scientific reports

OPEN

The impact mechanism of media use on the green and low carbon consumption behavior of China: integrating planned behavior theory and social cognitive theory

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As a crucial medium for information dissemination and public opinion guidance, how to leverage media to promote the development of public green and low-carbon consumption (GLC) is a major challenge in the new era. This study, based on the Theory of Planned Behavior and Social Cognitive Theory, employs PLS-SEM and MGA methods to construct a model encompassing traditional media, online media, and social media channels, delving into the relationship between media use (MU) and GLC. The findings indicate that media usage is positively correlated with both aspects of GLC: green and low-carbon consumption intention, green and low-carbon consumption behavior. The order of correlation strength is social media > traditional media > online media. Further mechanistic analysis indicates that green and low-carbon knowledge and social norms mediate the relationship between MU and GLC. Additionally, there are differences in the correlation between MU and GLC among populations with varying levels of media trust and media use frequency. This study provides theoretical and quantitative guidance for leveraging traditional media, online media, and social media to promote GLC among the Chinese public.

Keywords Media use, Green and low-carbon consumption, Social cognitive theory, PLS-SEM, Multi-group analysis

In recent years, global climate change and frequent extreme weather events have attracted widespread attention, prompting countries around the world to actively implement sustainable development concepts[1]. Against this backdrop, end-use consumption, as a major source of global energy demand growth and carbon emissions growth[2]has attracted widespread attention from governments, enterprises, and stakeholders[3]. In response, the Chinese government has put in place several measures and incentive programs to help change consumption habits to be more environmentally friendly and low in carbon, making sure they meet the “dual carbon” goals on time[4]. Green and low-carbon consumption (GLC) refers to the consumption behavior of consumers who prioritize the protection of the ecological environment, aim to minimize environmental pollution, and contribute to reducing carbon emissions when selecting, using, and disposing of goods[5,6].

Existing research primarily adopts an individual behavioral psychology[7] perspective to explore the psychological motivations and demographic characteristics influencing GLC[8,9]with a focus on analyzing the gaps between attitudes, intentions, and actual behavior. For example, environmental concern has been shown to positively influence consumers’ purchasing intentions[10]subjective norms, and perceived behavioral control (PBC), while environmental attitudes[11] also mediate the relationship between consumer perceptions[12] and intentions[13]. However, from a management perspective, these studies centered on individual variables have limited guidance for policymakers and organizational practices, as they struggle to change public consumption behavior in the short term[14]. Therefore, there is an urgent need to identify key variables that can be shaped by the external environment and incentivize collective behavioral change.

The media has facilitated the promotion of GLB by providing convenient avenues for individuals to access information related to the environment and products[15]. In particular, with the rapid development of new media forms, more and more people are beginning to obtain information about the environment and products through

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social networks, and use this information for analysis to form corresponding knowledge and value systems, thereby promoting the implementation of environmental responsibility[16]. On the other hand, the media also enables organizations committed to promoting public environmental behavior to make full use of various media channels, such as traditional newspapers, television, emerging internet platforms, and social media, to disseminate ecological information or attract public attention through event marketing[17]. This influences the public's knowledge, views, and perceptions of the environment and products[18]thereby encouraging them to make beneficial environmental changes[19]. Therefore, this study aims to investigate the following three issues concerning the relationship between media use (MU) and GLC:

RQ 1: What is the relationship between MU and GLC among the Chinese public?

RQ 2: Are there differences in the relationship between different types of MU and GLI\GLB?

RQ 3: Do respondents' varying degrees of MT and MUF affect the differences in the relationship between MU and GLI, GLB?

Therefore, based on social cognitive theory and planned behavior theory, supplemented by a decision-making theory perspective, this study constructed a comprehensive analytical framework for the relationship between MU and GLC, and made contributions in the following three aspects. First, the study examines MU's perspective and clarifies the relationship between MU and GLC. Meanwhile, incorporating relevant variables such as green low-carbon knowledge (GLK) and social norms (SON) into the comprehensive research framework validated that these variables serve as the connecting channels for the indirect relationship between MU and GLI, GLB, bringing a new perspective to academic discussions on GLC.

Secondly, based on the overall characteristics of different media channels, this paper categorizes media into three types: traditional media, online media, and social media. It constructs a multi-group analysis framework from dimensions such as media use volume, use frequency, and gender differences, which helps deepen our understanding of the relationship between MU and GLB. Finally, this paper establishes a GLC model based on MU behavior, and proposes corresponding policy recommendations from the perspectives of government, enterprises, and media. These recommendations provide theoretical basis and practical insights for governance entities in China and similar contexts, contributing to the achievement of the "dual carbon" goals. Table 1 summarizes the terms and abbreviations commonly used in this paper.

Theoretical analysis and research hypotheses

Literature review

This paper reviews existing relevant literature and summarizes the following three perspectives:

First, from the perspective of the relationship between media and green and low-carbon behavior, studies generally affirm the positive role of media in the field of public GLB, but systematic research on GLC is still insufficient[20]. On the one hand, existing research has primarily focused on recycling[21] or general environmental protection behaviors, with insufficient attention given to the specific composition and decision-making pathways of GLC[22]. On the other hand, research has mainly discussed the positive influence of media in shaping GLC attitudes and awareness[23]with relatively little discussion on actual green purchasing behavior. Additionally, research has often adopted a single perspective[17]focusing on the mediating role of variables such as environmental knowledge and social norms[24]lacking an integrated multi-perspective framework[25] and insufficient scientific explanations of potential influence mechanisms.

Second, in terms of the effectiveness of media influence on GLC, although existing research has begun to focus on the mechanisms through which media influence GLC, such research remains in its early stages. Most literature treats MU as a precursor variable for factors influencing GLC, such as SON[7]with little attention paid to its direct impact. Additionally, there are significant discrepancies in the conclusions drawn by different studies regarding the influence of media[26]. Some scholars emphasize its positive effects in enhancing environmental awareness and purchase intentions[27]while others point out that media has limited ability to translate into actual consumption behavior.

Third, from the perspective of potential differences in MU channels[28]existing research has begun to focus on the performance differences of various media types in terms of GLB[29]but most studies are limited to analyses of single media types. For example, some studies use "social media" or "online media" as core variables, overlooking the fundamental differences between traditional media, online media, and social media in terms of information dissemination speed, interactivity, and credibility[30]. In specific GLC behavioral scenarios, different media channels may influence consumers' attitudes and behaviors through distinct mechanisms. However, cross-sectional comparative studies in this dimension remain insufficient[31]particularly lacking systematic empirical analysis and mechanism exploration.

In summary, while the current literature provides a preliminary foundation for understanding the relationship between media and GLC, it still faces the following limitations: research focuses more on attitudes than behavior, more on individual variables than external mechanisms, and more on single media than on comparisons between multiple types. To address these research gaps, this study integrates the theory of planned behavior (TPB) and social cognitive theory (SCT) to construct a comprehensive analytical framework encompassing MU, GLK, SON, and GLI, GLB. Furthermore, media types are categorized into three subcategories—traditional media, online media, and social media—to explore differences in their relevance and indirect pathways, thereby providing theoretical support for understanding GLB within a media-influenced environment.

Theoretical analysis

Planed behavior theory (TPB) is a classic model for explaining individual behavioral intentions and is widely applied in the field of green behavior, including waste management, low-carbon transportation[32]and green consumption[30]. It emphasizes that individual behavioral intentions are primarily driven by three factors:

attitude, social norm, and PBC[33]. Numerous studies have also confirmed the effectiveness of TPB in explaining and predicting public environmental behavior and intentions[34].

Social cognitive theory (SCT) is an extension of Bandura's social learning theory (SLT). It emphasizes the dynamic interaction between behavior[35]individual cognition, and the environment, analyzing the determinants and social psychological mechanisms that shape human cognitive thinking and influence individual behavior[36]. In SCT, individual behavior is not only constrained by the environment but can also be actively regulated through psychological mechanisms such as observational learning, and outcome expectations[37]. This theory is widely used to explain the relationship between media using, social influence, and behavior adoption, particularly emphasizing the key roles of information acquisition[38]role model behavior, and self-regulation in the formation of behavior.

Moreover, in economic decision-making theory, individuals are typically assumed to pursue utility maximization[39]. Utility can be understood as the satisfaction or value obtained from a behavior or choice, minus the cost of performing that behavior[40]. When deciding whether to adopt GLBs, individuals will weigh the perceived benefits and costs to a certain extent[41]and their decisions will be influenced by the availability of information and the cost of obtaining it.

Although TPB performs well in predicting behavioral intentions, it cannot fully explain the cognitive and social learning processes involved in forming intentions, and its ability to explain the "intention-behavior gap"[34] is limited. SCT fills this gap. It emphasizes how individuals form cognitive and behavioral intentions through observational learning[42]and environmental feedback. It explains how individuals form cognitive and informational understandings of green behaviors through observational learning, media information acquisition, thereby linking these understandings to behavior. However, SCT is relatively inadequate in considering the rational trade-offs underlying individual behavior, such as cost-benefit judgments. GLC, as a behavior with economic attributes, is driven by social norms and knowledge, as well as influenced by factors such as information availability, economic returns, and behavioral convenience. Therefore, when explaining complex, multi-factor-influenced sustainable consumption behavior, a single theoretical framework often has limitations.

Based on the above analysis, this paper integrates TPB and SCT on the basis of decision theory to provide a comprehensive theoretical framework for a deeper understanding of the relationship between MU and GLC. Specifically, the advantages lie in the following three aspects. First, SCT emphasizes the influence of observational learning, role modeling, and environmental factors on individuals, elucidating the formation of individuals' green attitudes and thereby providing a richer cognitive foundation for the generation of intentions in TPB. This not only helps this paper understand how MU is associated with the intention or behavior of GLC but also further explains how MU positively correlates with individuals' GLC capabilities and confidence through role model information, and enhanced green knowledge, thereby bridging the "intention-behavior gap."

