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Adoption of artificial intelligence in smart animal husbandry in Qinghai pastoral areas: the driving mechanism of technological traits and user beliefs

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The rapid development of agricultural artificial intelligence (AI) supports the transformation of traditional to smart animal husbandry, yet its adoption in pastoral areas is constrained by complex geographical environments and uneven technological cognition. This study explores pastoralists' AI adoption intention using a framework integrating technological innovation characteristics (mobility, interactivity, autonomy), technological commitment (technological interest, competence belief, control belief), and the Technology Acceptance Model (TAM), with animal husbandry type and breeding scale as moderators. Partial Least Squares Structural Equation Modeling (PLS-SEM) analyzed 321 valid questionnaires. Results show: (1) Technological innovation characteristics: Mobility ($\beta = 0.375$, $p < 0.005$), interactivity ($\beta = 0.193$, $p < 0.05$), and autonomy ($\beta = 0.122$, $p < 0.05$) positively influence perceived usefulness; all three also enhance perceived ease of use (mobility: $\beta = 0.164$, $p < 0.005$; interactivity: $\beta = 0.273$, $p < 0.005$; autonomy: $\beta = 0.210$, $p < 0.005$). (2) Technological commitment: Technological interest promotes perceived usefulness ($\beta = 0.230$, $p < 0.005$) and ease of use ($\beta = 0.169$, $p < 0.05$), while competence and control beliefs show no significant effects. (3) Perceived usefulness ($\beta = 0.320$, $p < 0.001$) and ease of use ($\beta = 0.245$, $p < 0.001$) directly drive adoption intention. Moderating effects: Animal husbandry type positively moderates autonomy-perceived ease of use ($\beta = 0.086$, $p < 0.05$) and technological interest-perceived usefulness ($\beta = 0.099$, $p < 0.05$), but negatively moderates interactivity-perceived usefulness ($\beta = -0.220$, $p < 0.005$). Breeding scale positively moderates technological interest's effects on perceived usefulness ($\beta = 0.096$, $p < 0.05$) and ease of use ($\beta = 0.109$, $p < 0.05$). This study reveals differentiated AI adoption paths in Qinghai pastoral areas, providing a theoretical basis for targeted strategies. Recommendations include optimizing AI design by animal husbandry type, delivering hierarchical training by breeding scale, and strengthening technological competence and control belief cultivation to improve AI adaptability and sustainability.

KEYWORDS

adoption intention, agricultural artificial intelligence, driving mechanisms, PLS-SEM, smart animal husbandry, technological commitment, technological innovation characteristics

1 Introduction

With the rapid development of technology, agricultural AI has become a core driver for the global transformation of smart animal husbandry, with its applications deepening in scenarios such as livestock monitoring, grassland management, and epidemic prevention and control (Popa, 2011; Neumann et al., 2024; Pillai and Sivathanu, 2020). However, in alpine pastoral areas worldwide (e.g., the Qinghai-Tibet Plateau, Mongolian Grasslands, and South American Pampas), the adoption rate of agricultural AI is much lower than that in plain agricultural areas due to complex geographical conditions, weak infrastructure, and traditional production models (Melak et al., 2024; Zhang et al., 2024). China's five major pastoral areas (Qinghai, Inner Mongolia, Tibet, Xinjiang, and Sichuan) contribute over 60% of the national grassland animal husbandry output value, and their intelligent transformation is crucial to national food security and rural revitalization (Dong S. et al., 2023; Hua and Squires, 2015).

Among them, Qinghai pastoral area is a typical alpine pastoral area, featuring "high altitude, low network coverage, and extensive nomadism" that embodies both the representativeness of western Chinese pastoral areas and the commonalities of global alpine pastoral areas. It serves as an ideal sample for studying agricultural AI in extreme environments, and research on the driving mechanism of its adoption intention can provide theoretical and practical references for similar pastoral areas and global alpine animal husbandry regions. Located at the northern foot of the Qinghai-Tibet Plateau, Qinghai pastoral area has a total grassland area of 36.45 million hectares (Dong H. et al., 2023) and exhibits three aspects of representativeness: firstly, it has a fragile ecosystem with an average altitude of over 4,800 meters, imposing high requirements on the performance of agricultural AI equipment in withstanding extreme environments; secondly, it has a mixed production model, with nomadic, intensive indoor feeding, and extensive farming coexisting, reflecting the diversity of production models in Chinese pastoral areas; thirdly, it focuses on specific characteristic breeds, with yaks and Tibetan sheep as the core, leading to regional synergy in technical needs. Its characteristics of "fragile ecology + mixed models + specific breeds" make it a "microcosmic sample" for studying agricultural AI adaptability in Chinese pastoral areas, and the research conclusions can be horizontally extended and vertically applied to provide references for the implementation of smart animal husbandry in diverse scenarios.

The rapid development of agricultural AI provides crucial support for the transformation of traditional animal husbandry to smart animal husbandry. Nevertheless, in pastoral areas with complex geographical environments and significant differences in technological cognition, the actual intention to adopt agricultural AI still faces multiple constraints. Therefore, in-depth research on the driving mechanism of agricultural AI adoption intention in Qinghai pastoral area holds important practical significance. On one hand, it helps reveal the differentiated driving paths of agricultural AI adoption intention in Qinghai pastoral area, providing a theoretical basis for formulating targeted promotion strategies. By understanding the factors influencing herders' intention to adopt agricultural AI, the government and enterprises can develop more targeted promotion strategies to improve the efficiency of agricultural AI promotion (Wang et al., 2023). On the other hand, it provides decision-making references for the government and enterprises, promoting the widespread application of smart animal husbandry technologies in Qinghai pastoral area and enhancing the adaptability and sustainability of these technologies. The government can introduce relevant policy support measures based on the research results, such as subsidy policies and training policies, to encourage herders to adopt agricultural AI (Osorio et al., 2024); enterprises can optimize technology design according to market demand and develop agricultural AI products more in line with the actual conditions of Qinghai pastoral area (Li and Yu, 2025).

In the field of academic research, studies on agricultural AI adoption intention in the context of smart animal husbandry have two methodological gaps: first, the model framework is oversimplified. Existing studies mostly use the Technology Acceptance Model (TAM) or Diffusion of Innovations Theory (DIT) independently, failing to fully integrate the multi-dimensional interaction mechanism of "technological traits-user beliefs-scenario differences" (Georgopoulos et al., 2023; Melak et al., 2024), which makes it difficult to explain adoption intention differences in the complex scenarios of alpine pastoral areas; second, there is insufficient method adaptability. Most studies adopt the traditional Structural Equation Modeling (SEM), but this method has poor compatibility with small samples and non-normal data. However, surveys in pastoral areas often face problems of limited sample size and uneven data distribution due to geographical constraints, resulting in insufficient robustness of conclusions.

This study takes Qinghai pastoral area as the research object, aiming to accurately reveal the driving mechanism of agricultural AI adoption intention in this region through targeted methodological design. The selection and design of research methods are strictly adapted to the particularities of surveys in pastoral areas. Considering the vast area of Qinghai pastoral area and the scattered residence of herders, the survey adopts a combination of "online Wenjuanxing platform + offline assisted filling," and a total of 321 valid questionnaires are collected.

In view of the sample size and data characteristics, Partial Least Squares Structural Equation Modeling (PLS-SEM) is selected instead of traditional SEM, which can effectively avoid the problem of parameter estimation bias under small samples and ensure the model fitting effect (Hair et al., 2021); in the questionnaire design, all latent variable items are formulated in combination with the actual scenarios of pastoral areas rather than directly applying general scales, improving the content validity of measurement; at the same time, common method bias is controlled through "reverse-scored items +attention check items" to further ensure data quality; comprehensiveness of effect testing: with the help of SmartPLS 4.0 software, not only the main effects of technological innovation characteristics and technological commitment on perceived usefulness and perceived ease of use are tested, but also the moderating effects of animal husbandry type and breeding scale are systematically verified through Multi-Group Analysis and interaction term testing, fully revealing the multi-dimensional interaction mechanism of "technology - user - scenario" and avoiding the limitation of single effect analysis in methodology.

In summary, as a typical representative of alpine pastoral areas in western China and a research sample for global alpine animal husbandry scenarios, the development of smart animal husbandry in Qinghai pastoral area faces not only regional challenges of "difficult adaptation to extreme environments, complex adaptation to production models, and large differences in user cognition" but also reflects common problems in similar global pastoral areas (Ronaghi, 2023). In-depth research on the driving mechanism of agricultural AI adoption intention in this region can not only help formulate targeted promotion strategies for Qinghai pastoral area but also provide key support for the following scenarios: firstly, providing a "classified implementation" technology promotion template for China's five major pastoral areas such as Inner Mongolia and Tibet; secondly, providing technical design ideas for adapting to extreme environments for global alpine pastoral areas (e.g., grasslands in Mongolia and Nepal); thirdly, supplementing empirical evidence for "scenario moderation" to the theoretical system of smart animal husbandry. From regional practice to the overall industry, from Chinese experience to international reference, this study aims to promote the development of smart animal husbandry from "local pilots" to "large-scale implementation," and contribute solutions with ecological adaptability and scenario inclusiveness to the global digital transformation of animal husbandry.

2 Theoretical framework

2.1 Technology Acceptance Model (TAM)

Davis (1989) based on the Theory of Reasoned Action, the core assumption of the Technology Acceptance Model (TAM) is that an individual's intention to adopt technology is primarily driven by perceived usefulness and perceived ease of use. It provides a concise and explanatory pathway for understanding technology adoption. In the context of agricultural digital transformation, TAM has been widely used to analyze farmers' intention to adopt agricultural AI such as precision agriculture (Hussain et al., 2025) and Internet of Things (IoT) devices (Yang et al., 2024). Recent studies have focused on the synergistic relationship between "technology adoption and sustainable development." For instance, Ronaghi (2023) pointed out that agricultural AI adoption in manufacturing promotes the circular economy, and this logic is applicable to animal husbandry—agricultural AI can reduce waste and drug use through precision feeding and early epidemic warning, which aligns with clean farming practices (Ghosh et al., 2024).

Studies have shown that perceived usefulness often has greater explanatory power for adoption intention than perceived ease of use (Gefen and Straub, 2000), but there are differences across scenarios: farmers in developing countries pay more attention to economic benefits (Bontsa et al., 2023), while users in developed countries value sustainable value (Cao et al., 2025). The application of TAM in the animal husbandry field lags behind; existing studies mostly focus on livestock management systems (Michels et al., 2019a), and the "AI maturity model" proposed by Hansen et al. (2024) fails to delve into the psychological mechanism of user adoption. The particularity of Qinghai pastoral areas poses challenges to the application of TAM: the traditional framework does not consider the mediating effects of technological innovation characteristics (e.g., mobility, interactivity) nor integrate the impact of users' technological commitment (e.g., technological interest, competence belief). This study introduces technological innovation characteristics and technological commitment as antecedent variables to construct an extended TAM model.

