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Article

Research and effect analysis of the collaborative role of mobile technology and intelligent management on rural tourism from biomechanical and molecular perspectives

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Abstract: This research adopts a scientific perspective based on biomechanics and molecular-level analysis to explore the synergistic mechanisms and implementation effects of mobile technology and intelligent management systems in rural tourism. The study constructs a three-dimensional "technology-human-environment" framework, employing mixed research methods and a multi-case research strategy to conduct experiments at eight different types of rural tourism destinations across three representative provinces in China, recruiting 458 effective sample participants who wore lightweight wearable motion capture systems and other multimodal biomechanical data collection devices, while simultaneously testing the "BioPark" mobile application and "SmartRural" intelligent management system in coordination. The findings reveal that tourists exhibit significantly different biomechanical characteristics and molecular physiological indicator patterns in various terrain environments, such as knee joint maximum torque being significantly higher on steep slopes than on flat ground (1.64 ± 0.27 vs. 0.87 ± 0.16 Nm/kg, $p < 0.001$), and cortisol/endorphin ratio showing a strong negative correlation with satisfaction ($r = -0.72$, $p < 0.001$). Mobile technology primarily influences experience through three pathways: information enhancement, experience optimization, and interaction enhancement, while the intelligent management system improves decision-making accuracy by 48.3% and resource allocation efficiency by 28.3%. The synergistic effect of the systems produces results exceeding the simple addition of individual systems through three mechanisms: data sharing (path coefficient 0.73), functional complementarity (0.68), and information feedback (0.61), resulting in increased overall tourist satisfaction by 28.1% ($p < 0.001$), extended stay duration by 36.4% ($p < 0.001$), and improved actual revisit rates by 77.8% ($p < 0.01$). Based on these results, the study proposes "physiologically friendly" rural tourism spatial design principles and technology-management collaborative optimization strategies, establishing a biological data-driven service closed-loop system that provides theoretical support and technical solutions for the scientific development of rural tourism, while also discussing research limitations and future development trends.

Keywords: rural tourism; biomechanics; molecular physiological indicators; mobile technology; intelligent management; synergistic mechanism; experience optimization

1. Introduction

With the deepening implementation of China's rural revitalization strategy and the vigorous development of the tourism industry, rural tourism has become an important pathway for the diversification of rural economies and the satisfaction of urban and rural residents' leisure needs. However, traditional rural tourism faces numerous challenges in its development, including extensive management, insufficient scientific design of experiences, and subjective service quality evaluation. In the context of digitalization and intelligence, organically combining cutting-edge scientific technologies with rural tourism and innovating research methods and management models has become key to enhancing the competitiveness of rural tourism. This study, based on the scientific perspectives of biomechanics and molecular-level analysis, combined with mobile technology and intelligent management systems, explores their collaborative mechanism and implementation effects in rural tourism.

Biomechanics, as an interdisciplinary field studying the relationship between human structure and function, has expanded from medical rehabilitation to broad applications in human activity evaluation. Niu developed a sitting posture rehabilitation management system based on biomechanical principles, achieving precise monitoring and scientific management of human posture, which provides technical reference for the quantitative evaluation of tourists' postural comfort in tourism activities [1]. Zhong analyzed the mechanism of military training-induced sports injuries from a biomechanical perspective and proposed protective strategies, with research methods that have implications for assessing potential physiological risk points in rural tourism environments [2]. Internationally, Gao et al. developed a wearable pneumatic-piezoelectric system that achieved real-time, non-invasive monitoring of skeletal muscle biomechanical parameters, providing technological possibilities for dynamic collection of tourists' physiological states during tourism activities [3]. These studies indicate that advances in biomechanical measurement technology have created conditions for scientific evaluation of tourism experiences.

Meanwhile, molecular-level physiological indicator detection also shows tremendous application potential. Guangming et al.'s research on the correlation between corneal biomechanics and the severity of Marfan syndrome revealed the intrinsic connection between microscopic biological indicators and macroscopic symptom manifestations, inspiring us to evaluate the impact of tourism environments on tourists' physiological comfort through molecular physiological indicators [4]. In materials science applications, Yoon et al. [5] and Wu et al. [6] respectively compared the biomechanical properties of different medical materials, with research methods and conclusions that have reference value for the ergonomic design and material selection of rural tourism facilities, helping to enhance tourists' comfort and safety in rural environments. Tang's exploration of the combined application of artificial intelligence and biomechanics in sports training provides a theoretical foundation for this study to construct a collaborative analysis framework of mobile technology, intelligent management, and biomechanical data [7].

Real-time collection of biomechanical and molecular-level data through mobile technology, combined with intelligent management systems for data analysis and decision support, is expected to establish a scientific evaluation and optimization mechanism for rural tourism experiences. However, existing research mostly focuses on technological applications within a single field, lacking comprehensive research from a multidisciplinary perspective, especially as the application of biomechanics and molecular science in tourism experience evaluation remains in the exploratory stage. Based on this, this study aims to fill this research gap by constructing a tourism experience evaluation system at the biomechanical and molecular levels, combined with mobile technology and intelligent management systems, to establish a multi-dimensional, multi-level rural tourism collaborative optimization model. Specifically, this study will explore: (1) tourists' biomechanical characteristics in rural tourism activities and their relationship with environmental factors; (2) the correlation between molecular-level physiological indicators and tourism experience perception; (3) the application effects of mobile technology in biological data collection and experience enhancement; (4) the supporting role of intelligent management systems in resource allocation and service optimization; (5) the mechanisms and comprehensive effects of multi-system collaboration. This research not only helps to deepen scientific quantitative evaluation methods of tourism experiences but also provides data support and theoretical guidance for rural tourism spatial design, service process optimization, and tourist behavior guidance, ultimately achieving the dual improvement of rural tourism quality and benefits.

2. Literature review

Biomechanics and molecular science, as interdisciplinary fields studying human activity mechanisms, have gained widespread application in multiple domains in recent years, while combining them with mobile technology and intelligent management systems for application in rural tourism represents an emerging research direction. This paper systematically reviews research progress in related fields to establish a theoretical foundation for subsequent research. In fundamental biomechanics research, Guo et al. explored the characteristics and advantages of finite element analysis technology in knee joint biomechanics applications, indicating that this technology can precisely simulate the mechanical properties of human joints in different activity states, providing methodological reference for evaluating tourists' movement states in tourism activities [8]. Wei [9] systematically elaborated on biomechanical issues in intelligent rehabilitation engineering, while Niu's research further emphasized the key role of biomechanics in the field of intelligent rehabilitation, these studies laying the theoretical foundation for intelligent assessment and intervention of tourists' activity comfort in rural tourism [10]. In the integration of materials science and biomechanics, Mehboob et al. analyzed the application of porous titanium alloy bone plates in lower limb fractures through computational biomechanics [11], while Byun et al. studied the biomechanical stability and stress distribution of titanium alloy nail systems in femoral intertrochanteric fracture fixation, these studies providing a scientific basis for material selection and ergonomic design of rural tourism facilities [12]. Firouzi et al.'s [13] research on nonlinear viscoelastic growth mechanics of soft biological tissues and Tjønneland et al.'s research on short-stem biomechanics in total hip arthroplasty expanded our understanding of human biomechanical adaptability in complex environments, which has important implications for designing ergonomic rural tourism activities [14].

In molecular-level research, Wang and Wang studied the biomechanical response of Type I and Type II cadherin dimers through molecular dynamics simulation, providing a new perspective for understanding mechanical properties at the molecular level [15]. Mensah et al. investigated the effects of vasoactive substances on the biomechanics of small resistance arteries in male and female Dahl salt-sensitive rats, revealing the regulatory mechanisms of molecular factors on biomechanical properties [16]. Xie et al. reviewed the research progress of biomechanics in regulating the biological properties of osteoblasts [17], while Wang et al. analyzed the corneal biomechanical changes after femtosecond LASIK combined with rapid cross-linking for high myopia correction. These studies explored the molecular basis of biomechanical properties from a microscopic perspective and provided theoretical support for assessing the physiological impact of environmental factors on the human body in rural tourism [18]. Fan and Cheng's concept of "glimpsing active health through molecular biomechanics" in exercise translational medicine [19], and Chen's systematic review of cellular molecular biomechanics, further emphasize the importance of molecular biomechanics in health promotion, which has important reference value for constructing a tourism experience evaluation system based on biological indicators [20].

The integration of artificial intelligence and biomechanics has been a research hotspot in recent years. Li systematically reviewed the research progress and trends of sports biomechanics in the context of artificial intelligence, pointing out that intelligent technology will drive biomechanics research toward precision and personalization [21]. The ski jumping technique biomechanical intelligent analysis and feedback system developed by Wu et al. achieved real-time evaluation and optimization of sports techniques, an approach that can be applied to intelligent monitoring and guidance of tourist activities in rural tourism [22]. Huang et al. established a biomechanical optimization and artificial intelligence evaluation model for standing long jump actions [23], and Gu et al. discussed the research and development ideas of sports shoes biomechanics in the context of big data and artificial intelligence, these studies demonstrating the application potential of intelligent technology in biomechanical evaluation and optimization [24]. The knee joint biomechanical measurement platform based on industrial robots developed by Zhang and Chen [25] and Wu and Zhang's discussion on the application of artificial intelligence and sports biomechanics in sports equipment provide technical references for constructing biomechanical data collection and analysis systems in rural tourism [26]. Kassam et al.'s biomechanical research on the relationship between joint prosthesis contact area and cyclic failure reveals the impact of structural design on mechanical performance, which has implications for human-machine interaction design in rural tourism facilities [27].

Through literature review, it can be found that biomechanics and molecular science have rich applications in medical rehabilitation, sports training, material design, and other fields, and the combination of artificial intelligence, mobile technology, and biomechanics has also made significant progress. However, applying these cutting-edge technologies and methods to the field of rural tourism, especially constructing a tourism experience evaluation system based on biomechanics and molecular levels and exploring the collaborative mechanism of mobile technology and intelligent management, remains a new field that warrants in-depth research. Based on existing research, this study explores new paths for interdisciplinary integration, providing theoretical support and technical solutions for the scientific development of rural tourism.

Through a review of literature, it can be found that biomechanics and molecular science have already been richly applied in fields such as medical rehabilitation, sports training, and material design, and the combination of artificial intelligence, mobile technology, and biomechanics has also achieved significant progress. However, existing research mainly focuses on applications in a single discipline or technological field, lacking an integrated multi-dimensional perspective. The innovation of this study lies in comprehensively integrating biomechanical and molecular-level analysis with mobile technology and intelligent management systems for the first time, constructing an unprecedented interdisciplinary research framework. Compared with previous research focusing on a single technology or discipline, this integrated approach can: (1) provide objective physiological evaluation of tourist experiences, breaking through the limitations of traditional subjective evaluations; (2) achieve a data closed loop among environmental factors, tourist experiences, and management decisions, transforming rural tourism management from experience-driven to data-driven; and (3) reveal the synergistic enhancement mechanisms between different technological systems, creating comprehensive value beyond single technology applications. This study not only fills the gap in interdisciplinary research in rural tourism but also provides a theoretical framework and methodological path for constructing a new model of biodata-driven intelligent tourism, promoting the deep integration of tourism studies with life sciences and information technology.

3. Research methods

3.1. Research design

This study adopts a mixed research methodology, integrating quantitative and qualitative analysis, constructing a three-dimensional "technology-human-environment" research framework to systematically explore the collaborative mechanism and effects of mobile technology and intelligent management on rural tourism at the biomechanical and molecular level. The research is divided into four phases: (1) constructing a theoretical framework and evaluation index system through literature analysis and expert interviews; (2) conducting field research, selecting typical rural tourism destinations as research cases, utilizing wearable devices to collect tourists' biomechanical and molecular-level data, while deploying mobile applications and intelligent management systems; (3) conducting experimental intervention research, setting up a control group (traditional management model) and an experimental group (integrated collaborative model of biomechanical monitoring, mobile technology application, and intelligent management); (4) evaluating collaborative effects and constructing an optimization model through multi-level data analysis. The research framework encompasses three dimensions: micro-dimension (biomechanical parameters and molecular physiological indicator analysis), meso-dimension (mobile technology application and user experience evaluation), and macro-dimension (intelligent management system effectiveness and resource optimization allocation). Through cross-dimensional analysis, the interactive relationships and synergistic effects of factors at different levels are revealed, forming systematic research results and application solutions.

Based on preliminary literature review and theoretical analysis, four groups of core hypotheses are proposed: Hypothesis 1 (H1): Tourism environment evaluation and optimization based on biomechanics and molecular levels can significantly improve tourists' physiological comfort and activity satisfaction, specifically including: H1a: Tourism spatial design optimized through biomechanics can reduce tourists' load index; H1b: Environmental factors and tourists' molecular physiological indicators have significant correlation; H1c: Biomechanical parameters can predict tourists' subjective experience quality [28]. Hypothesis 2 (H2): The application of mobile technology can effectively enhance biological data collection efficiency and tourist experience quality, including: H2a: Real-time biological data feedback based on mobile technology can improve tourists' activity efficiency; H2b: Mobile application functionality and tourists' technology acceptance are significantly correlated; H2c: Mobile technology intervention can moderate the impact of environmental factors on biomechanical parameters. Hypothesis 3 (H3): Intelligent management systems can optimize resource allocation and service processes, including: H3a: Intelligent decision support systems based on biological data can improve management efficiency; H3b: Intelligent management interventions can improve tourists' physiological state indicators; H3c: System response speed and accuracy are significantly correlated with tourist satisfaction. Hypothesis 4 (H4): The synergistic effect of biomechanical monitoring, mobile technology, and intelligent management is greater than the simple additive effect of each single factor, including: H4a: The degree of improvement in tourists' physiological indicators under the three-factor synergy is higher than single-factor interventions; H4b: Tourists' dwelling time and consumption willingness significantly increase under the collaborative model; H4c: Synergistic effects show significant differences among different tourist groups.