Second, the integrated model helps reveal how media, as an external environmental variable, indirectly influences GLC through two core pathways—normative shaping and knowledge dissemination—thereby providing a systematic explanation of the indirect and direct relationships between MU and GLC. Finally, by identifying the pathways through which MU influences GLC, this paper not only enriches the theoretical framework of green behavior research[43] but also provides more operational theoretical support for policy-making and behavioral intervention. The overall framework of this paper is shown in Fig. 1.

Research hypothesis

Media use and green and low-carbon consumption

Media use is a key external factor influencing individual prosocial behavior, playing a significant role in shaping individual cognition, attitudes, and social behavioral norms[44]. According to SCT, individuals form behavioral patterns through four key mechanisms: observational learning, knowledge acquisition, self-efficacy development, and outcome expectations formation[45]. While self-efficacy is also a key SCT component, our current study focuses on the knowledge acquisition and observational learning pathways. As a primary information transmission channel, media can provide knowledge about GLC[46]exemplary cases, and positive and negative incentives related to environmental issues, thereby enhancing individuals' environmental awareness. Additionally, MU plays a crucial role in reinforcing SON and forming social expectations. Within the TPB framework, attitudes, SONs, and PBC collectively determine behavioral intent, ultimately influencing actual behavior[47]. Therefore, within an integrated framework combining TPB and SCT, media use may exhibit a positive correlation with GLI or GLB through its interplay with the aforementioned cognitive factors.

With the development of media technology, the forms of MU have become increasingly diverse. Different types of media may vary in terms of the depth of information transmission, interactivity, and social influence, thereby giving rise to distinct patterns of association with GLC[48]. This study categorizes MU into traditional media use, internet media use, and social media use to conduct a more detailed examination of these associations.

First, traditional media, such as television and newspapers. These typically disseminate information in an authoritative, one-way manner, primarily by providing environmental knowledge and policy promotion to enhance the public's green awareness and values, thereby influencing their GLC attitudes and intentions[49].

Second, online media, such as news websites and environmental forums. These platforms offer richer background information and user-generated content, enabling individuals to actively and deeply acquire environmental knowledge and understand green product information[50]. They may also enhance their PBC through search and comparison behaviors.

Finally, social media, such as WeChat and Weibo. These platforms are characterized by interactivity, community-building, and the influence of role models[51]. They not only efficiently disseminate information but also reinforce SONs, enhance individual belonging through user interaction, analysis, and celebrity influence, and provide real-time feedback, thereby impacting individuals' SONs regarding GLC.

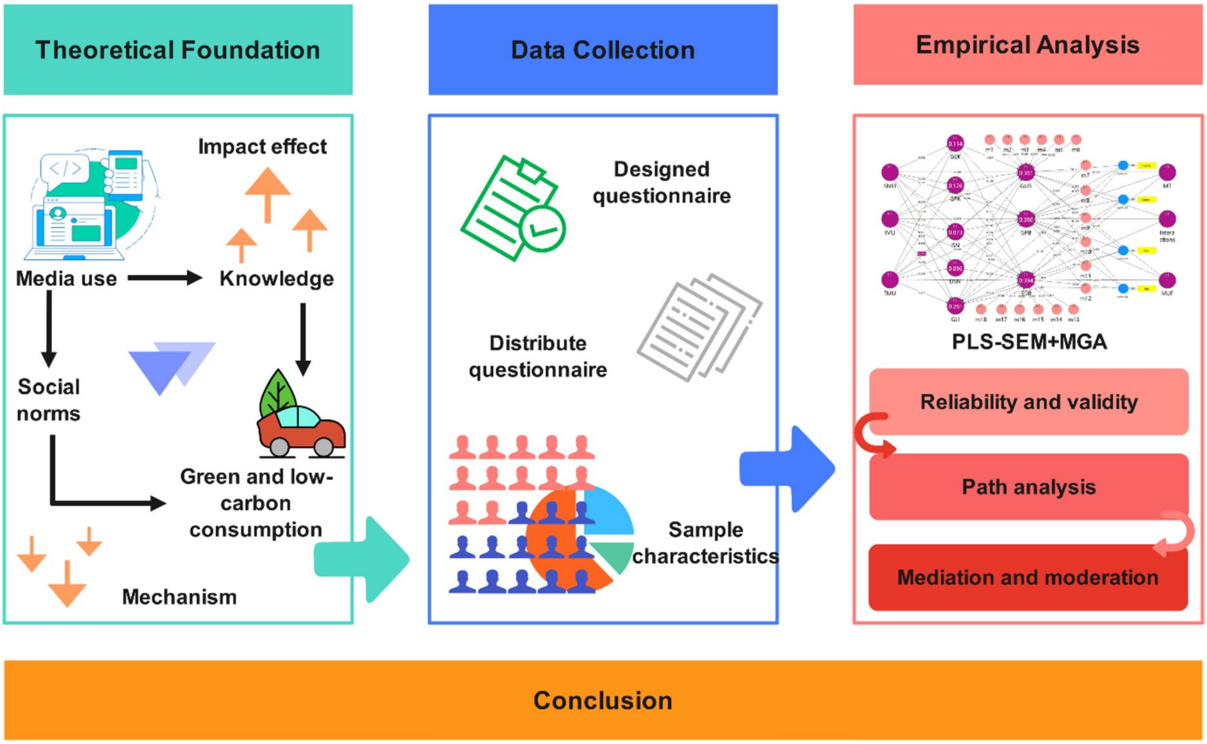

Fig. 1. Overall framework diagram.

Based on this, the following hypotheses are proposed in this paper:
H1: MU is positively correlated with GLB.
H1a: TMU is positively correlated with GLB.
H1b: IMU is positively correlated with GLB.
H1c: SMU is positively correlated with GLB.
H2: MU is positively correlated with GLI.
H2a: TMU is positively correlated with GLI.
H2b: IMU is positively correlated with GLI.
H2c: SMU is positively correlated with GLI.

Green and low-carbon consumption knowledge and green and low-carbon consumption behavior
Existing research indicates that knowledge is closely associated with behavioral intentions in the formation of consumer behavior, particularly playing a foundational role when consumers assess feasibility and anticipate outcomes[32]. The more thoroughly consumers understand a particular field, the more likely they are to transform their cognitive understanding into internal beliefs, thereby facilitating the transition from intention to behavior.

In the context of green low-carbon consumption knowledge typically refers to an individual's understanding of the relationship between humans and nature, environmental responsibility, and the consequences of low-carbon behavior[52]. Its content primarily includes two components: first, understanding of macro-level issues such as environmental responsibility and the consequences of carbon emissions (environmental knowledge)[53]; second, understanding of the functions, prices, attributes, and identification methods of green low-carbon products (product knowledge), such as eco-labels[54].

According to the TPB, an individual's level of cognitive understanding of a specific behavior can influence their PBC. Higher levels of GLK indicate that individuals have a better understanding of how to engage in GLC, including how to identify GLP and how to address potential challenges, thereby enhancing their confidence and ability to execute GLB[55]. Additionally, knowledge can shape an individual's green attitude, making them more positively inclined toward GLC, which is consistent with SCT's emphasis on the role of knowledge in individuals.

Furthermore, from an economic perspective, if individuals can understand the environmental value and usage benefits of GLP, it may also increase their perceived benefits of green consumption, thereby positively correlating with their GLI or GLB[54]. Based on the above analysis, this paper proposes the following hypotheses:
H3: GLK is positively correlated with GLI.
H4: GLK (environmental knowledge, product knowledge) is positively correlated with GLB.

Social norms and green and low-carbon consumption
Social norms are generally regarded as an important mechanism for maintaining consistency in group behavior and social order[55]. It reflects an individual's perception of the expectations of significant others or groups in society[56]i.e., the group's general attitude and behavioral standards toward a particular behavior[21]. In behavioral

research, SON is considered to be positively correlated with an individual's behavioral attitudes, intentions, and decision-making tendencies.

Within the TPB framework, SON is one of the three core elements constituting behavioral intention. When individuals perceive that important others or groups in their surroundings generally support a particular behavior, they are more likely to exhibit a higher level of intention toward that behavior. SCT further emphasizes that individual behavior is often adjusted through observation of the external environment and role model behavior. When the media and social groups consistently highlight the positive aspects and universality of GLC, this environmental information reinforces individuals' perceptions of SON and prompts them to actively adjust their behavior to align with societal expectations[57].

Therefore, the stronger an individual's perception of SON, the higher their GLI, and the greater the likelihood of adopting GLB. Based on this, the present study proposes the following hypothesis:

H5: SON is positively correlated with GLI.

H6: SON is positively correlated with GLB.

The mediating role of green and low-carbon knowledge and social norms

Green and low-carbon knowledge, which encompasses an understanding of environmental issues and awareness of GLP, is a key factor influencing the public's sustainable consumption behavior[37]. Media information dissemination and corporate green marketing are important channels for individuals to acquire such knowledge[55]. From the TPB perspective, GLK primarily serves as an antecedent variable in forming the core belief structure[58]and it has a close relationship with behavioral attitudes and PBC. Existing research indicates that if individuals receive clear information about GLPs through the media, their attitudes toward the products and their behavioral PBC may exhibit a higher positive correlation[37].

From the perspective of SCT, GLK plays a more direct and dynamic role as a personal cognitive factor[42]. On the one hand, possessing sufficient green knowledge may enable individuals to more easily anticipate the outcomes of their behavior, such as environmental benefits, social approval, health improvements, or economic savings, thereby enhancing their confidence in successfully executing the behavior[59]. On the other hand, higher levels of GLK may enhance individuals' ability to observe and understand others' green behaviors, thereby facilitating behavioral mimicry or attitude adjustment.

