned behavior (TPB) posits that attitudes, subjective norms, and perceived behavioral control (PBC) determine behavioral intention, allows PBC to have a direct effect on behavior, and thus explains how contextual factors—such as resource availability, time costs, and skill constraints—produce intention–behavior gaps; however, it engages less with upstream value- and norm-based motivations (Qin and Song, 2022). To bridge these boundaries, the comprehensive action determination model (CADM) integrates the norm activation model (NAM), VBN, and TPB, and introduces "habit" and "situational" mechanisms. CADM argues that social or personal norms often influence behavior indirectly through intentions and habits, thereby accounting for the execution gap characterized by "high cognition/high support but low action" (Klöckner and Blöbaum, 2010).

Prior campus- and individual-level carbon-footprint and mitigation-behavior studies often rely on a single behavioral theory. This practice can inadvertently attribute the "high intention–low action" gap to one dominant mechanism while overlooking competing pathways. To address this limitation, we integrate the Theory of Planned Behavior (TPB), the Value–Belief–Norm (VBN) theory, and the Comprehensive Action Determination Model (CADM)—not to merely stack predictors, but to decompose and compare the multi-mechanism causal structure of low-carbon lifestyle behavior within a single structural equation model. Specifically, TPB emphasizes a "deliberative planning" pathway, VBN highlights a moral–norm internalization pathway, and CADM further introduces an automation and contextual constraint/enabler pathway (where habits and external conditions can influence behavior directly and weaken the translation from intention to action). Estimating these three mechanisms simultaneously in one model enables us to: (1) compare the relative explanatory power of normative motivation, capability/feasibility, and habitual inertia; (2) more precisely locate whether the intention–action gap arises primarily during intention formation or intention implementation; and (3) test whether habits and contextual factors operate as suppressing/moderating mechanisms—rather than as mere correlates—thereby providing a more targeted theoretical basis for subsequent intervention design.

Given that low-carbon behavior involves multi-level latent psychological constructs and chain-type transmission mechanisms, we employ structural equation modeling (SEM) rather than single-equation regression. SEM simultaneously estimates the measurement and structural models within one framework, explicitly treats measurement error via factor loadings, and supports the decomposition of parallel and serial mediation as well as direct and indirect effects—features that make it well suited to unpack the psychological–behavioral chain "values and norms → intention → habit and context → behavior" (Bai and Liu, 2013; Chen and Li, 2019; T. Wang et al., 2021). In addition, global fit indices provide statistical tests of the plausibility of the theoretical model, superior to multiple regression, which examines only local relationships. Accordingly, we classify the determinants into three categories: first, demographic characteristics to capture individual heterogeneity; second, internal factors, covering values, ascription of responsibility, and personal norms (VBN); attitudes, subjective norms, and perceived behavioral control (TPB); as well as knowledge and habit as endogenous capability elements; and third, external factors, primarily the influences of situational and institutional environments.

2.3. Carbon emissions and reduction potential

A diverse methodological system has emerged for assessing carbon emissions in higher education institutions, encompassing accounting approaches centered on life cycle assessment (LCA) and carbon-footprint models, as well as ecological footprint evaluation (EFE), multi-objective linear programming, and fuzzy two-stage algorithms (Elsayed et al., 2025; Ho et al., 2014; Lambrechts and Van Liedekerke, 2014; Paredes-Canencio et al., 2024; Rus et al., 2025). Carbon-footprint analysis not only identifies emission sources but also enhances the carbon-related knowledge and awareness of faculty and students with respect to everyday campus activities. Evidence indicates that conducting regular emissions assessments and communicating the results facilitates a better understanding of the impacts of energy consumption (Loyarte-López et al., 2020).

In terms of forecasting and evaluation, top-down models such as LEAP, MARKAL/TIMES, MESSAGE, CGE, and RETScreen can simulate the emissions responses to different policy packages at the energy–economy system level (Kumar and Madlener, 2016). However, these models primarily rely on macro-average parameters and simulate emissions using an aggregate perspective, neglecting feedbacks, delays, and nonlinear relationships related to modeled factors. As a result, they struggle to address errors arising from the complex interactions among social, economic, environmental, and technological factors (Ahmad et al., 2016). System dynamics models, by contrast, are advantageous for capturing complex feedbacks and dynamic decision-making and have been applied to analyze drivers and scenarios of urban-scale carbon emissions; yet they require long time-series, multidimensional, high-quality data, and data collection at community and campus scales is costly, limiting reusability (H. Yang et al., 2021). In recent years, integrated assessment models (IAMs) have begun to incorporate lifestyle scenarios into mitigation pathway assessments—for example, IMAGE specifies behavior–structural transformations under a 2 °C constraint and shows that lifestyle change can affect end-use sector emissions through direct or indirect pathways (van Sluisveld et al., 2020). Nevertheless, such studies mostly focus on national or regional scales, with behavioral parameters often extrapolated from average adoption rates or expert judgment. Heterogeneity across groups and consumption domains, as well as the implementability of campus governance instruments, facilities, and institutional designs, is insufficiently addressed.

In view of the above, this study adopts a bottom-up, integrated framework to evaluate mitigation potential. First, within a university Scope 3 boundary, we construct an inventory of students' lifestyle carbon footprints using the emission-factor method, achieving fine-grained accounting across apparel, diet, housing, mobility, and use categories. Second, we integrate VBN, TPB, and CADM to build a structural equation model (SEM) that explicitly distinguishes the measurement and structural models and, within a single framework, elucidates the chain transmission from values and norms, to intention, to habit and context, and finally to behavior; we decompose direct and indirect effects to identify the key levers of behavioral change. Finally, we pioneer the coupling of mechanism-identification results with the ASI framework by constructing a 2 × 2 intervention matrix—"internal cognition vs. external context" crossed with "passive vs. active"—parameterizing adoption rates, intensity-reduction coefficients, and consumption-substitution coefficients, and explicitly accounting for rebound effects to quantify the mitigation potential of lifestyle change. The innovations of this study are: (1) mechanism–scenario coupling, whereby the psychological–behavioral chain identified by SEM is tightly linked to ASI-based scenario evaluation at the university scale to quantify students' behavioral mitigation potential; (2) actionability, whereby the correspondence from variables to paths to intervention options enables statistically significant path coefficients to be directly translated into governance toolkits for key domains such as diet and transport; and (3) a portable and reusable model, with moderate data requirements and model complexity, allowing replication across universities following a common workflow. This combined approach fills the gaps of LCA/IAM/system dynamics with respect to micro-level behavioral mechanisms and implementability, and provides a low-cost, scalable pathway for evaluation and decision support for Scope 3 mitigation on campuses.

2.4. Research hypothesis

Grounded in the university context, we integrate the value–belief–norm (VBN) theory, the theory of planned behavior (TPB), and the comprehensive action determination model (CADM) to develop an overarching hypothesis framework. Accordingly, the overarching hypotheses are as follows: internal factors—by strengthening value endorsement, sense of responsibility, and personal norms—enhance low-carbon intentions and promote actual behaviors. Attitudes, subjective norms, and perceived behavioral control jointly determine intention, with perceived behavioral control also exerting a direct effect on behavior. Contextual support and habitual patterns increase the efficiency of intention–behavior translation and additionally influence behavior. Demographic characteristics, as exogenous conditions, affect both the magnitude and the direction of intention and behavior. Improvements in low-carbon behavior directly determine measurable mitigation potential, which corresponds in the short term to reductions in university Scope 3 and campus emissions, and in the long term to individual life-cycle abatement and societal progress toward carbon neutrality. Heterogeneous effects exist across consumption domains: mobility behaviors depend more on context and perceived control, whereas dietary behaviors are more constrained by norms and habits. Under this hypothesis framework, the model takes internal factors, external factors, and demographic characteristics as antecedents; low-carbon intention and low-carbon behavior as the core mediating–outcome chain; and mitigation potential as the key output projecting to short- and long-term effects. Together these elements form a closed loop from antecedents to governance targets, guiding subsequent structural equation estimation and scenario evaluation (Fig. 1).

Based on VBN and empirical studies, there is a significant sequential interrelationship among ecological values, awareness and sense of responsibility, personal norms, and low-carbon behavioral intentions. Tolppanen et al. used the VBN theoretical model to find that ecological values significantly influence low-carbon lifestyles among student populations (Tolppanen and Kang, 2021). Fornara et al. confirmed the positive relationships in the VBN chain by exploring intentions to improve household energy efficiency (Fornara et al., 2016a).

Therefore, this study proposes a series of hypotheses (Fig. 2), including the following first set of hypotheses:

Hypothesis 1. (H1): Biological values (BV) have a positive impact on Ascription of Responsibility (AR);

Hypothesis 2. (H2): Ascription of Responsibility (AR) have a positive impact on Personal Norms (PER);

Hypothesis 3. (H3): Personal Norms (PER) positively influence Behavioral Intention (BI).