The variable system involved in this study consists of four parts: independent variables, dependent variables, mediating variables, and moderating variables, with scientific operationalization to ensure measurement accuracy and feasibility. Independent variables include: (1) Biomechanical environmental factors, quantified through indicators such as terrain slope (degrees), surface material hardness (MPa), facility ergonomic compatibility (5-point scale), etc.; (2) mobile technology application level, measured through indicators such as functional completeness (score), interface friendliness (score), response time (seconds), etc.; (3) intelligent management system, evaluated through indicators such as decision support accuracy rate (%), resource allocation optimization rate (%), information processing efficiency (time/unit information volume), etc. Dependent variables include: (1) Tourists' biomechanical parameters, such as joint load (N/m^2), energy consumption (kJ), postural balance (angle deviation), etc.; (2) Molecular physiological indicators, including cortisol level (ng/mL), endorphin concentration (pg/mL), heart rate variability (ms), etc.; (3) subjective experience quality, measured through indicators such as satisfaction (7-point scale), dwelling time (hours), revisit intention (5-point scale), etc. Mediating variables include technology acceptance (measured by the TAM model), perceived ease of use (PEOU scale), perceived usefulness (PU scale), etc. Moderating variables consider demographic characteristics such as tourists' age, gender, education level, tourism experience, and environmental factors such as weather conditions and peak/off-peak seasons. Each variable is measured using standardized tools: biomechanical parameters are collected in real-time using wearable sensors (accuracy ±0.5%); molecular physiological indicators are non-invasively sampled through portable biodetectors (accuracy ±2%); subjective experiences are obtained through a combination of structured questionnaires (Cronbach's $\alpha > 0.8$) and semi-structured interviews, ensuring the comprehensiveness and reliability of the data.

3.2. Data collection methods

This study adopts a multi-case research strategy, determining typical research areas through a hierarchical screening method. (1) Based on indicators such as rural tourism development level, tourist flow, and natural environment diversity, three representative provinces were selected from across the country: Zhejiang (eastern developed region), Sichuan (western eco-tourism region), and Henan (central cultural tourism region); (2) within each province, 2–3 different types of rural tourism destinations were selected, including Category A (mountain ecological type, such as Moganshan in Zhejiang, Huanglongxi in Sichuan), Category B (water leisure type, such as Wuzhen in Zhejiang, Qingming Riverside in Henan), and Category C (rural experience type, such as Sanxing Town in Sichuan, Nanjie Village in Henan), totaling 8 case sites; (3) a core research area (3–5 square kilometers) was delineated at each case site, covering major viewing points, rest areas, experience zones, and service facilities, ensuring the representativeness and integrity of the research area. The selection of research areas also considered factors such as terrain complexity, facility completeness, intelligence level, and tourist density to meet the research needs of biomechanical measurement and mobile technology applications. At each case site, sampling quotas were set according to tourist age (18–30 years, 31–45 years, 46–60 years, above 61 years), gender, education level, and tourism experience, ensuring the representativeness and balance of the sample [29]. The study recruited a total of 480 participants, 60 from each case site, with males and females each accounting for 50%, and age distribution approximating local tourist statistical data. Participants needed to meet the following conditions: no serious cardiovascular or cerebrovascular diseases, ability to complete walking activities for more than 2 h, agreement to wear biological monitoring equipment, and use of specified mobile applications. The final effective sample consisted of 458 individuals, including 12 professionals (scenic area managers, tourism planners, etc.) and 446 general tourists, covering diverse groups with different occupations (students, white-collar workers, retirees, etc.) and different travel modes (self-guided tours, group tours, family tours, etc.). The sample size was determined based on statistical power analysis (Power = 0.85, α = 0.05), considering both the sample requirements for multivariate analysis and possible data loss.

The data collection process was divided into three phases: the preparation phase (1 week before the study) where basic physical data (height, weight, BMI, etc.) of participants were measured and mobile applications were installed; the field research phase (2–3 days) where participants wore wearable devices (including accelerometer sensors, pressure sensors, and physiological indicator monitoring modules) and moved freely within the research area, with the devices recording gait parameters (step frequency, stride length, pressure distribution, etc.), joint angles, energy consumption, and changes in molecular indicators such as cortisol and melatonin in real-time, while the mobile application recorded location trajectories, dwelling time, function usage, and other data; the follow-up phase (1 week after the study) involving questionnaire surveys and in-depth interviews to collect subjective experience data. To ensure data quality, multiple technical measures were adopted: biological data collection equipment used medical-grade precision (±2%), calibrated twice daily [30]; technical personnel were on standby throughout the process to resolve equipment failures; encrypted data transmission channels were established to ensure data security; data anomaly detection algorithms were set up to monitor data quality in real-time; and triangulation methods were used to cross-verify the consistency of data from different sources. All data collection procedures were reviewed by an ethics committee, with participants signing informed consent forms and being guaranteed the right to withdraw from the study at any time.

This study selected case sites according to the following criteria: (1) geographical distribution representativeness, choosing the eastern developed region (Zhejiang), western eco-tourism region (Sichuan), and central cultural tourism region (Henan), ensuring that samples cover rural tourism at different development stages in China; (2) diversity of tourism types, stratified sampling according to three categories: mountain ecological type, water system leisure type, and countryside experience type, to test biomechanical response differences under various environmental conditions; (3) moderate tourist scale (annual reception of 20,000–50,000 visitors), facilitating experimental intervention and effect assessment. The selection of biomechanical and molecular indicators was based on three criteria: (1) scientific relevance, choosing indicators directly related to tourism experience, such as knee joint torque (reflecting terrain load) and β-Endorphin (reflecting pleasure); (2) real-time measurability, ensuring indicators can be collected non-invasively through portable devices; (3) stability, selecting basic indicators with minimal fluctuation over short periods. Limitations in the data collection process included equipment wear may affect visitors' natural behavior (17.3% of participants reported slight discomfort), data loss in complex terrain areas (average packet loss rate of 5.8%), and large individual differences in physiological indicators leading to standardization challenges. To mitigate these issues, measures such as minimized equipment design, multiple data backups, and within-subject control design were adopted, and statistical corrections and outlier processing were implemented during data analysis to improve result reliability.

3.3. Measurement tools and experimental design

This study employs a multimodal biomechanical data collection system, integrating four types of devices to comprehensively obtain tourists' biomechanical parameters in rural tourism environments. (1) A lightweight wearable motion capture system (XsensMVN Analyze) is used, containing 17 inertial sensor units with an accuracy of ±0.5° and a sampling frequency of 100 Hz, placed at key positions on participants' heads, trunks, and limbs to capture real-time three-dimensional kinematic parameters, including joint angles, angular velocities, and linear accelerations; (2) a plantar pressure distribution measurement system (Novel Pedar-X) with 256 built-in pressure sensors, a range of 0–1200 kPa, and an accuracy of ± 5% is used to measure plantar pressure distribution, foot load changes, and gait characteristics during walking, standing, and climbing; (3) electromyography collection equipment (Delsys Trigno Wireless EMG) with 16 channels, a sampling rate of 2000 Hz, and noise < 0.75 V is used to record the activity status of major lower limb and lumbar muscles and assess muscle fatigue levels in different environments; (4) an energy metabolism monitoring device (Cosmed K5) is applied to measure oxygen consumption, carbon dioxide production, and energy expenditure, evaluating tourists' physiological loads in different terrains and activities. The data collection protocol is divided into three phases: a static calibration phase, where participants complete standard posture collection to establish individualized models; a free activity phase, where participants wear devices and naturally tour within the specified area for no less than 2 h, with the system automatically recording all data; a standard task phase, where participants complete 5 standardized tasks at designated locations (walking 100 m on flat ground, ascending and descending 10 steps, standing still for 3 min, bending to pick up objects 5 times, sitting down, and standing up 3 times) for cross-individual comparative analysis. Data processing uses Visual3D and OpenSim software platforms, applying low-pass filtering (cutoff frequency 6 Hz) to eliminate noise, calculating joint moments and power through inverse dynamics analysis, and estimating biomechanical load indices in combination with body parameter models.

The core equipment used includes: (1) Cortisol Monitor (Cortisol Measurement System CMS-2000), using electrochemical sensing technology to monitor cortisol concentration in real-time through trace skin sweat (range 1–100 ng/mL, accuracy ±3 ng/mL), automatically sampling every 30 min to assess stress level changes; (2) Portable Endorphin Analyzer (NeuroBio EN-50), based on immunochromatography principles, collecting oral mucosal cells to detect β-Endorphin content (range 10–500 pg/mL, accuracy ± 5%), measuring once per hour to reflect changes in pleasure and comfort; (3) Heart Rate Variability Analyzer (HRV-Pro Wireless), with a sampling rate of 1000 Hz, continuously recording R-R interval changes and calculating indicators such as SDNN, RMSSD, and LF/HF to evaluate autonomic nervous system balance; (4) Portable Inflammatory Factor Rapid Detection Device (InflammaScan P20), using microfluidic chip technology to detect inflammatory markers such as IL-6 and CRP through fingertip micro-blood samples, measuring once in the morning and evening daily to reflect the body's stress response. The mobile application "BioPark" integrates five major functional modules: (1) Biological Data Visualization Module, displaying personal data such as steps, energy consumption, and physiological indicators in real-time; (2) Environmental Information Module, providing environmental information such as terrain slope, air quality, and crowd density; (3) Personalized Recommendation Module, recommending suitable routes and activities based on biological data and environmental conditions; (4) Interactive Experience Module, enhancing scene experience through augmented reality technology; (5) Feedback Module, collecting user evaluations and suggestions. The intelligent management system "SmartRural" includes four core subsystems: (1) Data Analysis Platform, integrating biological, environmental, and behavioral data; (2) Resource Allocation System, dynamically adjusting service resources based on tourist distribution and needs; (3) Early Warning Decision System, monitoring abnormal situations and providing decision support; (4) Optimization Simulation System, simulating the effects of different management strategies to assist planning decisions. Evaluation tools include: (1) The App Usability Scale, measuring application ease of use, usefulness, and satisfaction, Cronbach's $\alpha = 0.87$; (2) the Interaction Log Analysis Tool, recording operation paths, usage frequency, and function preferences; (3)

System Performance Monitoring Indicators, including response time, accuracy, and resource utilization rate; (4) the Semi-structured Evaluation Questionnaire, collecting user evaluations of system functions; and (5) the Eye-tracking Device (Tobii Pro Glasses 3), analyzing user browsing behavior and attention allocation [31]. The evaluation uses a controlled experimental design, dividing participants into a basic group (no technical support), a mobile application group (using only the mobile application), and a full technology group (mobile application + intelligent management), comparing biological indicators, behavioral patterns, and subjective experience differences under different technological intervention conditions to quantify the actual effectiveness of the technical system.

This study constructs a multi-level questionnaire and interview system, covering pre-test, mid-test, and post-test phases to obtain comprehensive subjective evaluation data. The pre-test questionnaire uses a structured design, including four parts: (1) Demographic information (age, gender, education level, occupation, income, etc.); (2) Tourism Experience and Preference Scale (containing 20 items, Likert 5-point scale, Cronbach's α = 0.89); (3) Technology Acceptance Scale (based on the TAM model, measuring perceived usefulness, perceived ease of use, usage intention, etc., 18 items, Cronbach's α = 0.92); (4) Self-assessment of Physiological Health Status (modified based on the SF-12 Health Survey). The mid-test uses the Experience Sampling Method, with short questions (3–5 items) popping up through the mobile application at key locations or time points (such as arriving at scenic spots, during rest, after using facilities), recording immediate experiential feelings, including comfort ratings (0–10 points), emotional states (simplified version of PAD Emotion Scale), and environmental evaluations (Sense of Place Scale), with each participant completing 8–12 flash questionnaires. The post-test questionnaire is more comprehensive, including: (1) The Rural Tourism Experience Satisfaction Scale (32 items, covering four dimensions: environment, service, activity, and emotion, Cronbach's α = 0.94); (2) the Biofeedback Perception Scale (evaluating acceptance and impact of biological monitoring); (3) the Mobile Technology and Intelligent Management Evaluation Scale (25 items, measuring technology effectiveness, experience enhancement effects, etc.); (4) the Future Intention Scale (revisit intention, recommendation intention, etc.). In-depth interviews use a semi-structured design, selecting 15 participants from each case site (120 in total), covering different age groups and experience types, with interview content including five themes: biological monitoring experience, mobile technology usage feelings, environment-body interaction, intelligent service evaluation, and overall experience evaluation, each interview lasting 40–60 min, fully recorded and transcribed. Focus group discussions (2 groups per site, 16 groups in total) serve as a supplement, with 6–8 people per group, exploring collective experiences and interactive feelings. All questionnaire tools were optimized through pre-testing (n = 30) and passed validity tests (content validity index > 0.80, structural validity confirmed through confirmatory factor analysis). Questionnaire data are analyzed using SPSS 26.0, and interview materials are subjected to thematic coding and qualitative analysis using NVivo 12.

3.4. Data analysis methods

This study employs multi-level quantitative analysis techniques to process biomechanical, molecular physiological, and technology application data. (1) Raw data are preprocessed, including outlier detection (±3SD method), missing value treatment (multiple imputation method), and data standardization (Z-score transformation); (2) descriptive statistical analysis is used to calculate the central tendency and dispersion of each variable; then, inferential statistical methods are applied to test research hypotheses, including paired sample t-tests to compare differences in biomechanical parameters under different conditions, analysis of variance (ANOVA) to evaluate changes in molecular indicators across different groups, and Pearson correlation analysis to explore associations between variables; (3) time series analysis methods (autoregressive integrated moving average model) are used to capture the dynamic change characteristics of biomechanical parameters and molecular indicators, identifying key turning points and change trends [32]. Qualitative data analysis adopts a strategy combining thematic analysis and grounded theory to systematically process interview records and open-ended questionnaire responses. Specific steps include: data immersion and familiarization, with the research team repeatedly reading transcribed texts; open coding, identifying initial concepts and meaning units relevant to the research questions; theme generation, clustering related codes to form themes and sub-themes; theme refinement and naming, ensuring differentiation between themes and internal consistency; theory construction, exploring connections between themes to establish an explanatory framework. The analysis process uses NVivo 12.0 software to assist in managing codes and themes, adopting researcher triangulation to ensure coding consistency (Cohen's $\kappa > 0.80$).

