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ORIGINAL CONTRIBUTION

Social Support Outweighs Design in Digital Commerce: Explaining AI-Agent Adoption in Entrepreneurship

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Abstract— In a little over a span of time, AI is becoming an increasingly larger factor as it takes hold in the direction that entrepreneurship will take and, for sure, within the digital commerce space. This study builds on Technology Acceptance Model (TAM) by adding two additional external factors, social support and the particular features of AI agents, to see what makes young entrepreneurs decide to use these tools. According to 579 generation Y business owners from a survey within Beijing's digital business ecosystem, according to those individuals, fellow business people as well as advisers' views and statements regarding whether AI tools are valuable and if they are easy to utilize impact a business owner's feelings and thoughts on such tools. It is rather surprising, but it is the technical capabilities of the AI agent that seem to matter less than the influence of these, which is mediated by entrepreneurs' sense of the tool's value and ease of use. As opposed to just being there, it was also a major and direct motivator for them to be given emotional and informational support. All in all, it means that entrepreneurs are how AI is perceived socially and psychologically, rather than in what it is technically designed. And with this in mind, help to update TAM for digital entrepreneurship and offer practical suggestions for how we may be better about bringing AI tools into our business lives.

Index Terms— AI agents, Digital entrepreneurship, Social support, Technology acceptance model, Structural equation modeling

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Introduction

Today's ever-changing digital economy is not about making money. It's entrepreneurship. More and more, as a way for young people to be creative, have their own identity, and deal with problems that are important to all of society, like unemployment, factories making things differently, and taking care of the world around us (Dencker et al., 2021; Ramya et al., 2025). With digital technologies and business practices merging over time, it has begun spawning all new types of digital entrepreneurship as well, which then go on to change and reshape both markets as well as how startups are built (Giuggioli & Pellegrini, 2023; Zhai et al., 2023). So, as things go in kind of that kind of change, the fact that the young teenage young entrepreneur or the youth has, for lack of a better term, has got certain ideas of how they want to engage with smart tech, with technology overall, especially digital commerce where things can move at a very rapid pace and the pressures put upon being able to keep pace is a really high bar to go over.

In China, at the national level, strategies have reiterated the incorporation of AI into the larger digital economy to help businesses gain more strength through automation and smart systems (S. Yang et al., 2025). According to researcher, it will be more than 6.9 trillion as of 2025, which means internet platforms are very critical to economic development (Rosário & Raimundo, 2021). China is one of the top digital commerce users,

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especially in the cities, because over 80% use it there. In just 2022 alone, the online retail transactions in Beijing have already gone past RMB1.34 trillion (X. Sun & Lorenzo, 2025; Yin & Choi, 2022), which already has an established infrastructure. But really getting these smart tools to work well for younger business owners would be the big step.

Beijing is a cool place, but it's also a cool place to do business for the young entrepreneur. It's a place where you can do well, but it's a very, very cutthroat kind of city as well. In 2023, the digital economy of the city contributed close to 43% of its GDP, amounting to RMB 1.88 trillion (GBM, 2024). At the same time, by the end of 2024, there were 115 unicorn companies headquartered in the city, with a total value of nearly US$595 billion. It attracts the best of both people and capital, but makes life harder for newcomers. While entrepreneurship is becoming a growing necessity for a career for some, especially with the 15.7% youth unemployment rate in late 2024 (J. Huang & Liu, 2025), it has brought to light a weakness in startup resources, such as a lack of access to capital and skills development.

Although with the advancement of such AI as Chatbots, visual, and decision assistant technology. But most entrepreneurs find it difficult to incorporate these AIS (Al-Mamary, 2025; Hosseini & Seilani, 2025). Adoption tends to be all over the place. Those problems appear both in terms of how difficult things are as well as what people think about those tools. The digital natives are still experiencing the emotions of pause; I have no idea why it will be beneficial, and a lack of knowledge of how to use it hinders the ability to use it (Fei, 2024; J. C. Sun & Pratt, 2024). And it's made worse if those systems are themselves seen as hard to understand, hard to work with, or just not well-suited for entrepreneurial tasks (Chhillar & Aguilera, 2022; Jørgensen & Ma, 2025). More generally, bad peer mentorship networks combined with an institution that will not help one's individuality. This stops someone from trying to come up with something smart (Giuggioli & Pellegrini, 2023).

Much of our current academic knowledge stems from the Technology Acceptance Model (TAM), which is based on two primary beliefs of Perceived Usefulness (PU) and Perceived Ease Of Use (PEOU) (Ilyas et al., 2023; Wibowo et al., 2024). These ideas are very helpful when it comes to figuring out how people act around technology, but lots of research based on TAM tends to leave out the social and wishful situations where people make up their minds. Although social support has been researched in health and education, it is still underexplored in the area of entrepreneurship (Maziriri et al., 2025). And little thought to what about those special features of AI tools – like being able to change easily, work by yourself, or talk back and forth – might make people pick them (Upadhyay et al., 2022, 2023). With those gaps, I know we need a tactic that considers more than just making the design itself, but rather takes into account where the design will actually happen in terms of its societal surroundings as well.

AI in commerce may be progressing rapidly, but what actually gets used by young entrepreneurs is uneven. Previous work based on TAM is solid, but it doesn't account for how outside stuff like social support and design quirks unique to the tool change those basic user beliefs. The questions that still remain: can mentors, peers, or institutions change how useful or easy entrepreneurs see AI tools as being to use? Do the built-in features of an AI agent impact adoption directly, or does it happen indirectly through the formation of underlying opinions? Without such answers, we still struggle to grasp what makes Gen-Y entrepreneurs adopt or reject AI-like techs–in data-driven Beijing.

To deal with these worries, we have two main goals.

- To find out what social support and particular characteristics of AI agents affect their usefulness, ease of use, general attitude, and, in the end, the desire to use these tools in digital business.
- To explore the mediating role of the three factors - perceived usefulness, ease of use, and attitude - on the connection between external conditions such as social support and AI design, and the intention to adopt.