In summary, MU, as an external information input variable, may have a positive correlation with an individual's GLK level. The enhancement of GLK may indirectly influence an individual's attitudes, PBC, and outcome expectations, with knowledge serving as a foundation for environmental awareness and behavioral confidence, thereby generating indirect associations with GLI and GLB. Therefore, this paper proposes the following hypotheses:

H7: GLK mediates the relationship between MU and GLB.

H7a: GLK mediates the relationship between TMU and GLB.

H7b: GLK mediates the relationship between IMU and GLB.

H7c: GLK mediates the relationship between SMU and GLB.

H8: GLK mediates the relationship between MU and GLI.

H8a: GLK mediates the relationship between TMU and GLI.

H8b: GLK mediates the relationship between IMU and GLI.

H8c: GLK mediates the relationship between SMU and GLI.

Social norms provide individuals with important behavioral references and intangible social guidance for implementing GLC, making them one of the most widely studied variables in behavioral research.

Within the TPB framework, SON specifically refers to subjective norms, which are the social pressures individuals perceive from important others or groups. As the primary channels for information dissemination and social value construction, media play a potential role in individuals' perception of social expectations regarding GLC. Existing research indicates that different types of media coverage (such as news newspapers, television, radio, and social media) involving GLC cases, mainstream views, and policy promotion may have a significant association with the social expectations perceived by the public. For example, IPMI[24] (Influence of presumed media influence model) -related research points out that the degree of media exposure is positively correlated with the SON related to GLC[60] perceived by individuals, and that this perception of norms is also correlated with behavioral intentions.

SCT complements this perspective from a broader environmental and learning interaction angle[61]. On the one hand, individuals may internalize relevant SON through media exposure to discussions about GLC, demonstrations of exemplary behavior, and social feedback on such behaviors, thereby generating outcome expectations at the social cognitive level[55]. On the other hand, the interactive nature of social media provides a platform for the exchange of SON and the construction of consensus[4]further enhancing individuals' cognitive density and situational sensitivity toward SON.

Based on the above analysis, this paper argues that MU is positively correlated with the level of SON formed by individuals, and that SON further serves as a potential mediating pathway between MU and GLI, GLB. Therefore, this paper proposes the following hypothesis:

H9: SON mediates the relationship between MU and GLB.

H9a: SON mediates the relationship between TMU and GLB.

H9b: SON mediates the relationship between IMU and GLB.

H9c: SON mediates the relationship between SMU and GLB.

H10: SON mediates the relationship between MU and GLI.

H10a: SON mediates the relationship between TMU and GLI.

H10b: SON mediates the relationship between IMU and GLI.

H10c: SON mediates the relationship between SMU and GLI.

Green and low-carbon consumption intention and behavior

Green low-carbon consumption intention is typically regarded as the subjective tendency individuals exhibit toward GLB at the psychological level[62]. Within the TPB framework, behavioral intention is considered one of the most direct antecedent variables of behavior. Yadav and Pathak (2017)[63] found that there is a statistically significant positive correlation between individuals' purchase intentions and their actual purchase behavior; Sujata et al.[21] also discovered that the higher the level of recycling intention, the higher the probability of recycling behavior occurring, which supports the positive relationship between intention and behavior. Based on this, this study posits that the higher an individual's GLI level, the higher the likelihood of implementing GLB, i.e., GLI is positively correlated with GLB. Therefore, the following hypothesis is proposed:

H11: GLI is positively correlated with GLB.

The moderating effect of media trust and media use frequency

Media use frequency refers to the extent of an individual's interaction with a specific media channel. Previous studies have shown that different MUFs result in varying effects of MU on individuals' attitudes and behaviors[64]. According to SCT, frequent media exposure facilitates repeated reception and processing of information related to GLC, thereby enhancing the stability of observational learning and the internalization of information. Continuous exposure to specific information sources, akin to the "frog in boiling water" effect, can gradually alter an individual's cognitive framework and belief system, thereby aligning them with GLB. For example, Vassey et al.[59] found a positive correlation between adolescents' SMU and e-cigarette use, suggesting that MUF can serve as an important moderating variable in behavioral associations. Therefore, this study posits that MUF can moderate the relationship between MU and GLB. Figure 2 summarizes all hypothesized relationships in this paper.

Media trust reflects an individual's degree of dependence on and subjective evaluation of the media[65]. According to information processing theory and persuasion theory, the credibility of information sources directly affects the degree of information acceptance and persuasion effectiveness. The TPB framework also points out that the formation of attitudes and SONs is influenced by the degree of external information acceptance[66]. When individuals have a high level of trust in the media they encounter, they are more likely to agree with the GLC-related information disseminated by the media, thereby moderating the correlation between MU and GLB[67,68]. Additionally, previous studies have found that MT can moderate the relationship between MU and intention, behaviors, with differences depending on the type of media channel.

Therefore, this study posits that the relationship between MU and GLB may exhibit different levels of correlation intensity due to differences in individuals' levels of MT or MUF. In summary, this study proposes the following hypotheses:

H12: MUF strengthens the relationship between MU and GLB.
H12a: MUF strengthens the relationship between TMU and GLB.
H12b: MUF strengthens the relationship between IMU and GLB.
H12c: MUF strengthens the relationship between SMU and GLB.
H13: MT strengthens the relationship between MU and GLB.
H13a: MT strengthens the relationship between TMU and GLB.
H13b: MT strengthens the relationship between IMU and GLB.
H13c: MT strengthens the relationship between SMU and GLB.

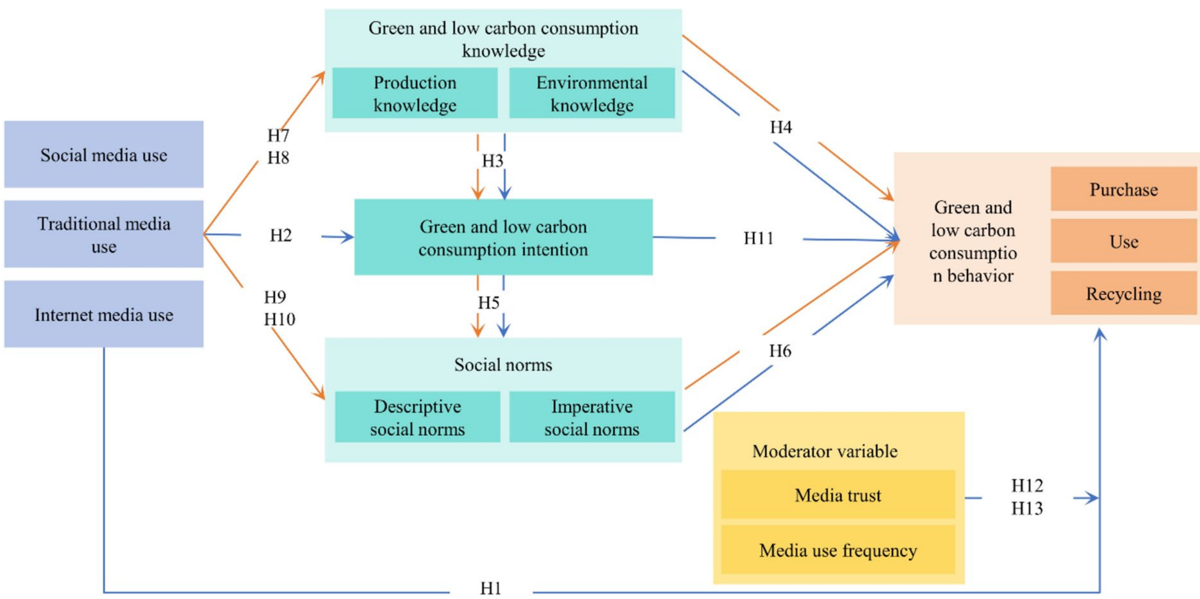

Fig. 2. Conceptual relationships and assumptions.

Research design
Questionnaire design
This study investigates the influence of MU on Chinese consumers' GLB. The research population comprises Chinese individuals engaged in GLB and purchasing green products like energy-efficient appliances, organic food, and eco-friendly building materials within the last year. We employed a questionnaire survey to gather data, adhering to a structured design process:

1) Reviewing relevant literature to clarify key concepts, including GLB components and MU classifications, and establishing the variables and relationship models.
2) Developing questionnaire items by adapting established scales in the field, aligning them with the study's focus and specific research questions.
3) Pre-test the questionnaire for validity and make necessary refinements.

The questionnaire consists of three sections:

1) Introduction, which states the purpose of the survey, background, defines key terms, and commits to data security.

2) Demographic information of the respondents, including gender, age, education level, etc..

3) Measurement of the main variables: GLB, intention to consume green products, GLK, SON, and MU. We assess these variables using a Likert scale, which ranges from 1 (very inconsistent) to 5 (very consistent).

Statement: All methods used in this study comply with relevant guidelines and regulations (the Declaration of Helsinki, the Personal Information Protection Law of China, and the Statistics Law of China). All participants were fully informed of the study objectives, data usage, and confidentiality measures through an electronic informed consent form prior to completing the questionnaire and voluntarily signed the electronic informed consent form. Data collection did not involve respondents under the age of 18. The questionnaire was distributed via an online platform certified by the Ministry of Industry and Information Technology of China and compliant with relevant regulations (www.wjx.cn) (Hunan Province ICP Filing Number: 17005436-1). All data has been de-identified to ensure anonymity.

Data collection
Distribute questionnaires
This study conducted a small-scale preliminary survey among undergraduates at the university to ensure the validity and reliability of the questionnaire, following the completion of the preliminary questionnaire design. The pre-survey distributed 100 questionnaires and collected 87 valid responses, resulting in an effective response rate of 87%. Based on the pre-survey results, the researchers further optimized and adjusted items that were difficult to understand and might lead to misunderstandings. They aimed to ensure that respondents had a consistent understanding of all items and that there were no errors or omissions.