Based on the structural relationships proposed by the TPB theory, the best predictor of behavior is behavioral intention, which depends on attitudes towards the behavior, subjective norms, and perceived behavioral control. Perceived behavioral control can mediate the effect of intention on behavior and can also directly influence behavior. Therefore, this study proposes the following second set of hypotheses:

Hypothesis 4. (H4): Attitude (AT) has a positive effect on Behavioral Intention (BI);

Hypothesis 5. (H5): Social norms (SN) have a positive effect on Behavioral Intention;

Hypothesis 6. (H6): Perceived Behavioral Control (PBC) has a positive effect on Behavioral Intention:

Hypothesis 7. (H7): Behavioral Intention has a positive impact on Low-Carbon Behavior (LCB);

Hypothesis 8. (H8): Social Norms positively influence Attitudes (AT);

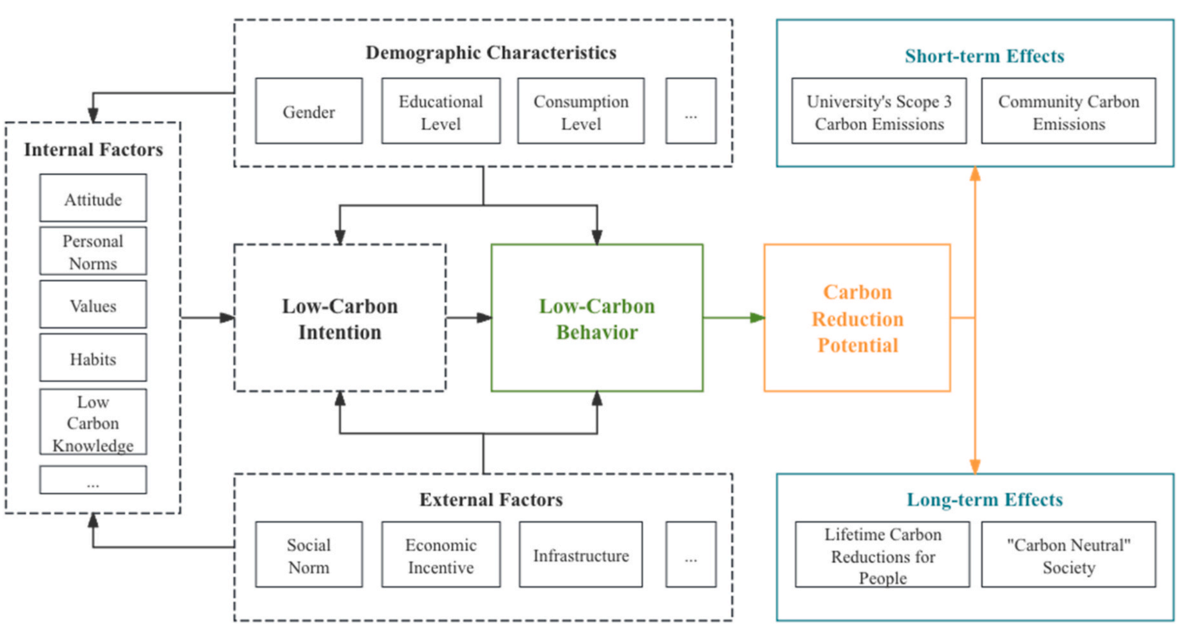

Fig. 1. Structural framework of the student behavior research model.

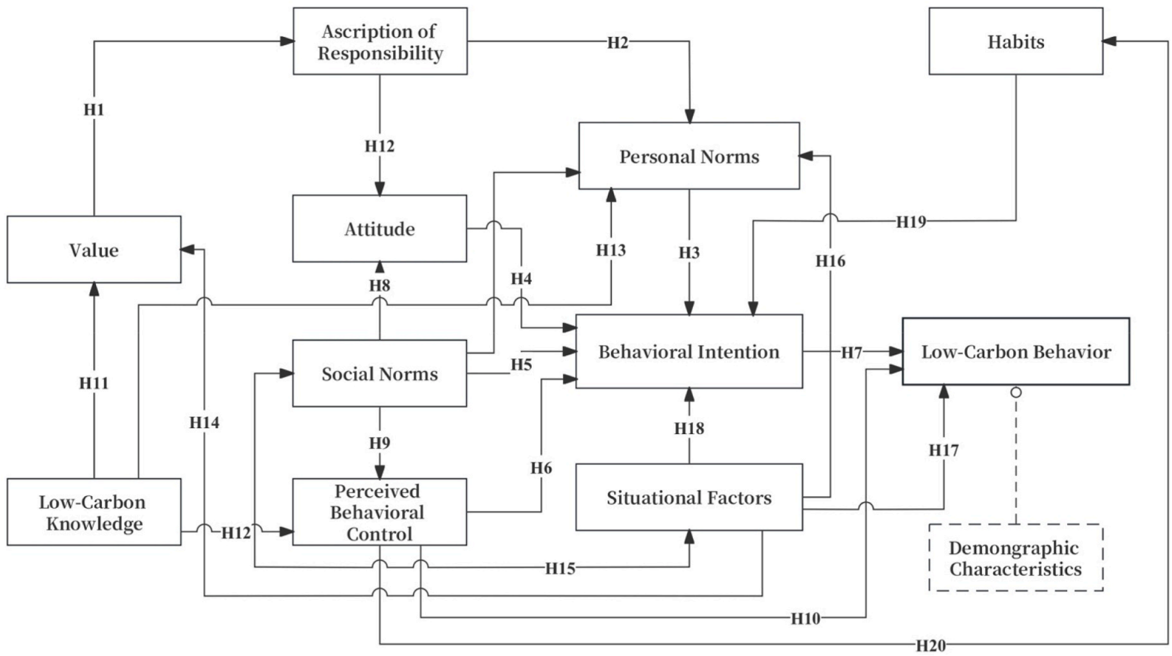

Fig. 2. The model of factors influencing students' low-carbon behavior based on research hypotheses.

Hypothesis 9. (H9): Social Norms have a positive impact on Perceived Behavioral Control (PBC);

Hypothesis 10. (H10): Social Norms have a positive impact on Personal Norms (PER);

Hypothesis 11. (H11): Perceived Behavioral Control has a positive impact on Low-Carbon Behavior.

Action-related knowledge has been empirically found to positively influence behavioral intentions (Lin and Yang, 2022). Therefore, this study proposes the following third set of hypotheses:

Hypothesis 12. (H12): Low-Carbon Knowledge(KNO) has a positive impact on Values;

Hypothesis 13. (H13): Low-Carbon Knowledge has a positive impact on Perceived behavioral control;

According to the ABC theory by Guagnano et al. and the Responsible Environmental Behavior Model by Hines et al., external factors significantly moderate behavior, but different studies and contextual variables have varying moderating effects on low-carbon behavior. Therefore, this study proposes the following fourth set of hypotheses:

Hypothesis 14. (H14): Situational Factors (SIT) have a significant impact on Values;

Hypothesis 15. (H15): Situational Factors interact with Social Norms;

Hypothesis 16. (H16): Situational Factors have a significant impact on Personal Norms;

Hypothesis 17. (H17): Situational Factors have a significant impact on Low-Carbon Behavior;

Hypothesis 18. (H18): Situational Factors have a significant impact on Behavioral Intention;

Empirical studies have found that habits significantly influence behavioral intentions and low-carbon behavior and that norms and perceived behavioral control partially influence the formation of habits (Klöckner C A et al., 2003; Verplanken B et al., 1994). Therefore, this study proposes the following fifth set of hypotheses:

Hypothesis 19. (H19): Habits (HB) have a significant effect on Behavioral Intention;

Hypothesis 20. (H20): Perceived Behavioral Control has a significant effect on Habits.

3. Methodology

3.1. Study area

This study focuses on Peking University and its students, selecting the main campus in Yanyuan, Haidian District, as the primary research subject. The spatial scope includes the Yanyuan campus, Changchun Garden, Zhongguanyuan Global Village, Wanliu Apartments, and the student residential areas around the Old Summer Palace (Fig. 3). The research scope focuses on Scope 3 emissions within the campus, emphasizing the accuracy of accounting by concentrating on the carbon emissions from students' living consumption.

The Yanyuan campus covers an area of 274.45 ha, with a total building area of 3.1642 million square meters and a green area of 123.36 ha. As of the end of 2021, the campus hosted a total of 58,831 faculty and students, including 12,683 faculty members and 46,148 students (Pekel et al., 2025).