And this piece does have some contribution to make. From a theoretical perspective, it adds the social support and design characteristics as two additional external variables with respect to the TAM model, showing that these variables can have both direct and indirect paths of influence on the entrepreneurial intentions. In practice, this can give guides to entrepreneurs and others involved in the systems design and ecosystem building, with respect to how they should architect their mentoring, training, and interfaces to make it easier for more to adopt AI. In context, by looking at Gen-Y entrepreneurs in Beijing, a major tech and digital business hub, we can get a better sense of why, in some cases, it might be more about the social dynamics rather than the actual design of the technology when it comes to affecting what entrepreneurs do.

Literature Review

Theoretical approach

In this paper, we construct a many-tiered system to grasp the reasons why entrepreneurs elect to employ AI-powered tools. It uses three ideas: TAM (Technology Acceptance Model), SST (Social Support Theory), and MEC (Means-End Chain).

TAM at its core provides a basis by proposing that a person's belief that something is useful and easy to use will determine their attitude towards the technology and thus how willing they are to use the technology (Davis, 1989). SST also provides the emotional support of encouragement by mentors and peers, informational support, and practical advice from digital communities, which can all help to lower the mental barriers to and increase confidence in new technologies (House, 1987). And then we get MEC, another layer, this one concerned with how the design qualities of AI tools, like their fit for use, two-way connection, and control over results, work on tasks for business as well as satisfying personal values for new ways of working, being on your own, and growing yourself (Borgardt, 2020; Ratsameemonthon, 2025).

By combining all three, the framework of this paper is presented as follows: from social inputs to cognitive judgments, and finally, to aligning values. This integrated model extends TAM to include both emotional and value-based factors, providing a fuller account of how Gen-Y entrepreneurs in Beijing, which is a fast-moving, data-saturated, and value-focused environment, make their adoption choices.

Hypothesis development

Social support comes in lots of different forms - it's there to offer you something emotionally, inform you of things, lend a hand in an action you want, or assist by making a decision - it just happens to be the most important thing determining if and how people take up a technology. When embedded in a person's social network or entrepreneurial community, this kind of support can have meaningful impacts on behavior – particularly when we consider established technology acceptance models (S. He et al., 2023; Karkouti et al., 2025). From a behavior perspective, getting support can help reduce anxiety and the amount of work one feels like they have to do; this then makes something seem easier to use (PEOU). At the same time, access to such information and sharing can also help entrepreneurs to have a better understanding of the possible value of the technology, which could increase their sense of usefulness (PU). As both beliefs become stronger, so do the positive attitudes toward the technology, and one is open to adoption (S. He et al., 2023).

Other studies that combined social support theory with the technology acceptance model found that the relationship held in different settings as well, such as digital education. At those kinds of places, social help forever and ever increases people taking action, PEOU, positive attitude, PU, which affects people's thoughts on the new thing (S. He et al., 2023). In high interconnection systems, especially online, informational and instrumental help could make digital tools more approachable and useful, which further enhances the effect of attitude on behavior intention (ElMadhi & Ait Nasser, 2024; Koranteng et al., 2025).

Entrepreneurs, when it comes to how social support works, usually find it a little more complicated. It directly relates to the core belief structures listed in TAM. Mentor and peer encouragement, like, for example, can ease the stress it would have normally taken to begin using the tech, giving you some sense of control, which would raise your PEOU (Alshammari & Babu, 2025). Similarly, accessing these cases, tutorials, or community guides as sources of information support aids in decreasing the search times, making this usage simpler and easier to perceive the usefulness of such a tool, so as to increase PEOU and PU. Instruments: It goes to the stuff-on-hands-to-help-you, that can be your data for helping, even if it might just be what computer you use, and these instruments can make what has been made so far, something that exists like a real thing in your everyday world of getting that business launched off the ground. At the same time, such evaluations, such as the appraisal of positive words from investors, vetters' comments, etc, can affect how one views or sees themselves. instill confidence, which can bring stronger and more determined feelings (Karkouti et al., 2025).

And quick, tense digital shopping like e-commerce, no need to mention. The need to learn and act fast and under time pressure means that whether the system feels useful and easy is super important. In this way, whether or not there is social support present can have a huge effect on whether the entrepreneur will adopt the AI solution or no (Alshammari & Babu, 2025; S. He et al., 2023). Based on the above insights, the following hypotheses are proposed:

H2: Social support improves how easily you feel like using AI agents.

H3: Social support improves attitude towards AI in entrepreneurship.

H4: Social support increases the perceived usefulness of AI agents.

AI agent attributes are defined as having particular qualities such as autonomy, interaction, adaptability, personalization, and real-time. It will also affect how it works and the way people feel, as well as an action, and evaluation (Bandi et al., 2025). For technology acceptance, we know from the literature on these system qualities that they have an influence on users' mental model via simplifying the user interaction, increasing the sense of control by the user, and making the system more in line with the real needs of the users (Davis, 1993). In terms of being user-friendly, adaptive interfaces, as well as responsive automation and interactive patterns that appear intelligent, all have a tendency to raise how simple people think the product is (Kolekar et al., 2019). Additionally, when AIT saves people time, helps them generate ideas, and makes processes easier, the more useful they become, making it more likely that they will be used (Gupta, 2024).

Building on this, e-commerce research shows us how attributes such as autonomy and personalization find a home within a user evaluation through the TAM framework, most often through such factors as Trust of Abilities, Interactivity, Adaptability, and Motivation. Smooth out talk and speedy system replies lessen problems and smooth learning slopes, which can boost how good people feel about using it (Lopes et al., 2024). Personalization and system adaptability also make the tools more valuable; this can promote PU and make entrepreneurs want to integrate such technology into their daily workflow (Ling et al., 2021; Marín Díaz, 2025).

But it's not the case for all the impacts of those traits. Research about digital shopping assistants shows that trust generally serves as the link between technical design and behavioral intention. Attributes may first influence how trustworthy or competent a system feels, and only then shape the user's overall attitude and decision to adopt (L. Zhang et al., 2024; R. Zhang et al., 2025). Related modeling work has argued that AI itself can be understood as a mediating element: it connects the platform's technical potential with the user's mental evaluations of ease and usefulness, forming a step-by-step decision chain. On the other hand, researchers have also cautioned that when AI tools become highly

autonomous, users may raise concerns about control, responsibility, and fairness, which could reduce the direct influence of technical features on actual adoption (Bandi et al., 2025; H. He & Zhang, 2022).