After multiple improvements and revisions, a total of 47 items were included in the formal scale used in this study. The specific settings and sources for these items are detailed in Appendix 1, Table 1. The formal questionnaire was distributed through the professional social survey platform www.wjx.cn/, which helps ensure that the samples accurately reflect the overall situation and that respondents complete the questionnaire objectively and truthfully. Additionally, the questionnaire was disseminated through channels such as QQ and

Terms	Abbreviations
Green and low-carbon consumption	GLC
Green and low-carbon consumption behavior	GLB
Green and low-carbon consumption intention	GLI
Green and low-carbon consumption knowledge	GLK
Green and low-carbon production	GLP
Media use	MU
Media trust	MT
Media use frequency	MUF
Traditional media use	TMU
Internet media use	IMU
Social media use	SMU
Social norms	SON
Social cognitive theory	SCT
Theory of planned behavior	TPB
Perceived behavioral control	PBC

Table 1. Terms and abbreviations.

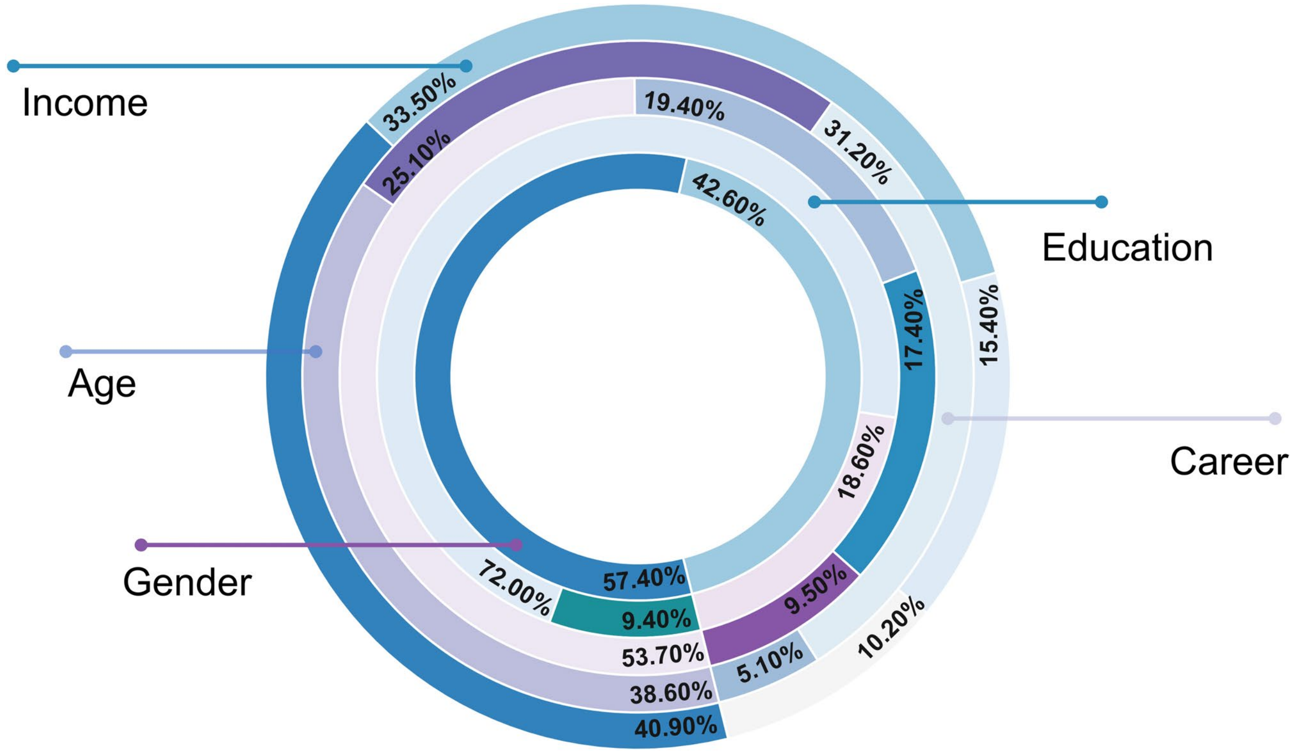

Fig. 3. Sample characteristics.

Variable	Obs	Mean	SD	Min	Max
Gender	1058	1.427	0.495	1	2
Age	1058	1.828	1.032	1	4
Edu	1058	2.093	0.521	1	3
Career	1058	2.028	0.949	1	4
Income	1058	1.949	0.985	1	4
GPK	1058	3.758	0.725	1.75	5
GEK	1058	3.797	0.766	1.75	5
DSN	1058	3.617	0.834	1	5
ISN	1058	3.718	0.866	1	5
GPB	1058	3.760	0.807	1.2	5
GUB	1058	3.716	0.867	1.33	5
RDB	1058	3.617	0.912	1	5
GLI	1058	3.764	0.762	1.2	5
TMU	1058	3.434	0.804	1.3	5
IMU	1058	3.600	0.818	1	5
SMU	1058	3.703	0.697	1.3	5
MUF	1058	3.606	0.754	1	5
MT	1058	3.770	0.756	1	5

Table 2. Descriptive statistics for main constructs.

WeChat. We collected 1,058 valid questionnaires after discarding 192 due to missing information, careless responses, and illogical answers. The effective response rate for the questionnaire is 84.64%.

Sample characteristics

Partial descriptive statistical results of the study sample distribution are shown in Fig. 3, and descriptive statistics of the main variables are shown in Table 2. In terms of gender, a total of 605 male respondents and 452 female respondents participated in this survey, accounting for 57.4% and 42.60% respectively. The proportion of males was slightly higher than that of females, with an overall balanced ratio, consistent with China's population characteristics. The age distribution of respondents is primarily concentrated between 18 and 30 years old, accounting for 53.7%; followed by 31–40 years old and 41–50 years old, accounting for 19.4% and 17.4%, respectively. The proportion of those aged 50 and above is 9.5%.

The respondents were primarily middle-aged and young adults aged 18–40, with the majority having a college or university degree, accounting for 72.0% of the total. Next were those with a master's degree, accounting for 18.6%, while those with a high school education had the lowest proportion, at only 9.4%. In terms of occupational distribution, the highest proportion was students, accounting for 38.5%, followed by government and public institution staff, accounting for 31.2%, and corporate employees, accounting for 25.1%. In terms of monthly income, the highest proportion of respondents had monthly incomes below 3,000-yuan, accounting for 40.9%, followed by those with monthly incomes between 3,001- and 5,000-yuan, accounting for 33.5%, and those with monthly incomes between 5,001- and 10,000-yuan, accounting for 15.4%. The lowest proportion was those with monthly incomes above 10,000-yuan, accounting for 10.2%. The characteristics of the sample in this study indicate that the respondents are relatively young and highly educated, reflecting a demographic bias. This also suggests that the findings of this study are specific in nature, primarily reflecting the relationship between MU and GLI, GLB among China's young and highly educated population.

In constructing the research model, this paper incorporates a series of key socio-economic demographic variables: age, education level, income, and occupation, as control variables[73]. Extensive prior research consistently indicates that these demographic factors influence individuals' values, lifestyles, ability to access information, and purchasing power, thereby shaping their environmental attitudes, intentions, and behaviors[74]. The primary methodological purpose of including these variables is to enhance the internal validity and rigor of the research. By statistically controlling for the potential confounding effects of these demographic predictor variables, we can eliminate biases in the dependent variables (GLI and GLB) caused by these variables. This procedure enables us to more accurately assess the explanatory power of the core constructs. Essentially, this approach ensures that the relationships identified in this paper are robust and not merely a product of sample demographic characteristics, thereby strengthening confidence in the theoretical mechanisms tested in this study.

Empirical results and analysis

SEM is a versatile tool for testing relationships. It combines various statistical techniques such as factor analysis, linear regression, and covariance analysis. It includes observable variables and latent variables, allowing simultaneous analysis of multiple dependent variables and consideration of measurement error.

Two main SEM approaches are Covariance-Based SEM (CB-SEM) and Partial Least Squares SEM (PLS-SEM). CB-SEM requires a strong theoretical foundation and strict assumptions about observation variables, sample size, and the number of latent variables. In contrast, PLS-SEM is more flexible and suitable for complex models with less stringent requirements. Given the nature of this study, PLS-SEM is the preferred method for analysis.

Assessment of the measurement model

Reliability analysis

Reliability refers to the ability of a measurement process to consistently measure the relevant variables involved in this study, primarily encompassing stability tests and consistency tests. The Cronbach's alpha coefficients for the first-order and second-order variables in this study ranged from 0.704 to 0.872 (innermost circle in Fig. 4(a)), and the standardized factor loadings for all measurement items exceeded 0.708 (innermost circle in Fig. 4(b)), meeting or exceeding the standard values; The AVE values for all variables exceed 0.5, and the composite reliability values are greater than 0.7 (outer circle in Fig. 4(a)), with CR exceeding 0.7 (second circle in Fig. 4(a)), indicating that the measurement scales used in this study possess good convergent validity. For details, see Appendix 2 (Table 4).

Validity analysis

First, validity measures whether a comprehensive evaluation system can accurately reflect its purpose and requirements. The higher the validity, the more the measurement results reflect the measured characteristics; conversely, the lower the validity. Convergent validity refers to the degree of correlation among measurement items when different measurement methods are used to measure the same construct. Commonly used measurement indicators include composite reliability (CR) (Fig. 4(a), second circle) and average extracted variance (AVE) (Fig. 4(a), outermost circle). Figure 4(b) illustrates the factor loadings of the measurement items in this study. As shown, the standardized factor loadings of each measurement item in the questionnaire used in this study exceed 0.708, which is greater than or equal to the standard value. The AVE of each variable exceeds 0.5, and the composite reliability is greater than 0.7, indicating that the measurement scales used in this study possess sufficient convergent validity.