2.2 Technological innovation characteristics

Technological innovation characteristics are key factors influencing herders' intention to adopt agricultural AI in pastoral areas. In the animal husbandry scenario of Qinghai pastoral areas, the three dimensions of mobility, interactivity, and autonomy play a core role in enhancing technology adaptability and users' value perception.

Mobility refers to the ability of agricultural AI to adapt to nomadic scenarios (Seiferth, 2020). Qinghai pastoral areas have vast grasslands, and herders need to engage in nomadic grazing; traditional animal husbandry relies on manual patrols, which are inefficient (Lai, 2021). Mobile technologies, through designs such as portable sensors and offline data processing, enable herders to obtain real-time information in areas without base stations (Nyamuryekung'e, 2024)—for example, smart collars that store physiological data (Lamanna et al., 2025) and drones that cover high-altitude regions (Mohsan et al., 2022)—which can improve perceived usefulness. Additionally, their designs that simplify interfaces and enhance portability (Michels et al., 2019b) can also strengthen perceived ease of use.

Interactivity emphasizes the efficiency of real-time human-computer communication and feedback (Jain B. et al., 2024), which can meet urgent needs in pastoral areas. For instance, intelligent systems allow herders to monitor livestock status and issue instructions (Ajani and Agbalaya, 2025), which can enhance perceived usefulness. Moreover, intuitive interfaces and simplified processes (Dakulagi et al., 2025) reduce operational difficulty and improve perceived ease of use.

Autonomy reflects the level of automated decision-making of technology (Ivanov, 2023), which can realize clean farming and sustainable development. Autonomous decision-making systems can reduce resource waste; in Qinghai pastoral areas, intelligent environmental control systems can reduce labor intensity and energy waste (George and George, 2023), and automated health monitoring can reduce the abuse of antibiotics (Folasole, 2023)—all of which can strengthen perceived usefulness. Furthermore, their designs that simplify processes (Franklin et al., 2024) can also improve perceived ease of use. In summary, the three dimensions of technological commitment— technological interest, technological competence belief, and technological control belief—are interrelated and collectively shape herders' intention to adopt agricultural AI (Shakeripour and Ronaghi, 2024).

2.3 Technological commitment

Technological commitment is a key psychological factor influencing users' intention to adopt agricultural AI (Rasheed et al., 2023). In the context of smart animal husbandry in Qinghai, its three dimensions—technological interest, technological competence belief, and technological control belief—are crucial for shaping herders' adoption intention. Theoretically, technological commitment reflects users' psychological and cognitive tendencies toward new technologies; it interacts with technological innovation characteristics to influence adoption intention and aligns with the view of Ajzen (1991) Theory of Planned Behavior that attitude, subjective norm, and perceived behavioral control determine adoption intention, thus providing a framework for explaining adoption intention.

Technological interest refers to herders' intrinsic curiosity and intention to explore agricultural AI. It can stimulate their curiosity and learning motivation, strengthen their recognition of technological value, and reduce psychological resistance to improve perceived ease of use. Technological competence belief refers to herders' confidence in their own ability to operate and master agricultural AI (Yerdelen-Damar et al., 2017), derived from self-efficacy theory. If herders have confidence in their technological competence, their probability of adoption intention is higher; otherwise, they may hesitate (Staddon, 2023). Technological control belief refers to herders' perception of autonomous control over technology (Stensson and Jansson, 2014). Users seek control over technology to meet their own needs (Sun, 2012); if herders can control technology operation and decision-making, their adoption intention will increase; otherwise, they tend to resist. In summary, these three dimensions produce a synergistic effect: technological interest provides motivation, technological competence belief shapes self-efficacy, and technological control belief ensures psychological belonging. Together, they explain the driving factors of herders' intention to adopt AI in pastoral areas and can provide insights for relevant parties to design solutions that meet herders' needs.

2.4 Moderating variables (animal husbandry type and breeding scale)

In the development of smart animal husbandry, animal husbandry type and breeding scale are important moderating variables affecting herders' intention to adopt agricultural AI in Qinghai pastoral areas. Both variables influence adoption intention by changing herders' needs, cognition, and application capabilities regarding agricultural AI.

Extensive animal husbandry is characterized by large scale and specialization, with vast pastures and advanced facilities, enabling it to give full play to the mobility, interactivity, and autonomy of agricultural AI—for example, intelligent grazing systems that can monitor livestock status in real time (Asmare, 2022). Operators in this type of husbandry have higher scientific literacy and economic strength, stronger acceptance of agricultural AI, and better technological interest and technological competence belief. Therefore, animal husbandry type may have a more significant positive moderating effect on the relationships between autonomy and perceived ease of use, and between technological interest and perceived usefulness.

Nomadic animal husbandry is characterized by seasonal migration and high mobility (Milner-Gulland et al., 2011), which imposes high requirements on the mobility and adaptability of agricultural AI. However, due to harsh production environments, limited network conditions, and weak application capabilities of herders, it may have a negative moderating effect on the relationship between interactivity and perceived usefulness, weakening the impact of interactivity on perceived usefulness. Intensive animal husbandry mainly relies on captive breeding, with a stable production environment (Menzi et al., 2010). Its needs focus on environmental control and feed management, and the autonomy and interactivity of agricultural AI are more in line with these needs—for example, intelligent feeding systems that can accurately adjust feed formulas (Su et al., 2024). Operators in this type pay more attention to the perceived usefulness and ease of use of technology.

Breeding scale also has a significant impact. Large-scale farms have strong economic and R&D capabilities, enabling them to bear technological costs and risks (MacDonald and McBride, 2009) and have an urgent demand for agricultural AI. They may have a more obvious positive moderating effect on the relationships between technological interest and perceived usefulness, and between technological interest and perceived ease of use. Medium-scale farms have a cautious but flexible attitude toward adoption intention. Small-scale farms have low adoption intention due to constraints such as funds and technology. In summary, promoting agricultural AI should take into account the characteristics of different animal husbandry types and breeding scales, and formulate targeted strategies to improve adoption rates and application effects.

2.5 Theoretical model

As shown in Figure 1, the theoretical framework constructed in this study takes the Technology Acceptance Model (TAM) as the core, integrates the Technology Innovation Characteristics Theory and the Technology Commitment Theory to form a multi-dimensional driving mechanism. Among them, technology innovation characteristics (mobility, interactivity, autonomy) and technology commitment (technology interest, technology competence belief, technology control belief) are used as antecedent variables. By improving the adaptability of agricultural AI to the pastoral production scene, they indirectly strengthen users' cognition of perceived usefulness and perceived ease of use.

At the same time, the types of animal husbandry (extensive, nomadic, confined) and the scale of breeding (large, medium, small) are used as moderating variables. By reflecting the differences in technology needs of different production modes, they reveal the differentiated paths of the adoption intention of agricultural AI in Qinghai pastoral areas. This framework breaks through the limitation of the single-technology-characteristic analysis of the traditional Technology Acceptance Model (TAM), introduces the interdisciplinary perspectives of the Technology Innovation Theory and the Theory of Planned Behavior, and constructs a multi-level model including antecedent variables, mediating variables and moderating variables.

3 Hypothesis proposal

3.1 Autonomy

Autonomy, as the core dimension of technology innovation characteristics, refers to the ability of agricultural AI to achieve intelligent control of the livestock production process through algorithm optimization and automated decision-making (McOmber, 1999). In the special environment of high cold, hypoxia and strong radiation in Qinghai pastoral areas, autonomy can effectively make up for the excessive dependence of traditional animal husbandry on manual experience (Stépanoff et al., 2017). For example, the intelligent environment control system can significantly reduce the labor intensity of herdsmen under extreme weather conditions by monitoring the temperature and humidity in livestock sheds in real-time and automatically adjusting parameters (Wang et al., 2018); the livestock health monitoring system can automatically issue disease risk warnings based on physiological data (Sharma and Koundal,

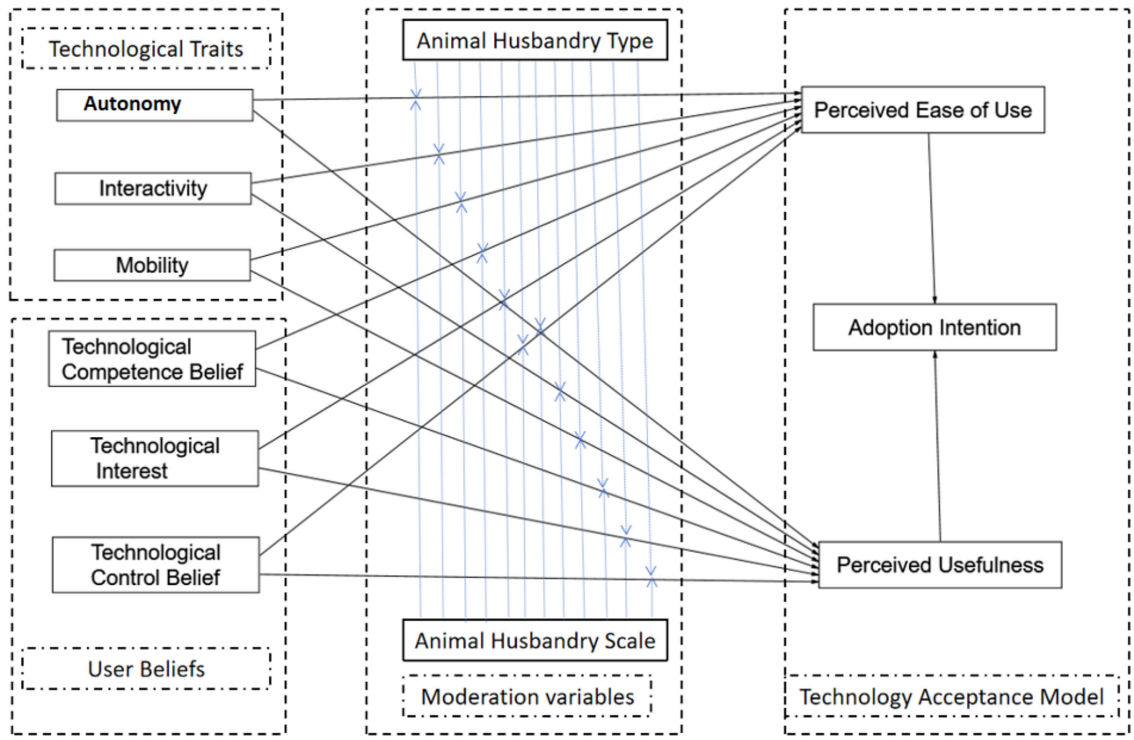

FIGURE 1
Theoretical model.

2018), thereby improving the efficiency of disease prevention and control. This autonomous decision-making ability of agricultural AI directly strengthens the herdsmen's perception of its value, forming a positive driving force for perceived usefulness.