In line with these findings, the following hypotheses are proposed:

H5: AI agent attributes positively influence the perceived ease of use of AI agents.

H6: AI agent attributes positively influence attitudes toward AI-enabled entrepreneurship.

H7: AI agent attributes positively influence the perceived usefulness of AI agents.

H8: AI agent attributes positively influence the intention to adopt AI agents for entrepreneurship.

Hypothesis in TAM

In TAM, Perceived Ease Of Use (PEOU) captures users' judgment about how effortless they find it to operate a system, whereas Perceived Usefulness (PU) refers to the extent to which they think the system helps them accomplish tasks more effectively (Davis, 1989). When a technology is experienced as intuitive, simple to handle, and not demanding in terms of learning, people tend to hold more positive evaluations of it and to feel more inclined to use it (Liesa-Orús et al., 2023). For AI agents specifically, natural-language interfaces, low-friction onboarding, and seamless human–agent handoff reduce perceived effort and learning costs, thereby enhancing PEOU and fostering more favorable attitudes toward use. Entrepreneurs will do so to the same degree as when the entrepreneur sees the technology as a real advantage in that it would enable her to make better judgments, to accomplish her work more quickly, or to interact better with the client, then she is likely to have a more favorable disposition toward it. The Perceptions of Usefulness (PU) directly support the favorable attitudes that align closely with the goals of the individual or business (Selvakumar et al., 2025). For example, AI agents could give adaptive personalization, do routine tasks automatically, and give timely recommendations. The abovementioned function would allow it to be used more clearly by someone like a customer service representative or for making decisions, etc. This would increase trust in the tool (K. Huang, 2025).

The link between usefulness and what one thinks of something in entrepreneurship, where uncertainty and scarce resources can be the norm. Entrepreneurs are more likely to favor tools that are evident in contributing to performance and cutting down on operational load under such circumstances (Xu et al., 2024).

In the recent past, it has become clearer that the beliefs based on the TAM framework develop and impact user attitudes in time, especially when there is involvement of an AI agent. For example, studies in service and hospitality research show that systems with natural language interface systems, an easy sign-in process, and clearly defined and predictable responses can also reduce the effort they think they should take when using the system, and also improve the perception that they have of the system. They all work out towards a better feeling about long-time use of technology (Bano & Siddiqui, 2024; K. Yang et al., 2021).

Other studies about other age groups have also found that cognitive load matters, especially for middle-aged users. When technologies give guidance step-by-step and lessen mental efforts, people are less opposed to learning. So it also makes the impact PEOU has on feeling good about the system stronger (Songkram et al., 2023).

Meta-analyses and typological summaries of complete smart product research all basically agree that even if AI abilities become more self-reliant and context-aware, basic beliefs in TAM remain primary predictors of user ratings of technology. PEOU and PU mediate the influence of design cues (e.g., adaptability, explainability, perceived controllability) on attitudes (Shin, 2021). Meanwhile, discussions around generative AIs make us recognize that there will be other factors, such as trust calibration, perceived agency, and ethical comfort, with a supplemental effect on how users make judgments, but they will not substitute the TAM pathway (Davis & Granić, 2024). It means that PU and PEOU are still the basics of forming an attitude; they only interact under the influence of AI-specific evaluation mechanisms.

All up, it looks like entrepreneurs will probably have positive adoption feelings if they see AI agents as simple to use and good at providing clear benefits, especially in digital startup places with little money and lots of uncertainty. Based on the above relationship building, the following hypotheses are proposed:

H9: Perceived Ease Of Use (PEOU) of AI agents will increase entrepreneurs' attitudes toward AI-enabled business ventures.

H10: Perceived Usefulness (PU) of an AI agent is positively associated with attitudes toward AI-enabled entrepreneurship.

Users tend to lower their psychological barriers when they think a system is easy to use. A thought that a tool is something that they themselves can use and doesn't necessarily need some deep technical know-how is also something that makes them alright with using. (Gupta, 2024). On the other hand, whether something is actually useful is also super important - this means how much it helps people get what they want. Entrepreneurially, the minute something is a tool for getting us efficient work, happy customers, and wonderful strategies, we're really considering it. This link between how much someone thinks a product will benefit them and if they will use it is something that has been proven by other research (Boute et al., 2021; Upadhyay et al., 2022). Attitude, being an emotional evaluation of technology, includes feelings of positivity about new things, trust, and willingness to try. It is always seen in previous studies as an important mediator between belief and adoption behavior (Duong et al., 2024).

In entrepreneurial contexts, due to high uncertainty and limited resources, entrepreneurs often need to weigh availability against value; therefore, these three factors are particularly crucial to their decision-making.

Based on the above discussion, this study proposes the following hypotheses:

H11: Perceived ease of use of AI agents positively affects the intention to adopt AI agents for entrepreneurship.

H12: Attitude toward AI-enabled entrepreneurship positively affects the intention to adopt AI agents for entrepreneurship.

H13: Perceived usefulness of AI agents positively affects the intention to adopt AI agents for entrepreneurship.

Mediating role of perceived ease of use

In technology acceptance studies, Perceived Ease Of Use (PEOU) is often treated as an intervening belief through which facilitating conditions influence adoption decisions by lowering cognitive load and anticipated effort (Tennakoon et al., 2023).From the perspective of SST, informational and instrumental support such as mentoring, peer training, and resource sharing help entrepreneurs acquire knowledge and confidence in using new technologies, thereby increasing their perception of usability (Lall et al., 2023; Mohamed et al., 2024). As a result, this perceived ease makes them more willing to integrate AI tools into entrepreneurship. Similarly, certain design elements of AI agents, such as user-friendly design, interaction style adaptation, and automated features, all contribute to the way entrepreneurs see AI tools. When those characteristics lessen the technical obstacle and make the system seem easier to deal with, people are probably going to see the technology as simple to apply and can smoothly be used every day (Alshammari & Babu, 2025; Chalmers et al., 2021). In such instances, the perception of ease serves as an entry point to more intention to adopt. Those entrepreneurs who have those kinds of beliefs about technology, in terms of them think that technology just feels like it should be integrated with their workflow, they're probably going to use technology a bit more than those who don't have this belief. (Venkatesh, 2000).