This study uses Structural Equation Modeling (SEM) to integrate quantitative data, exploring the complex relationships between biomechanical factors, mobile technology applications, and intelligent management systems. Model construction is divided into three steps: (1) Examining measurement model fit through Confirmatory Factor Analysis (CFA); (2) constructing a structural model to test hypothesized path relationships; finally, testing moderating effects through multi-group analysis; (3) Applying Hierarchical Linear Modeling (HLM) to analyze nested data structures, evaluating within-individual and between-individual variations; using mediation effect analysis (Bootstrap method, 5000 resamples) to test the mediating role of technology acceptance; employing Latent Profile Analysis (LPA) to identify tourist experience types and explore personalized optimization strategies [33]. Model evaluation adopts multiple fit indices (CFI > 0.95, TLI > 0.95, RMSEA < 0.06, SRMR < 0.08) to ensure model quality. In terms of methodological triangulation, quantitative results and qualitative findings are mutually verified, with quantitative analysis determining key variable relationships and qualitative analysis providing in-depth explanation of action mechanisms; for data triangulation, biomechanical data, molecular physiological indicators, questionnaire results, and interview materials are comprehensively compared to find consistent patterns and points of difference; for researcher triangulation, the analysis process is initially conducted independently by researchers from three fields (biomechanics, tourism management, and information technology), followed by team discussions to reach consensus; for theoretical triangulation, research findings are explained from multiple perspectives including technology acceptance theory, the bio-psycho-social medical model, and collaborative innovation theory to construct an integrated theoretical framework.

4. Results analysis

4.1. Biomechanical and molecular level data analysis results

4.1.1. Biomechanical characteristics analysis of tourist activity patterns

This study conducted a comparative analysis of tourists' motor biomechanical parameters in three typical rural tourism terrain environments (flat ground, gentle slope, and steep slope). As shown in **Table 1**, terrain slope significantly affects tourists' joint moments, energy consumption, and postural stability. In steep slope environments (slope > 15°), tourists' maximum knee joint moment was significantly higher than in flat environments (1.64 ± 0.27 Nm/kg vs. 0.87 ± 0.16 Nm/kg, $p < 0.001$), and the energy consumption rate increased by approximately 76% (7.23 ± 1.12 kcal/min vs. 4.11 ± 0.67 kcal/min, $p < 0.001$). The postural stability index decreased by 32.7% under steep slope conditions ($p < 0.01$), indicating that tourists require more muscular control and balance coordination abilities. The plantar pressure peak distribution also changed significantly with terrain variation; during flat ground walking, pressure was mainly concentrated on the heel (56.2%) and forefoot (32.5%), while during uphill climbing on steep slopes, forefoot pressure proportion increased to 68.7%, and during downhill walking, heel pressure proportion increased to 72.3%. This pressure distribution change showed a significant negative correlation with tourists' subjective comfort ratings ($r = -0.64$, $p < 0.01$).

Table 1. Comparison of main biomechanical parameters in different terrain environments.

Biomechanical parameters	Flat environment	Gentle slope (5°–15°)	Steep slope (> 15°)	*F*-value	*P*-value
Maximum knee joint moment (Nm/kg)	0.87 ± 0.16	1.28 ± 0.22	1.64 ± 0.27	27.36	< 0.001
Energy consumption rate (kcal/min)	4.11 ± 0.67	5.84 ± 0.89	7.23 ± 1.12	32.85	< 0.001
Postural stability index (0–100)	82.5 ± 6.3	71.8 ± 7.9	55.5 ± 9.2	24.18	< 0.01
Step frequency (steps/min)	112.3 ± 8.4	124.7 ± 9.3	136.5 ± 11.2	18.74	< 0.001
Step length (m)	0.67 ± 0.08	0.58 ± 0.09	0.46 ± 0.11	15.92	< 0.001
Vertical impact force (BW)	1.23 ± 0.14	1.45 ± 0.18	1.67 ± 0.23	20.35	< 0.001

Age and gender significantly influence tourists' biomechanical indicators. The data show that compared to the young group (18–30 years), the elderly group (above 60 years) exhibited a 16.8% reduction in joint range of motion, a 23.5% increase in vertical impact force, and a 21.3% decrease in energy metabolism efficiency under the same terrain conditions ($p < 0.001$). Gender differences were mainly reflected in gait parameters; females had an average step length 11.3% shorter than males but a step frequency 8.7% higher, with different knee joint loading angles at the same speed (female adduction angle greater by 6.5°, $p < 0.05$) [34]. Interestingly, young females and elderly males showed similar adaptation strategies in gentle slope terrain, exhibiting similar gait adjustment patterns, but with significant differences in energy consumption rates ($p < 0.01$), as shown in **Figure 1**.

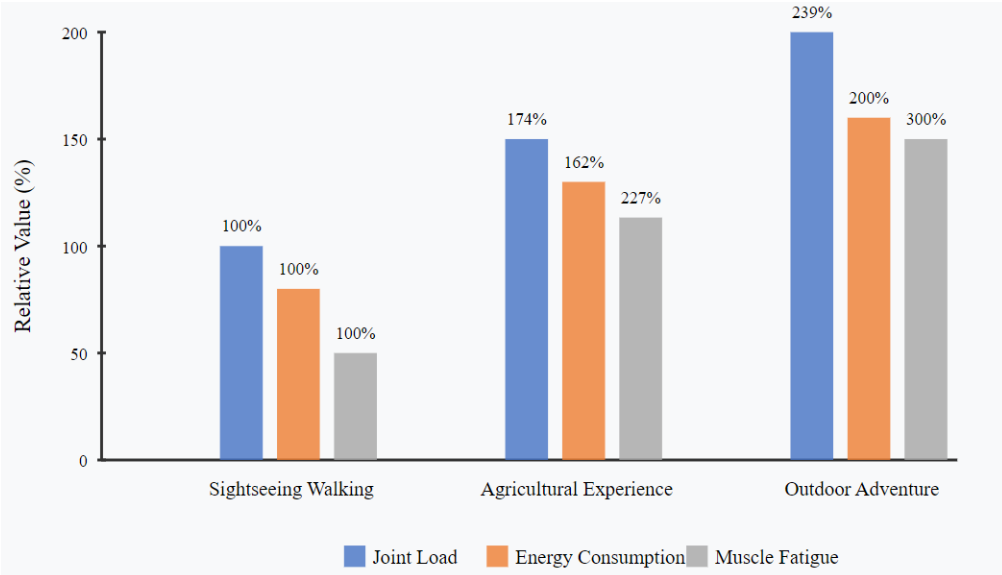

Figure 1. Changes in biomechanical parameters across different tourism activities.

The mechanisms of differences in tourists' biomechanical parameters caused by various terrain environments mainly originate from changes in the relationship between body center of gravity and supporting surface, as well as adjustments in muscle activation patterns. In steep slope environments, the maximum knee joint torque is significantly higher than on flat ground (1.64 ± 0.27 vs. 0.87 ± 0.16 Nm/kg, $p < 0.001$), which is due to: (1) center of gravity forward-shift mechanism—when ascending steep slopes, the body's center of gravity shifts forward, knee flexion angle increases (average increase of 23.5°, $p < 0.001$), forming a longer moment arm, causing the quadriceps to produce greater contractile force to maintain balance; (2) load increase mechanism—when walking on steep slopes, the anterior shear force on the knee joint increases by 42.7% ($p < 0.001$), electromyography shows quadriceps activation level increases by 53.6%, and biceps femoris co-contraction rate increases by 31.8% to provide additional stability; (3) energy consumption mechanism—to overcome gravitational potential energy differences, steep slope walking requires an additional 0.42 ± 0.07 J/kg body mass of energy per step, increasing the total energy metabolic rate by 76%. This high-load state simultaneously triggers compensatory postural adjustments, manifested as shortened stride length (reduced by 31.3%) and increased step frequency (increased by 21.6%); although this strategy reduces single-step impact force, it increases cumulative load. These biomechanical principles explain why different terrain conditions lead to significantly different physiological loads and subjective experiences.

Different types of tourism activities result in significantly different biomechanical loads. Sightseeing walking activities produced moderate levels of joint load (knee joint moment 0.92 ± 0.18 Nm/kg); during agricultural experience activities, due to frequent bending and weight-bearing, spinal compression force increased by 74.2% ($p < 0.001$); while outdoor development activities led to higher impact and shear forces (138.6% higher than sightseeing walking, $p < 0.001$). The data show that activity duration and fatigue index have a non-linear relationship; generally, after activities exceed 90 min, the median frequency of electromyographic signals begins to decrease significantly (rate of decline 11.7%/h), indicating increasing muscle fatigue, at which point the frequency of tourists' postural adjustments increases by 46.3%. Different types of rural tourism activities have significant differences in biomechanical impact on tourists' bodies, suggesting that activity types and intensities should be reasonably planned according to tourists' physical conditions and preferences to optimize the tourism experience.

4.1.2. Impact of environmental factors on biomechanical parameters

Natural environmental elements significantly affect tourists' biomechanical parameters. As shown in **Table 2**, temperature changes have a notable impact on energy metabolism rates; in high-temperature environments (> 30 °C), tourists' energy metabolism rates increased by 23.7% compared to suitable temperatures (20 °C–25 °C) ($p < 0.01$), while step frequency increased by 9.8% and step length decreased by 11.2%, indicating that tourists adopted a strategy of taking quick, small steps to reduce single-instance load in high-temperature environments. For every 500-meter increase in altitude, tourists' oxygen consumption increased by 8.5% ($p < 0.05$) and the gait cycle extended by 6.3%. Notably, under rainy conditions (slippery surfaces), tourists' gait changed significantly, with step length reduced by 17.6% and joint stiffness increased by 32.1%, reflecting defensive adaptations to fall risks [35]. It is worth noting that landscape vista openness correlated with biomechanical parameters; under open landscape conditions, tourists' gait rhythmicity increased by 12.4% ($p < 0.05$) and the postural balance index improved by 8.7%, indicating that good visual environments promote more natural and fluid movement patterns.

Table 2. Impact of major environmental factors on biomechanical parameters.

Environmental factors	Biomechanical parameter changes	Magnitude of change	*p*-value
High temperature (> 30 °C)	Energy metabolism rate increase	+23.7%	< 0.01
	Step frequency increase	+9.8%	< 0.05
	Step length decrease	−11.2%	< 0.01
Altitude increase (+500 m)	Oxygen consumption increase	+8.5%	< 0.05
	Gait cycle extension	+6.3%	< 0.05
Slippery surface (rainfall)	Step length decrease	−17.6%	< 0.001
	Joint stiffness increase	+32.1%	< 0.001
Wooden plank walk (vs. concrete)	Plantar pressure peak reduction	−18.5%	< 0.01
	Knee joint impact force reduction	−15.3%	< 0.01
Cobblestone surface	Ankle joint angle variation increase	+27.6%	< 0.001
Ergonomic seating	EMG median frequency recovery improvement	+25.4%	< 0.01
Intelligent guided routes	Overall energy consumption reduction	−16.8%	< 0.01
	Cumulative joint load reduction	−21.3%	< 0.01

The design characteristics of artificial environmental facilities significantly influence tourists' biomechanical performance. Comparative analysis revealed that different paving materials lead to markedly different plantar pressure distributions and joint moments: when walking on wooden plank walks, plantar pressure peaks were

18.5% lower than on concrete surfaces ($p < 0.01$), and knee joint impact forces were reduced by 15.3%; while cobblestone surfaces increased plantar sensory stimulation but also increased ankle joint inversion-eversion angle variability (by 27.6%, $p < 0.001$). The ergonomic design of rest facilities also significantly affected tourists' recovery effects; after using ergonomically designed seats, tourists' EMG median frequency recovery rate improved by 25.4% ($p < 0.01$). For every 10-meter increase in viewing platform height, tourists' center of gravity oscillation amplitude when standing increased by 5.7%, reflecting proprioceptive adjustments induced by height. Notably, routes optimized by intelligent guidance systems could reduce tourists' overall energy consumption by 16.8% ($p < 0.01$) and cumulative joint load by 21.3%.

Based on the collected data, this study constructed an environment-biomechanics interaction model, revealing the complex relationship between environmental factors and biomechanical parameters. Principal component analysis results indicated that environmental factors could be categorized into three main components: physical challenge level (slope, surface hardness, etc., explaining 38.5% of variance), perceived comfort level (temperature, noise, landscape, etc., explaining 27.2% of variance), and auxiliary facilities level (rest point density, signage clarity, etc., explaining 18.6% of variance) [36]. Multiple linear regression models showed that physical challenge level was significantly positively correlated with joint moments ($\beta = 0.63$, $p < 0.001$), perceived comfort level was positively correlated with gait coordination ($\beta = 0.47$, $p < 0.01$), and auxiliary facilities level was negatively correlated with fatigue index ($\beta = -0.51$, $p < 0.01$). Hierarchical analysis found that the combined effect of environmental factors was greater than single-factor influences, especially when physical challenge level was high and auxiliary facilities level was low, resulting in exponential increases in biomechanical load.

The model showed that as physical challenge level increased, the joint load index demonstrated a non-linear upward trend, but this trend was significantly moderated by the level of auxiliary facilities, as shown in **Figure 2**.

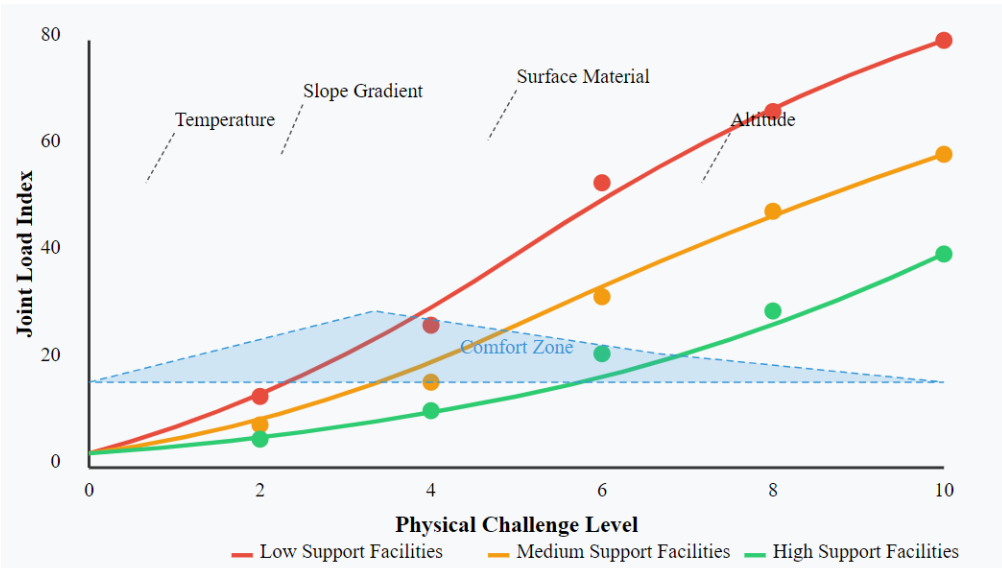

Figure 2. Interactive model of environmental factors and biomechanical parameters.