At the same time, autonomy reduces the user's learning cost by simplifying the operation process (Soma et al., 2022). Even herdsmen with limited educational levels can use agricultural AI efficiently, thus improving perceived ease of use. Existing studies have shown that there is a significant positive correlation between the agricultural AI adoption intention and autonomy in the agricultural field (Corral et al., 2020; Devitt, 2021), which provides theoretical support for the hypotheses of this study. In Qinghai pastoral areas, autonomy has special adaptability to scenarios such as the seasonal migration management of nomadic animal husbandry and the precise feeding control of sedentary animal husbandry. By reducing the demand for manual intervention, it not only meets the core demand of herdsmen for the practicality of technology, but also alleviates the operation obstacles brought by the complex geographical environment, and finally forms a double-promotion effect on the adoption intention. Therefore, the following hypotheses are proposed in this study:

> *H1a*: Autonomy has a positive impact on perceived ease of use;
>
> *H1b*: Autonomy has a positive impact on perceived usefulness.

3.2 Interactivity

Interactivity, as a key dimension of technology innovation characteristics, emphasizes real-time interaction and feedback efficiency (Yadav and Pavlou, 2020). In the livestock production process, real-time and efficient human-machine interaction can timely meet the herdsmen's needs in livestock health management, grazing scheduling and other aspects (Weston, 2017). For example, the intelligent grazing system supports herdsmen to receive real-time information such as the location and health status of livestock through mobile terminals and issue instructions in a timely manner (Sadiq et al., 2024), so as to effectively manage grazing activities and improve operational efficiency, which directly strengthens the herdsmen's perceived usefulness of agricultural AI. In addition, a well-designed interactive interface makes the agricultural AI operation more intuitive and convenient, reducing the learning cost and operation difficulty. Even herdsmen with weak technical foundations can easily master artificial intelligence, thereby improving perceived ease of use. Therefore, the following hypotheses are proposed in this study:

> *H2a*: Interactivity has a positive impact on perceived ease of use;
>
> *H2b*: Interactivity has a positive impact on perceived usefulness.

3.3 Mobility

Mobility, as a key dimension of technology innovation characteristics, refers to the ability of agricultural AI to adapt to nomadic scenarios. Its core value lies in breaking through geographical limitations and meeting the mobility needs of livestock production (Turner et al., 2014). In Qinghai pastoral areas, herdsmen have long faced challenges such as vast grassland areas, inconvenient transportation and imperfect network coverage. The traditional livestock-raising methods rely on manual inspections and experience-based judgments, which are inefficient and have limited ability to cope with extreme weather (Abdela, 2024). Technologies with mobility, through innovative designs such as portable sensors, mobile terminals and offline data processing, enable herdsmen to obtain real-time information on livestock locations and grassland conditions in environments without fixed communication infrastructure. For example, intelligent livestock collars can store physiological data offline in scenarios without network, and the drone-based grazing monitoring system can cover high-altitude areas that are difficult to reach by manual inspections (Lamanna et al., 2025). These technical characteristics directly strengthen the herdsmen's recognition of the practical value of agricultural AI, driving a positive cognition of perceived usefulness.

In addition, the mobility-oriented design simplifies the user interface and improves the portability of equipment, significantly reducing the adoption threshold. In remote pastoral areas with scarce network, even herdsmen with limited technical literacy can complete basic operations without frequent parameter adjustments. Empirical studies have confirmed that there is a positive correlation between the adoption rate of mobile technologies in the agricultural field and technology mobility (Kabbiri et al., 2018). Combining with the unique high-altitude nomadic production mode in Qinghai, the demand for agricultural AI with mobility is particularly urgent. Therefore, the following hypotheses are proposed in this study:

> *H3a*: Mobility has a positive impact on perceived ease of use;
>
> *H3b*: Mobility has a positive impact on perceived usefulness.

3.4 Technological interest

As the core dimension of technological commitment, technological interest reflects herders' intrinsic motivation to explore agricultural AI and their recognition of its value. In Qinghai pastoral areas, technological interest stimulates herders' curiosity and intention to learn about agricultural AI (Arnone et al., 2011), directly strengthening their cognitive understanding of technological value. When herders have a high level of interest in agricultural AI, they are more inclined to proactively understand its functions, application scenarios, and potential benefits. This proactive cognitive process significantly enhances their perceived usefulness.

Meanwhile, technological interest indirectly improves perceived ease of use by reducing psychological resistance. Herders with strong technological interest are more willing to invest time in learning operational processes (Autry, 2009). Even when facing complex interfaces or new functions, their intrinsic motivation helps them overcome learning barriers more easily, forming psychological expectations of perceived ease of use. In the unique context of Qinghai pastoral areas, the motivating effect of technological interest may be more prominent: herders have long faced issues of low efficiency and high environmental risks in traditional animal husbandry, and thus have an intrinsic demand for technologies that solve practical problems. Therefore, this study proposes the following hypotheses:

> *H4a*: Technological interest has a positive impact on perceived ease of use;
>
> *H4b*: Technological interest has a positive impact on perceived usefulness.

3.5 Technological competence belief

As a key dimension of technological commitment, technological competence belief reflects herders' confidence in their own ability to operate agricultural AI. In the unique scenario of Qinghai pastoral areas, technological competence belief strengthens herders' cognitive understanding and sense of control over technological functions (Yerdelen-Damar et al., 2017), directly influencing their judgment of agricultural AI's value. When herders possess technological competence belief, they are more likely to recognize AI's practical value in improving livestock production efficiency (Gieselmann and Sassenberg, 2023)—for instance, optimizing feed ratios through precision feeding systems (Sonea et al., 2023) or improving livestock shed conditions via intelligent environmental control systems (Yu and Yu, 2014). This confidence in operational ability directly enhances perceived usefulness.

In addition, technological competence belief indirectly improves perceived ease of use by alleviating operational anxiety. Herders with strong technological competence belief can more easily overcome learning barriers caused by complex interfaces and diverse functions—such as proficiently using integrated space-air-ground monitoring systems to analyze grassland data, or efficiently scheduling livestock activities through intelligent grazing terminals. This operational confidence fosters psychological expectations of perceived ease of use. Therefore, this study proposes the following hypotheses:

> *H5a*: Technological capability belief has a positive impact on perceived ease of use;
>
> *H5b*: Technological capability belief has a positive impact on perceived usefulness.

3.6 Technological control belief

As an important dimension of technological commitment, technological control belief reflects herders' confidence in their ability to control agricultural AI's operation and decision-making processes. In Qinghai pastoral areas, this belief enhances herders' trust and sense of security in agricultural AI, directly affecting their evaluation of perceived usefulness. When herders perceive that they can effectively control technological operations, they are more likely to recognize agricultural AI's practical value in livestock production—for example, independently adjusting grazing routes through intelligent grazing systems (Cao et al., 2023) or precisely regulating feed distribution using intelligent feeding equipment (Su et al., 2024). This sense of control directly strengthens perceived usefulness.

At the same time, technological control belief indirectly improves perceived ease of use by reducing operational uncertainty. Herders with strong technological control belief are more willing to proactively explore technological functions; even when facing complex operational processes, their sense of control helps them overcome technical barriers, forming a psychological expectation of "ease of use." In the unique scenario of Qinghai pastoral areas, the driving effect of technological control belief may be more significant: under complex geographical environments and limited technical resources, herders need to rely on their own capabilities to ensure the effective application of technology. Therefore, this study proposes the following hypotheses:

> *H6a*: Technological control belief has a positive impact on perceived ease of use;
>
> *H6b*: Technological control belief has a positive impact on perceived usefulness.

3.7 Mediating variables: perceived usefulness and perceived ease of use

As core mediating variables of the Technology Acceptance Model (TAM), perceived usefulness and perceived ease of use play a key role in the driving mechanism of agricultural AI adoption intention in Qinghai pastoral areas (Caffaro et al., 2020). Perceived usefulness refers to herders' belief that AI can improve livestock production efficiency and economic benefits. In Qinghai pastoral areas, if herders perceive that agricultural AI—such as intelligent grazing systems, livestock health monitoring systems, and precision feeding technologies—can effectively address the pain points of traditional animal husbandry, they are more likely to consider the technology highly practical, thereby strengthening their adoption intention. For example, intelligent feeding systems that precisely control feed distribution can reduce breeding costs and improve livestock growth quality, making herders truly recognize the technology's value and increasing the likelihood of adoption intention.

Perceived ease of use reflects herders' cognitive evaluation of the simplicity of technology operation and the difficulty of learning (Saadé and Bahli, 2005). When herders perceive agricultural AI as easy to learn and use, they are more psychologically receptive and tend to engage in adoption intention, thereby enhancing perceived ease of use. For instance, portable livestock health monitoring equipment with low operational thresholds increases herders' adoption intention (Sadiq et al., 2024). Therefore, this study proposes the following hypotheses:

> *H7*: Perceived ease of use has a positive impact on adoption intention;
>
> *H8*: Perceived usefulness has a positive impact on adoption intention.

3.8 Moderating variables (animal husbandry type and breeding scale)

In the study of the driving mechanism of agricultural AI adoption intention in Qinghai pastoral areas under the context of smart animal husbandry, animal husbandry type and breeding scale serve as key moderating variables. Through differentiated production models and technological demand characteristics, they significantly influence the relationships between technological innovation characteristics, technological commitment, and core mediating variables (perceived usefulness, perceived ease of use).

Differences in animal husbandry type are mainly reflected in the mobility of production scenarios, the complexity of agricultural AI scenarios, and herders' level of technological cognition. Extensive animal husbandry is characterized by large-scale and intensive operations (Kerven et al., 2021), with relatively fixed production scenarios and prominent demand for autonomy. For example, intelligent environmental control systems can reduce labor input through automated decision-making (Alavian et al., 2020); this scenario adaptability strengthens the positive correlation between autonomy and perceived ease of use. Meanwhile, operators of extensive animal husbandry usually have higher technological sensitivity, and the positive moderating effect of technological interest on perceived usefulness is significant—meaning they are more likely to convert cognitive recognition of technological value into adoption intention. However, the mobility of nomadic animal husbandry limits the application of interactive technologies. Affected by insufficient network coverage and frequent switching of operational scenarios, the promoting effect of interactivity on perceived usefulness is weakened, forming a negative moderating effect. Intensive indoor animal husbandry has higher requirements for technological control belief; herders tend to achieve precision management by independently adjusting feeding parameters, and this control demand indirectly strengthens the relationship between autonomy and perceived ease of use.

Differences in breeding scale are reflected in resource endowments and technological adoption capabilities (Sui and Gao, 2023). Large-scale farms, relying on financial and technological advantages, are more likely to drive the improvement of perceived usefulness and perceived ease of use through technological interest, forming a positive moderating effect. In contrast, small-scale farms, constrained by training resources and operational capabilities, have a relatively weaker moderating effect of technological commitment on mediating variables. Therefore, this study proposes the following hypotheses:

> *H9*: Animal husbandry type has a partial moderating effect on the relationships between external variables, as well as between external variables and perceived ease of use and perceived usefulness;
>
> *H10*: Breeding scale has a partial moderating effect on the relationships between external variables, as well as between external variables and perceived ease of use and perceived usefulness.