Drawing upon such reasoning and those preceding results, the following assumptions are put forth:

H14: Perceived ease of use of the AI agent mediates the relationship between social support and intention to adopt the AI agent for entrepreneurship.

H15: Perceived ease of use of the AI agent mediates the relationship between AI agent attributes and the intention to adopt the AI agent for entrepreneurship.

Mediating role of attitude

Attitudes refer to a person's overall evaluation of a system, and it has long been considered a significant link between internal beliefs and external behavioral intentions (Ajzen, 1980). In those supporting settings, when businessmen get pushed or commended, such support turns more impractical. And it builds confidence, and it encourages deeper engagement, and at the end of the day, that might shape the way that we're more willing to take on new technology (Chang et al., 2024).

And kind of like how the kind of functions and also experience qualities of what an AI agent does, as it kind of affects the way in which we see the kind of these intelligent kind of assistants as well that, in a sense, in a way, that it gives more of a positive impression towards the value in having to have them for doing these types of activities kinds of business kind of work (Giuggioli & Pellegrini, 2023). In terms of studies involving e-commerce, digital services, and organizational IT, it has been found across all of them that attitude is the most common mediator that links external enablers and system features to the user's final decision to adopt (Chawla & Joshi, 2023; Wang & Yang, 2021).

However, it is still difficult to find evidence of this path through the real situation of AI entrepreneurship, especially for Generation Y entrepreneurs who are active in digital commerce. To be able to do that, I'm going to assume this:

H16: Attitude toward adopting AI agents mediates the effect of social support on the intention to adopt AI agents for entrepreneurship.

H17: Attitude toward adopting AI agents is a mediator for the relationship between AI agent attributes and intention to adopt AI agents for entrepreneurship.

Mediating role of perceived usefulness

PU operates as a mediating belief that transmits the influence of external enablers—such as social support and system/agent attributes—onto adoption intention by reducing uncertainty and emphasizing instrumental value. In AI-agent contexts, capabilities such as real-time responsiveness, predictive analytics, and adaptive personalization function as task-level affordances that make usefulness salient for entrepreneurial decision support (Ghosh, 2025; Kim et al., 2021). When these features are perceived as instrumental to business performance, PU becomes the key psychological conduit linking technical attributes to attitude and intention, consistent with TAM's beliefs-to-behavior pathway. We posited:

H18: Perceived usefulness of adopting AI agents mediates the relationship between social support and the intention to adopt AI agents for entrepreneurship.

H19: Perceived usefulness of adopting AI agents mediates the relationship between AI agent attributes and the intention to adopt AI agents for entrepreneurship.

As illustrated in Figure 1, the present research specifies a structural scheme linking social support, AI-agent attributes, perceived ease of use, perceived usefulness, attitude, and intention to use AI agents within a single model. The scheme incorporates both direct connections

among these variables and indirect, mediated links, clarifying how cognitive evaluations, affective responses, and social conditions jointly explain entrepreneurs' intention to employ AI agents in digital-commerce settings. It serves as the conceptual structure upon which the following empirical work will be based, as well as the basis for the formulation of the study's hypotheses.

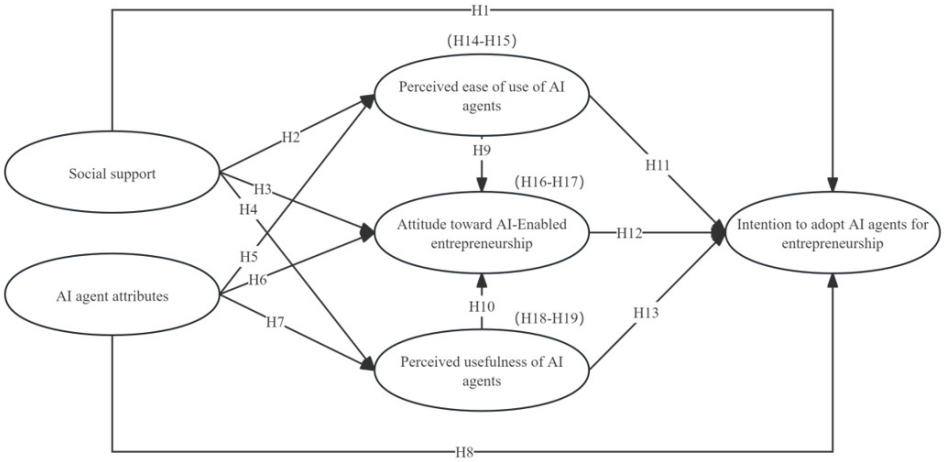


Fig. 1 *Empirical framework*

Methodology

Data collection

The information of Generation Y entrepreneurs who are running digital enterprises is collected from a cross-sectional survey via questionnaire. The target group was people actively engaged in startup activity who regularly utilized AI tools like conversational agents, virtual assistants, and algorithms for recommendations in their daily startup business operations. I want to have a little easier life, so I'm just gonna call Generation Y the people who were born from 1980 to 1995. Entrepreneurs were qualified for inclusion in the sample if they were founders or co-founders of a digital venture at the time of the survey, had continuing managerial responsibility for the business, and had started generating revenue. Individuals who used AI tool(s) purely in a work capacity as an employee and had no involvement with being an entrepreneur were excluded from the sample. I picked this group because they are very good at using computers, want to start their own businesses more than others do, and were some of the first to use new smart tools – these things make them good at figuring out how AI gets used in starting up new businesses (Frunzaru & Cismaru, 2021).

Data was collected twice in two months in 2025. In every round, the research team would distribute the online survey links through multiple channels such as startup incubators, science parks, and entrepreneurship service platforms. And they were also being shared amongst the online entrepreneur communities that existed on platforms such as WeChat and QQ.

In the first round, the participants were mainly from the university-linked incubators, makerspaces, and co-working hubs. Round two extended reach to creator studios, social commerce workspaces, and small to medium-sized businesses located in tech-focused industrial zones. To prevent duplicate responses, the questionnaire included a screening item to check if the respondents had participated in an earlier round. Then the IP addresses were checked for repeats, and responses were cleansed. Therefore, the two rounds of sampling can be considered as two independent samples from the same target group, and thus merged into a single cross-sectional dataset for analysis. After removing incomplete and invalid questionnaires, a total of 579 valid samples of Generation Y entrepreneurs in the digital business sector were obtained.