3.2. Scope and calculation method

The most commonly used greenhouse gas emission inventory regulatory frameworks are the Greenhouse Gas Protocol (GHG Protocol, 2004), ISO 14064–1 (2006), ISO/TR 14069 (2013), PAS 2050 (2011), and PAS 2060 (2014). Building on the established greenhouse-gas inventory standards noted above, we further reviewed and compared relevant domestic and international practices in campus carbon inventories and student lifestyle carbon-footprint accounting to ensure that our boundary definition and emission-source identification are methodologically comparable and reproducible (Clabeaux et al., 2020a; Li et al., 2015b; Santovito and Abiko, 2018; Sippel et al., 2018; Yusoff et al., 2021). On this basis, we developed an emission-source inventory for Peking University that includes student business travel, commuting, on-campus municipal solid waste treatment, and consumption

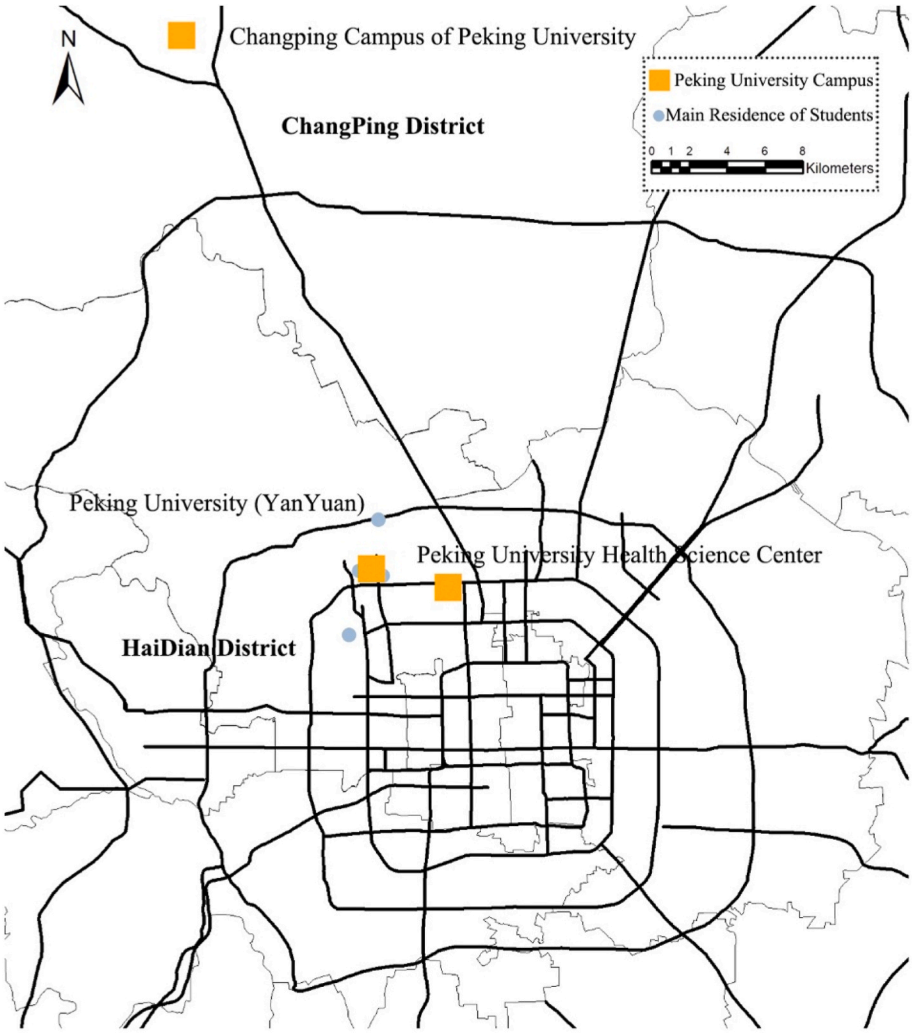

Fig. 3. Distribution of Peking University campuses and student residences.

associated with the procurement of work-related supplies. The final inventory is organized into student lifestyle categories—clothing, food, housing, mobility, and other consumption—to align emissions with a behavior-based classification scheme.

The estimation of carbon emissions is based on the carbon emission factor method provided by the IPCC. The basic idea of calculating the carbon emission estimate is to multiply the activity level of each fuel combustion by the corresponding emission factor for that fuel, as expressed in the following formula:

$$E_{CO2} = \sum A_i \times C_i \tag{1}$$

In the formula, E_{CO2} denotes total CO_2e emissions (t).; Ai is i activity intensity or substance quantity; Ci is the carbon emission factor corresponding to each unit i activity or substance. The emission factors are derived from the IPCC Guidelines for National Greenhouse Gas Emission Inventories, the Manual for National Energy Conservation and Emission Reduction issued by the Ministry of Science and Technology of China, the Guide for the Compilation of Provincial Greenhouse Gas Inventories, the Guide for Carbon Dioxide Accounting and Reporting of Enterprises (Units) in Beijing (2014), and the greenhouse gas emission coefficient database for the whole life cycle of Chinese products (Environmental Planning Institute of the Ministry of Ecology and Environment and Chinatown) Municipal Greenhouse Gas Working Group) (annex materials for a detailed list).

3.3. Behavioral questionnaire design and SEM

The behavioral research questionnaire references the questionnaire design concepts of scholars such as Ajzen, Stern, Hines, and Guagnano on behavioral theory, as well as mature scales used in current empirical studies. It has been revised based on the actual conditions of student participation in low-carbon behaviors, preliminary survey results, and expert interviews. Items in the original questionnaire that did not meet the validity and reliability tests were deleted or modified, resulting in the final version of the questionnaire on low-carbon behaviors and their influencing factors among Peking University students. The response options for the student behavior research questionnaire use a Likert scale (Likert, 1932), with 1–5 representing "strongly disagree," "disagree," "neutral," "agree," and "strongly agree," respectively. Detailed content of the survey questionnaire can be found in the supplementary materials.

Structural Equation Modeling (SEM) can effectively replace methods such as multiple regression, path analysis, factor analysis, and covariance analysis, providing a clear analysis of the overall relationship between individual indicators (Hair et al., 2019). SEM can be expressed using the following matrix equations (Bollen, 1989; Jöreskog and Sörbom, 1996):

$$\eta = \beta\eta + \Gamma\xi + \zeta \tag{2}$$

$$X = \Lambda_x \xi + \delta \tag{3}$$

$$Y = \Lambda_y \eta + \varepsilon \tag{4}$$

(2) is the structural model equation, (3) and (4) are the measurement model equation. X is the exogenous observed variable, ξ is the exogenous potential variable, "Λ" _x is the factor load matrix of X indicator and the ξ potential variable, Y is the endogenous observed variable, η is the endogenous potential variable, "Λ" _y is the factor load matrix of Y indicator and ζ potential variable, β is the relationship between the exogenous variable and the endogenous potential variable, Γ is the influence of exogenous variable on the endogenous variable. Both are path coefficients, and δ and ε are errors on X and Y measurements.

3.4. Behavioral carbon reduction potential assessment model

The study further aims to analyze and quantify, in the context of carbon neutrality, the potential benefits of lifestyle changes and social-ideational innovation, and to explore feasible solution pathways. To quantify the mitigation benefits associated with lifestyle change and social innovation, we adopt a baseline–scenario accounting logic (Creutzig et al., 2022; Koide et al., 2021a, 2021b). First, baseline student lifestyle emissions are calculated by multiplying activity levels across lifestyle domains by the corresponding emission factors and then aggregating the results. Next, intervention measures are parameterized within the Avoid–Shift–Improve (ASI) framework: "avoid" is represented by reductions in activity levels or demand, "shift" by substitutions in travel or service-mode shares, and "improve" by decreases in emission intensity per unit of activity. For each measure, we specify a scenario-specific participation/adoption rate. Scenario emissions are then obtained by applying these adjustments to baseline activity and intensity and summing across domains, while mitigation potential is calculated as the difference between baseline and scenario totals. In this study, "social innovation" refers to institutional and governance arrangements that reduce behavioral frictions and increase accessibility and uptake (e.g., choice architecture, service provision, and information mechanisms); in the model, its effects are reflected through parameters such as participation/adoption rates, substitution intensity, and the magnitude of intensity improvements.

In summary, we first define two key variables and combine them into a 2 × 2 matrix, yielding four future scenarios. The scenario quadrants are constructed using the Shell/GBN scenario method (Wack, 1985). The two key uncertainties defined in this study are the evolution of factors influencing low-carbon behavior (y-axis) and the evolution of proactive-passive behavior (x-axis). The scenarios are defined as follows:

(1) The evolution of internal and external factors influencing low-carbon behavior.
(2) The evolution of proactive-passive behavior.