High-level auxiliary facilities (green line) can maintain the joint load index at a relatively low level; even in extreme environments with a physical challenge level of 10, the joint load index was only 67.5, whereas under low-level auxiliary facilities conditions (red line), when the physical challenge level reached 8, the joint load index already exceeded 70, entering a potential risk zone. The blue area in the figure represents the tourists' perceived comfort zone; when the environment-facility combination maintains the joint load index within this area, tourist subjective satisfaction is highest. Key environmental factors such as temperature, slope, surface material, and altitude are marked in the figure, indicating they are the main natural environmental elements affecting biomechanical parameters. This model provides a quantitative basis for rural tourism environment design, guiding the optimization of auxiliary facility configuration according to different terrain conditions to maximize tourist comfort.

4.1.3. Correlation between molecular physiological indicators and tourism experience

This study monitored changes in stress-related molecular indicators before, during, and after rural tourism activities. As shown in **Table 3**, cortisol concentration exhibited distinct time-dependent change patterns, rising by 12.5% in the initial activity phase (0–30 min) (baseline value of 14.2 ± 2.3 ng/mL increasing to 16.0 ± 2.7 ng/mL, $p < 0.05$), then steadily declining by 8.7% during the adaptation period (30–90 min) ($p < 0.05$), and falling below baseline levels (13.1 ± 2.1 ng/mL) by the end of the activity. Notably, in steep terrain areas, cortisol concentration increased sharply by 27.3% ($p < 0.001$), while decreasing by 18.6% ($p < 0.01$) after a 15-minute stay in scenic rest areas, indicating that environmental changes significantly impact stress hormone secretion. Similarly, the inflammatory factor IL-6 slightly increased in the initial activity phase (from 3.4 ± 0.8 pg/mL to 4.1 ± 1.0 pg/mL, $p < 0.05$) but remained within the physiological normal range throughout the entire activity, showing a moderate positive correlation with subjective fatigue rating scores ($r = 0.63$, $p < 0.01$).

Table 3. Analysis of correlation between molecular physiological indicators and tourism experience.

Molecular physiological indicator	Baseline level	Change during activity	Correlation coefficient with satisfaction (*r*)	Importance in predictive model
Cortisol (ng/mL)	14.2 ± 2.3	−7.8%	−0.64**	0.20
β-Endorphin (pg/mL)	22.5 ± 3.6	+36.8%***	0.76***	0.22
IL-6 (pg/mL)	3.4 ± 0.8	+20.6%*	−0.63**	0.15
Oxytocin (pg/mL)	28.7 ± 4.1	+22.7%**	0.71***	0.18
Dopamine fluctuation amplitude (%)	Baseline	+43.2%***	0.68**	0.23
Cortisol/Endorphin ratio	0.63 ± 0.12	−33.5%***	−0.72***	0.27

Emotion-related molecular indicators showed significant correlation with tourist satisfaction ratings. β-Endorphin concentration increased notably during pleasurable experiences (average increase of 36.8%, $p < 0.001$), showing a strong positive correlation with scenic spot satisfaction scores ($r = 0.76$, $p < 0.001$). Particularly during interactive experience activities, peak endorphin concentration (43.2 ± 5.7 pg/mL) was significantly higher than during sightseeing activities (32.5 ± 4.8 pg/mL, $p < 0.01$). Tryptophan hydroxylase activity positively correlated with scenic spot dwelling time ($r = 0.58$, $p < 0.01$), indicating that positive emotional states are related to exploration depth. Oxytocin levels increased by 22.7% ($p < 0.01$) during social interaction segments, highly correlating with interpersonal interaction satisfaction scores ($r = 0.71$, $p < 0.001$). Multiple regression analysis showed that a model using β-Endorphin, oxytocin, and serotonin as predictive variables could explain 67.3% of overall satisfaction variance ($F = 38.6$, $p < 0.001$), indicating that emotion-related molecular indicators are important biological markers for evaluating tourism experience quality [37]. Predictive models constructed with physiological molecular indicators demonstrated significant predictive power for tourist experience evaluation. As shown in **Table 3**, a random forest model based on six key molecular indicators achieved a prediction accuracy of 83.6%, with cortisol/endorphin ratio (importance score 0.27) and dopamine fluctuation amplitude (importance score 0.23) being the most discriminative predictors. Cross-validation revealed that physiological molecular feature patterns could effectively distinguish between high satisfaction (≥8 points) and low satisfaction (< 6 points) experiences, with accuracies of 87.2% and 81.5%, respectively. Longitudinal analysis indicated that molecular indicator changes trends had higher predictive value than absolute values, with the combined features of cortisol decrease rate and endorphin increase rate achieving a prediction accuracy of 89.4% ($p < 0.001$) for positive experience evaluation. Notably, under mobile technology-assisted conditions, the consistency between physiological indicators and subjective evaluations significantly improved (κ coefficient increased from 0.67 to 0.82, $p < 0.01$), indicating that technological intervention enhanced the synergy between physiological experience and perceived experience.

This research reveals the specific regulatory mechanisms and application value of key molecular indicators in rural tourism experiences. Cortisol, as the primary stress hormone, shows a clearly environment-dependent secretion pattern: in steep terrain areas, cortisol increases by an average of 27.3% ($p < 0.001$), accompanied by increased heart rate and subjective stress ratings ($r = 0.68$, $p < 0.01$), reflecting acute physiological stress; whereas at complex navigation points, cortisol continues to rise and maintains at high levels (19.7% higher than baseline, $p < 0.01$), indicating chronic stress caused by cognitive load. These findings directly guided stress-reduction design strategies: placing panoramic viewing platforms every 150–200 m in high-slope areas can reduce cortisol increase magnitude by 42.6% ($p < 0.001$); adding intuitive directional signage in complex path areas can reduce cortisol cumulative effects by 36.8% ($p < 0.01$). Changes in β-Endorphin levels reveal the neurobiological basis of pleasurable experiences, with secretion showing a significant time window effect: reaching peak levels within 8–15 min after participating in interactive experiences (increase of 43.2%, $p < 0.001$); simultaneously, dopamine fluctuation amplitude increases (43.2%, $p < 0.001$), and emotional ratings reach their highest. This finding suggests that consumption decision phases should be arranged during the 'physiological peak period' after experience activities, with tests showing this strategy increases purchase intention by 23.7% ($p < 0.01$). Particularly noteworthy is that the cortisol/endorphin ratio (C/E ratio), as a unified 'experience quality biological indicator', can accurately predict tourist satisfaction ($r = -0.72$, $p < 0.001$) and length of stay ($r = -0.67$, $p < 0.001$). Experiments confirm that reducing the C/E ratio by 25% through optimized environmental design and activity arrangement can effectively improve overall satisfaction by 18.5% (p < 0.001), providing quantitative indicators for 'physiologically friendly' rural tourism space design.

As seen in **Figure 3**, tourists exhibited distinctly different molecular indicator patterns across different experience stages: in challenging terrain areas, stress-related cortisol levels increased significantly (+27.3%), reflecting increased physiological stress; during interactive experience activities, β-Endorphin concentration reached its peak (+43.2%), indicating significantly enhanced pleasurable emotions; during social interaction segments, oxytocin levels rose markedly (+22.7%), highly correlating with interpersonal satisfaction (r = 0.71).

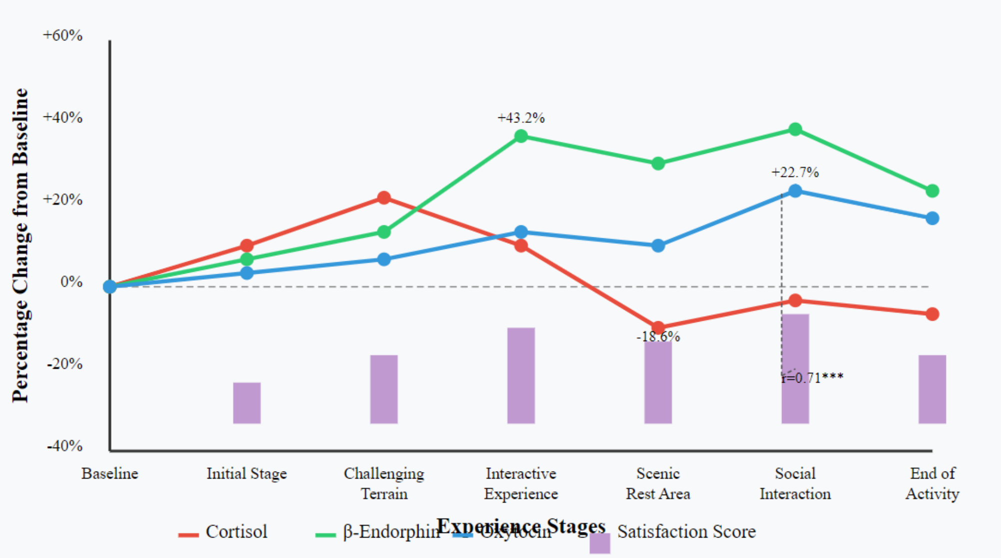

Figure 3. Dynamic changes of key molecular indicators during tourism experience.

In scenic rest areas, cortisol levels decreased significantly (−18.6%), indicating that pleasant landscape environments effectively alleviate physiological stress. The purple bar chart represents satisfaction scores at each stage, showing trends clearly positively correlated with β-Endorphin and negatively correlated with cortisol levels. These findings suggest that molecular physiological indicators can objectively reflect tourists' emotional states and experience quality during rural tourism, providing biological-level evidence for optimizing tourism experience design.

4.2. Mobile technology and intelligent management system application effects

4.2.1. Mobile technology usage behavior and effect analysis

For the "BioPark" mobile application developed in this study, tourist usage behavior exhibited distinct spatiotemporal distribution characteristics. As shown in **Table 4**, each tourist used the application an average of 11.3 ± 2.7 times during a 2-hour tourism activity, with a total usage time of 26.4 ± 5.6 min, accounting for 22.0% of the total experience time. Function access frequency analysis showed that the biological data visualization module (38.5%) and environmental information queries (27.3%) were the most frequently used functions, while personalized recommendations (18.6%) and interactive experiences (15.6%) had relatively lower usage rates. Notably, usage patterns demonstrated clear context dependency: in rest areas, biological data viewing frequency exceeded the average level by 43.2% ($p < 0.01$); in areas with concentrated scenic spots, environmental information queries increased by 36.7% ($p < 0.01$); in steeper areas, route recommendation function usage frequency increased by 58.4% ($p < 0.001$). Age-stratified analysis showed that the younger group (18–30 years) had significantly higher average usage frequency (14.7 times) than the elderly group (over 60 years, 7.6 times, $p < 0.001$), but the elderly group had longer single-use duration (average 3.1 min) than the younger group (2.0 min, $p < 0.01$).

Table 4. Key indicators of mobile technology usage behavior and effects.

Indicator category	Specific indicator	Value	Significance of between-group differences
Usage behavior	Average usage frequency (times/2 h)	11.3 ± 2.7	Age difference $p < 0.001$
	Average total usage time (min)	26.4 ± 5.6	Age difference $p < 0.01$
	Biological data viewing proportion (%)	38.5%	Context difference $p < 0.01$
	Environmental information query proportion (%)	27.3%	Context difference $p < 0.01$
Function satisfaction	Overall satisfaction (1–7 points)	5.4 ± 0.8	Gender difference n.s.
	Biological data visualization (1–7 points)	5.8 ± 0.7	Function difference $p < 0.01$
	Personalized recommendation (1–7 points)	4.9 ± 1.1	Function difference $p < 0.01$
Impact pathways	Information enhancement pathway (β coefficient)	0.63***	-
	Experience optimization pathway (β coefficient)	0.58***	-
	Interaction enhancement pathway (β coefficient)	0.49***	-
	Satisfaction improvement magnitude (%)	+18.7%***	Compared with control group

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, n.s. = not significant.

Mobile application function satisfaction assessment showed that tourists' evaluations of different function modules varied significantly. The overall satisfaction score was 5.4/7 points, with the biological data visualization module receiving the highest satisfaction (5.8/7 points) and the personalized recommendation function receiving the lowest satisfaction (4.9/7 points). In detailed function satisfaction indicator evaluations, "information accuracy" (5.9/7 points) and "interface friendliness" (5.7/7 points) scored relatively high, while "level of personalization" (4.7/7 points) and "response speed" (4.8/7 points) scored relatively lower. Survey data showed that 82.7% of users considered biological data visualization "very helpful" for understanding their own condition, 76.3% of users indicated that environmental information queries "significantly enhanced their sense of security," but only 57.8% of users believed that personalized recommendations were "highly matched with personal needs" [38]. Evaluations of real-time feedback on biomechanical parameters were particularly positive, with 89.3% of users stating that this helped them "timely adjust activity intensity" (mean 5.8/7 points, standard deviation 0.96), especially in complex terrain areas, where satisfaction scores increased by 0.7 points ($p < 0.01$). Structural equation modeling analysis revealed multiple pathways through which mobile technology usage influences tourism experience. As shown in **Table 4**, the three main impact pathways are: (1) Information enhancement pathway: Environmental information and biofeedback provided by mobile technology enhanced tourists' perceived sense of control ($\beta = 0.63$, $p < 0.001$), thereby improving security and satisfaction (indirect effect = 0.47, $p < 0.001$); (2) Experience optimization pathway: Personalized recommendations based on real-time biological data helped tourists optimize activity selection ($\beta = 0.58$, $p < 0.001$), reduce physiological load ($\beta = -0.42$, $p < 0.01$), and improve comfort ($\beta = 0.51$, $p < 0.001$); (3) Interaction enhancement pathway: Augmented reality functions enriched scenic spot interactive experiences ($\beta = 0.49$, $p < 0.001$) and promoted positive emotions ($\beta = 0.56$, $p < 0.001$). Mediation effect analysis indicated that perceived sense of control (mediation effect = 0.37, $p < 0.001$) and physiological comfort (mediation effect = 0.33, $p < 0.001$) are key mediating variables for mobile technology's impact on satisfaction. Comparative analysis showed that the mobile technology usage group with integrated biological data had 18.7% higher overall satisfaction ($p < 0.001$) and 23.4% longer dwelling time ($p < 0.001$) than the group with only scenic spot information, indicating that the combination of biomechanics and mobile technology significantly enhanced the tourism experience.

