The Market Acceptance Mechanism of AI Psychological Screening Products: A Process Tracking Based on the "Xinqing AI" Brand

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Abstract. With the rapid development of digital healthcare, AI psychological screening products have gradually become an important means of mental health services due to their efficiency and convenience. However, their promotion faces two major obstacles: privacy concerns and lack of trust. Taking the representative domestic brand "Xinqing AI" as a case study, this paper examines its development process of "rapid growth—negative public opinion—growth stagnation" through data analysis, aiming to address three key issues: the factors influencing users' acceptance of such products, the relationship between privacy risks and trust, and strategies to overcome market promotion challenges. The study finds that users' privacy concerns mainly manifest in worries about data collection and storage security, as well as resistance to being labeled with mental health issues. Meanwhile, insufficient trust stems from opaque medical collaborations, lack of professional certification, non-transparent algorithm mechanisms, and absence of third-party validation. These two factors together form a vicious cycle of "privacy concerns → distrust of products → refusal to use products," resulting in extremely low product retention and payment rates. Therefore, this paper proposes addressing the issue from both "formal trust" and "emotional trust" perspectives: enhancing users' privacy autonomy, improving transparency and security guarantees, and optimizing service connectivity to meet differentiated needs. This study constructs an influence model of "privacy risk perception—technical trust—usage satisfaction—continuance intention," providing insights for theoretical research and practical application of AI psychological screening products.

Keywords: AI psychological screening; market acceptance; privacy risk; trust; user stickiness.

1. Introduction

The development of artificial intelligence technology has promoted the popularization of psychological screening products, allowing users to complete preliminary assessments via mobile applications with convenient operations. However, in practical application, such products face two major obstacles: privacy concerns and lack of trust. Some users worry about personal data being collected or leaked, or about being labeled with mental health issues; meanwhile, products lack hospital certification and algorithmic transparency, leading to insufficient reliability, and users often stop using them after the first experience. For example, "Xinqing AI" experienced rapid growth followed by stagnation due to negative public opinion, with both retention and payment rates remaining low.

The objectives of this study are to analyze the factors influencing users' acceptance of AI psychological screening products, explore the relationship between privacy risks and trust, and propose solutions to promotion dilemmas. Specific research questions include: What factors affect users' willingness to use such products? What is the interactive relationship between privacy risk perception and trust? How to improve product promotion effectiveness? Using 'Xinqing AI' as a case study, this paper employs literature and report analysis, enterprise development process tracking, and event-chain analysis to connect 'users' privacy concerns,' 'distrust of products,' and 'refusal to use products,' in order to identify their interrelationships and propose solutions. The conclusions provide references for theoretical research and practical application of AI psychological screening products.

2. Research Status of Market Acceptance of AI Psychological Screening Products

2.1. Theoretical Context of Existing Research

Li Existing studies have shown that when deciding whether to use digital health products, users typically weigh their potential benefits against risks [1]. However, few studies have focused on the risk of "social labeling." For instance, if corporate human resources departments can access employees' psychological assessment results, users may worry about restricted career development, thereby reducing willingness to use the products. Academia generally believes that trust originates from three dimensions: product reliability, commitment to user interests, and information transparency [2]. However, previous studies have often been limited to single perspectives, such as focusing on whether products have medical institution endorsements or only examining algorithm accuracy, lacking systematic integration of multi-dimensional trust.

2.2. Limitations of Existing Research

Regarding user stickiness, relevant models generally emphasize "instrumental value," i.e., whether products can meet core needs [3]. For example, users use WeChat daily because it enables instant communication. However, in mental health services, users not only require instrumental value but also "emotional support," i.e., feeling understood and cared for during use—such as receiving personalized feedback and comfort after assessments. Yet, existing research has paid insufficient attention to this aspect. Mitigations of Existing Research

Existing research still has deficiencies in three areas: privacy risks, trust mechanisms, and user stickiness. First, privacy risk research has mostly focused on users' worries about data leakage, while neglecting risks of "social labeling" and "secondary use of data (e.g., selling to third parties)."[1]. These factors often intertwine, exacerbating users' insecurity and reducing willingness to use. Second, trust research has primarily focused on formal trust—such as whether products have medical institution certification or technical endorsements—while paying insufficient attention to emotional trust, i.e., whether users perceive goodwill and care from the platform [4]. If formal trust and emotional trust are separated, they cannot fully explain the process of user trust formation. Finally, user stickiness research has typically focused on product functions (e.g., test accuracy) while ignoring users' need for emotional support in mental health services [5]. For example, users may desire feedback or care after completing assessments; if products lack such functions, users often stop using them after the first experience.