The final matrix combination yields four scenarios with progressively increasing carbon reduction intensity:

(1) Scenario I-P (Internal-Passive): This scenario sets low-carbon behavior internal influences to trigger passive low-carbon behaviors among students. This includes triggering low-carbon behaviors by satisfying physiological, safety, love and belonging, and self-esteem needs through methods such as low-carbon education courses and information dissemination.
(2) Scenario I-A (Internal-Active): This scenario involves internal influences on low-carbon behavior to actively engage students in low-carbon behaviors. It is based on the needs for self-actualization and dignity, where students are well aware of the environmental impact of their behaviors and consciously change their lifestyles and habits.
(3) Scenario E-P (External-Passive): In addition to the internal influences of the I-A scenario, this scenario adds external factors influencing low-carbon behavior to further trigger passive low-carbon behaviors among students. This includes more convenient infrastructure, relevant policies and regulations, and campus activities, gradually changing lifestyles by altering historical choice experiences.
(4) Scenario E-A (External-Active): This scenario involves external factors influencing low-carbon behavior to actively engage students in low-carbon behaviors. It aims to completely change students' behavioral habits and preferences, encouraging them to actively participate in carbon neutrality actions.

The study ultimately constructs a carbon reduction potential scenario analysis and evaluation model based on lifestyle changes (Fig. 4). The scenario planning is integrated into the carbon emission model simulating students' end-use consumption, setting scenario parameters for demand-side carbon reduction optimization, and analyzing the carbon reduction potential of lifestyle changes.

Based on the campus emission source inventory and literature research, the study summarizes the options for changing student lifestyles, categorized according to the Avoid-Shift-Improve (ASI) framework, which includes avoiding high-carbon consumption, shifting between consumption items, and adopting improved products and related services (Creutzig et al., 2018; van den Berg et al., 2019). The study classifies behavior choices into four main consumption categories: transportation, food, housing, and daily goods consumption, with an emphasis on waste recycling. Each category outlines specific action changes according to the ASI framework, as shown in Table 1.

The impact of lifestyle change on carbon-footprint reduction is determined by reductions or shifts in consumption and by changes in CO_2 emission intensity (Sippel et al., 2018). Two metrics are useful for understanding pathways to carbon-footprint reduction: decreases in consumption levels and decreases in carbon intensity. Equations (5)–(11) operationalize the Avoid–Shift–Improve (ASI) logic within an emission-factor accounting framework by quantifying demand-side mitigation potential through interpretable adjustments to activity levels, service/mode shares, and emission intensities. Accordingly, following established approaches in the literature, we specify the calculation formulas below to quantify the mitigation potential of specific lifestyle-change options under the best-case scenario setting (Koide et al., 2021a).

$$IMP_k^S = CF_k^s - CF_k^b \tag{5}$$

$$CF_k^b = \sum_i \left(HI_i^b \times HC_{i,k}^b \right) \tag{6}$$

$$CF_k^s = \sum_i H\left(I_{i,k}^s \times HC_{i,k}^s \right) \tag{7}$$

In the formula, IMP_k^S is the reduction impact of per capita carbon footprint of lifestyle change options under the set scenario, k is the lifestyle change option, s is the set scenario, i is the consumption type, CF_k^b is the carbon emission of a specific lifestyle under the baseline scenario, CF_k^s is the carbon emission of lifestyle change under the set scenario, and CF_k^s is the carbon emission of lifestyle change under the set scenario. HI_i^b is the carbon emission intensity of the consumption type under the baseline scenario, and $HC_{i,k}^b$ is the consumption of the consumption type under the baseline scenario.

$$HI_{i,k}^s = HI_i^b \times \left(1 - SI_{i,k} \times R_k\right) \tag{8}$$

$$HC_{i,k}^s = HC_i^b \times \left(1 - SC_{i,k} \times R_k\right) + HC_{i,k}^{sub} \tag{9}$$

$$0 \le R_k \le 1 \tag{10}$$

In the formula, $HI_{i,k}^s$ is the carbon emission intensity after lifestyle

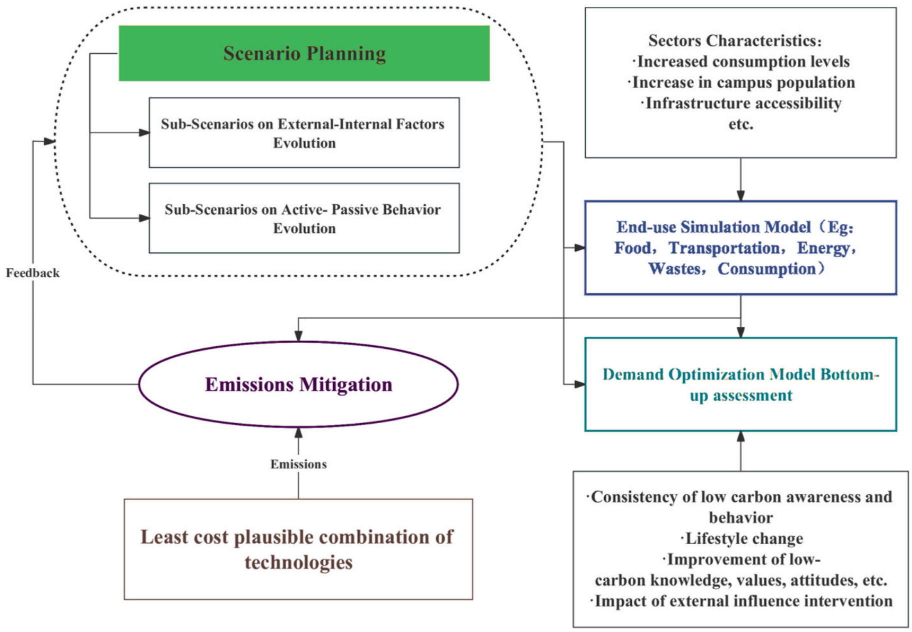

Fig. 4. Scenario analysis assessment model of carbon reduction potential for lifestyle change.

Table 1
Lifestyle change options under scenario analysis.

	Types	Lifestyle Change Options
Transportation	Transportation Mode Shareability	Carpooling
	Modal shift	Modal shift in daily commuting (prioritizing public transportation, biking, walking, etc.), modal shift in private and business travel (prioritizing trains, high-speed rail, etc.), urban cycling
	Demand Reduction	Reduction of unnecessary transportation trips and car trips (including taxi)
	Compact Campus	Co-location of dormitories and academic buildings
Residence	Electrical Improvements	Use of energy-saving electrical appliances
	Reducing Wasteful Energy Use	Saving energy in daily use (air-conditioning temperature not lower than 26 °C, reducing water waste, wearing appropriate clothing to control temperature, etc.)
Eating and Drinking	Dietary structure and preference shifts	Healthy dietary structure (balanced meat to vegetable ratio (1:4))
	Protein Shift	Meat substitution (shift from high carbon emission red meat (beef and lamb, etc.) to poultry and fish)
	Reducing Food Waste	Reduce food waste and loss
	Shift in student meal pathways	Prioritize cafeteria meals and reduce takeaway consumption
	Seasonal and Local	Prioritize seasonal and locally produced foods
Daily Consumption	Durability of everyday items	Use clothing, household items, electronics, etc. for longer periods of time
	Low carbon leisure and living	Participate in campus recreational activities (including carbon neutral related activities), eco-trips, sports
	Demand Reduction	Reduce excessive consumption behavior
Waste	Recycling	Separate and recycle garbage

change under the set scenario, $SI_{i,k}$ is the intensity reduction coefficient under specific consumption type and lifestyle, $SC_{i,k}$ is the consumption reduction coefficient, and R_k is the adoption rate under different scenarios. $HC_{i,k}^{sub}$ is the increase in consumption of replacement items after the shift of behavior change, $SI_{i,k}$ and $SC_{i,k}$ have a maximum value of 1, but maybe negative, and there is an unexpected increase in carbon footprint due to the rebound effect.

$$HC_{i,k}^{sub} = \sum_{i' \epsilon S_k} \left(HC_{i'}^{b} \times SC_{i',k} \times R_k \right) \tag{11}$$

In the formula, I ′refers to the type of items that reduce consumption of alternative products, such as the Food Guide for a Balanced Diet recommends reducing meat consumption by first calculating the reduction of meat or grain foods, plus the substitution of other foods, such as vegetables and fruits. R_k is the degree of change relative to the baseline scenario consumption pattern, such as full substitution, partial substitution, and so on.

4. Results

4.1. Data collection and sample characteristics

The study ultimately collected 410 valid questionnaires to account for and conduct descriptive statistics on the carbon emissions from the lifestyle consumption of Peking University students (Table 2). The first part of the questionnaire surveyed and analyzed respondents' gender, student status, locational characteristics, consumption levels, and living scale. In terms of student status, undergraduates accounted for 45.4 %, master's students for 42.9 %, and doctoral students for 11.7 %. Regarding average monthly consumption levels, the ranges of 2001–3000 yuan and 1001–2000 yuan had the highest proportions, reaching 34.4 % and 29.3 %, respectively. The distribution of the questionnaire data sample approximately reflects the current natural distribution of Peking University students.