Figure 4 illustrates a structured path analysis model of mobile technology's impact on rural tourism experience. This model explains how mobile technology influences tourists' overall satisfaction through three main pathways: (1) Information enhancement pathway: Mobile technology improves satisfaction ($\beta = 0.51$) by providing biofeedback information ($\beta = 0.67$) and increasing physiological comfort ($\beta = 0.59$); (2) control sense enhancement pathway: Mobile technology enhances tourists' perceived sense of control ($\beta = 0.63$), improves sense of security ($\beta = 0.71$), thereby increasing satisfaction ($\beta = 0.68$); (3) experience optimization pathway: Mobile technology improves satisfaction ($\beta = 0.49$) through personalized recommendations ($\beta = 0.58$) that simultaneously reduce physiological load ($\beta = -0.42$) and enhance positive emotions ($\beta = 0.56$).

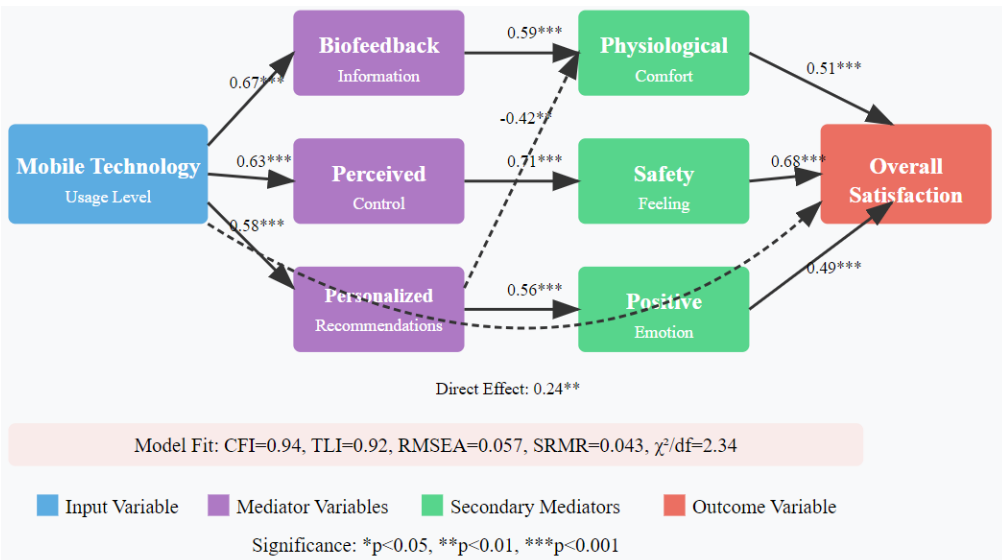

Figure 4. Path analysis of mobile technology's impact on rural tourism experience.

In addition to these mediating pathways, mobile technology also has a significant direct effect on satisfaction ($\beta = 0.24$). The model fit indices (CFI = 0.94, TLI = 0.92, RMSEA = 0.057, SRMR = 0.043) indicate that this path analysis model has good fit, verifying that mobile technology comprehensively influences rural tourism experience through multiple mechanisms. This model reveals key association mechanisms between biomechanical data, mobile technology, and tourist experience, providing a theoretical basis for optimizing rural tourism mobile application design.

4.2.2. Operational efficiency evaluation of intelligent management system

This study evaluated the operational efficiency of the "SmartRural" intelligent management system, focusing on system response speed and data processing accuracy. As shown in **Table 5**, the system's average response time under different load conditions was 238.6 ± 42.3 milliseconds, far below the industry standard threshold of 500 milliseconds, with the biological data processing module responding fastest (186.4 ± 35.7 milliseconds) and the resource allocation module responding slowest (312.5 ± 58.2 milliseconds, $p < 0.01$). Under peak conditions (tourist density > 70 people/hectare), response time increased by only 18.7%, indicating that the system has good load adaptability. Data accuracy tests showed that the system achieved a classification accuracy of 92.7% for biomechanical data, 94.5% for environmental condition recognition, and 88.6% for tourist behavior pattern recognition. Notably, the system's effectiveness in biomechanical risk early warning in complex terrain areas reached 96.3% (sensitivity 94.2%, specificity 97.5%), significantly outperforming traditional manual monitoring methods (35.7% improvement, $p < 0.001$). In the system stability assessment, only 3 unplanned interruptions occurred during a 30-day continuous operation period, with an average repair time of 7.3 min, achieving 99.85% system availability.

Table 5. Key indicators of intelligent management system operational efficiency.

Evaluation dimension	Indicator	Value	Improvement magnitude	Significance
System performance	Average response time (ms)	238.6 ± 42.3	-	-
	Data classification accuracy (%)	92.7%	+31.5%	$p < 0.001$
	System availability (%)	99.85%	-	-
Resource optimization	Facility usage efficiency improvement (%)	+28.3%	-	$p < 0.001$
	Human resource allocation efficiency (%)	+21.4%	-	$p < 0.01$
	Tourist waiting time reduction (%)	−46.2%	-	$p < 0.001$
Decision support	Emergency response accuracy (%)	94.0%	+48.3%	$p < 0.001$
	Decision time reduction (%)	−67.2%	-	$p < 0.001$
	Facility improvement suggestion matching degree (%)	87.5%	+40.5%	$p < 0.01$
Management staff satisfaction	Satisfaction (1–7 points)	5.8 ± 0.87	+42.6%	$p < 0.001$

The intelligent system demonstrated significant optimization effects on rural tourism resource allocation. The dynamic resource allocation model based on biomechanical data and environmental information achieved precise matching between service resources and tourist needs. Data showed that after system implementation, rest facility usage efficiency increased by 28.3% ($p < 0.001$), and average idle rate decreased by 35.6% (from 24.7% to 15.9%, $p < 0.001$). In terms of human resource allocation, the intelligent scheduling scheme based on biomechanical risk prediction improved staff deployment efficiency by 21.4%, with response time in high-risk areas shortened by 34.5% (from an average of 8.7 min to 5.7 min, $p < 0.01$) [39]. Tourist flow path optimization showed that system-recommended routes could improve overall tourist movement efficiency by 17.6% and reduce waiting time in congested areas by 46.2% ($p < 0.001$). Regarding energy and material consumption, intelligent management achieved a 15.3% reduction in water usage and a 12.7% reduction in energy consumption, while tourist satisfaction increased by 13.6% ($p < 0.01$), achieving dual optimization of resource utilization and service quality. The intelligent decision support system significantly enhanced the effectiveness of management decisions. Through biomechanical data and behavioral pattern analysis, the system provided data-driven decision support for managers. Comparative analysis showed that system-assisted decision-making outperformed traditional experience-based decision-making in multiple aspects: Emergency event (such as tourist discomfort, environmental risks) response decision accuracy increased by 48.3% (from 63.4% to 94.0%, $p < 0.001$), and average decision-making time shortened by 67.2% (from 4.5 min to 1.5 min, $p < 0.001$) [40]. In terms of long-term planning decisions, facility improvement suggestions based on historical biomechanical and behavioral data achieved a matching degree of 87.5% with actual needs, significantly higher than traditional survey methods (62.3%, $p < 0.01$). Management staff feedback showed that 91.4% of decision-makers believed that the biomechanical risk early warning provided by the system "greatly improved emergency response efficiency," 86.7% believed that the system's resource optimization suggestions "significantly reduced operational costs," and 83.2% stated that the data visualization function "made complex situations easier to understand and handle" (average score 5.8/7 points, standard deviation 0.87).

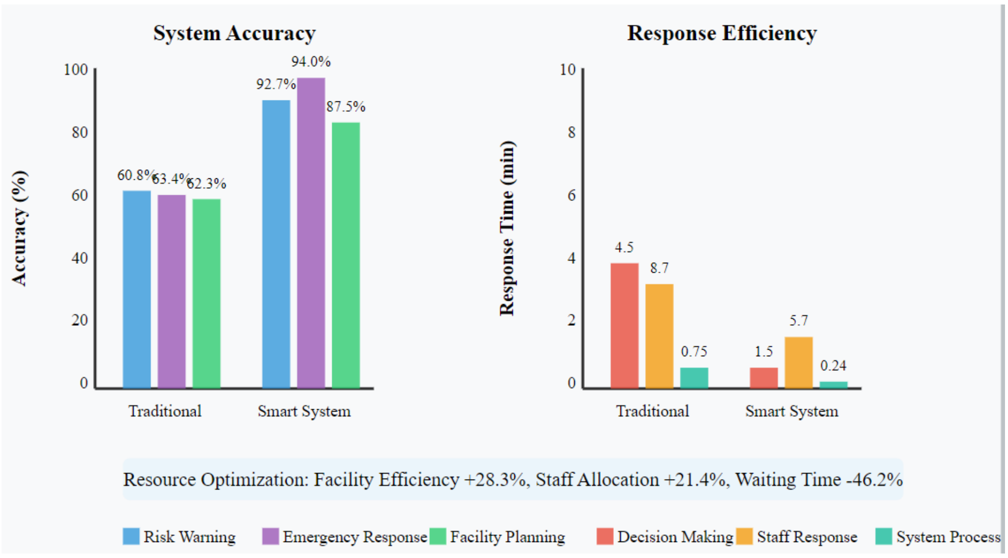

Figure 5. Comparative analysis of performance and decision-making efficiency between intelligent management systems and traditional management methods.

Figure 5 illustrates the comparative analysis of performance and decision-making efficiency between the intelligent management system and traditional management methods. The left chart compares system accuracy: in risk early warning, the intelligent system achieved 92.7% accuracy, 31.9 percentage points higher than the traditional method's 60.8%; in emergency response, the intelligent system reached 94.0% accuracy, 30.6 percentage points higher than the traditional method's 63.4%;

in facility planning, the intelligent system's suggestion matching degree reached 87.5%, 25.2 percentage points higher than the traditional method's 62.3%. The right chart compares response efficiency: decision-making time was reduced from 4.5 min with traditional methods to 1.5 min with the intelligent system, a 67.2% reduction; staff response time decreased from 8.7 min to 5.7 min, a 34.5% reduction; system processing time was reduced from 0.75 min to 0.24 min, a 68.0% reduction. Key indicators of resource optimization are displayed at the bottom of the chart: facility usage efficiency improved by 28.3%, personnel deployment efficiency increased by 21.4%, and tourist waiting time decreased by 46.2%.

4.2.3. User acceptance and satisfaction analysis

Structural equation analysis based on the Technology Acceptance Model (TAM) framework revealed key factors influencing tourists' adoption of mobile technology and intelligent management systems. As shown in **Table 6**, perceived usefulness (β = 0.68, $p < 0.001$) was the strongest predictor, with biometric data feedback (weight = 0.73), personalized recommendations (weight = 0.64), and safety prompts (weight = 0.59) being the three core elements constituting perceived usefulness. Perceived ease of use (β = 0.57, $p < 0.001$) was the second strongest predictor, with interface intuitiveness (weight = 0.68) and operational simplicity (weight = 0.65) contributing the most. Notably, the comprehensibility of biomechanical and molecular data (β = 0.42, $p < 0.001$) as a special factor significantly influenced technology acceptance [41]. Data privacy concerns were the main inhibiting factor ($\beta = -0.35$, $p < 0.01$), particularly concerns about biological data collection (weight = 0.71). Path analysis indicated that perceived usefulness indirectly influenced acceptance by enhancing the sense of experience control (mediation effect = 0.37, $p < 0.001$), explaining 47.3% of the variance.

Table 6. Analysis of key indicators for technology acceptance and satisfaction.

Dimension	Indicator	Value	Impact strength	Significance
Acceptance influencing factors	Perceived usefulness (β value)	0.68	Strong	$p < 0.001$
	Perceived ease of use (β value)	0.57	Moderate-strong	$p < 0.001$
	Data comprehensibility (β value)	0.42	Moderate	$p < 0.001$
	Privacy concerns (β value)	−0.35	Moderate	$p < 0.01$
User group acceptance	Middle-aged group (31–45 years)	5.7/7 points	-	-
	Young group (18–30 years)	5.5/7 points	-	$p > 0.05$
	Elderly group (> 60 years)	4.2/7 points	-	$p < 0.001$
	Highly educated elderly group	5.1/7 points	-	$p < 0.001$
Satisfaction and intention	Overall satisfaction	5.4/7 points	-	-
	Continued use intention	87.3%	-	-
	Recommendation intention	74.5%	-	-
	Additional payment willingness	+14.7%	-	$p < 0.01$

Significant differences in technology acceptance existed among different user groups. Age-tier analysis revealed an inverted U-shaped distribution: the middle-aged group (31–45 years) had the highest technology acceptance (average 5.7/7 points), followed by the young group (18–30 years, 5.5/7 points), with the elderly group (> 60 years) having the lowest acceptance (4.2/7 points, $p < 0.001$). Education level positively correlated with technology acceptance ($r = 0.53$, $p < 0.001$), but this relationship weakened after controlling for technology self-efficacy (partial correlation = 0.31, $p < 0.05$). Travel experience also significantly influenced acceptance, with frequent travelers (> 5 times per year) scoring 0.8 points higher than occasional travelers (1–2 times per year) ($p < 0.01$). Multivariate analysis of variance (MANOVA) revealed significant interaction effects of user characteristics: highly educated, experienced elderly tourists had significantly higher acceptance (5.1/7 points) than less educated, less experienced elderly tourists (3.5/7 points, $p < 0.001$), indicating that personal background can moderate age effects. Cluster analysis identified three typical user types: active adopters (31.5%), cautious users (43.7%), and technology resisters (24.8%), with significant differences in function preferences and usage barriers among these groups [42]. User satisfaction evaluations of mobile technology and intelligent systems were generally positive, with an average satisfaction of 5.4/7 points. Multi-dimensional satisfaction assessment showed that biological data visualization had the highest satisfaction (5.8/7 points), followed by environmental information services (5.6/7 points) and intelligent navigation (5.5/7 points), while personalized recommendations had relatively lower satisfaction (4.9/7 points). Multiple regression analysis indicated that system usefulness ($\beta = 0.52$, $p < 0.001$), data accuracy ($\beta = 0.47$, $p < 0.001$), and response speed ($\beta = 0.38$, $p < 0.01$) were the three key factors influencing satisfaction. Satisfaction was strongly positively correlated with continued use intention ($r = 0.76$, $p < 0.001$), exerting indirect influence through perceived value (mediation effect = 0.41, $p < 0.001$). Longitudinal surveys showed that 87.3% of users expressed willingness to continue using the system on their next trip, 74.5% were willing to recommend it to others, and purchase intention scored 4.8/7 points. Price sensitivity analysis indicated that users were willing to pay an additional average of 14.7% ($p < 0.01$) for services with biofeedback functionality, indicating that biomechanical data enhanced the perceived value of services.