This study employed a convenience sampling recruitment strategy. Researchers contacted incubator managers, entrepreneurial community organizers, and online community administrators, requesting them to distribute the questionnaire link among their network members. Therefore, the scope of this study is not all entrepreneurs in Beijing, but rather those active in incubators and digital communities engaged in digital business. This sampling framework reflects the entrepreneurial ecosystem group where artificial intelligence tools are most visible and where digital innovation pressures are most significant.

Research site

Beijing constitutes China's leading digital-commerce hub, characterized by a dense concentration of research universities, platform firms, and specialized industrial parks that provide the infrastructure and market conditions necessary for AI-enabled entrepreneurship. In Beijing, local-government programs aimed at commercializing science and technology, as well as pilot projects around AI applications, have led to a great deal of startup experimentation. At the same time, they have raised the compliance bar and the technical bar at the same time. It's an even higher bar for smaller entrepreneurial teams.

Beijing is China's most advanced AI-digital-commerce hub, with a very high concentration of research universities, platform companies, and specialized industrial parks that provide both the infrastructure and markets for AI-enabled entrepreneurship. In Beijing, programs by the local government that revolve around the commercialization of science and technology, as well as pilot programs involving the use of AI applications, have produced many opportunities for experimentation by startups. And also at a higher need for compliance and technology, which also imposes greater challenges on small entrepreneurial teams.

To account for both opportunities and limitations of the structure, and to capture diversity under varying application contexts of AI, I collected my data across four key districts of the city, each representing a unique portion of Beijing's AI-entrepreneurship scene. In Haidian (Zhongguancun Science City), the study reached participants through university-based incubators, makerspaces, and coworking hubs, which tend to attract ventures that focus on software and model-based technologies. In Chaoyang, famous for its central business district and bustling creator economy, we went to MCN studios, content-commerce companies, and social e-commerce spaces. We went to the Daxing/Yizhuang area, which is also known as Beijing E-town, by going through technology parks and service centers for small and medium-sized companies focusing on smart manufacturing, logistics, and embodied AI. Lastly, Changping has put its effort into the Future Science City corridor, where suburban entrepreneurship service windows and science park offices are linking broader markets and innovation ecosystems. The four were taken together as the main recruitment areas for digital commerce entrepreneurs who already knew about AI tools and systems.

China is the only research site in this study due to its worldwide reputation for having AI and a highly advanced digital business system. Among Chinese cities, Beijing is unique as a platform and incubator of technological innovations, digital platforms, as well as incubators and accelerators for start-ups. Beijing is a very suitable place for studying AI adoption by start-ups.

This research wants to figure out what parts of social structure (social help), AI system qualities (smart stuff), and what you think are all playing together to decide if you want to use it. Instead of seeking to make a comparison with respect to different institutions or cultures of countries, this article would like to investigate internal mechanisms within a control environment. Cross-region would have differences in stuff like regulation, how mature the platform is, and what kind of help is available that could hide the stuff we're looking at. If concentrating on one interlocking innovation environment, we can split and optimize the principal connections, as well as the internal correctness of the research's outcomes.

Research tools

The questionnaire used by the author in the study has been divided into six large parts. I collected basic demographics, and then the first meaningful section was social support. This is measured by the entrepreneurs' ratings on indicators of how much help they received from digital communities in terms of emotional, informational, and instrumental. Three items that were adopted from Sheikh et al. (2019) were used to assess this dimension.

Second section on attributes of an AI agent. Focuses particularly on features such as autonomy, interaction, and adaptability for entrepreneurial tasks. This part is according to a set of 13 items developed by Kang and Shao (2023).

In terms of how easy I found the system to be, the questionnaire asked five questions about whether or not I understood things that happened during the interaction, and if it was fun to learn from the system. These items are from Herzallah AT, Mukhtar, et al. (2016).

The following section measured participants' attitudes towards AI agents, concentrating on their overall evaluation, including being satisfied, having a preference for it, and wanting to adopt it. This part was based on five parts taken from Kusumojanto et al. (2021).

Perceived usefulness was also measured with six factors, which focused on the idea of how much the AI agents have helped with efficiency, enhancement of performance, and how they helped with decision-making. These, too, came from Herzallah AT, Mukhtar, et al. (2016).

The final section gathered entrepreneurs' intentions to adopt AI agents, containing short-term plans to put into action, long-term intentions to implement the use, as well as a general willingness to adopt such tools. Based on the 6 items from (Kusumojanto et al., 2021).

The questionnaire in total has 38 items and was rated with a 5-point Likert scale. And this framework gave a total structure to look at the big ideas around how AI gets used by people starting businesses. All items were taken from validated scales from other research and adjusted for the context of digital entrepreneurship and AI agents.

Data analysis

Data analysis relied on SPSS 26.0 together with AMOS 26.0 and followed a staged procedure. Structural equation models were estimated using maximum likelihood, which is appropriate for continuous indicators and the sample size in this study. Descriptive statistics were first produced to profile respondents and summarize scores on all latent constructs. Scale reliability was then examined by calculating Cronbach's alpha for each multi-item measure. The adequacy of the measurement structure was subsequently assessed through confirmatory factor analysis, in which standardized factor loadings, composite reliability, and average variance extracted were inspected for evidence of convergent validity, and the Fornell–Larcker test was used to evaluate discriminant validity. After establishing an acceptable measurement solution, structural equation modeling was employed to test the proposed paths and intervening effects, and overall model adequacy was judged from a set of fit indicators, including χ^2/df, CFI, TLI, RMSEA, and SRMR, against commonly accepted benchmarks.

Pilot study

Before distributing the full questionnaire, a small-scale trial was run with 24 participants to check item wording and overall scale performance. Evidence from this pilot indicated satisfactory psychometric properties: Cronbach's alpha values for every construct were at least .85, suggesting strong scale reliability, the Kaiser–Meyer–Olkin coefficient reached .945, and Bartlett's test of sphericity was highly significant (χ^2 = 11,842.736, df = 703, p < .001). On this basis, exploratory factor analysis was undertaken, and the instrument was considered suitable for use in the main survey. Exploratory factor analysis extracted six factors explaining 69.577% of total variance, with all items loading above .50 and minimal cross-loadings. The participant feedback prompted the researchers to make minor wording revisions to a few of the items to make them clearer. The pretest results gave us assurance in the questionnaire structure, and we were able to use it for data collection purposes. This provided us with a strong structure to do the analysis in the next part.