4 Research materials and methods

4.1 Positioning of research paradigm

This study adopts the positivist research paradigm, which is characterized by observability, verifiability, and objectivity. It reveals the causal relationships between variables through hypothesis testing and quantitative data analysis, and is applicable to social science research with clear variable relationships such as technology adoption behavior (Clark et al., 2021). Its adaptability is reflected in three aspects. Firstly, the study aims to verify the causal path of "technological innovation characteristics - technology commitment - perceived usefulness/ease of use - adoption intention" and the moderating effects of animal husbandry type and breeding scale. It requires empirical data to test preset hypotheses, which is highly consistent with the positivist logic of "hypothesis-driven and causal verification." Secondly, core variables are all quantifiable constructs, which can be converted into observable data through a 7-point Likert scale, meeting the requirement of "measurable variables." Thirdly, the partial least squares structural equation modeling (PLS-SEM) is used as the core analysis tool. This method is a mainstream approach for testing complex causal models under positivism. It can objectively verify theoretical hypotheses through reliability and validity tests and path coefficient significance analysis, avoiding subjective biases (Hair et al., 2021). To make up for the limitation of this paradigm in "ignoring situational complexity," the study is optimized from two aspects. On one hand, scenario-based items related to the "alpine and nomadic" characteristics of Qinghai pastoral areas are integrated into the questionnaire design to improve the situational adaptability of variable measurement. On the other hand, animal husbandry type and breeding scale are set as moderating variables, and multi-group analysis is conducted to reveal the differences in mechanisms under different production scenarios, balancing the rigor of empirical research and the particularity of scenarios.

4.2 Questionnaire design

Guided by the principles of "scale standardization and measurement repeatability" under the positivist paradigm, this study designs a structured questionnaire as the data collection tool based on the theory of technological innovation characteristics, the theory of technology commitment, and the Technology Acceptance Model (TAM), ensuring the objectivity of the measurement process and the comparability of data. The questionnaire structure includes three core modules. The first module is "research description and informed consent," which clearly informs respondents of the research purpose, data usage, and anonymity protection, in line with the ethical norms of empirical research. The second module is "demographic and situational variables," covering gender, years of work experience, animal husbandry type (extensive/nomadic/confined), and breeding scale (large/medium/small). Among these, animal husbandry type and breeding scale are key variables for subsequent moderating effect analysis, and are presented in the form of multiple-choice questions to ensure the objectivity of data coding, with a total of 5 items. The third module is "measurement of core latent variables." Based on existing mature scales and combined with the scenario of Qinghai pastoral areas, the questionnaire is adapted to include 38 items, covering 9 latent variables (see Table 1). All items adopt a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree), and convert subjective perceptions into analyzable data through the gradient quantification of "complete negation to complete affirmation."

For scale sources and situational adaptation, to ensure measurement validity, the scales for core latent variables are all derived from mature scales verified in empirical studies, and items are adjusted according to the characteristics of Qinghai pastoral areas. For technological innovation characteristics, the scales of Seiferth (2020) and Ivanov (2023) are referred, and scenario-based items such as "The equipment can store data in pastures without network access" (mobility) and "Operation can be conducted through Tibetan-Chinese bilingual interfaces" (interactivity) are added. For technology commitment (technological interest, technological competence belief, technological control belief), the scales of Rasheed et al. (2023) and Yerdelen-Damar et al. (2017) are used for reference, and items such as "I am confident in learning to use intelligent grazing equipment" (technological competence belief) are adjusted. For perceived usefulness, perceived ease of use, and adoption intention, based on the original TAM scale of Davis (1989), items such as "The use of artificial intelligence can reduce the number of patrols in alpine weather" (perceived usefulness) are adapted.

For pre-survey and scale optimization, to improve scale reliability, a pre-survey was conducted in Yushu, Qinghai in March 2025, with 50 questionnaires distributed and 46 valid ones recovered. Through item analysis (critical ratio method), items with factor loadings < 0.5 (e.g., "I can quickly understand all functions of the technology") were deleted. Meanwhile, items with ambiguous expressions were adjusted according to herders' feedback (e.g., changing "intelligent monitoring" to "intelligent collar monitoring"). Finally, the formal questionnaire

TABLE 1 Core latent variables and item distribution.

Latent variable	Number of items	Scale source	Example of scenario-adapted item
Mobility	4	Songol et al. (2021)	The device can store data in pastures without network access.
Interactivity	3	Holzinger et al. (2024)	The device can be operated via a Tibetan-Chinese bilingual interface.
Autonomy	4	Khanna et al. (2024)	The device can automatically alert to abnormal livestock health.
Technological interest	3	De Witt et al. (2021)	I am willing to learn about the usage of intelligent grazing technology.
Technological competence belief	4	Adenan et al. (2025)	I am confident in learning to use intelligent grazing devices.
Technological Control Belief	3	von Rübcke Veltheim and Heise (2021)	I can independently adjust the monitoring frequency of the device.
Perceived usefulness	6	Caffaro et al. (2020)	Using artificial intelligence can reduce the number of patrols in alpine weather.
Perceived ease of use	6	Arrang et al. (2025)	I think it is not difficult to master the operation of artificial intelligence.
Adoption intention	6	Sood et al. (2024)	I may use artificial intelligence devices within the next year.

was formed to ensure the scientificity and scenario adaptability of the measurement tool.

4.3 Data collection

In line with the principles of "sampling representativeness and data objectivity" under the positivist paradigm, this study adopted a combination of "stratified sampling + convenience sampling" for data collection. The specific procedures and quality control measures are as follows. For the sampling framework design, a stratified sampling framework was constructed based on the administrative divisions and distribution of animal husbandry types in Qinghai pastoral areas. The first layer was stratified by administrative region, covering 6 major pastoral prefectures in Qinghai (Yushu, Golog, Hainan, Haibei, Haixi, Huangnan) to ensure the regional representativeness of the sample. The second layer was stratified by animal husbandry type. According to the pre-survey data, the proportion of nomadic, confined, and extensive animal husbandry in Qinghai pastoral areas was approximately 5:3:2. The sampling proportion for each type was determined based on this ratio to avoid biases caused by over-sampling of a single type. Finally, the formal survey was conducted from April to May 2025 through a combination of the "Wenjuanxing online platform + offline distribution with the assistance of local animal husbandry departments," ensuring coverage of samples in remote pastoral areas.

The sample size needed to meet the dual requirements of "model complexity" and "statistical power." The sample size estimation referred to the "10-times rule for the number of latent variable paths" proposed by Hair et al. (2011). The model in this study included 14 core paths, requiring a minimum sample size of ≥ 140. Meanwhile, based on the effect size analysis using G*Power 3.1 software (medium effect $f^2 = 0.15$, significance level $\alpha = 0.05$, power $1-\beta = 0.8$), the calculated minimum required sample size was 220. A total of 500 questionnaires were distributed in the formal survey, with 374 recovered. After validity checks (deleting questionnaires completed in < 60 s and those with regularized responses), 321 valid questionnaires were finally obtained, resulting in an effective recovery rate of 64.2%. This met the sample size requirement, and the sample structure was basically consistent with the distribution of animal husbandry types in Qinghai pastoral areas (see Table 2), ensuring the representativeness of the data.

To avoid "common method bias" and "response bias" commonly seen in empirical studies, the following quality control measures were adopted for data quality. Firstly, the questionnaire instructions emphasized that "there are no right or wrong answers, and only truthful responses are required." Reverse-scored items were used to test the seriousness of respondents' answers. Secondly, Harman's single-factor test was conducted to perform an unrotated exploratory factor analysis on all latent variable items. The results (see Table 3) showed that the variance explained by the first factor was 28.76% (< 40%), indicating no serious common method bias (Podsakoff et al., 2003). Thirdly, Cronbach's α coefficient was used to test the internal consistency of each latent variable. The pre-survey results showed that the α value of all latent variables was > 0.7, ensuring the stability of the measurement tool.

4.4 Data analysis methods

This study adopted a "step-by-step verification" logic for data analysis, and systematically tested the theoretical model using SmartPLS 4.0 and SPSS 26.0 software. For descriptive statistical analysis, SPSS 26.0 was used to conduct descriptive statistics on sample characteristics. This helped verify the consistency between the sample structure and the research population, ensuring data representativeness, and initially determined the distribution characteristics of variables, providing a basic reference for subsequent hypothesis testing. In line with the standard procedure of PLS-SEM analysis (Hair et al., 2021), the measurement model test verified the reliability and validity of the measurement tool through the following indicators, ensuring the "objectivity of variable measurement." Based

TABLE 2 Comparison between sample structure and overall structure of Qinghai pastoral areas.

Comparison dimension	Category/region/scale	Sample proportion (n = 321)	Overall proportion	Proportion difference
Animal husbandry type	Nomadic	55.29%	54.8%	< 0.5%
	Confined	26.89%	27.1%	< 0.5%
	Extensive	17.82%	18.1%	< 0.5%
Breeding scale	Small and medium-scale	44.41%	45.2%	No significant deviation
	Medium-scale	41.39%	40.7%	No significant deviation
	Large-scale	14.20%	14.1%	No significant deviation
Regional distribution	Yushu	26.17%	26.3%	Basically consistent
	Haixi	25.86%	25.9%	Basically consistent
	Hainan	24.29%	24.1%	Basically consistent
	Huangnan	23.67%	23.7%	Basically consistent
Device usage experience	Used intelligent livestock- raising devices	38.63%	37.9%	In line with current situation
	Never used intelligent livestock-raising devices	61.37%	62.1%	In line with current situation

TABLE 3 Results of common method bias test.

Test method	Test indicator	Test result	Critical threshold	Conclusion
Harman's single-factor test	Variance explained by the first common factor.	28.76%	<40%	No significant common method bias
Common method factor test	Average variance explained by the common method factor.	6.32%	<10%	Impact of common method bias is controllable
Common method factor test	Average change in item factor loadings.	<0.05	<0.10	Latent variable structure is undisturbed

on the verified measurement model, the structural model test examined the causal relationships between variables using PLS-SEM, including collinearity test, path coefficient and significance test, and evaluation of model explanatory power and predictive power. For the moderating effect test, targeting the two moderating variables, a combination of "multi-group analysis (MGA) + interaction term test" was adopted to ensure the robustness of the conclusions. The above analysis steps strictly followed the principles of the positivist paradigm, with each step verified by objective indicators to avoid subjective inference and ensure the scientificity and reliability of the research conclusions.

5 Research results

5.1 Assessment of the measurement model

In structural equation modeling (SEM), the validation of the measurement model is a critical step to ensure that the relationships between latent variables and their observed indicators are theoretically consistent and valid (Mueller and Hancock, 2018). This study employs the partial least squares structural equation modeling (PLS-SEM) for empirical analysis. This method has advantages in handling complex models and small-sample issues, while also enabling strict control of measurement errors to validate theoretical hypotheses (Hair et al., 2023). The assessment of the measurement model focuses on three core dimensions: (1) Reliability assessment: Internal consistency indicators such as Cronbach's α and composite reliability (CR) are used to evaluate the stability of observed variables in measuring latent variables; (2) Validity assessment: Convergent validity is tested through factor loadings and average variance extracted (AVE), and combined with content validity to ensure that observed variables fully reflect the theoretical connotations of latent variables; (3) Discriminant validity: The correlation coefficients between latent variables are compared with the square roots of AVE values to verify the uniqueness of different latent variables. This systematic validation process lays a solid foundation for subsequent structural model analysis, thereby enhancing the robustness and credibility of the research conclusions.