Secondly, discriminant validity (also known as discriminant validity) is commonly used to measure the degree of correlation between different construct indicators to ensure that there is no high correlation between constructs. The three commonly used assessment methods in academia include the Fornell-Larcker criteria, cross-loadings, and HTMT. This study employed these three methods to assess the discriminant validity of the scales used, and the results indicated that satisfactory discriminant validity was achieved between the scales. Detailed test results are presented in Appendix 2 (Tables 1, 2 and 3).

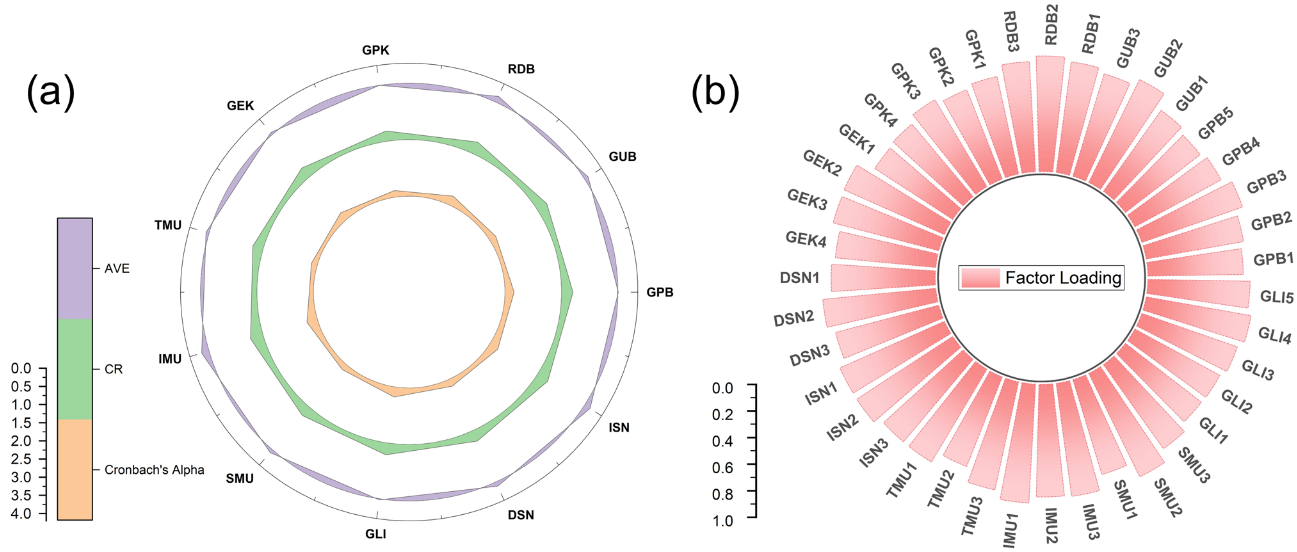

Fig. 4. Reliability and convergent validity testing of the model. (**a**) Internal consistency reliability and convergent validity of each construct. The composite reliability (CR) and Cronbach's alpha for all constructs in the figure exceed the recommended threshold of 0.7, and the average variance extracted (AVE) exceeds the threshold of 0.5, indicating that the model has good reliability and convergent validity. (**b**) Factor loadings of each measurement item. All factor loadings are significantly higher than the recommended level of 0.7, further validating the model's convergent validity.

	R^2	Adjusted R^2
GLB	0.576	0.570
GLI	0.389	0.381
GLK	0.161	0.159
SON	0.128	0.126

Table 3. Determination coefficients of endogenous latent variables.

Structural model assessment

Collinearity test

In the PLS-SEM model, the path coefficients of the SEM model that characterize the relationships between the latent variables are obtained by estimating a series of regression equations. Therefore, before formally assessing the structural relationships between the constructs, it is necessary to test the explanatory variables for multicollinearity to avoid the influence of multicollinearity on the subsequent path coefficient analysis. The Variance Inflation Factor (VIF) is a commonly used metric for assessing multicollinearity. Currently, the academic community generally considers a VIF value greater than 5 to indicate a significant risk of collinearity, while values between 3 and 5 may also suggest the presence of collinearity. Ideally, the VIF value should be less than 10 [69]. As shown in Fig. 5, the outer model VIF results indicate that the VIF values between constructs in the current structural model range from (1.028–2.073), far below the acceptable standard(VIF<3). This suggests that there is no significant multicollinearity between variables in this study, thereby ensuring the stability and reliability of path coefficient estimates. In addition, this paper also used Harman's single-factor test. Appendix Table 5 – 3 shows the results of Harman's one-factor test. The key statistic of this test, the variance explained by the first unrotated factor, is 20.488%. Since this value is far below the common threshold of 50%, we can conclude that common method variance is not a significant problem in this study. The correlation coefficient matrix of key constructs is shown in Table 6 in Appendix 2.

Analysis of the coefficient of determination

The coefficient of determination, also known as R^2, the explanatory power of endogenous latent variables in PLS-SEM, is measured by calculating the square correlation between the predicted value of endogenous constructs and the actual value. R^2 Between 0 and 1, the larger the value, the stronger the explanatory power of the model, usually bounded by 0.1. A value higher than 0.1 indicates that the model's explanatory power is acceptable. According to Hair's proposal of R^2 Standard, R^2, the explanatory power of endogenous latent variables is weak between 0.10 and 0.25, moderate between 0.25 and 0.75, and strong between 0.75 and 0.9. According to the results in Table 3, the R^2 of the endogenous latent variables involved in this study ranges from 0.128 to 0.576,

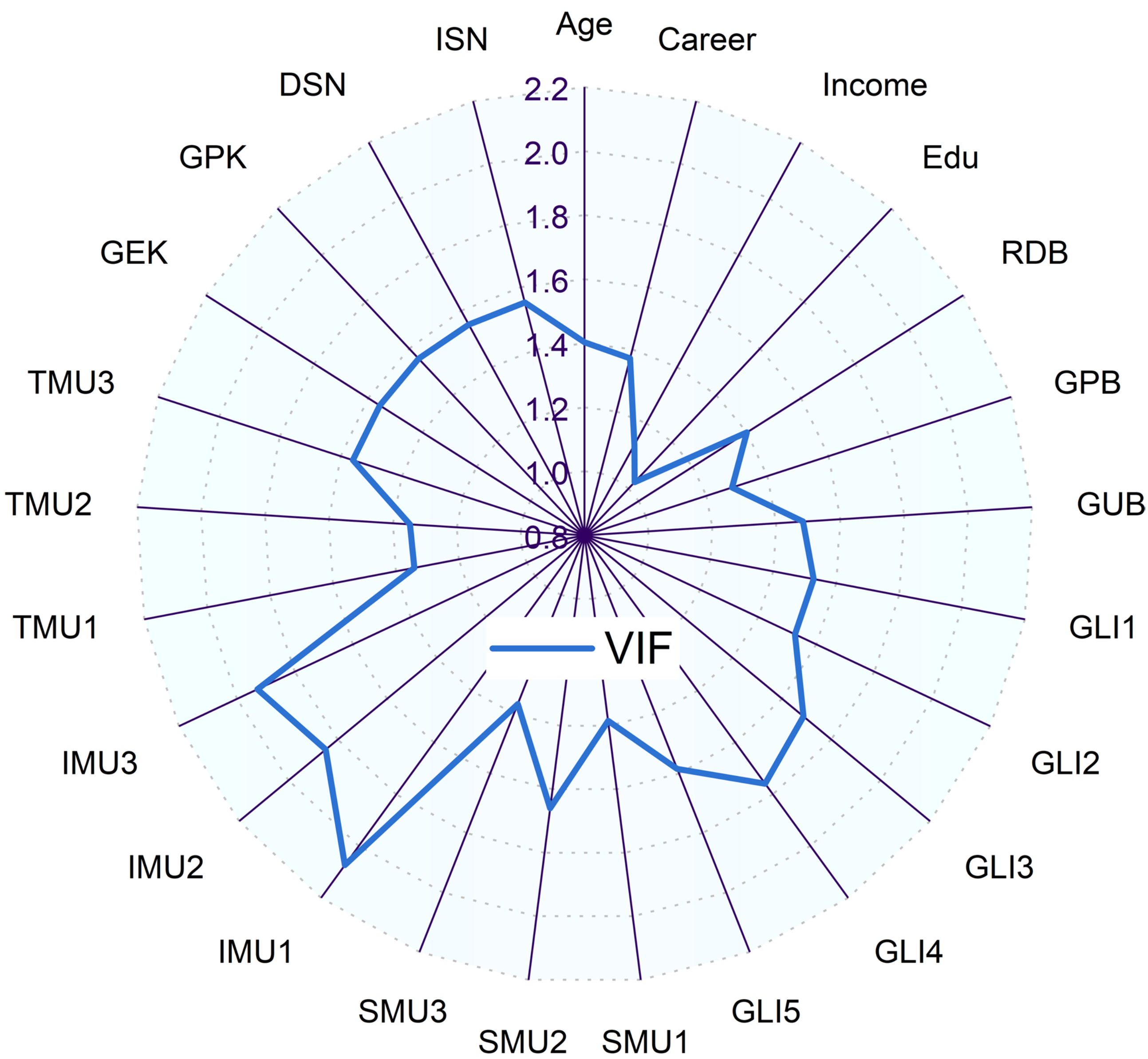

Fig. 5. Outer model VIF value (Appendix 2, Table 5 – 1, 5 – 2 for details).

which is higher than the critical criterion of 0.1, indicating that the model in this study has good explanatory power.

Analysis of predictive correlation

The PLS-SEM model is more suitable for predictive and exploratory research than the CB-SEM. Therefore, in addition to analyzing the determinability coefficients of endogenous latent variables, Stone Geisser's Q^2 is also needed. Value is used to evaluate the performance of the research model in predicting correlation. It is generally believed that Q^2 Greater than zero indicates that the model has a predictive correlation, while conversely, it indicates that the model does not have a predictive correlation. Q^2 the calculation formula is as follows:

$$Q^2 = 1 - \frac{SSE_D}{SSO_D}$$

Among them, SSE_D is the sum of squared errors (predicted value actual value); SSO_D is the sum of squared errors replaced by the mean.