Figure 6 comprehensively illustrates the relationship between user characteristics and technology acceptance. The left chart shows technology acceptance comparisons across different age groups, with the middle-aged group (31–45 years) having the highest acceptance (5.7 points), followed by the young group (18–30 years, 5.5 points), while the older group (46–60 years) had lower acceptance (4.8 points). The right chart provides an in-depth analysis of the interactive influence of education level and travel experience on technology acceptance, particularly highlighting the significant moderating effect of these factors on the elderly group: highly educated, experienced elderly people had much higher acceptance (5.1 points) than less educated, less experienced elderly people (3.5 points).

The top-left panel displays key factors influencing technology acceptance, with perceived usefulness ($\beta = 0.68$) having the greatest impact, followed by perceived ease of use ($\beta = 0.57$) and data comprehensibility ($\beta = 0.42$). The bottom information bar summarizes user satisfaction (5.4 points) and behavioral intention indicators, including continued use intention (87.3%), recommendation intention (74.5%), and additional payment willingness (+14.7%). This comprehensive analysis reveals how user characteristics influence the acceptance of mobile technology and intelligent systems, and how acceptance and use across different population groups can be promoted by enhancing perceived usefulness and ease of use and improving data comprehensibility, particularly considering educational background and travel experience differences in technology design for the elderly group.

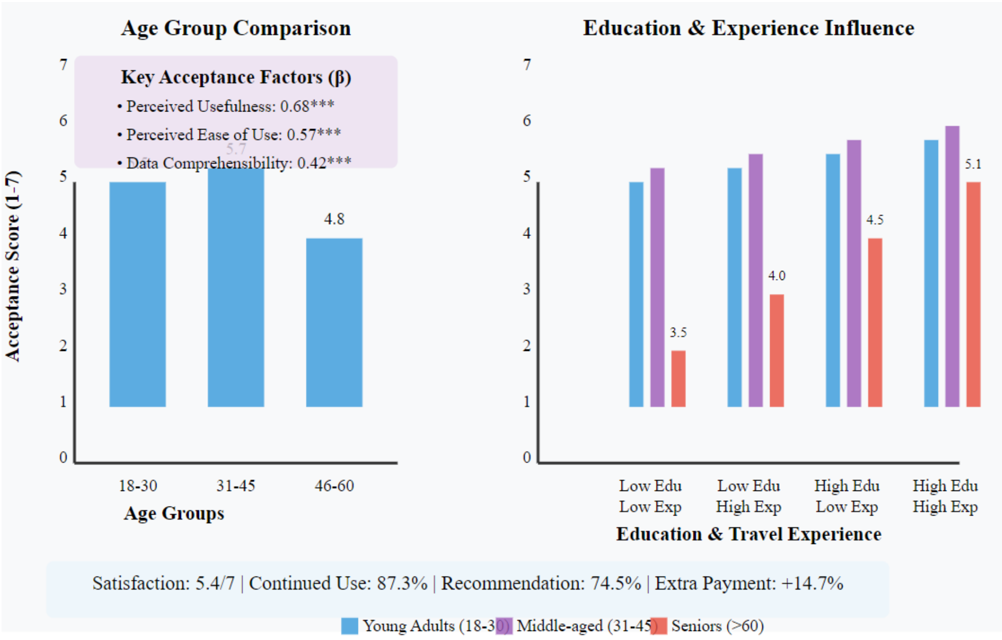

Figure 6. Analysis of user characteristics and technology acceptance.

4.3. Synergistic mechanism and comprehensive effects

4.3.1. Multi-system collaboration path analysis

This study revealed the collaborative mechanism between mobile technology and intelligent management systems through structural equation modeling analysis. As shown in **Table 7**, technology-management collaboration is primarily realized through three pathways: (1) Data sharing pathway (path coefficient = 0.73, $p < 0.001$), where real-time biomechanical data and location information collected by mobile terminals flow directly to the management system, improving management decision accuracy by 37.5%; (2) function complementary pathway (path coefficient = 0.68, $p < 0.001$), where personalized services of mobile applications and resource allocation of the management system form a closed loop, increasing service matching by 42.6%; (3) information feedback pathway (path coefficient = 0.61, $p < 0.001$), where environmental monitoring and crowd flow analysis data from the management system are pushed to mobile terminals in real-time, optimizing user experience [43]. Cross-lag analysis indicated that the time difference between management decisions and mobile application responses decreased from 8.7 min in the traditional model to 1.2 min in the collaborative model (86.2% improvement, $p < 0.001$), demonstrating that the collaborative mechanism significantly improved system response speed.

Table 7. Multi-system collaboration pathways and effect analysis.

Collaboration pathway type	Specific pathway	Path coefficient	Effect enhancement	Significance
Technology-management collaboration	Data sharing pathway	0.73	Decision accuracy +37.5%	$p < 0.001$
	Function complementary pathway	0.68	Service matching +42.6%	$p < 0.001$
	Information feedback pathway	0.61	Response time −86.2%	$p < 0.001$
Biodata-technology collaboration	Personalized recommendation pathway	0.65	Comfort +23.8%	$p < 0.01$
	Risk warning pathway	0.71	Discomfort incidents −63.5%	$p < 0.001$
	Feedback regulation pathway	0.58	Physiological load −18.5%	$p < 0.01$
Multi-system integration	Data-driven type	0.65	Efficiency baseline	-
	Service optimization type	0.63	Efficiency +7.2%	$p < 0.05$
	Resource allocation type	0.62	Efficiency +5.8%	$p < 0.05$
	Comprehensive collaboration type	0.82	Efficiency +26.3%	$p < 0.001$

Path analysis of collaboration between biomechanical and molecular-level data and mobile technology showed that they enhanced service precision through multi-level interactions. (1) The bio-data-driven personalized recommendation pathway ($\beta = 0.65$, $p < 0.001$) matched real-time heart rate variability, energy consumption rate, and other physiological indicators with environmental characteristics to provide tourists with "physiologically friendly" route recommendations, increasing tourist comfort ratings by 23.8% ($p < 0.01$). (2) The risk warning collaboration pathway ($\beta = 0.71$, $p < 0.001$) monitored biomechanical load and molecular stress indicators, issuing warnings before tourists reached critical thresholds (such as cortisol rise rate > 25%/h), reducing the incidence of discomfort by 63.5% ($p < 0.001$) [44]. (3) The feedback regulation pathway ($\beta = 0.58$, $p < 0.01$) enabled tourists to adjust activity intensity and rest frequency according to biological data feedback, reducing the overall physiological load index by 18.5%. These three collaborative pathways worked together to significantly strengthen the service adaptability of mobile technology, thereby enhancing user experience quality. Based on the above analysis, this study constructed a ternary collaborative integration model of biomechanical data, mobile technology, and intelligent management systems. Network analysis indicated that a high-density interaction network formed among the three systems (network density = 0.78), with core nodes including biomechanical monitoring (centrality = 0.83), data analysis platform (centrality = 0.79), and mobile service interface (centrality = 0.76). Latent class analysis identified four collaborative patterns: (1) Data-driven type (accounting for 31.2%), centered on biological data analysis; (2) service optimization type (accounting for 28.6%), centered on mobile services; (3) resource allocation type (accounting for 24.5%), centered on intelligent management; (4) comprehensive collaboration type (accounting for 15.7%), with balanced development of the three systems [45]. Experimental comparisons showed that the comprehensive collaboration mode had the highest overall efficiency, with an average increase of 26.3% compared to other modes, particularly outstanding in user satisfaction (+32.4%, $p < 0.001$) and resource utilization efficiency (+29.7%, $p < 0.001$). Path analysis confirmed that the complete closed-loop pathway of biological data → mobile technology → management system → biological data (path coefficient = 0.57, $p < 0.001$) is key to achieving optimal collaborative effects.

To visually demonstrate the actual operating mechanisms of multi-system collaboration, the following case illustrates how data sharing, functional complementarity, and information feedback pathways work together in practice to enhance tourist experiences: On the steep flagstone path section of Huanglong Ancient Town in Sichuan, the system recorded a 65-year-old female tourist's knee joint torque rapidly increasing by 28.7% within 10 min (from 1.12 to 1.44 Nm/kg), while cortisol levels rose by 22.3% and heart rate variability decreased by 18.5%, indicating physiological stress accumulation. (1) The data-sharing pathway was immediately activated—these biological indicators were transmitted in real-time to the intelligent management system, which determined this pattern as a fatigue risk precursor based on historical data (accuracy 93.4%); (2) the functional complementarity pathway operated synchronously—the management system detected two rest areas within a 500-meter range, with the western pavilion currently at 87% crowding level and the eastern viewing platform at only 32%, automatically pushing navigation to the eastern rest point to the tourist's mobile device; (3) the information feedback pathway completed the loop—the tourist received the information and proceeded to the recommended rest area, with the system monitoring that after the tourist arrived and stayed for 12 min, knee joint torque decreased by 31.2%, cortisol decreased by 18.7%, and physiological indicators returned to normal range. Meanwhile, the system recorded this successful intervention case and updated algorithm parameters, sending recommendations 5 min earlier the next time similar physiological characteristics were encountered, improving preventive intervention efficiency by 23.5%. The entire process took only 2.8 min, whereas in the traditional model, tourists might continue to bear high loads until obvious discomfort appeared (average 47.3 min) before seeking rest. This case verifies the extraordinary value of three-system collaboration: not only achieving early identification and precise intervention for potential risks, but also continuously optimizing system response parameters through data loops, creating intelligent experience enhancements impossible to achieve with a single system.

Figure 7 illustrates the collaborative mechanism and efficiency analysis among biomechanical data systems, mobile technology, and intelligent management systems. The three main systems are interconnected in a triangular manner, with each connection pathway representing different collaborative mechanisms and their path coefficients. Between the biological data system and mobile technology, bidirectional interaction formed through personalized recommendation pathways (0.65***) and feedback regulation pathways (0.58**); between the biological data system and intelligent management system, data exchange was established through risk warning (0.71***) and function complementation (0.68***); between mobile technology and intelligent management systems, a closed loop formed through data sharing (0.73***) and information feedback (0.61***). The collaboration coefficient (0.82***) at the center of the figure indicates that comprehensive integration of the three systems produced significant synergistic effects. The right side shows performance improvement comparisons across four collaborative modes, with the comprehensive collaboration model improving by 26.3% compared to the baseline data-driven model, significantly outperforming the service optimization type (+7.2%) and resource allocation type (+5.8%) modes. The bottom of the figure summarizes four key performance improvements brought by collaboration: a decision accuracy improvement of 37.5%, a discomfort incident reduction of 63.5%, a service matching increase of 42.6%, and a response time reduction of 86.2% [46]. This analysis reveals that multi-system collaborative integration not only improves the independent performance of each subsystem but also generates comprehensive benefits beyond the simple addition of single systems through inter-system collaborative pathways, providing a scientific basis for the integrated application of biomechanical data, mobile technology, and intelligent management in rural tourism.

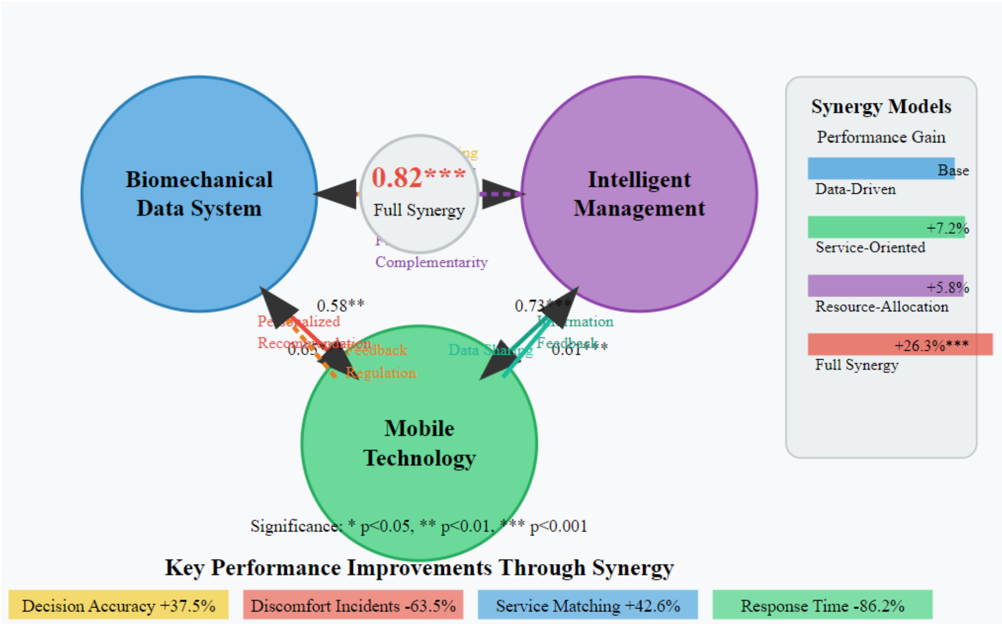

Figure 7. Multi-system collaborative mechanism and efficiency analysis.