4.2. Carbon footprint and characteristics

The study finds that the per-capita annual carbon footprint of Peking University students is 2535.53 kg, arising primarily from food consumption, transport-related consumption, and routine electricity use. Food accounts for the largest share at 47.36 %, followed by transport

Table 2
Descriptive statistical analysis of demographic characteristics.

Demographic Characteristics	Classification	Items	Percentage	Demographic Characteristics	Classification	Items	Percentage
Gender	Male	188	45.9 %	Average Monthly Consumption Level	0-1000 RMB	17	4.1 %
	Female	222	54.1 %		1001-2000 RMB	120	29.3 %
Status	Undergraduate	186	45.4 %		2001-3000 RMB	141	34.4 %
	Master	176	42.9 %		3001-4000 RMB	57	13.9 %
	Doctor	48	11.7 %		4001 RMB and above	75	18.3 %
District	Yan Yuan	148	36.1 %	Scale of residence	1 person	35	8.5 %
	Chang chunYuan	15	3.7 %		2 persons	77	18.8 %
	Chang chun xin yuan	17	4.1 %		3 persons	48	11.7 %
	Zhong guan xin yuan	24	5.9 %		4 persons	242	59.0 %
	Wan liu Apartment	129	31.5 %				
	Off-campus Residence	77	18.8 %				

(24.05 %) and routine electricity use (17 %) (Fig. 5). This composition is consistent with recent demand-side research that identifies diet and mobility as the two key end-use sectors for individual emissions abatement, underscoring the systemic leverage effects of shifts in dietary structure and travel modes. It also accords with evidence from Chinese universities that the carbon footprint of food waste is dominated by meat contributions, indicating the priority of optimizing dietary structures and governing takeaway consumption behaviors (Duan et al., 2024; Qian et al., 2022).

The results reveal a pronounced "high-intention–low-execution" mismatch among students. High-emission behaviors are concentrated in takeaway dining and meat-heavy dietary structures and preferences on the food side, and in business travel and ride-hailing on the transport side. Specifically, 77.7 % of students self-report a preference for low-carbon travel, yet 68 % spend more than 1 h per week commuting by ride-hailing/taxi. Nearly 40 % take fewer than half of their meals in campus canteens, and delivery-related annual emissions reach as high as 485.85 kg; only 16.3 % of respondents report routinely practicing a "clean-plate" (food waste–avoidance) behavior. The dietary pattern of Peking University students is also shifting from an Eastern pattern toward a Western pattern characterized by high meat, high energy, high fat, high protein, and low dietary fiber.

Further Kruskal–Wallis tests and post hoc multiple comparisons (Fig. 6) indicate that monthly average expenditure is the primary demographic driver of emission differences: for every additional 1000 CNY, annual per-capita emissions increase by approximately 12.76 %. Gender differences are evident in diet and apparel consumption, while master's students exhibit higher transport-related emissions due to locational factors.

4.3. *Low-carbon behavioral influences and hypothesis testing*

Based on the questionnaire data, the mean scores across 35 items for 11 variables range from 3.26 (HB2) to 4.46 (BV1), indicating an overall pro-environmental orientation above the midpoint (Fig. 7). First, the cognitive and attitudinal dimensions (awareness and responsibility,

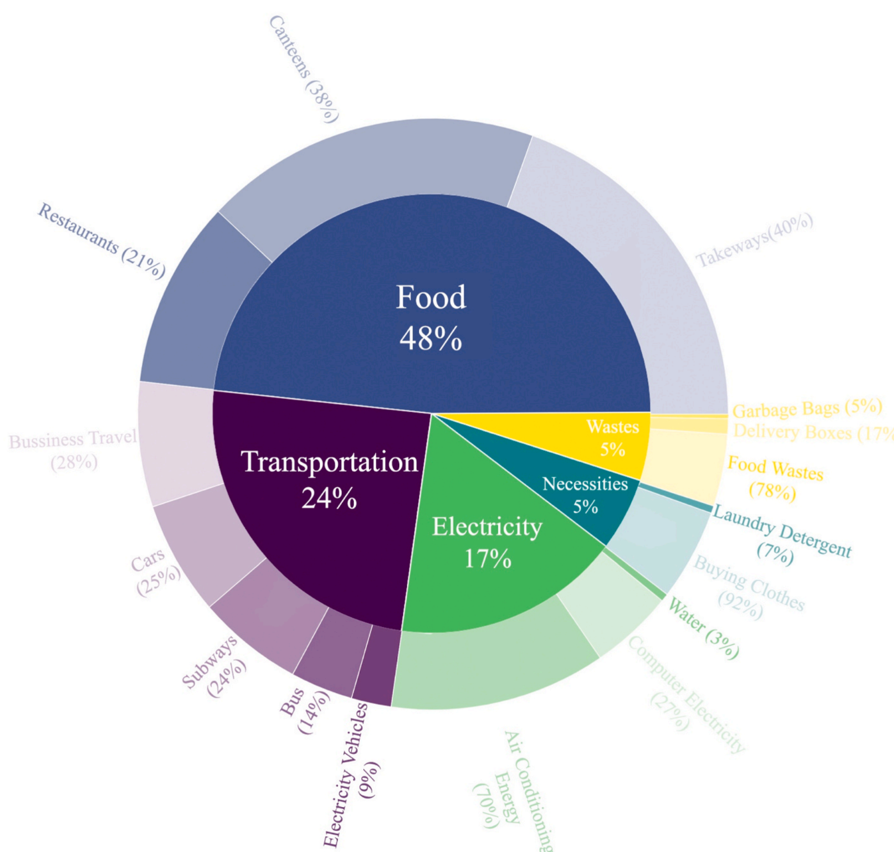

Fig. 5. Carbon emissions and percentage of students' living consumption classification at Peking university.

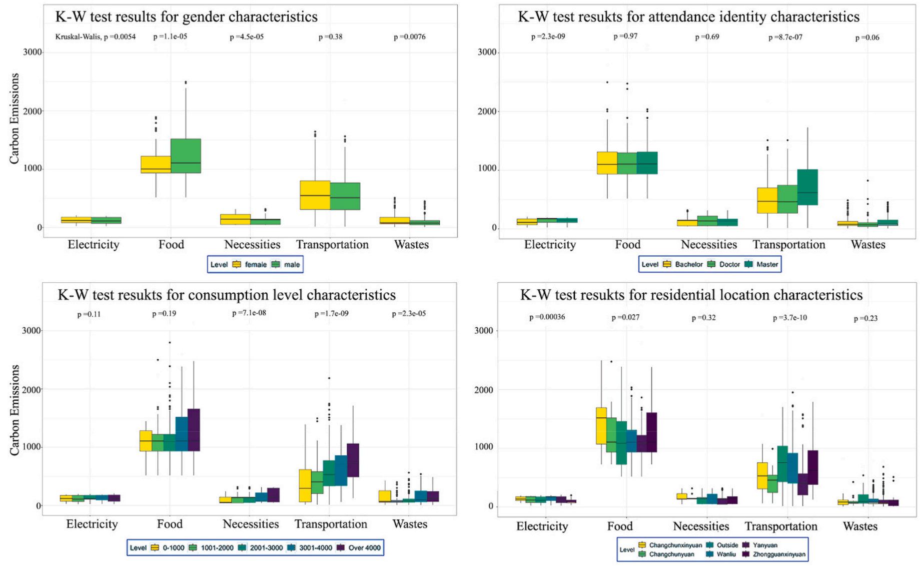

Fig. 6. Scenario analysis assessment model of carbon reduction potential for lifestyle change.