This study used Blindfolding to calculate the Stone-Geisser's Q^2 of the current research model. In addition, when using Blindfolding in Smart PLS, it is necessary to specify the omission distance, which ranges from 5 to 12 and cannot be evenly divided by the number of samples. The sample size of this study is 1058, and the software default omission distance of 7 was selected. The final calculated Q^2 values are shown in Table 4.

	SSO	SSE	Q^2 (=1-SSE/SSO)
GLB	3174	2024.349	0.362
GLI	5290	4282.244	0.191
GLK	211	1851.540	0.125
SON	2116	1896.816	0.104

Table 4. Prediction correlation analysis.

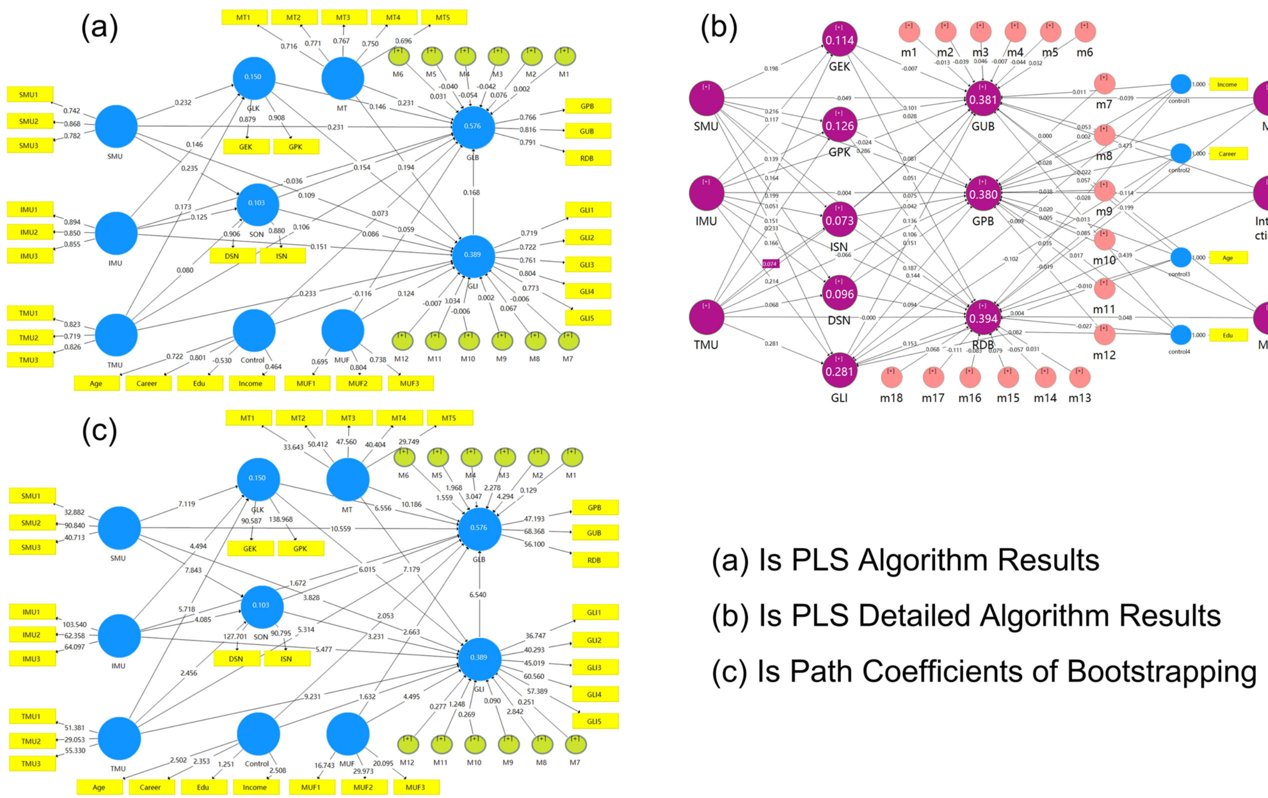

Fig. 6. SEM model and path analysis results.

Analysis of the goodness of fit of the model
According to the standard root mean square residual (SRMR) PLS-SEM goodness of fit metric proposed by Helseler et al., when the SRMR value is less than 0.08, the model is considered to have a good fit[70]. This study calculated the SRMR value of the research model through Smart PLS, which is 0.057, less than the acceptable standard. Therefore, it can be concluded that MU is adaptable to the structural GLC model.

Hypothesis testing

The previous analysis has fully demonstrated that the current SEM has good reliability and validity, as well as good explanatory power, and can be used for analyzing the impact of MU on GLB. Based on the empirical analysis results, the hypotheses proposed in this study will be tested separately below.

Path coefficient significance test
PLS-SEM does not require observed data to follow a normal distribution. It primarily uses the non-parametric bootstrapping method to test the significance levels of coefficients. The principle of bootstrapping involves repeatedly trying various combinations to minimize the difference between the estimated matrix and the observed matrix, thereby obtaining the optimal results. Bootstrapping provides the standard error of estimated coefficients, enabling the calculation of empirical T-values, which in turn determine whether variables are correlated.

This paper builds upon the research of Charbel[71] and Thomas et al.[72]., utilizing the Bootstrapping operation in SmartPLS 3.2.9 software (with a subsample size of 5,000, with all other settings remaining at their defaults) to estimate the path coefficients between the latent variables within the model (including the control variables). The PLS algorithm results are shown in Figs. 6(a) and 6(b). As can be seen in (a), the control variables $P_{GLB, GLI}$ =0.073, -0.116. In detail, career, education, income, and age are shown in (b), $P = 1.000$. Figure 6 (c) shows the

Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	*P* Values
Control -> GLB	0.073	0.065	0.036	2.053	0.041
Control -> GLI	-0.116	-0.099	0.071	1.632	0.103
GLI -> GLB	0.168	0.168	0.026	6.54	0.000
GLK -> GLB	0.146	0.146	0.022	6.556	0.000
GLK -> GLI	0.154	0.154	0.026	6.015	0.000
IMU -> GLB	-0.036	-0.038	0.022	1.672	0.095
IMU -> GLI	0.151	0.152	0.028	5.477	0.000
IMU -> GLK	0.146	0.143	0.032	4.494	0.000
IMU -> SON	0.125	0.125	0.031	4.085	0.000
SMU -> GLB	0.231	0.229	0.022	10.559	0.000
SMU -> GLI	0.109	0.107	0.028	3.828	0.000
SMU -> GLK	0.232	0.233	0.033	7.119	0.000
SMU -> SON	0.235	0.235	0.03	7.843	0.000
SON -> GLB	0.263	0.264	0.021	12.361	0.000
SON -> GLI	0.086	0.087	0.027	3.231	0.001
TMU -> GLB	0.106	0.107	0.02	5.314	0.000
TMU -> GLI	0.233	0.232	0.025	9.231	0.000
TMU -> GLK	0.173	0.173	0.03	5.718	0.000
TMU -> SON	0.08	0.079	0.032	2.456	0.014

Table 5. Path coefficients.

Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	*P* Values
Control -> GLB	-0.019	-0.017	0.012	1.571	0.117
TMU -> GLB	0.091	0.090	0.014	6.428	0.000
TMU -> GLI	0.034	0.033	0.007	4.530	0.000
IMU -> GLB	0.085	0.085	0.013	6.480	0.000
IMU -> GLI	0.033	0.033	0.008	4.178	0.000
SMU -> GLB	0.123	0.123	0.014	9.072	0.000
SMU -> GLI	0.056	0.056	0.010	5.545	0.000
GLK -> GLB	0.026	0.026	0.006	4.292	0.000
GLK -> GLI	0.154	0.154	0.026	6.015	0.000
SON -> GLB	0.014	0.014	0.005	3.038	0.003

Table 6. Total indirect effects.

bootstrapping calculation results for path coefficients. Overall, it can be concluded that the control variables have no significant impact on GLB and GLI. The path coefficient test values of the structural equation model are shown in Table 5. Among them, the association between IMU and GLB (IMU→GLB) ($T = 1.672 < 1.96$, O=-0.036, $P = 0.095 > 0.05$) did not reach statistical significance, while all other paths were significant at the 95% or 99% confidence level. For detailed confidence intervals, see Appendix Table 7.

Additionally, since there are two mediating variables in this study, GLK and SON, it is necessary to examine the effects of these paths. Table 6 shows the statistical results of the total indirect effects of the model. According to Table 6, except for the SON→GLB, SON→GLI, and TMU→SON paths, which are significant at the 95% confidence level (O = 0.014, 0.086, 0.080, $P = 0.003$, 0.001, 0.014), all other paths are significant at the 99.9% confidence level ($P < 0.001$).

Analysis of mediation effects and model pathways

Table 6 shows that TMU, IMU, and SMU are positively correlated with GLB and GLI, with $O_{GLB} = 0.091, 0.085, 0.123$, and $O_{GLI} = 0.034, 0.033, 0.056$, $P < 0.001$. In terms of the degree of correlation, the relationship between MU and GLB follows the order SMU > TMU > IMU, and the relationship between MU and GLI follows the order SMU > TMU > IMU. This indicates that the correlation between SMU and GLB, GLI is stronger, which may be attributed to the rapid development of the internet, which has increased the social interaction effects brought by social media.