Previous studies have lacked a theoretical model of "privacy risk—trust—user stickiness." Furthermore, no research has specifically examined "the sensitivity of psychological data combined with new technologies like AI," nor considered differentiated user needs (e.g., young people may care more about algorithm clarity, while middle-aged and elderly users may trust hospital recommendations more). Through the case of "Xinqing AI," this paper integrates these elements to construct an influence model of "user psychology—trust—usage—continuance intention."

3. Development History and Market Dilemma of "Xinqing AI"

"Xinqing AI" is one of the earliest domestic enterprises engaged in AI psychological screening, representative of the industry. Its development trajectory reflects the development of domestic AI mental health products to some extent. From initial high attention to declining user reputation and reduced usage, its market fluctuations and challenges are typical, with relevant news reports and user reviews publicly available, making it a representative and operable case study.

The product's development can be divided into three stages: R& D Stage (March–December 2020): The company received tens of millions of yuan in investment, trained algorithms using 500,000 hospital psychological test data, and launched Version 1.0, capable of assessing depression and anxiety with a claimed "92% accuracy."

Promotion Stage (January 2021–June 2022): Launched Version 2.0 with voice assessment, paid psychological reports, and course sales. It collaborated with over 30 major hospitals and 10 companies to provide employee psychological assessments, completing approximately 500,000 assessments.

Crisis Stage (July 2022–present): Removed from app stores due to privacy disputes over its "facial expression analysis" function. The number of collaborating hospitals and enterprises decreased by approximately 40%, university projects were reduced to 3, and cumulative assessments dropped to 300,000.

In terms of marketing and user response, "Xinqing AI" built a professional image by emphasizing collaborations with major hospitals and inviting internet-famous doctors for recommendations, but users remained skeptical about the authenticity of collaborations. It attracted new users through social campaigns like "mental health self-test challenges," with approximately 40% of users registering via such activities; however, only 8% remained active after 30 days, and paid users accounted for only 1.2%, indicating low user stickiness. User feedback focused on overly vague assessment results, overly strict privacy terms, and lack of follow-up intervention and guidance, limiting the product's practical effectiveness.

Market dilemmas mainly manifest in insufficient algorithm credibility, data ethics controversies, and poor user experience. For example, in 2022, a user was judged as "high risk of severe depression" due to exam stress, triggering public attention. Data usage clauses in the registration agreement raised concerns about commercial exploitation of data. Additionally, most users viewed it as a one-time tool, lacking continuous intervention or interactive functions, with monotonous push notifications failing to sustain long-term usage and behavioral change. In summary, the "Xinqing AI" case fully demonstrates typical issues in AI mental health products regarding technology, marketing, user trust, and data ethics, providing important references for related research.

4. Case Analysis: Triple Mechanism of Trust Crisis and Usage Disruption

Users' willingness to use AI mental health products is influenced by multiple factors, including privacy concerns, insufficient trust, and lack of functional experience.

Privacy concerns primarily manifest in two dimensions. First, users often show resistance to data collection, as they feel uncomfortable with the possibility of their personal information being gathered. For instance, they may worry about the undisclosed analysis of voice assessments or mood diaries, which resembles the strong aversion many individuals have toward mobile applications requesting access to contact information without clear justification. Second, concerns about data security are prevalent, as users fear that sensitive psychological data could be leaked or sold. Such breaches may not only compromise privacy but also affect essential personal rights, including the fairness of insurance applications and other forms of social participation.

Fear of labeling: For example, worrying that colleagues may misunderstand their mental state after being assessed as "moderately anxious," leading them to delete the app. These privacy concerns directly weaken users' trust in the product.

Trust problems also significantly restrict product usage:

Insufficient formal trust: Although the product claims collaborations with over 30 Grade A tertiary hospitals, specific collaborating hospitals and content are opaque, and it lacks medical device registration certificates, making it difficult for users to confirm its professionalism.

Insufficient technical trust: Low algorithm transparency—users cannot understand the calculation logic behind assessment results like "mild depression," and the claimed "92% accuracy" lacks third-party validation, leading users to doubt assessment results.