5.1.1 Reliability assessment

Reliability assessment aims to verify the stability and internal consistency of the scale measurement results, which serves as the basis for ensuring the validity of subsequent analyses (Kimberlin and Winterstein, 2008). This study adopts a tri-indicator framework of Factor Loading, Cronbach's α and composite reliability (CR), and the combination of the two can comprehensively evaluate the measurement quality. As shown in Table 4: All factor loadings are greater than 0.7, meeting the standard of convergent validity (Hair et al., 2021). And as shown in Table 5: All latent variables have Cronbach's α values ranging from 0.765 to 0.898, which are far higher than the critical standard of 0.7, indicating that the measurement items of each construct have good internal consistency; The composite reliability (CR) values all range from 0.785 to 0.903, meeting the ideal threshold of 0.7, and the CR values of most constructs exceed 0.8, indicating that the measurement accuracy of latent variables is high and can stably capture herders' cognition and attitudes towards artificial intelligence; The average variance extracted (AVE) values all range from 0.607 to 0.799, all higher than the minimum standard of 0.5, further indicating that the measurement items of each latent variable can effectively extract the core information of the construct. In conclusion, both the reliability and convergent validity of the measurement model meet the standards, and the scale design is scientific and reasonable, which can be used for subsequent structural model analysis.

5.1.2 Validity assessment

Discriminant validity is used to verify the independence between different latent variables and ensure that the scale does not confound the measurement of similar constructs (Ab Hamid et al., 2017). This study adopts a dual-method approach of "Fornell-Larcker Criterion + Heterotrait-Monotrait Ratio" for testing, with specific results shown in Table 6. This criterion requires that "the square root of the AVE value of any construct is greater than the correlation coefficient between that construct and all other constructs." As can be seen from the diagonal data in Table 6: the square root of AVE for "autonomy" is 0.894, and its highest correlation coefficient with "perceived ease of use" is 0.543. Since 0.894 > 0.543, it indicates that "autonomy" and "perceived ease of use" are two independent constructs without measurement confusion; the square root of AVE for "technological interest" is 0.858, and its highest correlation coefficient with "adoption intention" is 0.723. As 0.858 > 0.723, it shows that although "technological interest" and "adoption intention" are highly correlated, they still have clear construct boundaries; all constructs meet this criterion, confirming that the measurement indicators of different latent variables can accurately capture their respective core connotations without cross-interference.

The HTMT value reflects the ratio of "the average correlation between items of the same construct" to "the average correlation between items of different constructs," with the critical value usually set at 0.9 or 0.95 (Henseler et al., 2015). The results show that (Table 7): Most constructs have HTMT values below 0.9. For example, the HTMT between "mobility" and "perceived usefulness" is 0.797, and the HTMT between "technological control belief" and

TABLE 4 Measurement index and factor load table.

Latent variable	Observed indicator	Factor loading
Mobility (MO)	MO1: The device can store data in pastures without network access.	0.819
	MO2: The device is portable and suitable for nomadic grazing.	0.873
	MO3: The device can work normally in remote high-altitude areas.	0.851
	MO4: The device supports offline data synchronization when network is available.	0.878
Interactivity (IN)	IN1: The device can be operated via a Tibetan-Chinese bilingual interface.	0.854
	IN2: The device provides real-time feedback on operation results.	0.849
	IN3: The device's operation steps are intuitive and easy to interact with.	0.862
Autonomy (AU)	AU1: The device can automatically alert to abnormal livestock health.	0.875
	AU2: The device can automatically adjust parameters according to environmental changes.	0.884
	AU3: The device can complete routine monitoring tasks without manual intervention.	0.922
Technological interest (TI)	TI1: I am willing to learn about the usage of intelligent grazing technology.	0.873
	TI2: I am curious about the functions of agricultural AI devices.	0.877
	TI3: I actively pay attention to the application cases of agricultural AI in pastoral areas.	0.824
Technological competence belief (TCB)	TCB1: I am confident in learning to use intelligent grazing devices.	0.872
	TCB2: I can solve simple operational problems of AI devices independently.	0.835
	TCB3: I can master new functions of AI devices through short-term learning.	0.836
	TCB4: I can explain the basic working principles of used AI devices.	0.831
Technological control belief (TCoB)	TCoB1: I can independently adjust the monitoring frequency of the device.	0.794
	TCoB2: I can customize the alert threshold of the device according to my needs.	0.876
	TCoB3: I can control the start and stop of the device's core functions freely.	0.800
Perceived usefulness (PU)	PU1: Using artificial intelligence can reduce the number of patrols in alpine weather.	0.857
	PU2: Using artificial intelligence can improve the accuracy of livestock health monitoring.	0.867
	PU3: Using artificial intelligence can reduce breeding costs (e.g., feed, medicine).	0.875
	PU4: Using artificial intelligence can improve the survival rate of livestock.	0.803
	PU5: Using artificial intelligence can increase breeding income.	0.701
	PU6: Using artificial intelligence is helpful for long-term breeding management.	0.787
Perceived ease of use (PEU)	PEU1: I think it is not difficult to master the operation of artificial intelligence.	0.778
	PEU2: The operation steps of artificial intelligence devices are simple and clear.	0.792
	PEU3: I can use artificial intelligence devices proficiently without professional training.	0.767
	PEU4: The interface design of artificial intelligence devices is user-friendly.	0.808
	PEU5: It is easy to troubleshoot common problems of artificial intelligence devices.	0.807
	PEU6: Learning to use artificial intelligence does not require too much time and energy.	0.707
Adoption intention (AI)	AI1: I may use artificial intelligence devices within the next year.	0.758
	AI2: I am willing to recommend artificial intelligence devices to other herders.	0.832
	AI3: I plan to increase the use of artificial intelligence in breeding management.	0.812
	AI4: Even if there is a small cost, I am willing to try artificial intelligence devices.	0.800
	AI5: I believe that using artificial intelligence is a necessary trend in pastoral breeding.	0.813
	AI6: I will actively understand the update of artificial intelligence breeding technology.	0.833

All factor loadings are greater than 0.7, meeting the standard of convergent validity (Hair et al., 2021).

"perceived ease of use" is 0.614, indicating that these constructs have good discriminability; only the HTMT values of "interactivity" and "adoption intention" and "interactivity" and "mobility" are slightly higher than 0.90, but do not exceed the lenient critical value of 0.95. Moreover, this can be explained in combination with the actual scenario: "interactivity" is an important prerequisite for herders to perceive the value of technology and form adoption intention, and the strong correlation between them is a reasonable phenomenon that will not affect the overall discriminant validity. In conclusion, the test results of the two methods consistently show that the discriminant validity of the measurement model meets the standards, and the boundaries of each construct are clear, which can be used for the path relationship analysis of the subsequent structural model.

TABLE 5 Reliability test.

Constructs	Cronbach's alpha	CR	AVE
Autonomy	0.876	0.890	0.799
Adoption intention	0.894	0.898	0.654
Interactivity	0.816	0.817	0.731
Mobility	0.878	0.881	0.732
Perceived ease of use	0.872	0.886	0.607
Perceived useful	0.898	0.903	0.665
Technological competence belief	0.867	0.892	0.712
Technological control belief	0.765	0.785	0.679
Technological interest	0.821	0.823	0.736

TABLE 6 Validity of discrimination (FLC).

Constructs	1	2	3	4	5	6	7	8	9
Autonomy	**0.894**								
Adoption intention	0.465	**0.808**							
Interactivity	0.517	0.782	**0.855**						
Mobility	0.435	0.786	0.81	**0.855**					
Perceived ease of use	0.543	0.608	0.666	0.639	**0.779**				
Perceived useful	0.453	0.7	0.681	0.711	0.776	**0.816**			
Technological competence belief	0.329	0.148	0.184	0.227	0.236	0.179	**0.844**		
Technological control belief	0.533	0.487	0.5	0.556	0.497	0.416	0.354	**0.824**	
Technological interest	0.46	0.723	0.68	0.719	0.606	0.651	0.171	0.507	**0.858**

Values on diagonal indicate the square root of the AVE.

TABLE 7 Validity of discrimination (HTMT).

Constructs	1	2	3	4	5	6	7	8	9
Autonomy									
Adoption intention	0.52								
Interactivity	0.598	0.915							
Mobility	0.483	0.880	0.953						
Perceived ease of use	0.612	0.653	0.766	0.699					
Perceived useful	0.508	0.775	0.793	0.797	0.849				
Technological competence belief	0.382	0.172	0.212	0.255	0.278	0.197			
Technological control belief	0.645	0.579	0.624	0.674	0.614	0.497	0.442		
Technological interest	0.532	0.843	0.831	0.845	0.687	0.758	0.193	0.638	

5.2 Assessment of the structural model

After completing the assessment of the reliability and validity of the measurement model, this study uses partial least squares structural equation modeling (PLS-SEM) to conduct an empirical analysis of the path relationships between latent variables in the theoretical framework. The core objectives of the structural model assessment are closely aligned with the research objectives. Through the significance test of path coefficients (with 5,000 Bootstrap samples), the statistical rationality of 14 research hypotheses, such as "the impact of technological innovation characteristics and technology commitment on perceived usefulness and perceived ease of use," is determined; by quantifying the magnitude of direct effects between latent variables (e.g., the β value of mobility on perceived usefulness is 0.375), the order of influence intensity of each driving factor is clarified; through indicators such as R^2, the explanatory power of the model for herders' intention to adopt agricultural AI in pastoral areas and its out-of-sample predictive power are tested, ensuring that the research conclusions can effectively serve the practical goal of "formulating precise promotion strategies."

5.2.1 Collinearity test

Multi-collinearity refers to a high degree of linear correlation between different exogenous variables, which may lead to deviations in path coefficient estimation. Therefore, a variance inflation factor (VIF) test is required before structural model analysis (Ramli et al., 2018). The critical standard for VIF values is usually 5, and a value exceeding 10 indicates a serious multi-collinearity problem (Osrof et al., 2025). As shown in Table 8, the VIF values of all exogenous variables for the same endogenous variable range from 1.195 to 3.353, which are far lower than the critical value of 5, and there is no significant multi-collinearity; the path with the highest multi-collinearity risk is "mobility → perceived ease of use" (VIF = 3.69), but this value is still within the safe range. The reason is that although "mobility" and "interactivity" both belong to technological innovation characteristics, the former focuses on "adaptation to usage scenarios" while the latter focuses on "human-computer communication efficiency," with significant differences in core connotations, which will not lead to deviations in path coefficient estimation; the VIF value of "technological competence belief" on "perceived usefulness" is 1.195, the lowest among all paths, indicating that "technological competence belief" has a weak correlation with other exogenous variables and has independent explanatory power. In conclusion, the model has no significant multi-collinearity problem, and subsequent path coefficient estimation and hypothesis testing can be carried out with confidence.