Secondly, from the perspective of specific implementation pathways, the association between MU and GLB, GLI can also be indirectly influenced through GLK and SON (Tables 6 and 7). Among these, MU is positively correlated with GLK ($O_{TMU, IMU, SMU} = 0.173, 0.146, 0.232$, $P < 0.001$). In Table 7 Specific indirect effects, MU is also associated with GLB and GLI through GLK ($O_{IMU, SMU, TMU \rightarrow GLK \rightarrow GLB} = 0.021, 0.034, 0.025$, $P < 0.001$;

Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	*P* Values
IMU -> GLK -> GLB	0.021	0.021	0.006	3.818	0.000
SMU -> GLK -> GLB	0.034	0.034	0.007	4.865	0.000
TMU -> GLK -> GLB	0.025	0.025	0.006	4.286	0.000
IMU -> SON -> GLB	0.024	0.025	0.008	2.940	0.003
SMU -> SON -> GLB	0.062	0.062	0.009	6.632	0.000
TMU -> SON -> GLB	0.021	0.021	0.009	2.446	0.015
IMU -> GLK -> GLI	0.022	0.022	0.006	3.546	0.000
SMU -> GLK -> GLI	0.036	0.036	0.008	4.621	0.000
TMU -> GLK -> GLI	0.027	0.027	0.007	4.102	0.000
IMU -> SON -> GLI	0.011	0.011	0.004	2.544	0.011
SMU -> SON -> GLI	0.02	0.02	0.007	2.904	0.004
TMU -> SON -> GLI	0.007	0.007	0.004	1.822	0.069

Table 7. Specific indirect effects.

$O_{IMU,\ SMU,\ TMU \to GLK \to GLI}$ = 0.022, 0.036, 0.027, P < 0.001). Therefore, MU may be positively correlated with improvements in individual GLK, and improvements in GLK are positively correlated with GLI and GLB. However, SON only mediates the relationship between MU and GLB ($O_{IMU,\ SMU,\ TMU \to SON \to GLB}$ = 0.024, 0.062, 0.021, P_{SMU} < 0.001, $P_{IMU,\ TMU}$ < 0.05) and does not mediate the relationship between TMU and GLI (O = 0.007, P = 0.069>0.05), while all other indirect effects are significant.

The estimated results are shown in Table 8, "Total effects and hypothesis testing results." Except for H10a, "TMU -> SON -> GLI" (O = 0.005, P = 0.069>005), which did not pass the significance test and was therefore rejected, all other paths were statistically significant (P < 0.05).

Multiple-group analysis

To further analyze the specific mechanisms by which MU promotes GLI and behavior, this study conducted a multi-group analysis of the dimensions of gender and age. Before conducting a multi-group comparative analysis between different groups[78]invariance testing must be conducted through the MICOM program, including configuration invariance, component invariance, and equal distribution of variance, to ensure that respondents from different groups have similar understandings of the measurement structure.

Figure 7 shows the visualization results of the moderation effect, where the lines in m2 and m8 are not parallel, indicating that the relationship between SMU and GLB varies significantly across consumer groups with different MT. The results of the multiple group analysis in Table 9 also indicate that the magnitude of the positive correlation effect differs between high MT groups (β =0.343, P = 0.000) and low MT groups (β = 0.212, P = 0.000). This result supports hypothesis H13c, which states that the higher the level of consumer trust in the media, the greater the likelihood of a positive correlation between SMU and GLB. However, the positive correlation effects between TMU, IMU, and GLB did not differ across consumer groups with varying levels of trust. In Fig. 7, the lines m1, m2, m3, m7, m8, m9 are parallel. In Table 9, TMU: $\beta_{\text{high MT}}$ = 0.086**, $\beta_{\text{low MT}}$ = 0.113***; IMU: $\beta_{\text{high MT}}$ = 0.024, $\beta_{\text{low MT}}$ = 0.050, which refutes hypotheses H13a and H13b. Additionally, in Fig. 7, the lines for m10, m11, and m12 are parallel. Although the slopes for m4, m5, m6. are inconsistent and intersect, statistically $\beta_{\text{high–low}}$ < 0.1, and the results did not match the expected direction, indicating that the three MU groups did not show significant differences across different MUF groups, thus rejecting hypotheses H12a, H12b, and H12c.

Conclusions and discussion

Based on economic decision-making theory, this paper integrates TPB and SCT to construct an analytical framework, systematically testing the mediating role of GLK and SON and the moderating role of MT and MUF, providing a new perspective for understanding the underlying mechanisms between MU and GLC.

First, regarding direct effects. The study found that MU exhibits significant positive correlations with both core dimensions of GLC, GLI and GLB. Additionally, this study observed differences in the strength of associations between various media channels and GLC. The association strength follows the order SMU > TMU > IMU. This finding contradicts previous research results[59]. This discrepancy may be attributed to the evolution of MU habits: compared to the one-way information transmission of traditional media, the interactivity of social media may be more favored by respondents. As times change, respondents are more inclined to obtain environmental information through SMU, thereby enhancing its association strength. Overall, MU may increase individuals' knowledge of GLC by providing successful case studies and operational guidelines, thereby promoting behavioral change.

Second, regarding indirect effects. The results of this study indicate that, in addition to TMU → SON → GLI, GLK and SON mediate the relationship between MU and GLI and GLB. These differences may stem from the limitations of traditional media, such as its one-way transmission characteristics in shaping social norms. Of course, in today's world, social norms are more often formed through social interaction rather than authoritative communication. Notably, this study did not find that MUF moderates the relationship between MU and GLC, which differs from previous research findings. This may be attributed to desensitization phenomena caused by media information overload or inappropriate media promotion in the current environment.

Path		Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	*P* values	Sig_L	Adjusted *P* values	A _Sig_L	Decision	f^2	Effect size
Control -> GLB		0.054	0.049	0.03	1.797	0.073	ns	/	/	/	0.009	<0.02
Control -> GLI		-0.116	-0.099	0.071	1.632	0.103	ns	/	/	/	0.024	Small
H1a	TMU-> GLB	0.197	0.197	0.021	9.538	0.002	**	0.0026	**	Accept	0.022	Small
H1b	IMU-> GLB	0.049	0.047	0.024	2.056	0.040	*	0.0418	*	Accept	0.002	<0.02
H1c	SMU-> GLB	0.354	0.353	0.022	15.972	0.000	***	0.0000	***	Accept	0.099	Small
H2a	TMU-> GLI	0.267	0.266	0.025	10.533	0.000	***	0.0000	***	Accept	0.090	Small
H2b	IMU-> GLI	0.184	0.185	0.028	6.688	0.000	***	0.0000	***	Accept	0.041	Small
H2c	SMU-> GLI	0.165	0.163	0.028	5.830	0.000	***	0.0000	***	Accept	0.022	Small
H3	GLK-> GLB	0.172	0.172	0.022	7.755	0.000	***	0.0000	***	Accept	0.040	Small
H4	GLK-> GLI	0.154	0.154	0.026	6.015	0.000	***	0.0000	***	Accept	0.041	Small
H5	SON-> GLB	0.277	0.278	0.021	13.106	0.000	***	0.0000	***	Accept	0.130	Small
H6	SON-> GLI	0.086	0.087	0.027	3.231	0.001	**	0.0014	**	Accept	0.016	<0.02
H11	GLI-> GLB	0.168	0.168	0.026	6.540	0.000	***	0.0000	***	Accept	0.040	Small
H7a	TMU-> GLK-> GLB	0.025	0.025	0.006	4.286	0.000	***	0.0000	***	Accept	/	/
H7b	IMU-> GLK-> GLB	0.021	0.021	0.006	3.818	0.000	***	0.0000	***	Accept	/	/
H7c	SMU-> GLK-> GLB	0.034	0.034	0.007	4.865	0.000	***	0.0000	***	Accept	/	/
H8a	TMU-> GLK-> GLI	0.027	0.027	0.007	4.102	0.000	***	0.0000	***	Accept	/	/
H8b	IMU-> GLK-> GLI	0.022	0.022	0.006	3.546	0.000	***	0.0000	***	Accept	/	/
H8c	SMU-> GLK-> GLI	0.036	0.036	0.008	4.621	0.000	***	0.0000	***	Accept	/	/
H9a	TMU-> SON-> GLB	0.021	0.021	0.009	2.446	0.015	*	0.0164	*	Accept	/	/
H9b	IMU-> SON-> GLB	0.024	0.025	0.008	2.940	0.003	**	0.0034	**	Accept	/	/
H9c	SMU-> SON-> GLB	0.062	0.062	0.009	6.632	0.000	***	0.0000	***	Accept	/	/
H10a	TMU-> SON-> GLI	0.005	0.005	0.003	1.627	0.069	ns	0.0690	ns	Reject	/	/
H10b	IMU-> SON-> GLI	0.011	0.011	0.004	2.544	0.011	*	0.0127	*	Accept	/	/
H10c	SMU-> SON-> GLI	0.020	0.020	0.007	2.904	0.004	**	0.0048	**	Accept	/	/

Table 8. Total effects and hypothesis testing results. 1. Multiple comparison adjustment method: FDR-BH. We use Benjamini-Hochberg procedure with reference to Garcia's practice[75]which aims to control the false discovery rate (FDR), that is, the proportion of null hypothesis incorrectly rejected. The results show that the significant number is consistent with the original results, and the significant hypothesis is 22, accounting for 95.7% of the total. 2. Adjusted P values are FDR adjusted p-values. 3. Sig_L: Significant Level; A_Sig_L: Adjusted Sig_L: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, ns is not significant. 4. f^2, < 0.02 no effect, 0.02–0.15 small effect size, 0.15–0.35 medium, > 0.35 large[76]. Notably, in path analysis, we found that some of the hypothesized paths were statistically significant, but their corresponding $f^2 < 0.02$, indicating no effect. However, given that this study analyzed a relatively complex model using 1,058 samples, these paths still have theoretical value for further exploration[77].