Results

Descriptive analysis

Table I shows the sociodemographic summaries and basic entrepreneurial venture information of the respondents. The sample is highly educated, wise, and quite elevated; most participants have done at least a master's, with around a third having gotten doctorates. And there are a lot of people. There are a lot of humans. Capital density among the people that we're surveying, the entrepreneur.

Nearly everyone said their ventures lasted at least a year but no more than 5. That is to say, it is mostly those at the beginning of entrepreneurship and the consolidation period of entrepreneurship, and the sample is unlikely to include people just entering entrepreneurship or people who have already been in business for quite some time.

The gender composition within the sample is roughly even. Married participants just edge out the unmarried; thus, quite a few of these entrepreneurs might be taking on technology adoption within a setting that contains family help, instead of entirely on their own.

In terms of the type of business involved, most of the participants are engaged in different sectors of digital commerce. Social commerce and content-driven models were the most popular with online retail and cross-border e-commerce ventures. From the pattern, we can see that the study mainly contains types of businesses that depend heavily on digital and engaging directly with the audience, hence it is more relevant for those who sell to people.

Mostly distributed and collected through WeChat and QQ, and a small part through Xiaohongshu and Weibo. This distribution shows that the study reached a large group of entrepreneurs who are active on the main communication and social media platforms in China.

Table I
Sample Information

Information and options	Information and options	Frequency	Percent
Marital Status	Married	338	58.4
Marital Status	Unmarried	241	41.6
Gender	Male	313	54.1
Gender	Female	266	45.9
Education Level	Bachelor's Degree	172	29.7
Education Level	Master's Degree	212	36.6
Education Level	PhD	195	33.7

Cont...

Information and options	Information and options	Frequency	Percent
Entrepreneurial Experience	Less than 1 year	104	18
Entrepreneurial Experience	1-3 years	258	44.6
Entrepreneurial Experience	3-5 years	133	23
Entrepreneurial Experience	More than 5 years	84	14.5
Entrepreneurial Sector	Online retail	116	20
Entrepreneurial Sector	Social commerce	135	23.3
Entrepreneurial Sector	Cross-border commerce	76	13.1
Entrepreneurial Sector	Content-based commerce	133	23
Entrepreneurial Sector	Vertical niche commerce	56	9.7
Entrepreneurial Sector	B2B commerce	34	5.9
Entrepreneurial Sector	Digital product sales	29	5
Survey Platform	QQ	140	24.2
Survey Platform	WeChat	292	50.4
Survey Platform	Weibo	40	6.9
Survey Platform	Xiaohongshu	107	18.5
AI Technology Adoption	AI Chatbots for customer service	83	14.3
AI Technology Adoption	AI-based recommendation systems	33	5.7
AI Technology Adoption	Intelligent virtual assistants	143	24.7
AI Technology Adoption	Predictive analytics for business decision-making	57	9.8
AI Technology Adoption	AI-powered marketing automation tools	45	7.8
AI Technology Adoption	AI-generated content	160	27.6
AI Technology Adoption	Smart agents for supply chain or logistics	24	4.1
AI Technology Adoption	AI for personalized education or training	23	4
AI Technology Adoption	Natural Language Processing (NLP) applications	11	1.9

Figure 2 is the current use of artificial intelligence applications by 579 entrepreneurs. It can be seen that the most frequently used AI-generated content is 27.6%. Intelligent virtual assistants are 24.7%. Other common forms are chatbots for customer service at 14.3% and predictive analytics for business decisions at 9.8%.In contrast, some more specialized applications, such as logistics agents, personalized education tools, and natural language processing applications, have lower usage rates, all at 4.1% or below. Overall, Figure 2 indicates that young digital entrepreneurs tend to adopt artificial intelligence tools that support customer interaction, content creation, and front-end decision making, while paying less attention to transformative applications for back-end operations such as supply chain management or advanced language processing. This usage structure provides important context for interpreting the subsequent structural equation model results, helping to explain how social support and entrepreneurs' beliefs about artificial intelligence agents influence their intention to further deepen or expand their use of such applications.

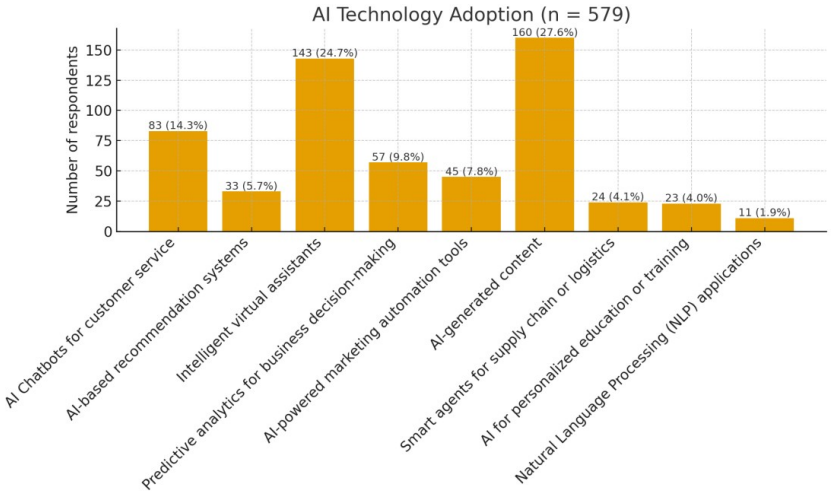


Fig. 2 *Adoption of AI technologies among Generation-Y entrepreneurs in Beijing (n = 579)*

Structural Equation Model (SEM)

Measurement model and fit metrics

Table II summarises the goodness-of-fit statistics for the measurement specification. All reported indicators reach or exceed commonly accepted cut-off values. The ratio of chi-square to degrees of freedom (1.405) is far below the reference value of 3, and the RMSEA of 0.026 points to a very close approximation of the data. The Global Fit Indices (GFI = 0.924, AGFI = 0.913, NFI = 0.944, TLI = 0.982, CFI = 0.983) are all higher than 0.90, indicating satisfactory overall model performance. Taken together, these results show that the measurement model is statistically adequate for subsequent structural modelling.