5.2.2 Model explanatory power (R^2) and predictive relevance (Q^2)

Model explanatory power (R^2), predictive relevance (Q^2), and effect size (f^2) together constitute the core effectiveness indicators of the structural model. Among them, R^2 measures the degree to which exogenous variables explain the variance of endogenous variables, Q^2 evaluates the out-of-sample predictive ability of the model, and f^2 quantifies the influence intensity of a single exogenous variable (Akter et al., 2011).

In social science research, an R^2 value greater than 0.4 indicates strong explanatory power, a value between 0.2 and 0.4 indicates moderate explanatory power, and a value less than 0.2 indicates weak explanatory power (Yusif et al., 2020). The R^2 results of the three core endogenous variables in this study all perform excellently, and the explanatory logic of each variable is highly consistent with the actual scenario of the Qinghai pastoral area. For perceived usefulness ($R^2 = 0.574$), six exogenous variables—"mobility," "interactivity," "autonomy," "technological interest," "technological competence belief," and "technological control belief"—jointly explain 57.4% of its variance (Table 8). This shows that herders' perception of whether agricultural AI is "useful" is significantly affected by both the adaptability of the technology itself and users' psychological traits. Further analysis reveals that technological innovation characteristics contribute more overall, among which "mobility" ($\beta = 0.375$) and "technological interest" ($\beta = 0.230$) are the core driving factors. This reflects the geographical characteristics of the vast grasslands and nomadic production in the Qinghai pastoral area, making "device portability" and "offline usage capability" the primary criteria for herders to perceive the value of technology. In contrast, "technological interest" strengthens herders' active recognition of the practical value of technology by stimulating their motivation to explore. For perceived ease of use ($R^2 = 0.540$), exogenous variables jointly explain 54% of its variance, with "interactivity" ($\beta = 0.273$) and "autonomy" ($\beta = 0.210$) making the most prominent contributions.

This is highly relevant to the reality that herders in the Qinghai pastoral area have significant differences in educational levels. "Interactivity" lowers the learning threshold by simplifying the operation interface, and "autonomy" reduces manual intervention through automated decision-making. Together, they alleviate herders' concerns about "complex technology operations" and become key paths to improve perceived ease of use. For adoption intention ($R^2 = 0.500$), "perceived usefulness" ($\beta = 0.573$) and "perceived ease of use" ($\beta = 0.163$) jointly explain 50% of its variance, which is consistent with the typical explanatory level of the TAM in agricultural scenarios (Michels et al., 2019a,b).

It is worth noting that the path coefficient of "perceived usefulness" is significantly higher than that of "perceived ease of use," indicating that in the Qinghai pastoral area, herders are more concerned about whether agricultural AI can solve practical production pain points than simply pursuing ease of operation. This is consistent with the characteristics of the harsh production conditions in pastoral areas and the focus of core needs on "efficiency improvement." At the same time, the R^2 value of 50% also suggests that there are potential variables not included in the model, such as policy subsidies, technology costs, and social network influences, which need to be further explored in subsequent studies.

Q^2 is calculated using the blindfolding method. If $Q^2 > 0$, it indicates that the model has out-of-sample predictive power; a Q^2 between 0.25 and 0.5 indicates moderate predictive power; and a $Q^2 > 0.5$ indicates strong predictive power (Hair et al., 2011). The results of this study (Table 8) show that Q^2 for "perceived ease of use" is 0.373, Q^2 for "adoption intention" is 0.322, and Q^2 for "perceived usefulness" is 0.308. All three values are greater than 0 and fall within the range of 0.25–0.5, indicating that the model has moderate predictive power for core endogenous variables, and can be used to make reasonable predictions about the intention to adopt artificial intelligence in different types of pastures in the Qinghai pastoral area.

According to Cohen's criteria, an $f^2 > 0.35$ indicates a large effect, an f^2 between 0.15 and 0.35 indicates a moderate effect, an f^2 between 0.02 and 0.15 indicates a small effect, and an $f^2 < 0.02$ indicates a negligible effect (Cohen, 2016). Combined with the data in Table 8, the effect sizes of each path differ significantly, providing a clear basis for identifying key intervention points. Among them, there is one path with a moderate effect: "perceived usefulness → adoption intention" ($f^2 = 0.262$), indicating that improving "perceived usefulness" is the core focus for promoting herders' adoption of agricultural AI. There are eight paths with small effects, covering the core dimensions of technological innovation characteristics (mobility → perceived usefulness, $f^2 = 0.089$; interactivity → perceived ease of use, $f^2 = 0.048$) and the key role of technological interest (technological interest → perceived usefulness, $f^2 = 0.054$). Although the effect sizes of these paths are smaller than the moderate effect, they are still important driving factors. There are five paths with negligible effects, mainly focusing on paths related to "technological competence belief" and "technological control belief" (e.g., technological competence belief

TABLE 8 Collinearity test, model explanatory power (R^2) and predictive validity (Q^2).

Pathway name	VIF	R^2	Adjusted R^2	f^2	Q^2
Autonomy → Perceived ease of use	1.683	0.540	0.531	0.057	0.373
Autonomy → Perceived usefulness	1.683			0.021	
Interactivity → Perceived ease of use	3.353			0.048	
Interactivity → Perceived usefulness	3.353			0.026	
Mobility → Perceived ease of use	3.690			0.016	
Mobility → Perceived usefulness	3.690			0.089	
Technological interest → Perceived ease of use	2.306	0.574	0.566	0.027	0.308
Technological interest → Perceived usefulness	2.306			0.054	
Technological competence belief → Perceived ease of use	1.195			0.001	
Technological competence belief → Perceived usefulness	1.195			0.000	
Technological control belief → Perceived ease of use	1.805			0.005	
Technological control belief → Perceived usefulness	1.805			0.007	
Perceived ease of use → Adoption intention	2.513	0.500	0.497	0.021	0.322
Perceived usefulness → Adoption intention	2.513			0.262	

Adjusted R^2 is calculated based on the formula: Adjusted $R^2 = 1 - [(1 - R^2)(n - 1)/(n - k - 1)]$, where $n = 321$ (sample size) and k is the number of exogenous variables for each endogenous variable.

→ perceived usefulness, $f^2 = 0$). This indicates that herders' "confidence in technology operation" and "sense of technological control" in the Qinghai pastoral area currently have minimal impact on perceived usefulness and perceived ease of use. This is mutually confirmed by the result in the subsequent path analysis that "the influence of technological competence belief and technological control belief is not significant," reflecting the shortcomings in the local technical training system, which need to be targeted improved in practice.

5.2.3 Path analysis and hypothesis testing

Based on the 14 research hypotheses proposed in the theoretical framework, this study used PLS-SEM to estimate path coefficients and tested their significance via the Bootstrap method (with 5,000 repeated samples) (Dwivedi et al., 2017), and the results are shown in Table 9 and Figure 2. All three dimensions of technological innovation characteristics passed the significance test, and the logic of their influence on perceived usefulness and perceived ease of use was highly consistent with the pastoral scenario. Mobility had the largest path coefficient on perceived usefulness ($\beta = 0.375$, $p < 0.005$) and also had a significant positive impact on perceived ease of use ($\beta = 0.164$, $p < 0.005$). This result is directly related to the characteristics of the Qinghai pastoral area, such as "vast grassland area, nomadism as the main production mode, and poor network coverage." Technologies with mobility can break through geographical and network constraints, allowing herders to obtain real-time data on livestock location and health even in pastures without base station coverage.

Interactivity had the strongest impact on perceived ease of use ($\beta = 0.273$, $p < 0.005$) and also had a significant impact on perceived usefulness ($\beta = 0.193$, $p < 0.05$). This is related to the current situation in the Qinghai pastoral area where some herders have "low educational levels and weak technical foundations." Technologies with strong interactivity simplify the operation process, enabling herders to use them without complex learning; at the same time, the real-time feedback function helps herders quickly respond to production issues, enhancing perceived usefulness. The path coefficient of autonomy on perceived ease of use was 0.210 ($p < 0.005$), and its coefficient on perceived usefulness was 0.122 ($p < 0.05$). In the Qinghai pastoral area's environment of "high altitude, oxygen deficiency, and high labor intensity," autonomous technologies can reduce manual intervention, alleviate herders' labor burden, and improve perceived usefulness; meanwhile, the "one-click start and automatic operation" design simplifies operation steps, enhancing perceived ease of use.

Among the three dimensions of technology commitment, only "technological interest" passed the test, while "technological competence belief" and "technological control belief" were not supported, reflecting significant differences in the psychological traits of herders regarding technology in the Qinghai pastoral area. Technological interest had a significant positive impact on both perceived usefulness ($\beta = 0.230$, $p < 0.005$) and perceived ease of use ($\beta = 0.169$, $p < 0.05$). The survey found that young herders (under 35 years old) accounted for approximately 38% of the total in the Qinghai pastoral area. This group has a strong curiosity about new

TABLE 9 Path coefficient analysis.

Pathway name	Original sample (O)	p values	Labels
Autonomy → Perceived ease of use	0.210	0.000	H1
Autonomy → Perceived usefulness	0.122	0.017	H1
Interactivity → Perceived ease of use	0.273	0.002	H2
Interactivity → Perceived usefulness	0.193	0.016	H2
Mobility → Perceived ease of use	0.164	0.050	H3
Mobility → Perceived usefulness	0.375	0.000	H3
Technological interest → Perceived ease of use	0.169	0.012	H4
Technological interest → Perceived usefulness	0.230	0.000	H4
Technological competence belief → Perceived ease of use	0.029	0.475	H5
Technological competence belief → Perceived usefulness	0.005	0.880	H5
Technological control belief → Perceived ease of use	0.062	0.265	H6
Technological control belief → Perceived usefulness	−0.072	0.181	H6
Perceived ease of use → Adoption intention	0.163	0.005	H7
Perceived usefulness → Adoption intention	0.573	0.000	H8