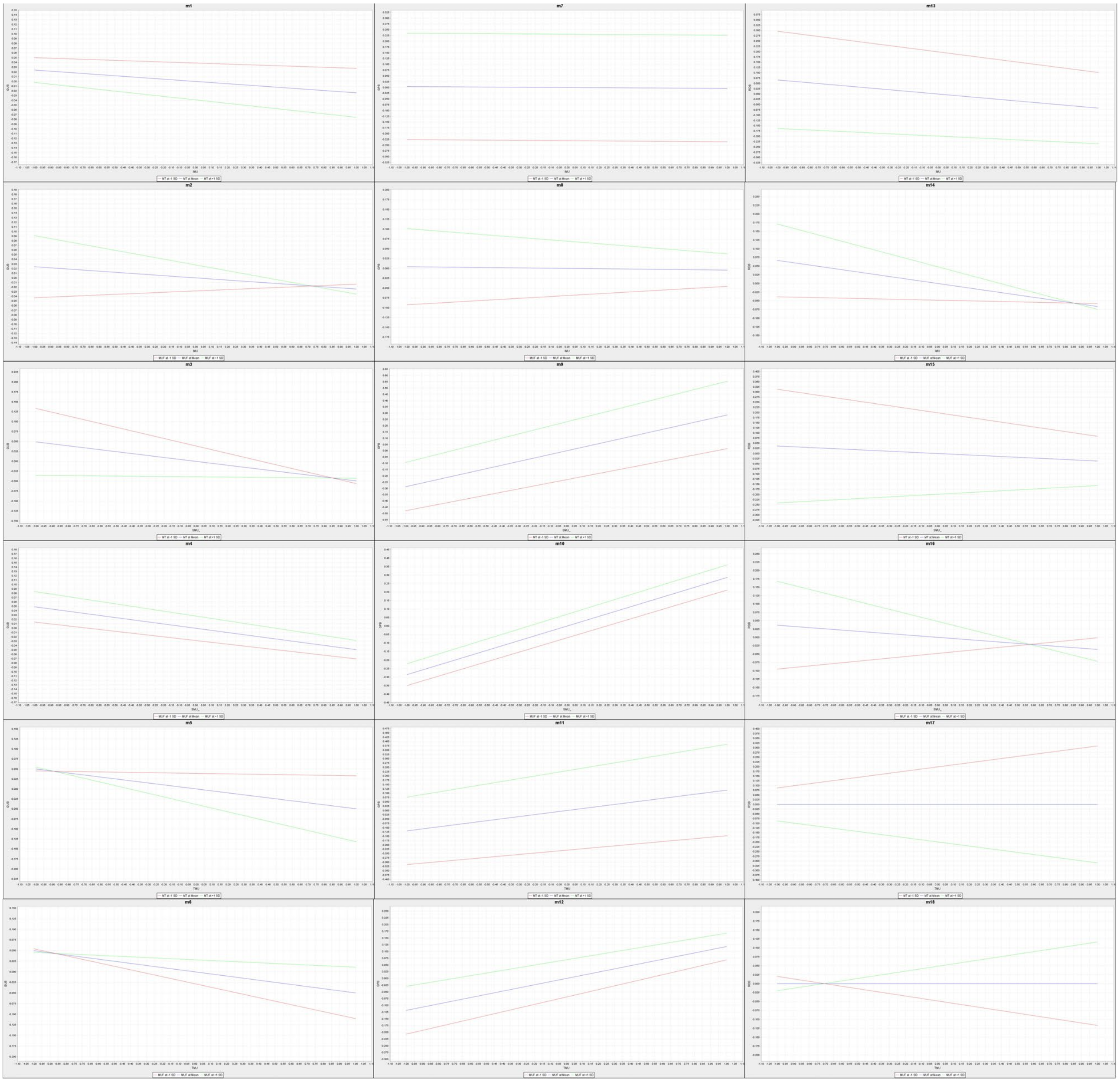

Fig. 7. Moderating effect visualization. High moderating variable line: Relationship when the moderating variable is at a high level (usually + 1SD - green line); Low moderating variable line: Relationship when the moderating variable is at a low level (usually – 1SD - red line); Mean line: Relationship when the moderating variable is at the average level (usually mean - blue line). If the slopes of the lines are different, there is a regulatory effect. If the lines are parallel, there is no regulatory effect. The greater the difference in slope, the stronger the regulatory effect. A positive slope indicates a positive correlation, while a negative slope indicates the opposite. A horizontal line indicates no relationship.

Path	Total	High-MT	Low-MT	High-MUF	Low-MUF
TMU -> GLB	0.080^{**}	0.086^{**}	0.113^{**}	0.116^{***}	0.100^{**}
IMU -> GLB	0.000	0.024	0.050	-0.002	0.068^{*}
SMU -> GLB	0.285^{***}	0.343^{***}	0.212^{***}	0.287^{***}	0.272^{***}
N	1058	569	489	587	471

Table 9. Results of multi-group analysis based on MT and MUF. In multiple group analysis, *, * *, and * * * correspond to significance at the 10%, 5%, and 1% confidence levels.

Additionally, the control variables (occupation, education level, age, and income) had no significant effect on green low-carbon intentions (GLI) or behavior (GLB). A reasonable explanation is that the influence of these demographic factors is overshadowed by more direct psychological variables in the model used in this study. Specifically, factors such as individuals' green knowledge (GLK), perceived social norms (SON), and green consumption intentions (GLI) are more direct and powerful drivers of behavior. This suggests that once these key cognitive and social factors are taken into account, the predictive power of broad demographic categories decreases significantly. This has important practical implications: interventions aimed at promoting GLC may be more effective if they focus on enhancing knowledge levels and shaping social norms, rather than targeting specific demographic groups. Therefore, this study retains these insignificant control variables in its analysis to strengthen the robustness of the core findings, demonstrating that the relationships identified in this study remain valid even after controlling for key demographic influences.

Finally, cultural context may also play a role. Unlike Vu et al.'s Europe-focused study[28]this study was conducted within a Chinese cultural context. In the Chinese cultural context, factors such as collectivism may exert a strong influence on MU, MT, and media content dissemination, playing a unique role in the formation of SON and the dissemination of GLK. In Western cultures with lower levels of collectivism, the correlation between MU and GLC, as well as the strength of the mediating role of SON, may be relatively weakened. Therefore, promoting GLC may require greater emphasis on shaping individual attitudes rather than merely emphasizing social pressure or group identity.

However, the theoretical framework and core mechanisms proposed in this study regarding the association between MU and GLC still hold significant implications for other countries with similar cultural backgrounds, facing similar environmental challenges, and committed to green transformation (particularly developing countries). For example, when designing media communication strategies, one can draw on the patterns of association between different media types and GLC/SON outlined in this study and adapt them according to the specific national context and media ecosystem to more effectively promote individual GLC.

Recommendations, limitations, and outlook

Recommendations

Governments, businesses, and media organizations may consider the following recommendations to promote the development of green and low-carbon consumption: First, governments should not only provide policy support to guide the public in forming GLC concepts but also utilize a variety of media tools to expand the influence of GLC policies. Second, from the business perspective, companies should continuously enhance the public's understanding of the value of GLPs during product promotions. When the public recognizes the benefits of GLC and the environmental benefits they can achieve through such consumption, GLC will gradually transition from an externally driven model to an internally driven one. Finally, from the media perspective, media outlets should, on one hand, leverage their role in guiding public opinion to vigorously advocate the importance of GLC. On the other hand, various media platforms should proactively assume their social responsibility for science popularization and policy promotion, intensify publicity and policy interpretation efforts, and gradually cultivate the public's awareness of GLC, as well as their ability to control and act upon such consumption behaviors.

Limitations and outlook

This study provides new insights into the impact of MU on GLC. However, there are still some areas that need further improvement.

First, this study relies on self-reported questionnaire surveys from participants, which may not fully reflect consumers' actual behavioral performance. Due to the influence of social desirability bias and recall bias, respondents may overestimate their participation in green behaviors, thereby reducing the objectivity of behavioral measurement. In addition, this study is limited by the questionnaire design, which does not comprehensively measure key constructs of SCT, such as the influence of self-efficacy. Future research can integrate multiple measurement methods, such as consumption records, observation methods, and experimental methods, to more objectively and accurately reveal GLC and the influence of self-efficacy in SCT, thereby improving the accuracy of green behavior measurement and the validity of research conclusions.

Secondly, this study did not include all potential confounding variables in the model construction process. Although some demographic variables were controlled for, the analysis may not have been comprehensive enough, as variables such as awareness of environmental policies were not included in the structural model for control analysis. Future research could build on this foundation by adopting a more comprehensive approach or utilizing methods such as multilevel structural equation modeling (SEM) to more fully identify influencing pathways and enhance the explanatory power of the model. Additionally, this study is designed as a cross-sectional study and cannot identify the causal order between variables. It is recommended that future research strengthen validation through longitudinal data collection, experimental methods, and other approaches.

Finally, the data in this study primarily come from a young, highly educated consumer group in China, which may result in the following two limitations. First, cultural differences such as collectivism may limit the generalizability of the study results. Second, this sample does not represent the broader association between MU and GLC in China. Future research could expand the sample sources to include individuals from different cultural backgrounds, educational levels, and age groups, examining how the association between MU and GLC varies across different cultures and broader populations, thereby deepening our understanding of consumer behavior in different contexts.

Data availability

The datasets used and analyzed during the current study are available from the corresponding author upon reasonable request, the data for this article are stored at the following link.https://drive.google.com/drive/folders/1r8OWsdVJmmOAjoFWnE_yk2n1xc2Q32tq? usp=drive_link.

Received: 24 February 2025; Accepted: 4 August 2025
Published online: 15 August 2025

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Funding
The research is supported by the National Social Science Fund of China (24FJYB037).

Declarations

Competing interests
The authors declare no competing interests.

Ethical approval
This study conforms to the ethical and moral requirements.

Consent to participate
All the authors of this article were consented to participate.

Additional information
Supplementary Information The online version contains supplementary material available at https://doi.org/10.1038/s41598-025-14905-0.

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