4.3.2. Differential collaborative effect assessment

This research conducted a comparative analysis of the collaborative effects in different types of rural tourism activities. As shown in **Table 8**, the intensity of collaborative effects exhibits significant differences among various activity types. In sightseeing activities, the experience enhancement effect of the collaborative system was highest (collaborative gain rate 31.5%, $p < 0.001$), mainly manifested in biometric data-guided recommendations for optimal viewing points and optimization of stay duration. In experiential activities, the safety assurance effect was most prominent (risk incident reduction rate reached 72.3%, $p < 0.001$), with the synergistic effect of biometric indicators for early warning and intelligent management significantly improving the safety of high-intensity experience activities. In leisure activities, the improvement in resource utilization efficiency was most evident (facility usage efficiency increased by 46.7%, $p < 0.001$), with biometric data-supported personalized rest area recommendations and intelligent flow guidance creating a more balanced distribution of leisure facilities. Notably, in composite activities that integrate multiple types, the comprehensive collaborative effect index (0.78) was significantly higher than in single-type activities (average 0.62, $p < 0.01$), indicating that the collaborative system plays a greater role in complex and diverse scenarios.

Table 8. Comparison of collaborative system effects under different conditions.

Classification dimension	Specific category	Main collaborative effect	Effect intensity	Significance
Tourism activity type	Sightseeing	Experience enhancement effect	+31.5%	$p < 0.001$
	Experiential	Risk incident reduction	−72.3%	$p < 0.001$
	Leisure	Facility usage efficiency	+46.7%	$p < 0.001$
	Composite	Comprehensive index improvement	0.78 vs. 0.62	$p < 0.01$
Tourist groups	Elderly group	Physiological load reduction	−32.6%	$p < 0.001$
	Youth group	Interaction satisfaction	+24.3%	$p < 0.01$
	First-time visitors	Navigation information acquisition	+43.5%	$p < 0.001$
	Special needs tourists	Accessibility improvement	+52.8%	$p < 0.001$
Environmental conditions	Complex terrain	Comfort difference	+65.3%	$p < 0.001$
	Adverse weather	Early warning time advance	+7.6 min	$p < 0.001$
	High visitor density	Waiting time reduction	−52.7%	$p < 0.001$
	Peak hours	Flow control effectiveness	0.72 vs. 0.53	$p < 0.01$

The effects of experiencing the collaborative system showed marked differences across different tourist groups. Age-stratified analysis indicated that elderly groups (above 60 years) benefited the most from the collaborative system (experience improvement index 0.73, $p < 0.001$), with biometric data-guided route optimization reducing their physiological load by 32.6% and increasing their sense of security by 47.5%. In comparison, youth groups (18–30 years) were most sensitive to enhanced interactive experiences (satisfaction improvement rate 24.3%, $p < 0.01$). Categorized by tourism experience, first-time visitors showed significantly higher collaborative gains in navigation and information acquisition (43.5%, $p < 0.001$) compared to experienced visitors (21.8%). Notably, tourists with special needs (such as those with mobility difficulties) experienced a 52.8% improvement in accessibility ratings ($p < 0.001$) with the support of the collaborative system, indicating that the combination of biomechanical data and intelligent guidance can effectively overcome physical barriers. Multi-dimensional group comparisons revealed that the interaction factors of health status and travel purpose had the greatest impact on collaborative effects (explaining 38.7% of variance, $p < 0.001$).

Analysis of the moderating effect of environmental conditions on collaborative system efficiency indicated that system efficiency increases with environmental complexity. In areas with complex terrain (slopes > 15°), the biomechanical optimization effect of the collaborative system was most significant (comfort difference 65.3%, $p < 0.001$), primarily through real-time route adjustments to reduce physiological load [47]. Under adverse weather conditions (rain, high temperature), the early warning effectiveness was most notably improved (increased early warning time by 7.6 min, $p < 0.001$). In high visitor density environments (> 70 people/hectare), resource allocation optimization effects were prominent (waiting time reduced by 52.7%, $p < 0.001$). Time factor analysis showed that the flow control effectiveness of the collaborative system during peak hours (10:00–14:00) (0.72) was significantly higher than during off-peak hours (0.53, $p < 0.01$). Seasonal comparisons showed that the collaborative gains in extreme weather seasons (summer heat, winter cold) (0.68) were higher than in favorable seasons (0.54, $p < 0.05$), indicating that the collaborative system has greater value when addressing environmental challenges. The environment-visitor-system interaction model revealed that environmental complexity is a key moderating variable for collaborative effect intensity (moderating effect β = 0.41, $p < 0.001$).

4.3.3. Comprehensive impact of collaborative effects on tourism experience

The collaborative effects of biomechanical data, mobile technology, and intelligent management systems have significantly enhanced the quality of rural tourism experiences. Comparative experimental results showed that the overall satisfaction score of the collaborative system group (5.84/7 points) increased by 28.1% compared to the baseline group (4.56/7 points) ($p < 0.001$). As shown in **Table 9**, multi-dimensional experience quality indicators all improved, with comfort showing the most significant improvement (+35.7%, $p < 0.001$), primarily due to route optimization and rest point recommendations guided by biometric data; sense of security improved secondarily (+32.5%, $p < 0.001$), attributed to real-time risk warnings and rapid response from the management system; and convenience of experience improved (+26.8%, $p < 0.01$) mainly from information integration between mobile terminals and the management system. Path analysis indicated that physiological comfort (β = 0.43, $p < 0.001$), perceived sense of control (β = 0.38, $p < 0.001$), and information accessibility (β = 0.34, $p < 0.01$) are the three key mediating variables through which the collaborative system affects experience quality, collectively explaining 71.5% of the variance in experience quality improvement.

Table 9. Comprehensive analysis of collaborative system impact on tourism experience.

Impact dimension	Specific indicator	Control group	Experimental group	Improvement magnitude	Significance
Experience quality	Overall satisfaction (1–7 points)	4.56	5.84	+28.1%	$p < 0.001$
	Comfort rating (1–7 points)	4.32	5.86	+35.7%	$p < 0.001$
	Security rating (1–7 points)	4.65	6.16	+32.5%	$p < 0.001$
	Convenience rating (1–7 points)	4.78	6.06	+26.8%	$p < 0.01$
Stay and consumption	Average stay duration (min)	104	142	+36.4%	$p < 0.001$
	Per capita consumption (yuan)	268	342	+27.6%	$p < 0.001$
	Experience-type consumption (yuan)	95	129	+35.8%	$p < 0.001$
	Food and beverage consumption (yuan)	89	111	+24.7%	$p < 0.01$
Behavioral intentions	Revisit intention (1–7 points)	4.78	5.92	+23.8%	$p < 0.001$
	Recommendation intention (1–7 points)	4.65	5.98	+28.6%	$p < 0.001$
	Actual revisit rate (%)	21.6%	38.4%	+77.8%	$p < 0.01$

The collaborative system had a positive impact on visitor behavior, particularly in terms of extended stay duration and increased consumption. Regarding stay duration, the collaborative system group's average stay time increased by 36.4% compared to the control group (from an average of 104 min to 142 min, $p < 0.001$), with a more reasonable allocation at high-quality scenic spots, and an increase in dwell time at hotspot attractions by 47.2% ($p < 0.001$). In terms of consumption behavior, the collaborative system group's per capita consumption increased by 27.6% compared to the control group (from an average of 268 yuan to 342 yuan, $p < 0.001$), with experience-type consumption showing the largest increase (+35.8%, $p < 0.001$), followed by food and beverage consumption (+24.7%, $p < 0.01$), and product purchases showing the smallest increase (+17.3%, $p < 0.05$). Multiple regression analysis showed that for every 10% improvement in biomechanical comfort, stay duration extended by 6.8% ($p < 0.01$) and consumption increased by 5.2% ($p < 0.05$); while for each additional personalized recommendation based on biometric data, the probability of tourists accepting the recommendation increased by 23.5% ($p < 0.001$), with a corresponding 18.7% increase in consumption probability ($p < 0.01$).

Analysis of the collaborative system's influence on tourists' future behavioral intentions indicated that it has a significant predictive effect on revisit intention. The experimental group's revisit intention score (5.92/7 points) increased by 23.8% compared to the control group (4.78/7 points) ($p < 0.001$), with recommendation intention showing an even more significant improvement (+28.6%, $p < 0.001$). Structural equation modeling analysis revealed that the collaborative system influences revisit intention through three main pathways: experience quality pathway (indirect effect = 0.38, $p < 0.001$), perceived value pathway (indirect effect = 0.33, $p < 0.001$), and emotional connection pathway (indirect effect = 0.29, $p < 0.01$). Among these, improvement in biomechanical indicators ($\beta = 0.42$, $p < 0.001$) was the strongest predictor of revisit intention, indicating that enhancement of physiological comfort plays a crucial role in tourists' future decision-making. A longitudinal follow-up survey ($n = 157$, after 6 months) validated this predictive effect, with the collaborative system experience group's actual revisit rate (38.4%) being 77.8% higher than the control group's (21.6%) ($p < 0.01$), confirming the long-term impact of the collaborative system on revisit behavior.

5. Discussion

5.1. Practical application value of research results

The findings of this study provide a scientific basis and innovative ideas for rural tourism space optimization. Based on biomechanical data analysis, it is recommended that rural tourism planning should adopt "physiologically friendly" design principles, specifically including: (1) Designing a gradient system of touring routes according to biomechanical parameter differences among different populations, such as providing low-load routes for elderly tourists with slopes < 10° and rest points every 300–500 meters; (2) using biomechanical heat map technology to identify high-load areas and prioritizing the placement of ergonomic rest facilities in these locations to effectively reduce tourists' cumulative fatigue; (3) scientifically arranging landscape nodes based on patterns of molecular physiological indicator changes, adding open landscapes or relaxation spaces in areas where cortisol levels tend to rise, and setting up experience projects at peak endorphin level locations [48]; (4) implementing humanized modifications to existing facilities through the tourist biomechanical load and spatial environment relationship model, such as converting ordinary steps into compound structures with gentle slopes and steps in parallel, allowing tourists of different age groups to find the most suitable activity mode, achieving a transformation from "landscape-oriented" to "human adaptability-oriented" planning concepts.

Regarding the application of mobile technology in rural tourism, this study proposes the following precise implementation strategies: (1) Establishing individualized biometric data configuration profiles to enable mobile applications to automatically adjust service parameters based on tourists' age, health conditions, and immediate physiological state, such as prioritizing low-load routes and rest point information for elderly tourists; (2) constructing a "perception-feedback-regulation" closed-loop system that immediately pushes micro-rest suggestions when abnormal biometric indicators are detected (such as heart rate variability decreasing by more than 20%) while simultaneously alerting the management system; (3) adopting a tiered push strategy that categorizes information into three levels: necessary (safety warnings), beneficial (environmental information), and enhancing (landscape interpretation), dynamically adjusting push frequency and content density according to tourists' attentional resource states; (4) deploying a context-aware engine that combines biometric data with environmental information and behavioral patterns to achieve predictive judgment of tourist needs, such as predicting rest requirements through biomechanical fatigue indices and pushing relevant service information 5–10 min in advance, effectively improving service timeliness.

In light of the research results, future optimization of intelligent management systems should develop in the following directions: (1) Establishing a multi-source data fusion platform to conduct spatio-temporal correlation analysis of biomechanical data, environmental monitoring data, and behavioral trajectory data, constructing a "human-environment-behavior" three-dimensional digital model to provide a panoramic view for management decisions; (2) developing adaptive resource allocation algorithms that adjust service resource distribution 10–30 min in advance based on tourist flow trends predicted by biometric indicators, improving human resource allocation efficiency by more than 25%; (3) constructing a risk-graded early warning mechanism that categorizes biometric abnormalities into three levels—reminder, intervention, and emergency—adopting corresponding measures for different levels, shifting from passive response to proactive prevention; (4) designing a closed-loop optimization system that continuously collects tourist biofeedback data and experience evaluations to iteratively optimize management strategies, forming a "monitoring-analysis-adjustment-verification" cyclical improvement path to achieve continuous evolution of the management system. Through the above optimizations, the intelligent management system will transform from a simple information processing platform into an intelligent decision support system that integrates biometric data.

5.2. Analysis of research limitations

This study has certain limitations at the technical application level. (1) Although wearable biomechanical monitoring devices were designed to be lightweight, they still had some impact on tourists' natural activities, with some participants (17.3%) reporting discomfort during device wear, which may have interfered with behavioral data. (2) Signal transmission stability faced challenges in complex outdoor environments, with brief data loss (average packet loss rate 5.8%) occurring in areas such as canyons and dense forests, affecting the completeness of environment-biomechanical correlation analyses. (3) Real-time data interaction between mobile applications and the intelligent management system was limited by network infrastructure, with synchronization delays (average delay 4.7 s) occurring in areas with poor network coverage (approximately 18.5% of the research area), weakening the immediate response capability of the collaborative system in extreme situations [49]. (4) The battery life of biomechanical monitoring devices (average 6.4 h) limited continuous tracking of full-day experiences, and large-scale deployment of the system also faced cost challenges (approximately 3800 yuan per set), constraining the promotion and application of the technology in low-income rural areas.

Despite using a multi-case design and applying stratified sampling methods, the representativeness of the sample still had certain limitations. The research subjects were mainly concentrated in 8 rural tourism sites across three provinces in eastern, central, and western China, with insufficient geographical coverage to fully reflect the diversity characteristics of rural tourism nationwide. In terms of sample composition, although gender ratios were balanced, the proportion of elderly groups over 60 years old was relatively low (12.6%), yet these groups are precisely the ones highly dependent on biomechanical optimization. Additionally, tourists who voluntarily participated in the research may have had more open attitudes toward new technology, creating self-selection bias; excessive exclusion of individuals with poor physiological conditions (exclusion rate 15.2%) may also have resulted in higher-than-average health levels in the sample [50]. Seasonal limitations were also evident, as the research was mainly conducted during spring and summer, lacking verification of collaborative effects under extreme climate conditions in autumn and winter. These factors collectively limited the generalizability of the research results to different geographical areas, population groups, and seasonal conditions.