Table II
Measure model fit metrics

Fit index	χ2/df	RMSEA	GFI	AGFI	NFI	TLI	CFI
Reference standards	<3	<0.08	>0.90	>0.90	>0.90	>0.90	>0.90
Result	1.405	0.026	0.924	0.913	0.944	0.982	0.983

Convergent validity

Evidence for convergent validity is summarised in Table III. For every construct, the standard criteria for factor loadings, Composite Reliability (CR), and Average Variance Extracted (AVE) are satisfied. Standardised loadings are all above 0.65, indicating that the indicators are closely associated with their respective latent factors. CR estimates range from 0.867 to 0.946, exceeding the 0.70 benchmark and reflecting high internal consistency. AVE values lie between 0.574 and 0.707, higher than the commonly used cut-off of 0.50, which shows that a substantial share of variance is accounted for by each construct. Taken together, these statistics indicate satisfactory convergent validity and suggest that the scale represents the underlying dimensions of AI agent adoption for entrepreneurial purposes.

Table III
Convergence validity

Latent variables	Observation indicators	Factor loading	CR	AVE
Social support	SS1	0.807	0.867	0.685
Social support	SS2	0.834	0.867	0.685
Social support	SS3	0.841	0.867	0.685
AI agent attributes	MA1	0.853	0.946	0.574
AI agent attributes	MA2	0.714	0.946	0.574
AI agent attributes	MA3	0.705	0.946	0.574
AI agent attributes	MA4	0.678	0.946	0.574
AI agent attributes	MA5	0.667	0.946	0.574
AI agent attributes	MA6	0.774	0.946	0.574
AI agent attributes	MA7	0.792	0.946	0.574
AI agent attributes	MA8	0.752	0.946	0.574
AI agent attributes	MA9	0.754	0.946	0.574
AI agent attributes	MA10	0.655	0.946	0.574
AI agent attributes	MA11	0.848	0.946	0.574
AI agent attributes	MA12	0.824	0.946	0.574
AI agent attributes	MA13	0.799	0.946	0.574
Perceived ease of use of AI agents for entrepreneurship	PE1	0.869	0.897	0.637
Perceived ease of use of AI agents for entrepreneurship	PE2	0.823	0.897	0.637
Perceived ease of use of AI agents for entrepreneurship	PE3	0.732	0.897	0.637
Perceived ease of use of AI agents for entrepreneurship	PE4	0.803	0.897	0.637
Perceived ease of use of AI agents for entrepreneurship	PE5	0.757	0.897	0.637
Perceived usefulness of AI agents for entrepreneurship	PU1	0.872	0.925	0.673
Perceived usefulness of AI agents for entrepreneurship	PU2	0.859	0.925	0.673
Perceived usefulness of AI agents for entrepreneurship	PU3	0.811	0.925	0.673
Perceived usefulness of AI agents for entrepreneurship	PU4	0.755	0.925	0.673

Cont...

Latent variables	Observation indicators	Factor loading	CR	AVE
Perceived usefulness of AI agents for entrepreneurship	PU5	0.837	0.925	0.673
Perceived usefulness of AI agents for entrepreneurship	PU6	0.781	0.925	0.673
Attitude toward adopting AI agents for entrepreneurship	AT1	0.838	0.906	0.659
Attitude toward adopting AI agents for entrepreneurship	AT2	0.832	0.906	0.659
Attitude toward adopting AI agents for entrepreneurship	AT3	0.767	0.906	0.659
Attitude toward adopting AI agents for entrepreneurship	AT4	0.798	0.906	0.659
Attitude toward adopting AI agents for entrepreneurship	AT5	0.822	0.906	0.659
Intention to adopt AI agents for entrepreneurship	IT1	0.9	0.935	0.707
Intention to adopt AI agents for entrepreneurship	IT2	0.734	0.935	0.707
Intention to adopt AI agents for entrepreneurship	IT3	0.779	0.935	0.707
Intention to adopt AI agents for entrepreneurship	IT4	0.845	0.935	0.707
Intention to adopt AI agents for entrepreneurship	IT5	0.851	0.935	0.707
Intention to adopt AI agents for entrepreneurship	IT6	0.922	0.935	0.707

Discriminant validity

Table IV summarises the assessment of discriminant validity using the Fornell–Larcker criterion. For every latent construct, the square root of the AVE, shown on the main diagonal of the correlation matrix, is larger than its correlations with any other construct, meaning that each factor explains more variance in its own indicators than in those of alternative factors (Fornell & Larcker, 1981). For example, the square root of the AVE for intention to adopt AI agents is 0.841, which is greater than its correlations with attitude (0.647) and perceived usefulness (0.604), indicating a clear separation of this construct. A similar pattern appears for the remaining variables, where diagonal entries range from 0.758 to 0.841 and consistently exceed the corresponding off-diagonal coefficients. Taken together, these statistics support adequate discriminant validity, showing that the latent variables in the model are empirically distinct while still theoretically related.

Table IV
Discriminant validity test

Latent variables	IT	AT	PU	PE	MA	SS
Intention to adopt AI agents	0.841 ***					
Attitude toward adopting AI agents	0.647***	0.812 ***				
Perceived usefulness	0.604***	0.544***	0.820 ***			
Perceived ease of use	0.551***	0.516***	0.331***	0.798 ***		
AI agent attributes	0.462***	0.469***	0.469***	0.394***	0.758 ***	
Social support	0.586***	0.491***	0.453***	0.503***	0.483***	0.828 ***

Note: The diagonal values (bold) represent the square root of the Average Variance Extracted (AVE) for each construct, all significant at ***$p < 0.001$. Off-diagonal values are inter-construct correlations. IT: Intention to adopt AI agents; AT: Attitude toward adopting AI agents; PU: Perceived Usefulness; PE: Perceived Ease of Use; MA: AI agent attributes; SS: Social support. ***: $p < 0.001$.