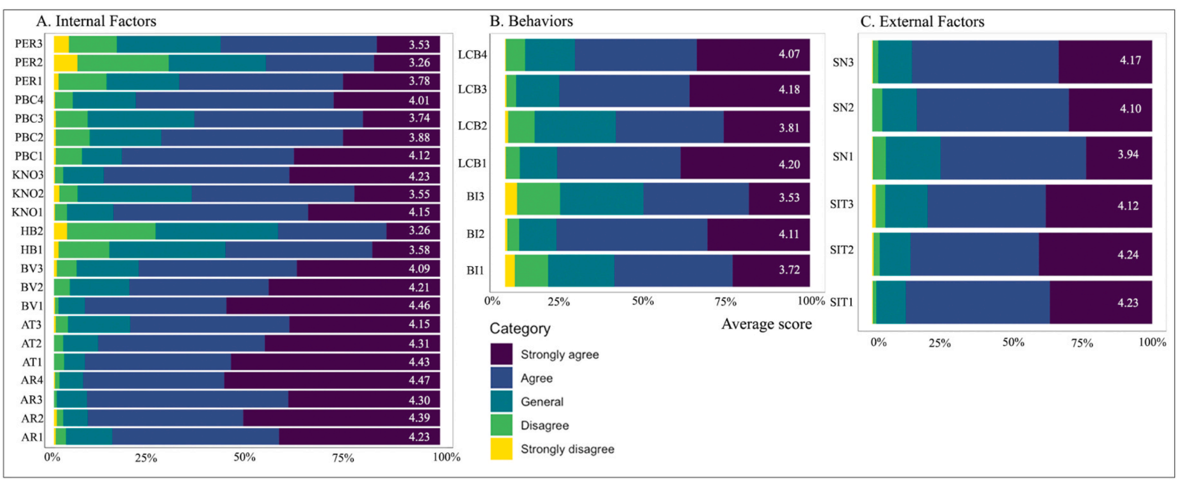

Fig. 7. Scenario analysis assessment model of carbon reduction potential for lifestyle change.

attitudes, and values) score highest, showing strong student endorsement of low-carbon concepts; however, personal norms are significantly lower than these dimensions, revealing a translation gap from "knowing and agreeing" to the normative sense of "ought to." Second, the mean of behavioral intention is lower than that of reported low-carbon behavior, implying that some behaviors rely more on contextual support or constraints than on intention itself, consistent with the subsequent SEM finding that context and perceived behavioral control directly drive behavior. Finally, habit-related items score relatively low, indicating continued inertia in existing consumption and travel patterns.

We used SPSS 27.0 and AMOS to assess the reliability and validity of the survey instrument, which comprises 11 construct dimensions and 35 items. In the reliability analysis of the final questionnaire, the overall Cronbach's alpha of the behavioral instrument was 0.922. In addition, item-level corrected item–total correlations (CITC) all exceeded the commonly used threshold ($\geq$0.30), indicating that each item contributed meaningfully to its intended construct and supporting high internal consistency. For sampling adequacy and factorability, the overall KMO value was 0.916 (>0.70), and Bartlett's test of sphericity was significant ($\chi^2 = 5944.895$, df = 595, $p < 0.001$), meeting standard criteria. For model fit assessment, confirmatory factor analysis (CFA) was conducted within the structural equation modeling framework. The fit indices were $\chi^2/df = 2.270$, GFI = 0.844, RMSEA = 0.056, and CFI = 0.877. Considering the relatively high dimensionality and structural complexity of the model, these indices fall within acceptable ranges, indicating satisfactory structural validity and interpretability of the measurement model. Overall, the instrument demonstrates adequate reliability and validity for subsequent structural-path estimation, providing a sound measurement basis for analyzing the mechanisms of low-carbon behavior and for scenario evaluation in this study (see Appendix for detailed model-fit diagnostics). Studies that develop or validate carbon-footprint-related scales in university-student samples typically follow comparable reliability and validity assessment procedures (e.g., internal consistency and structural validity), which is consistent with the measurement-validation framework adopted here (Pekel et al., 2025).

Spearman's rank correlation coefficients were used to assess associations among study variables. Low-carbon behavior (LCB) showed correlations with attitude (AT), situational factors (SIT), social norms (SN), personal norms (PER), and behavioral intention (BI); correlations with SIT, SN, PER, and BI were statistically significant ($p < 0.05$) (Fig. 8).

Using AMOS, the study analyzed factors influencing students' low-carbon behavior and posited 20 hypothesized relationships when constructing the model (Table 3). Based on the ranking of standardized

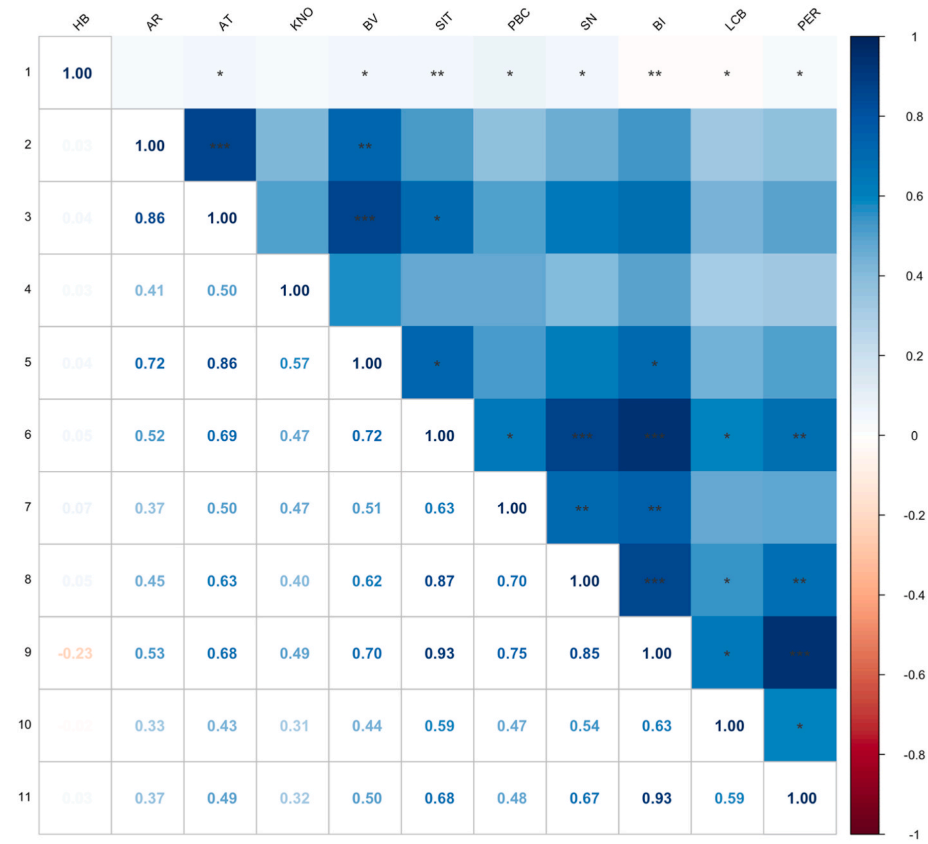

Fig. 8. Correlation analysis between the variables influencing low carbon behavior.
Note: Significance level $p < 0.05$ (*), $p < 0.01$ (**), $p < 0.001$ (***).

Table 3
Results of SEM of factors influencing students' low-carbon behavior.

No.	Independent variable	Dependent variable	Unstandardized coefficient	C.R.	Standardized coefficient	Conclusion
H1	Value	AR	0.647***	9.560	0.724	Established
H2	Awareness and Responsibility	Personal Norm	0.018	0.267	0.019	Not established
H3	Personal Norm	Behavior Intention	0.825***	6.670	0.561	Established
H4	Attitude	Behavior Intention	0.069	0.792	0.045	Not established
H5	Social Norm	Behavior Intention	0.225	1.098	0.153	Not established
H6	Perceived behavioral control	Behavior Intention	0.333***	4.414	0.258	Established
H7	Behavior Intention	Low-Carbon Behavior	0.398***	8.504	0.631	Established
H8	Social Norm	Attitude	0.147*	2.180	0.152	Established
H9	Social Norm	Perceived behavioral control	0.692***	8.303	0.608	Established
H10	Social Norm	Personal Norm	0.343*	1.862	0.344	Established
H11	Perceived behavioral control	Low-Carbon Behavior	0.406***	4.749	0.479	Established
H12	Low-carbon Knowledge	Value	0.467***	5.980	0.503	Established
H13	Low-carbon Knowledge	Perceived behavioral control	0.261***	3.420	0.224	Established
H14	Situational Factors	Value	0.609***	7.869	0.581	Established
H15	Situational Factors	Social Norm	0.281***	8.974	0.865	Established
H16	Situational Factors	Personal Norm	0.332*	1.940	0.370	Established
H17	Situational Factors	Low-Carbon Behavior	0.158*	1.120	0.183	Established
H18	Situational Factors	Behavior Intention	0.648***	3.469	0.492	Established
H19	Habits	Behavior Intention	−0.791**	−3.045	−0.770	Established
H20	Perceived behavioral control	Habits	0.079	1.086	0.072	Not established

Note: Significance level $p < 0.05$ (*), $p < 0.01$ (**), $p < 0.001$ (***).

coefficients, we find, first, at the behavior-formation level, low-carbon behavior is directly driven by behavioral intention ($\beta = 0.398$, $p < 0.001$) and perceived behavioral control ($\beta = 0.406$, $p < 0.001$), with situational factors also exerting a significant direct effect ($\beta = 0.158$, $p < 0.05$). This indicates that constraints and supports are as important as willingness to act, and that optimization of facilities and institutions can augment intention-enhancing measures in parallel. Second, at the intention-formation level, personal norms are the strongest positive determinant ($\beta = 0.825$, $p < 0.001$); situational factors also have a substantial positive influence ($\beta = 0.648$, $p < 0.001$); perceived behavioral control ranks next ($\beta = 0.333$, $p < 0.001$); whereas habit significantly suppresses intention ($\beta = -0.791$, $p < 0.01$), revealing that the implementation gap between high cognition/support and low action is more strongly constrained by existing consumption and travel inertia. At the same time, social norms do not raise intention directly but act mainly as upstream variables via the pathways "social norms → attitude/perceived behavioral control/personal norms” (H8/H9/H10 supported), consistent with the transmission from external to personal norms and thence to intention.