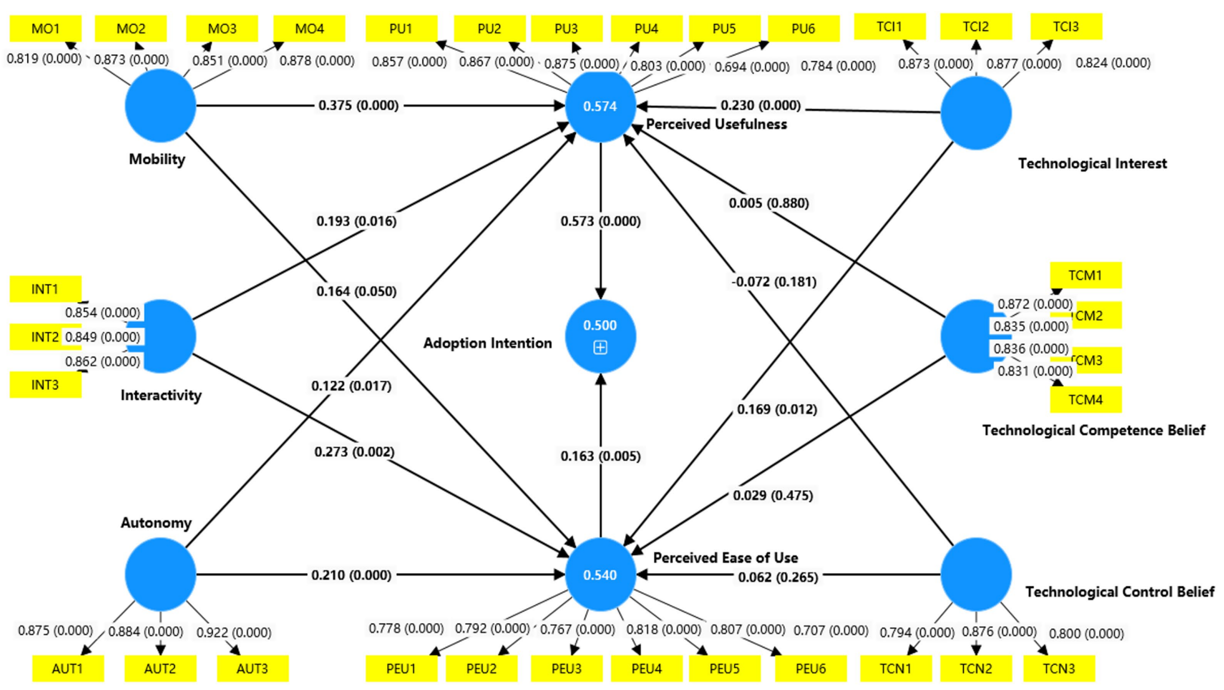

FIGURE 2
Path coefficient analysis.

technologies and is more willing to proactively understand the functions and advantages of intelligent devices. This intrinsic interest not only makes it easier for them to perceive the value of technology but also motivates them to invest time in learning how to operate it. The impact of technological competence belief on perceived usefulness ($\beta = 0.005$, $p > 0.05$) and perceived ease of use ($\beta = 0.029$, $p > 0.05$) was not significant. The reason is that technical training in the Qinghai pastoral area mainly adopts the "centralized teaching" model, lacking practical training tailored to herders' production scenarios. As a result, although herders participate in training, they still lack confidence in their own operational capabilities; at the same time, the interface design of some intelligent devices does not consider herders' usage habits, further weakening their technological competence belief. The impact of technological control belief on perceived usefulness ($\beta = -0.072$, $p > 0.05$) and perceived ease of use ($\beta = 0.062$, $p > 0.05$) was not significant, and its coefficient on perceived usefulness was negative. This is related to the "closed functions and inability to customize" of some intelligent devices.

Both the direct effects of perceived usefulness ($\beta = 0.573$, $p < 0.001$) and perceived ease of use ($\beta = 0.163$, $p < 0.005$) on adoption intention were significant, and the impact of perceived usefulness was far greater than that of perceived ease of use. This result is consistent with the "production demand priority" characteristic of the Qinghai pastoral area. Herders are more concerned about whether technology can solve practical problems such as "tiring herding work, frequent diseases, and low income" than about the simplicity of operation.

5.3 Moderating effect analysis

To ensure the clarity and reproducibility of the moderating effect analysis, a three-step method was adopted: "grouping of moderating variables → test of differences in path coefficients between groups → verification of the significance of interaction terms."

5.3.1 Grouping of moderating variables and descriptive statistics

Samples were divided into three groups: nomadic ($n = 183$), confined ($n = 89$), and extensive ($n = 59$) (see Table 10). Among them, the path coefficient of "interactivity → perceived usefulness" in the nomadic group (0.082) was significantly lower than that in the confined group (0.315), suggesting that animal husbandry type may have a moderating effect; samples were divided into three groups: small-scale ($n = 147$), medium-scale ($n = 137$), and large-scale ($n = 47$). The path coefficient of "technological interest → perceived usefulness" in the large-scale group (0.352) was higher than that in the small-scale group (0.168), indicating the potential moderating role of breeding scale.

5.3.2 Test of inter-group path coefficient differences (PLS-MGA)

Partial Least Squares Multi-Group Analysis (PLS-MGA) was used to test the significant differences in path coefficients after grouping, and the results are shown in Table 11. The differences between the nomadic group and the confined group in the "interactivity → perceived usefulness" path ($\Delta\beta = -0.233$, $p < 0.001$), and between the nomadic group and the extensive group in the "mobility → perceived usefulness" path ($\Delta\beta = 0.189$, $p < 0.05$) were both significant; the differences between the large-scale group and the small-scale group in the "technological interest → perceived usefulness" ($\Delta\beta = 0.184$, $p < 0.05$) and "technological interest → perceived ease of use" ($\Delta\beta = 0.156$, $p < 0.05$) paths were both significant.

5.3.3 Verification of interaction term significance

Interaction terms of "moderating variable × independent variable" were introduced into the model, and the moderating effect was further verified through the significance of the path coefficients of the interaction terms. The results are shown in Table 10: animal husbandry type had a significant moderating effect on "autonomy → perceived ease of use" ($\beta = 0.086$, $p < 0.05$) and "interactivity → perceived usefulness" ($\beta = -0.220$, $p < 0.005$); breeding scale had a significant moderating effect on "technological interest → perceived usefulness" ($\beta = 0.096$, $p < 0.05$) and "technological interest → perceived ease of use" ($\beta = 0.109$, $p < 0.05$).

Based on the moderating effect test results in Table 11, animal husbandry type and breeding scale exert a significant moderating effect on the paths of "technological innovation characteristics/technology commitment → perceived usefulness/perceived ease of use" by altering technology demand scenarios and resource endowments.

Animal husbandry type generates differentiated moderation on four core paths through production scenario characteristics and infrastructure conditions. Among the positively moderated paths, the effect of animal husbandry type × autonomy → perceived ease of use ($\beta = 0.086$, $p < 0.05$) is most significant in confined animal husbandry. The fixed captive breeding scenario has high demand for automated decision-making, and technologies such as intelligent feeding systems can reduce operational difficulty; the effect of animal husbandry type × technological interest → perceived ease of use ($\beta = 0.099$, $p < 0.05$) is prominent in extensive animal husbandry, where large-scale operation and relatively solid technical foundation promote the transformation of technological interest into operational capabilities; the effect of animal husbandry type × mobility → perceived usefulness ($\beta = 0.117$, $p < 0.05$) is strongest in nomadic animal husbandry, as technologies like offline intelligent collars align with the needs of migratory scenarios. Among the negatively moderated paths, the effect of animal husbandry type × interactivity → perceived usefulness ($\beta = -0.220$, $p < 0.005$) is attributed to insufficient network coverage in nomadic areas, which prevents real-time interactive technologies from functioning effectively and even reduces the perception of usefulness.

TABLE 10 Comparison of path coefficients by animal husbandry type group (PLS-MGA).

Core paths	Core paths nomadic group (n = 183)	Confined group (n = 89)	Extensive group (n = 59)	Inter-group difference (nomadic vs. confined)	p-value
Interactivity → Perceived usefulness	0.082	0.315	0.273	$\Delta\beta = -0.233$	<0.001
Mobility → Perceived usefulness	0.421	0.298	0.232	$\Delta\beta = 0.123$	0.112
Autonomy → Perceived ease of use	0.175	0.268	0.293	$\Delta\beta = -0.093$	0.087

TABLE 11 Moderation analysis.

Pathway name and moderation variables	Original sample (O)	*p* values
Animal husbandry type × Autonomy → Perceived ease of use	0.086	0.019
Animal husbandry type × Interactivity → Perceived usefulness	−0.220	0.001
Animal husbandry type × Mobility → Perceived usefulness	0.117	0.037
Animal husbandry type × Technological interest → Perceived usefulness	0.099	0.038
Breeding scale × Technological interest → Perceived ease of use	0.096	0.022
Breeding scale × Technological interest → Perceived usefulness	0.109	0.034

Breeding scale generates gradient moderation on the "technological interest - user belief" paths through differences in resource endowments. Large-scale farms, leveraging advantages in capital and technical personnel, exhibit significant moderating effects on breeding scale × technological interest → perceived usefulness ($\beta = 0.096$, $p < 0.05$) and breeding scale × technological interest → perceived ease of use ($\beta = 0.109$, $p < 0.05$). For instance, space-air-ground integrated monitoring systems can improve grassland utilization efficiency, and full-time personnel can accelerate the learning of equipment operation. The moderating effect of medium-scale farms falls between large-scale and small-scale ones; small-scale farms, due to limited resources, struggle to transform technological interest into actual adoption, resulting in a weak moderating effect.

In conclusion, animal husbandry type constructs a "scenario adaptation" moderation dimension, while breeding scale forms a "resource support" moderation dimension. Together, they constitute a "scenario-resource" dual moderating mechanism for agricultural AI adoption intention in the Qinghai pastoral area.

6 Discussion

6.1 Scenario adaptability of technological innovation characteristics: core drivers and differentiated demands

This study confirms that mobility ($\beta = 0.375$, $p < 0.005$) is the core technological driver for the adoption of agricultural AI in the Qinghai pastoral area. Its importance stems from the geographical and production characteristics of the pastoral area, such as "high altitude, poor network coverage, and dominant nomadic production." Mobile technologies with offline data storage and portable operation can break through the constraints of insufficient network coverage and address the core pain point of difficult livestock monitoring in nomadic scenarios. A case study in Yushu Prefecture shows that the efficiency of livestock health monitoring in pastures applying mobile technologies has increased by 40%, further verifying its scenario adaptation value. This finding aligns with Melak et al. (2024), who noted that "context-specific technological traits are decisive for AI adoption in alpine pastoral areas" in their study on East African plateau pastoralism. However, unlike their emphasis on "weather resistance" as the core trait, this study highlights mobility due to the unique nomadic production mode in Qinghai, reflecting the regional heterogeneity of technological demand.

Although interactivity ($\beta = 0.273$, $p < 0.005$) and autonomy ($\beta = 0.210$, $p < 0.005$) have secondary impacts, there are significant scenario differences: interactive technologies, through designs such as Tibetan-Chinese bilingual interfaces and voice commands, are more suitable for the "fixed scenario, high-frequency operation" needs of barn-fed pastures. After application in barn-fed pastures in Haixi Prefecture, the feeding error has decreased by 25%; this is consistent with Jain P. et al.'s (2024) conclusion that "localized interactive design reduces operational resistance in technology adoption among low-literacy groups." Autonomous technologies, through automated environmental control and disease early warning, meet the "large-scale operation, reduced labor input" demands of extensive pastures. After application in extensive pastures in Hainan Prefecture, labor costs have been reduced by 30%, which echoes Ivanov's view that "autonomy is the key to improving efficiency in large-scale agricultural production" (Ivanov and Kopsidis, 2023). This characteristic of "mobility as the core, interactivity and autonomy adapted to specific scenarios" breaks the perception of "homogenization of technological functions" in smart agriculture research (Georgopoulos et al., 2023) and highlights the scenario-specific nature of technology design in extreme environments.