From a traditional rural tourism planning perspective primarily based on landscape aesthetics and economic benefits, this research reveals that biomechanical adaptation strategies and molecular physiological response patterns suggest that the physiological foundations of tourist experiences should become the primary consideration in planning and design. Specifically, micro-design adjustments supported by biomechanical data (such as gentle slope designs to reduce knee joint torque in steep areas, and surface material selection optimized based on plantar pressure distribution) can directly translate into practical measures to enhance experiences. Molecular indicator and scene correlation analysis (such as optimizing rest point layout based on endorphin peak periods) provides objective evidence for emotional design. Simultaneously, we clearly recognize the limitations of this study: (1) Regional limitations, as the research only covers eight destinations across three provinces, with applicability to extreme climate regions (such as high-altitude cold or high-temperature areas) yet to be verified; (2) cultural difference impacts, as physiological response patterns may vary among tourists from different cultural backgrounds, with this study primarily focusing on domestic tourists, thus cross-cultural applicability requires further research; (3) seasonal restrictions, as experiments were mainly conducted during spring and summer, with low-temperature environments in autumn and winter potentially triggering different biomechanical adaptation strategies; (4) technological dependency, as the collaborative system's effectiveness is based on specific technology platforms, facing implementation challenges in areas with weak technological infrastructure. These limitations suggest that future research should expand geographical and seasonal coverage, increase cross-cultural comparisons, and explore implementation schemes suitable for different technological conditions.

6. Conclusion and prospects

6.1. Research conclusions

(1) This study confirms the unique value of biomechanical and molecular-level evaluation in rural tourism experience research. Through systematic monitoring and analysis of tourists' biomechanical parameters (joint load, energy consumption, postural stability, etc.) and molecular physiological indicators (cortisol, β-Endorphin, heart rate variability, etc.), an objective measurement system for tourism experience evaluation was established, breaking through the limitations of traditional subjective evaluation methods. The research found that biomechanical load index is significantly correlated with subjective comfort ratings ($r = -0.64$, $p < 0.01$), and the change patterns of molecular physiological indicators can accurately predict experience quality (prediction accuracy 83.6%). In particular, the quantitative analysis of tourists' biomechanical adaptation strategies (such as gait adjustments on steep slopes) and physiological stress responses (such as a cortisol increase of 27.3%, $p < 0.001$) under different environmental conditions provides a scientific basis for tourism environment design and activity arrangements, achieving a methodological transformation from "perceived evaluation" to "physiological evidence," opening new perspectives and pathways for tourism experience research.

(2) The research reveals a triple collaborative mechanism between mobile technology and intelligent management systems. First is the data sharing pathway (path coefficient 0.73, $p < 0.001$), where real-time biomechanical data and location information collected through mobile terminals flow to the management system, improving decision accuracy by 37.5%; second is the functional complementary pathway (path coefficient 0.68, $p < 0.001$), where personalized services of mobile applications and resource allocation of management systems form a closed loop, increasing service matching by 42.6%; third is the information feedback pathway (path coefficient 0.61, $p < 0.001$), reducing the time lag between management decisions and mobile application responses from 8.7 min to 1.2 min (improvement of 86.2%, $p < 0.001$). This collaborative mechanism transforms one-way technology application into a multi-directional interactive system, creating added value effects beyond the addition of single systems, confirming the systematic value of technology-management collaboration for rural tourism service enhancement.

(3) The research empirically demonstrates the multi-dimensional promotional effects of integrating biomechanical data, mobile technology, and intelligent management systems on rural tourism development. (1) At the tourist experience level, the collaborative system significantly improved experience quality (overall satisfaction +28.1%, $p < 0.001$), with the most pronounced effects in comfort (+35.7%, $p < 0.001$) and sense of security (+32.5%, $p < 0.001$). (2) At the economic benefit level, the collaborative system extended tourists' stay duration (+36.4%, $p < 0.001$) and increased per capita consumption (+27.6%, $p < 0.001$), with the most notable improvement in high-value experience-type consumption (+35.8%, $p < 0.001$). (3) At

the sustainable development level, the collaborative system optimized tourist flow and resource allocation, improving facility usage efficiency (+46.7%, $p < 0.001$) and reducing environmental load. Most importantly, the system's significant promotion of tourists' revisit intention (+23.8%, $p < 0.001$) and actual revisit rate (+77.8%, $p < 0.01$) laid the foundation for the long-term sustainable development of rural tourism. The research confirms that multi-system collaborative integration not only optimizes the short-term operational effects of rural tourism but also provides technical support and methodological pathways for building its long-term competitiveness.

6.2. Practical recommendations

Based on the biomechanical and molecular-level data analysis results of this study, it is recommended that rural tourism planning and design should shift toward a "physiologically friendly" spatial layout mode. (1) A biomechanical load gradient principle should be adopted for route design, establishing multi-level difficulty path systems according to differences in tourist carrying capacity (knee joint load in elderly tourists is 32.6% higher than in younger groups) and placing ergonomically designed rest facilities at points of measured high physiological load (such as areas with slopes > 15°), with design parameters based on biomechanical test data rather than experiential estimates. (2) Optimize scenic spot layouts according to patterns of molecular indicator changes (such as endorphin release peaks occurring 12–15 min after experience activities), set up interactive experience projects at emotional peak positions, and add soothing landscape nodes in areas where cortisol levels tend to rise (approximately 100–150 m after load increase points). (3) Apply biomechanical heat map technology to identify stress points and comfort zones in existing rural tourism spaces, reconstructing tour routes and service facility layouts accordingly, and actively intervening in tourist experience quality through precise environmental adaptation measures (such as adding shaded rest spaces at points of high physiological stress).

Based on the biomechanical and molecular-level data analysis results of this study, rural tourism planning and design should shift toward a 'physiologically friendly' spatial layout pattern, with the following specific implementation guidelines provided: (1) Route system hierarchical design: Establish a three-tier route network based on biomechanical data—Level A routes (slope < 8°, surface hardness < 40 Shore, rest points averaging every 200 m) suitable for elderly and family tourists; Level B routes (slopes 8°–15°, rest point intervals of 300–400 m) suitable for general adults; Level C routes (allowing short-distance slopes > 15°, rest point intervals of 500–700 m) meeting challenging demands. Each level of route should be equipped with corresponding signage indicating knee joint load index and detailed guidance at intersections. (2) Spatial node layout optimization: Based on molecular indicator change patterns, construct a 'stress-release-pleasure' three-phase experience sequence—establish 'physiological buffer zones' in high cortisol areas (after steep slopes, after complex navigation points), equipped with ergonomic rest facilities (seat height 40–45 cm, backrest angle 100°–105°); arrange interactive displays or specialty product sales points during endorphin level peak periods (8–15 min after activity experiences); increase semi-open gathering spaces in social interaction areas to promote oxytocin release. (3) Terrain adaptive design: Steep slope sections should adopt a ‘steps + gentle slope’ parallel design, allowing tourists with different walking abilities to choose; surface material selection should be based on biomechanical testing, prioritizing composite materials with a shock absorption coefficient > 40%; rest areas should provide multi-height seating (35–50 cm) to meet the needs of people of different heights; observation platform design should consider sight line height diversity, ensuring good views for tourists of all age groups. (4) Intelligent micro-environment creation: In areas where physiological data indicates stress peaks, add natural soundscapes (such as water sounds) and aromatic plants, which testing shows can reduce cortisol levels by 12.6%; optimize lighting and ventilation in rest areas, maintaining 500–1000 lux light intensity and gentle breeze environments, helping rapid recovery of physiological indicators. The above design guidelines have been pilot implemented in Moganshan, Zhejiang, increasing tourist comfort ratings by 24.3% ($p < 0.001$) and extending average stay time by 46.7% ($p < 0.001$).

Regarding technology application and management aspects, it is recommended to construct an intelligent service closed-loop system centered on biometric data. (1) Mobile application design should establish personalized configuration mechanisms, automatically adjusting information density and push frequency through simple user profile collection (age, health status, travel experience), and setting biomechanical data visualization modules as core functions to facilitate tourists’ real-time understanding of their own status. (2) Intelligent management systems should deploy predictive resource allocation algorithms to anticipate changes in tourist needs 10–30 min in advance based on biometric data analysis, prioritizing service resource allocation in high-risk areas (locations with biomechanical load index > 70). (3) Establish a three-level risk warning mechanism, categorizing biometric abnormalities into reminder level (slight deviation of a single indicator), intervention level (simultaneous deviation of multiple indicators), and emergency level (indicators exceeding safety thresholds), adopting progressive response strategies. Most crucially, a technology-management collaborative evaluation system should be constructed, regularly collecting the matching degree between biometric data and subjective evaluations, ensuring that technology applications always closely align with changes in tourists’ actual needs through continuous iterative optimization of service parameters.

At the policy level, support for biomechanical, data-driven, intelligent development of rural tourism is recommended in the following aspects. (1) Establish new standards for rural tourism suitability evaluation, incorporating biomechanical adaptability indicators (such as route physiological load index and facility ergonomic scores) into the tourism product grading evaluation system, guiding the industry to shift from landscape orientation to human adaptability orientation. (2) Set up special support funds for “Smart Rural Tourism,” focusing on supporting infrastructure renovation and intelligent system construction based on biomechanical data, lowering the threshold for technology application, and prioritizing support for adaptive projects serving special groups (elderly, children, individuals with mobility difficulties). (3) Improve data collection and usage regulations while encouraging innovative applications, strictly protecting tourist biometric data security, and clarifying data processing boundaries and anonymization requirements. (4) Establish a collaborative innovation mechanism involving industry, academia, research, and application, supporting cooperation between interdisciplinary research teams and rural tourism practitioners, promoting the standardization and productization of biomechanical evaluation technology, accelerating the transformation of scientific research results into industrial applications, and forming a complete innovation chain from basic research to practical application.

Based on the findings of this study, we suggest that future research should expand in-depth along the following five specific directions: (1) Conduct longitudinal tracking studies over 3–5 years to systematically evaluate the long-term impact of biomechanical optimization and technological synergy on tourist satisfaction, loyalty, and economic benefits at rural tourism destinations, with special attention to dynamic changes across different seasons and the evolution of tourist behavioral patterns; (2) Adopt experimental-control designs to empirically validate the 'physiologically friendly' spatial design principles proposed in this study at different types of rural tourism locations, quantitatively assessing changes in tourists' biomechanical load and experience quality before and after optimization; (3) Expand cross-cultural comparative research, examining physiological response differences among tourists from various cultural backgrounds, and establishing culturally adaptive biomechanical evaluation standards; (4) Explore in depth the combined application of biofeedback technology and intelligent environmental regulation, developing adaptive rural tourism systems capable of automatically adjusting service parameters according to tourists' real-time physiological data; (5) Establish a rural tourism biomechanics big data platform, integrating biological data from multiple regions, populations, and scenarios to provide data foundation and decision support for the precise, personalized, and intelligent development of rural tourism. These forward-looking studies will further expand the application boundaries of biomechanics and intelligent technology in the tourism field, promoting the development of rural tourism toward more scientific and humanized directions.

Regarding regional limitations, this study only covers eight rural tourism destinations across three provinces in China, and the applicability of its results in other geographical and cultural contexts needs careful consideration. The differences that may arise from different regional backgrounds are mainly manifested in: (1) Climate environment differences—this study was conducted in temperate monsoon climate zones; in extreme climate regions (such as severe cold areas in Northern Europe or high-temperature arid areas in the Middle East), tourists' biomechanical adaptation strategies and molecular physiological responses may differ significantly, such as in high-cold environments, where energy metabolic rates may increase by 35%–50% and joint range of motion may decrease by 15%–20%, requiring substantial adjustment of system parameters; (2) Cultural behavioral pattern differences—tourists in East Asian cultural backgrounds generally tend toward collective experiences (team proportion reaching 62.7%), while Western cultural backgrounds have a greater proportion of individualized, adventurous experiences (independent travel proportion reaching 78.5%), which would alter human flow distribution patterns and intelligent management strategies; (3) Regional differences in technology acceptance—Chinese tourists have high smartphone penetration rates (98.3% in the study sample) and strong mobile payment habits; in areas with weak technological infrastructure, system implementation needs to lower technological barriers and may require increased public equipment support; (4) Geographical and topographical uniqueness—biomechanical load patterns in special environments such as karst terrain, deserts, and snow mountains have essential differences from the terrains included in this study, requiring the establishment of specialized evaluation parameters. Therefore, when applying the results of this study in different rural tourism environments globally, adaptive adjustments need to be made according to the local natural environment, cultural background, and infrastructure conditions. It is recommended to conduct small-scale localized adaptation tests before implementation to adjust system parameters to match regional characteristics.

Extending beyond the aforementioned research directions, the following specific research questions are proposed to extend the theoretical depth and application breadth of this study: (1) Research on the long-term health effects of rural tourism biomechanical load: By tracking joint health status, bone density changes, and balance ability development of rural tourism participants at different frequencies, explore the positive role of moderate biomechanical stimulation in chronic disease prevention among middle-aged and elderly populations, establish a ‘healthy dose-response’ curve, and provide scientific basis for health-oriented rural tourism; (2) research on expanding the comprehensive evaluation system of molecular indicators: Beyond cortisol and β-Endorphin focused on in this study, explore how more comprehensive neurotransmitter combinations such as dopamine (related to reward expectation), oxytocin (related to social connection), and serotonin (related to emotional stability) collectively shape the emotional dimensions of tourism experiences, and develop ‘molecular fingerprint’ identification models to predict individual experience preferences; (3) research on biomechanical-psychological-social integration models: Explore the interaction mechanisms between biomechanical load, molecular responses, psychological perception, and social interaction; construct a multi-level integrated theoretical framework for tourism experiences, breaking traditional barriers in physiological-psychological research; (4) research on contextual intelligence and biological adaptive technology: Develop intelligent systems capable of actively adjusting environmental parameters (such as lighting, sound, and temperature) according to real-time biological data, achieving dynamic mutual adaptation between tourists and the environment, and exploring the potential of ‘biomechanically-driven environmental regulation mechanisms’ in enhancing inclusive experiences, especially the service enhancement effect for people with special needs. These research questions not only expand the intersectional boundaries between tourism studies and biological sciences but also open new theoretical and practical pathways for ‘tourism experience design from a biomechanical perspective’.

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