Notably, four hypothesized relationships are not supported. H2 is not supported, indicating a tendency toward external ascription of responsibility within the university cohort—i.e., mitigation is viewed primarily as a governmental or institutional responsibility rather than an individual moral obligation—so that a sense of responsibility fails to translate into personal norms, exposing a weak link in the internalization of responsibility in environmental education. H4 and H5 are not supported, suggesting that, after controlling for personal norms, context, and capability, neither a positive attitude alone nor generalized peer approval suffices to elevate intention; norms operate mainly through upstream pathways, aligning with theories positing mediating chains between values/attitudes and behavior. Finally, H20 is not supported, indicating strong path dependence and contextual stickiness in campus habits related to diet and mobility; short-term subjective improvements in perceived attainability do not readily overturn existing inertia, which also explains the significant negative effect of habit on intention.

The findings are mutually corroborative with the IPCC's judgment on the demand side and with recent SEM studies on university populations: food and mobility are priority domains, and perceived behavioral control together with context are necessary conditions for translating intention into behavior (Correia et al., 2021; Creutzig et al., 2024; Maleki et al., 2025; Maulana et al., 2025). Our results differ from some studies regarding the significant suppressive effect of habit on intention and the indirect role of social norms, which may relate to the high baseline of attitudes in our sample and to contextual features of facilities and institutions. This implies that intervention design should pivot from re-inculcating attitudes toward a combined strategy of norm internalization, capability enhancement, and context optimization (Hagger et al., 2023; Helferich et al., 2023).

Therefore, to bring about substantive changes in low-carbon behavior among Peking University students, further interventions are needed targeting behavioral intention, situational factors, and perceived behavioral control. Specific measures include strengthening education on low-carbon knowledge, instilling environmental values and other intrinsic enhancements, and reducing the influence of habitual preferences on intention. Situational factors have direct and significant effects on both intention and low-carbon behavior; a campus environment with a strong green, low-carbon ethos and abundant low-carbon themed activities is essential. In parallel, active interventions by the university and society—improving green infrastructure and lowering the cost and difficulty of student participation in low-carbon actions—will directly influence lifestyle transitions.

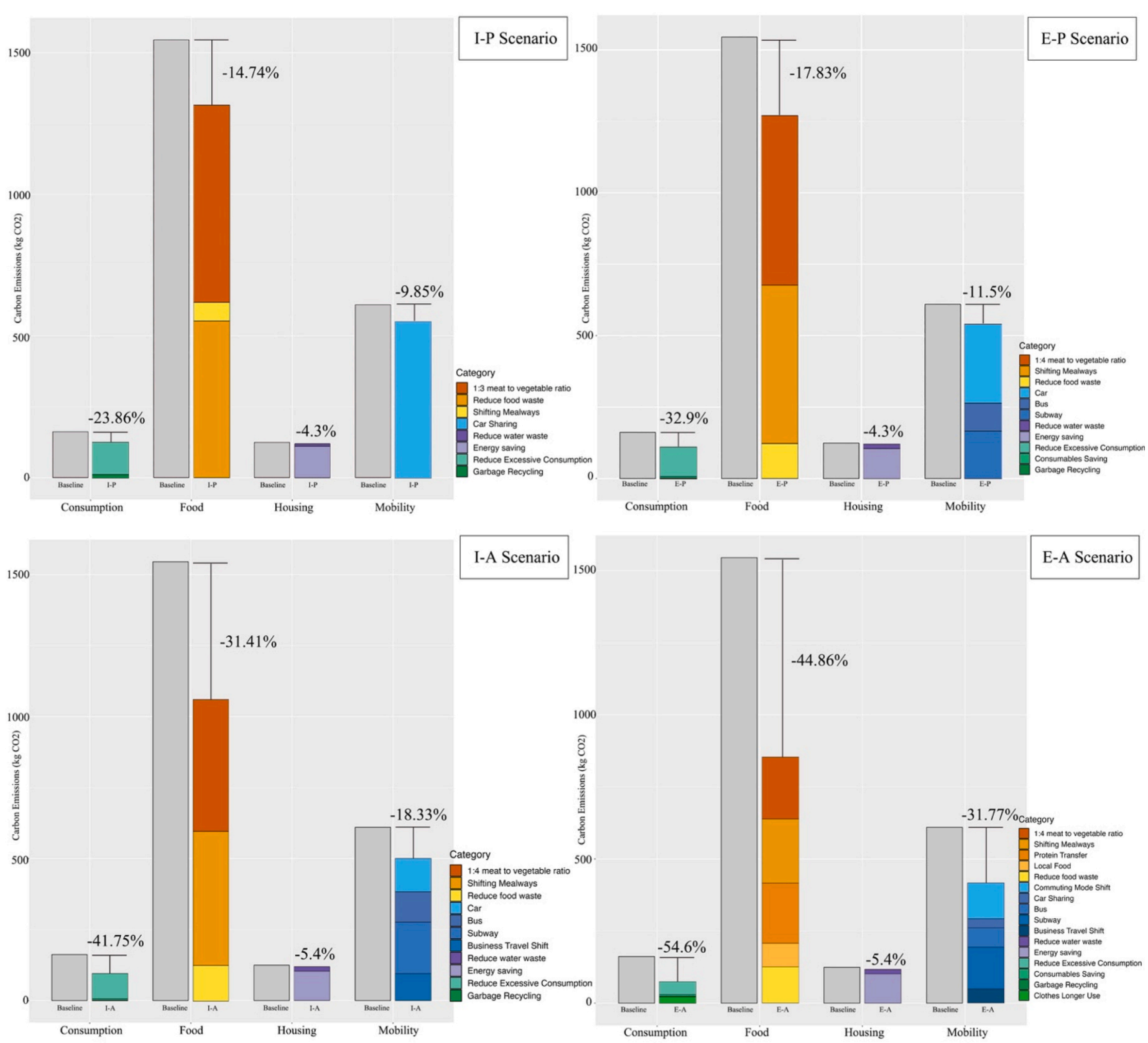

Fig. 9. Analysis of the carbon reduction benefits of the four scenarios.

4.4. Assessment of carbon reduction potential of domestic consumption

Building on a 2 × 2 design by intervention target (internal, I/external, E) and intervention intensity (passive, P/active, A), the four scenarios yield mitigation potentials ranging from 13.53 % to 40.23 %. The corresponding per-capita annual emissions are: I–P 2110.34 $kgCO_2e$ (−13.53 %), E–P 2036.36 $kgCO_2e$ (−16.56 %), I–A 1769.29 $kgCO_2e$ (−27.50 %), and E–A 1458.78 $kgCO_2e$ (−40.23 %) (Fig. 9). The results exhibit clear synergy. First, moving from passive to active interventions markedly amplifies the abatement magnitude. Second, at the same intensity, external context outperforms internal cognition, indicating that facilities, institutional arrangements, and price signals are more directly effective in translating intention into behavior. Finally, combined internal–external interventions display a super-additive effect; the E–A scenario delivers the largest reduction and thus represents the upper bound of behavior-driven mitigation. Scaled by the on-campus student population, the four scenarios correspond to annual Scope 3 reductions of approximately 15.6–46.4 thousand tonnes CO_2e, constituting a material contribution to the "carbon-neutral campus" goal.

By sector, food delivers the largest absolute abatement, rising continuously from I–P to E–A, consistent with its highest baseline share (47.36 %). Reductions primarily stem from lowering the intensity of meat consumption and takeaway meals, substituting toward legumes or plant proteins, and prioritizing dine-in with reusable packaging—a structural–contextual combination. Transport is the second-largest contributor and is most sensitive to external conditions (e.g., station accessibility, convenience, and pricing mechanisms); in active scenarios, substitution toward walking, cycling, and public transit strengthens markedly. Housing/household energy and daily-use goods show relatively moderate declines, relying more on baseline improvements in energy efficiency and electricity-saving behaviors, reflecting the limited marginal returns of improve-type measures.