6.2 Psychological mechanism of technology commitment: contradiction between interest dominance and competence shortcomings

The technology commitment dimension presents a "single-dimensional driving" feature. Technological interest ($\beta = 0.230$, $p < 0.005$) has a significant positive impact on both perceived usefulness and perceived ease of use, while the impacts of technological competence belief ($\beta = 0.005$, $p > 0.05$) and technological control belief ($\beta = -0.072$, $p > 0.05$) are not significant. This result reflects the unique user psychology in the Qinghai pastoral area: due to the low efficiency of traditional animal husbandry and high disease risks, herders have a strong intention to explore agricultural AI that can solve practical pain points. Young herders under 35 years old (accounting for 38%) have a significantly higher technological interest score (mean 5.9/7) than other groups, verifying the endogenous driving role of interest. This finding supplements Rasheed et al.'s (2024) research on agricultural technology adoption, which only emphasized the role of competence belief but ignored the dominant position of interest in resource-constrained environments.

However, shortcomings in technological competence and control belief also exist objectively: only 23.5% of herders have received systematic training, and 62.4% of intelligent devices lack parameter customization functions. As a result, although herders have interest, it is difficult to convert it into actual adoption due to "inability to use and difficulty in control." This contradiction is similar to the "intention-behavior gap" observed in Staddon's (2025) study on smallholder farmers' technology adoption, but the unique cause here lies in the mismatch between "scenario-specific training absence" and "device function closure" rather than pure psychological resistance. This contradiction of "high interest but low competence" suggests that the promotion of agricultural AI needs to balance "motivation stimulation" and "competence support" to avoid falling into the dilemma of "interest depletion."

6.3 Practical logic of moderating effects: dual constraints of scenarios and resources

Animal husbandry type and breeding scale form dual moderation through "scenario demands" and "resource endowments," further refining the adoption intention mechanism. From the perspective of animal husbandry type, the path coefficient of "mobility → perceived usefulness" in nomadic pastures (0.512) is 2.7 times that in barn-fed pastures (0.189), and there is a negative moderation effect on interactivity ($\beta = -0.220$, $p < 0.005$). The core reason is that the network bottleneck in nomadic scenarios weakens the value of real-time interactive functions; this is consistent with Nyamuryekung'e (2024) observation that "network infrastructure constraints directly reduce the utility of interactive technologies in nomadic areas." The coefficient of "autonomy → perceived ease of use" in barn-fed pastures (0.268) is higher than that in nomadic pastures (0.175), reflecting the higher demand for automated decision-making in fixed scenarios; the coefficient of "technological interest → perceived ease of use" in extensive pastures (0.294) is the highest, derived from the higher technical literacy of their operators and the demand for large-scale management.

From the perspective of breeding scale, the coefficient of "technological interest → perceived usefulness" in large-scale pastures (0.345) is 2.7 times that in small-scale pastures (0.128). The key lies in that large-scale pastures have resources such as capital and personnel, enabling them to convert technological interest into practical application capabilities; while small-scale pastures, due to cost constraints and lack of training, even with high interest, find it difficult to break through adoption barriers. This moderating law aligns with Weersink and Fulton's (2020) viewpoint in "Limits to Profit Maximization as a Guide to Behavior Change" that "behavior change in technology adoption is not only driven by profit pursuit but also constrained by resource endowments and scenario conditions." They argued that the traditional assumption of "profit maximization as the sole driver" ignores the multi-dimensional nature of adoption decisions, which is fully verified in this study: small-scale herders' low adoption rate is not due to insufficient profit perception but resource constraints in converting interest into adoption. This moderating law indicates that the promotion of agricultural AI needs to move away from the "one-size-fits-all" model and establish a precise strategy of "classifying by scenario and grading by scale" (Ronaghi and Ronaghi, 2025).

7 Conclusions and research limitations

7.1 Core conclusions

Based on 321 valid questionnaires from the Qinghai pastoral area, this study integrated the framework of "technological innovation characteristics-technology commitment-TAM Model" and conducted an empirical analysis using the PLS-SEM method. The results show that, in terms of technological innovation characteristics, mobility plays a primary driving role in the adoption of agricultural AI ($\beta = 0.375$, $p < 0.005$), while interactivity ($\beta = 0.273$, $p < 0.005$) and autonomy ($\beta = 0.210$, $p < 0.005$) exhibit more significant impacts in barn-fed and extensive breeding scenarios, respectively; all three indirectly promote herders' adoption intention by enhancing their perceived usefulness and perceived ease of use. In the dimension of technology commitment, only technological interest, as a psychological driving factor, shows a significant positive impact ($\beta = 0.230$, $p < 0.005$), while technological competence belief and technological control belief do not produce significant effects due to insufficient training and closed device functions. This highlights that the promotion of agricultural AI in this region should follow the logic of "prioritizing interest stimulation and subsequent competence development."

The study found that animal husbandry type and breeding scale, as moderating variables, have dual constraint effects: animal husbandry type mainly regulates the action path of technological characteristics by shaping different production scenario features; breeding scale mainly regulates the conversion efficiency of technological interest into adoption intention by influencing resource endowments. Together, they constitute a "scenario-resource" dual moderating mechanism. As core mediating variables, perceived usefulness ($\beta = 0.573$, $p < 0.001$) and perceived ease of use ($\beta = 0.163$, $p < 0.005$) both have significant positive impacts on adoption intention, and the impact intensity of perceived usefulness is significantly greater. This reflects herders' distinct practical orientation in agricultural AI selection—prioritizing attention to whether agricultural AI can effectively solve practical production pain points such as laborious herding and frequent diseases, rather than simply pursuing operational simplicity.

7.2 Theoretical and practical contributions

7.2.1 Theoretical contributions

To expand the scenario adaptability of the Technology Acceptance Model (TAM), this study incorporates the "mobility" dimension into the core construct of technological innovation characteristics. This effectively corrects the theoretical limitation of the traditional TAM model, which implicitly assumes fixed scenarios, thereby providing a new theoretical analysis framework for technology adoption research in extreme environments such as alpine pastoral areas and mountainous regions. In terms of the contextualized cognition of technology commitment, the study finds a special mechanism of "technological interest taking precedence over competence belief" under resource constraints. This finding supplements the universal conclusion of "competence belief dominance" in existing research and provides a breakthrough theoretical perspective for understanding the technology acceptance behavior of groups with low technical literacy in developing countries. In addition, by constructing a "technology- user-scenario" three-dimensional interaction model and combining the analysis of the moderating effects of animal husbandry type and breeding scale, this study successfully breaks through the research paradigm of traditional linear causal relationships, systematically reveals the heterogeneous characteristics of technology-driven paths in different scenarios, and further enriches the cross-scenario theoretical system in the field of smart agricultural technology adoption intention.

7.2.2 Practical contributions

In terms of technology design optimization, targeted at the characteristics of nomadic pastures, offline storage and lightweight devices have been developed; for barn-fed pastures, voice interaction and graphical interface technologies have been optimized; for extensive pastures, automated environmental control systems have been promoted, thus achieving precise matching between agricultural AI and specific scenarios. The construction of the training system stimulates herders' interest through the demonstration of pastoral technology cases; at the same time, hierarchical practical training is carried out—herders with low education levels focus on simulation exercises, and large-scale pastures are equipped with full-time technical personnel—to make up for the shortcomings in technological competence belief and technological control belief.

The classified promotion strategy, guided by Weersink and Fulton's (2020) insight into "limits of profit maximization," prioritizes the allocation of mobile technologies to nomadic pastures (focusing on solving survival-level pain points rather than pure profit pursuit), strengthens interactive technologies in barn-fed pastures (improving operational efficiency to enhance profit margins), promotes integrated intelligent platforms in large-scale pastures (giving play to scale advantages to maximize profits), and provides equipment rental and sharing services for small-scale pastures (reducing initial investment constraints to lower adoption thresholds). This strategy effectively addresses the multi-dimensional constraints of different groups and scenarios, and improves the adaptability and sustainability of agricultural AI promotion (Ronaghi, 2024).

7.3 Research limitations and future prospects

7.3.1 Research limitations

There are constraints on sample representativeness. The research data are only from the Qinghai pastoral area. Although this region has typical characteristics of "high altitude and dominant nomadism," differences in geographical environment and production models in other pastoral areas may affect the extrapolation of conclusions, so further verification of the model's universality is needed. There are deficiencies in variable design: potential variables such as policy subsidies, technology costs, and social networks are not included in the consideration; at the same time, the measurement items of technological control belief may not fully align with herders' actual operation scenarios, leading to insignificant impact effects. Therefore, the scale design needs to be optimized to improve alignment. There are also limitations in research methods: the use of cross-sectional data can only reveal the correlation between variables, and cannot track the dynamic changes of adoption intention; in addition, PLS-SEM analysis fails to conduct an in-depth test of the segmented paths of mediating effects, resulting in insufficiently detailed mechanism explanation.

7.3.2 Future prospects

Future research can further expand the geographical and application scope of empirical analysis. For example, extend sample collection to cover five typical pastoral areas including Inner Mongolia and Tibet. Through comparative analysis of cross-regional data, systematically test the universality of the "scenario-resource" moderating effect under different ecological and economic backgrounds. At the same time, the research scope can be extended to other key fields of smart agriculture, such as intelligent irrigation systems and precision planting technologies, to verify the scenario transfer ability of the core model in this study and the wide applicability of the research conclusions. In terms of variable selection and methodology, subsequent work should focus on incorporating key external environment variables such as policy support intensity and economic subsidy measures, and conduct an in-depth analysis of their actual impact on users' agricultural AI adoption decisions. The adoption of a longitudinal panel data design combined with a growth curve model will help accurately depict the dynamic mechanism of adoption intention evolving over time.

In addition, the mixed research method that integrates large-scale questionnaire surveys, in-depth case interviews, and practical technology prototype trial experiences can effectively utilize the insight of qualitative data, provide richer and more persuasive explanations for quantitative analysis results, and thus significantly enhance the depth and credibility of research conclusions. In terms of mechanism exploration, future research needs to conduct an in-depth test of how key variables such as technological innovation characteristics and technology commitment indirectly affect adoption intention through potential mediating variables such as perceived usefulness—for example, revealing the possible chain mediating effect. This will help construct and verify a more complete theoretical path model of "technology adaptation-psychological identification-behavioral adoption." At the same time, actively introducing cutting-edge algorithm technologies such as machine learning to construct an agricultural AI adoption intention prediction model based on multi-dimensional features will provide solid empirical support and decision-making basis for the formulation of precise promotion strategies for related technologies.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

JZ: Software, Writing – original draft, Resources, Investigation, Writing – review & editing, Visualization, Project administration, Formal analysis, Methodology, Data curation, Supervision, Conceptualization, Validation. KC: Data curation, Visualization, Formal analysis, Resources, Validation, Project administration, Writing – review & editing, Investigation, Methodology, Software, Writing – original draft, Conceptualization, Supervision.

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