Poor user experience further weakens product stickiness:

Disconnected functions: Lack of specific intervention suggestions or follow-up guidance after assessments, failing to meet users' need for solutions.

Absence of emotional connection: Cold interfaces and mechanical community interactions prevent users from developing attachment.

Low perceived utility: Users generally view psychological assessments as one-time tools, used only in specific situations (e.g., occasional temperature checks).

These factors overlap to form a negative cycle: privacy concerns lead to distrust; poor post-usage experience reduces usage frequency; companies invest more resources in acquiring new users, but new users still lack trust and stickiness due to the same issues—like a snowballing vicious cycle, ultimately making it difficult for the product to maintain sustained market activity.

5. Theoretical Refinement: Influence Model and Trust Solutions

5.1. Model Construction

Based on user behavior and psychological responses, this study constructs an influence model of “privacy risk perception—technical trust—usage satisfaction—continuance intention,” which presents a chained relationship [6]. For example, heightened perceptions of privacy risk reduce users’ technical trust, thereby lowering their satisfaction with product usage and ultimately weakening their intention to continue using the product [7]. User sees "permanent data authorization" clause → feels privacy insecurity (privacy risk perception) → thinks "will this company deceive me?" → distrusts the product (low technical trust) → finds interface unattractive and results useless → poor experience (low usage satisfaction) → deletes the app → no continuance intention.

Trust-building requires two-pronged efforts:

Formal trust construction: Clearly explaining hospital collaboration details and algorithm R& D processes, and obtaining medical device registration certificates (analogous to food obtaining "QS certification") to enhance professional reliability.

Emotional trust construction: Providing specific, caring intervention suggestions after assessments—e.g., prompting "You’ve stayed up late frequently recently; try a 5-minute relaxation exercise"—simulating friendly communication to make users feel goodwill and care.

Additionally, differentiated strategies should target user groups:

Young users (e.g., college students) care more about algorithm transparency and scientific support. Middle-aged and elderly users value the credibility of authoritative institution recommendations.

Anxious users prioritize assessment accuracy and problem-solving capabilities.

Mentally stable users worry most about being labeled and reputation/employment impacts.

This model and stratified strategy provide systematic references for trust-building and user stickiness improvement in AI mental health products.

5.2. Recommendations

Minimize data collection: Delete voice recordings after assessments, retaining only results; let users choose "how much privacy to share" (e.g., anonymous basic tests, with detailed reports requiring additional information—similar to "anonymous delivery" for food orders, giving users control) [8].

Enhance transparency: Publicize hospital collaboration contracts; invite third-party institutions (e.g., Chinese Psychological Society) to verify accuracy and release public reports [9].

Humanize functions: Respond to user inputs like "recently stressed" with empathetic emojis (e.g., a hugging icon) instead of cold text; provide immediate solutions after assessments (e.g., recommending "3-minute breathing relaxation" or nearby counselors for "mild anxiety").

Build genuine communities: Create mutual-support groups that facilitate user interaction rather than functioning primarily as advertising platforms. Such communities may operate in a manner similar to WeChat groups, where users share their moods and experiences, thereby fostering authentic communication and emotional exchange. Theoretically, this study constructs an influence model of "user cognition—trust—usage behavior," connecting privacy risk perception, technical trust, usage satisfaction, and continuance intention, providing a systematic framework for analyzing user behavior in AI mental health products [10].

6. Conclusion

The success of AI psychological screening products depends on three key factors: privacy security, user trust, and usage experience. Current problems include:

Inadequate privacy security: Users worry about data collection, sales, or labeling.

Lack of user trust: Opaque hospital collaborations, non-transparent algorithms, and absence of third-party validation.

Poor usage experience: Lack of follow-up guidance, cold interfaces, and failure to provide practical help, leading to reduced usage rates.

These issues interact to form a negative cycle, ultimately causing user loss. Practically, enterprises can take specific measures: allowing users to control privacy settings, disclosing hospital collaboration details, clarifying algorithm logic, providing actionable intervention suggestions after assessments, and adding humanized services and care.

Future research can further compare domestic and foreign AI psychological screening products in privacy protection and user trust-building, analyze cultural influences on user behavior, quantify the impact of privacy concerns on trust and usage intention through large-sample surveys, and explore data ethics norms (e.g., prohibiting the sale of user psychological data to insurance companies) to provide standards and guidance for industry development.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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