5. Discussion

Fine-grained accounting of students' carbon footprints not only helps universities identify high-contribution domains and key behavioral levers, but also provides an empirical basis for cultivating climate literacy and low-carbon lifestyles during students' time on campus. A cross-institutional comparison of studies from more than ten universities shows that, despite differences in accounting boundaries, Scope 3 typically accounts for a high share (most ≥40 %, some ≥70 %), and emissions related to student consumption constitute a substantial proportion of campus totals (Cano et al., 2023; Chang et al., 2019; Clabeaux et al., 2020; Filimonau et al., 2021; Gu et al., 2018; Kiehle et al., 2023b; Lambrechts and Van Liedekerke, 2014; Mendoza-Flores et al., 2019; Ridhosari and Rahman, 2020; Sun et al., 2022; Varón-Hoyos et al., 2021; C. Wang et al., 2023; Zheng et al., 2021b; Zhu et al., 2021). These results are consistent with our findings: food and mobility are the priority arenas for demand-side mitigation on campuses and the most malleable entry points for behavioral intervention. As increasing numbers of educated young people enter all sectors of society, their collective actions and advocacy may become a powerful force propelling society toward more sustainable development (Wynes and Nicholas, 2017). This will also directly determine the scale of attitudinal and lifestyle change acceptable to the public as China seeks to achieve carbon neutrality by 2060. Relative to the existing literature, this paper places greater emphasis on how structural change and capacity building constrain and enable behavior.

At the same time, our integrated model enables a form of mechanism diagnosis that is difficult to achieve with any single theory. By distinguishing and comparing the TPB-, VBN-, and CADM-based pathways within one causal framework, the study provides a more precise account of the "high intention–low action" paradox commonly observed in campus contexts. The results indicate that strong low-carbon intentions do not automatically translate into actual behaviors. The key bottleneck often lies in the intention-implementation stage. On the one hand, individuals' perceived behavioral control/feasibility and external conditions jointly determine whether intentions can be enacted. On the other hand, habitual behavior exhibits strong inertia and automaticity, which may directly suppress low-carbon actions and weaken the strength of the intention–behavior link.

In the Chinese context, universities are not only direct emitting entities but also key hubs of the national green and low-carbon education system. In terms of institutional alignment and localization pathways, China already provides relatively complete policy levers at both the top-level and the education front. The Ministry of Education's Notice on the Implementation Plan for Building a National Education System for Green and Low-Carbon Development (2022) explicitly requires the systematic integration of green, low-carbon concepts into curricula, campus governance, and social practice across all educational stages. It dovetails with earlier measures such as the Special Action Against Dining-Table Waste (2013), the Opinions on Practicing Thrift and Opposing Food Waste (2014), and energy-use statistics for universities under ministerial administration (2006), thereby providing a policy basis for universities to establish closed loops of education, governance, and disclosure in high-frequency settings such as canteens, dormitories, mobility, and procurement (Wu et al., 2023; J. Zhang, 2024). Following this orientation, we couple an integrated SEM with ASI scenarios: the former, at the micro level, reveals how personal norms and perceived behavioral control determine intention and behavior, the direct effect of context on behavior, and the significant suppressive effect of habit on intention; the latter, at the meso level, translates these mechanisms into measurable Avoid/Shift/Improve intervention options and bounds. Together, they show that attitude advocacy alone is insufficient to surpass an abatement threshold of roughly 30 %; only when internal norm and capability enhancement is coordinated with external redesign of contexts and institutions can lifestyle mitigation be amplified to an upper bound of about 40 % and be embedded—measurably and accountably—into the routine governance and educational objectives of universities. This also suggests a re-ordering of campus decarbonization strategies: placing Avoid and Shift (e.g., dietary structure and travel modes) ahead of Improve (efficiency). Visible carbon-performance feedback, default options, and convenience-oriented design should run in parallel with curricula and community commitments.

Unlike the governance pathway of autonomy, disclosure, and benchmarking common in European and American universities, Chinese universities have a clear "university–school–class (dormitory)" hierarchy and strong institutional executability. This implies that layered governance and system linkage will be critical channels for translating behavioral science into emissions outcomes. Drawing on the "up to 40 %" scenario range and the policy instruments above, we propose scalable, low-cost, yet accountable intervention bundles. At the university level, universities can publish an annual campus carbon report, connect with the national carbon market and voluntary offset schemes, and introduce price/constraint signals through comprehensive emissions inventories (including Scope 3), an internal carbon price, green-electricity procurement, and travel-related carbon accounting. At the canteen, mobility, and procurement fronts, campuses can deploy carbon labels and choice-architecture tools (e.g., default plant-based meals or half-portion options, refundable deposits for reusable packaging, dine-in/pick-up discounts, parking pricing, and public-transport-first reimbursement) to reduce monetary and convenience frictions while increasing perceived behavioral control and ease of action. At the school/department level, curriculum and organizational routines can be aligned by incorporating carbon-neutrality courses and practice components and by establishing benchmarking and feedback mechanisms. Through research and course projects, build the internalization chain from "social norms to personal norms." At the class and dormitory levels, focus on high-frequency micro-contexts and real-time feedback—for example, dorm energy dashboards; mobility points; and cafeteria anti-waste weighing, feedback, and incentives—to interrupt existing habits and promote re-learning through micro-incentives and default settings. In parallel, use international tools (STARS, the SDSN toolkit) to advance cross-campus benchmarking and continuous improvement (Beebeejaun, 2024).

This study nonetheless has several boundary conditions and uncertainties. First, the questionnaire and cross-sectional design may limit causal identification; although adoption rates, substitution coefficients, and rebound effects are parameterized in the scenarios, they remain sensitive across groups and over time. Second, a single-university sample entails specificity in campus morphology, urban location, and the provision of catering and transport; extrapolation should account for differences in energy structures, commuting patterns, and logistics systems across universities. Third, the suppressive effect of habit implies that one-off actions quickly revert to default trajectories, necessitating sustained feedback and institutional constraints to maintain steady states. Future research could employ longitudinal tracking and field randomized or quasi-experiments, combining revealed-preference data such as campus-card transactions, electricity and water meters, and mobility traces to calibrate the dynamic elasticities linking intention, behavior, and emissions; and test parameter heterogeneity in the SEM across multi-university, multi-city samples to further specify "which types of campuses, under what constraints, and with what combinations" deliver the greatest cost and carbon benefits.

6. Conclusion

This study is the first, in a university context, to couple the ASI (Avoid–Shift–Improve) framework with an integrated SEM for mechanism–scenario linkage. On one hand, it characterizes students' lifestyle carbon footprints using a unified quantitative protocol and identifies the mechanisms of behavior formation. On the other, it directly translates mechanism identification into ASI scenario parameters and abatement magnitudes. The results show that the mitigation potential on the student consumption side at Peking University ranges from 13.53 % to 40.23 %. When internal norm and capability enhancement (e.g., education, cognition, and self-efficacy) is coordinated with external contextual and institutional redesign (e.g., facilities, defaults, prices, and rules), the abatement magnitude increases substantially and represents the upper-bound scenario of behavior-driven decarbonization. At the campus scale, this translates into approximately 15.6–46.4 kt CO_2e per year of Scope 3 reductions. This alignment places student consumption, campus governance, and mitigation outcomes on a single quantitative axis and supports a low-cost, replicable, and accountable pathway toward a carbon-neutral campus.

Mechanistically, the SEM indicates that behavioral intention and perceived behavioral control are the decisive determinants of low-carbon behavior, personal norms are the strongest driver of intention, and habit significantly and negatively moderates intention (H19: $\beta = -0.791$). This finding has direct implications for education policy. Attitude-oriented advocacy alone is unlikely to close the execution gap. Instead, norm internalization (values → responsibility → personal norms) should be coupled with capability empowerment (attainability and self-efficacy) and sustained choice architecture interventions (e.g., defaults, convenience-oriented design, and pricing/reimbursement priorities) to stabilize the translation from 'willing to act' to 'able and easy to act' in everyday choices. Meanwhile, social norms operate mainly upstream by shaping personal norms and perceived control, implying that campus governance should embed group commitments, feedback, and evaluation into curricula and organizational routines, thereby forming a new governance paradigm that gives equal weight to educational objectives and mitigation outcomes. Overall, the study demonstrates that an ASI-based, SEM-revealed psycho–context–behavior chain for behavior-driven decarbonization can transform the prevalent "high support–low action" structural challenge in universities into measurable, comparable, and replicable governance practice. Moreover, the SEM path coefficients can be mapped directly to ASI scenario parameters, providing calibration for embedding behavioral parameters into ABM–CGE/IAM frameworks and helping bridge the long-standing gap between micro-level behavioral evidence and macro-level systems assessment.

CRediT authorship contribution statement

Weiwang Zhu: Conceptualization, Formal analysis, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Dihua Li:** Conceptualization, Methodology, Project administration, Resources, Supervision, Validation, Writing – review & editing. **Wei Liu:** Conceptualization, Methodology, Supervision, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.clrc.2026.100391.

Data availability

Data will be made available on request.

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