Structural model path analysis

Model fit metrics for the structural model

As shown in Table V, the structural model achieves a satisfactory overall fit. The chi-square to degrees of freedom value ($\chi^2/df = 1.407$) is lower than the commonly accepted upper limit of 3, and the RMSEA estimate of 0.027 indicates a close correspondence between the model and the observed covariance structure. The goodness of fit indices GFI (0.924) and AGFI (0.913) are both greater than 0.90, suggesting that the data are well represented by the model. In addition, the incremental fit indices NFI (0.944), TLI (0.982), and CFI (0.983) all exceed the 0.90 benchmark, providing further evidence of model adequacy (Hu & Bentler, 1999). Taken together, these indicators show that the structural specification fits the sample data well and is appropriate for subsequent hypothesis testing.

Table V
Model fit metrics

Fit index	χ2/df	RMSEA	GFI	AGFI	NFI	TLI	CFI
Reference standards	<3	<0.08	>0.90	>0.90	>0.90	>0.90	>0.90
Result	1.407	0.027	0.924	0.913	0.944	0.982	0.983

Path analysis for direct effects

Table VI reports the estimated direct paths among the core constructs, and the overall pattern of coefficients is consistent with most of the proposed hypotheses. Social support (SS) shows significant positive effects on perceived ease of use (PE, β = 0.411, p < 0.001; H2), perceived usefulness (PU, β = 0.300, p < 0.001; H4), attitude toward adoption (AT, β = 0.132, p = 0.009; H3), and intention to adopt AI agents (IT, β = 0.213, p < 0.001; H1). AI agent attributes (MA) are likewise positively associated with PE (β = 0.197, p < 0.001; H5), PU (β = 0.325, p < 0.001; H7), and AT (β = 0.140, p = 0.002; H6). In contrast, the direct path from MA to IT is not statistically significant (β = 0.018, p = 0.634; H8), indicating that any influence of MA on intention is transmitted mainly through cognitive or attitudinal mechanisms. Within the TAM structure, PE (β = 0.289, p < 0.001; H9) and PU (β = 0.327, p < 0.001; H10) both enhance AT, and PE (β = 0.202, p < 0.001; H11), PU (β = 0.284, p < 0.001; H13), and AT (β = 0.277, p < 0.001; H12) each exert significant positive effects on IT. Taken together, these paths suggest that the specified model offers a coherent explanation of intention formation, with PE, PU, and AT acting as immediate drivers of intention in the presence of SS and MA. Their indirect roles are elaborated in the following subsection on mediating effects.

Table VI
Direct path effects

Hypothesis	Path	β	S.E.	C.R.	p	Results
H1	SS → IT	0.213	0.042	4.859	***	Supported
H2	SS → PE	0.411	0.051	8.124	***	Supported
H3	SS → AT	0.132	0.050	2.632	0.009	Supported
H4	SS → PU	0.300	0.055	6.228	***	Supported
H5	MA → PE	0.197	0.051	4.226	***	Supported
H6	MA → AT	0.140	0.047	3.146	0.002	Supported
H7	MA → PU	0.325	0.057	7.032	***	Supported
H8	MA → IT	0.018	0.039	0.477	0.634	Non-Supported
H9	PE → AT	0.289	0.044	6.419	***	Supported
H10	PU → AT	0.327	0.038	7.345	***	Supported
H11	PE → IT	0.202	0.038	4.994	***	Supported
H12	AT → IT	0.277	0.043	6.238	***	Supported
H13	PU → IT	0.284	0.034	6.984	***	Supported

Note: SS = Social support; MA = AI agent attributes; PE = Perceived Ease of Use; PU = Perceived Usefulness; AT = Attitude toward adopting AI agents; IT = Intention to adopt AI agents. ***: p < 0.001.

Figure 3 displays the estimated structural model, in which external conditions and internal evaluations are linked to entrepreneurs' intention to employ AI agents. In the diagram, paths run from social support and AI agent attributes to perceived ease of use, perceived usefulness, and attitude, and these proximal beliefs in turn point to adoption intention.

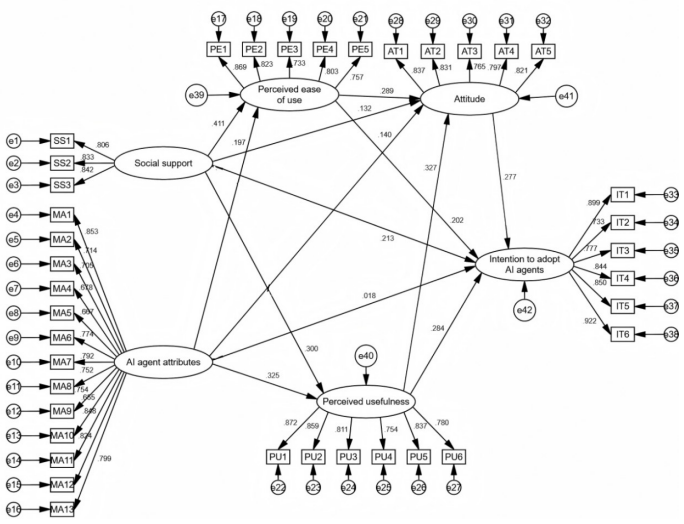


Fig. 3 *Structural model diagram)*

Standardized coefficients are reported next to each path so that the magnitude and sign of the relationships can be seen at a glance. The figure further indicates that cognitive and attitudinal constructs act as transmission channels through which external influences shape behavioral intention. Taken together, the visualized model clarifies how social, technological, and psychological elements jointly contribute to entrepreneurs' decisions to integrate AI agents into digital business activities.

Table VII reports the bootstrap results for indirect effects, confirming the mediating roles of Perceived Ease of Use (PE), Perceived Usefulness (PU), and Attitude (AT) between external factors and entrepreneurial intention to adopt AI agents (IT).

For social support (SS), the indirect effects are significant via PE (β = 0.083, p < 0.001; H14; 95% CI [0.047, 0.124]), via AT (β = 0.037, p < 0.01; H16; 95% CI [0.013, 0.067]), and via PU (β = 0.085, p < 0.001; H18; 95% CI [0.058, 0.119]). For AI agent attributes (MA), the corresponding indirect effects are also significant via PE (β = 0.040, p < 0.01; H15; 95% CI [0.016, 0.071]), via AT (β = 0.039, p < 0.01; H17; 95% CI [0.018, 0.067]), and via PU (β = 0.092, p < 0.001; H19; 95% CI [0.061, 0.131]). All confidence intervals exclude zero, demonstrating robust mediation across paths.

In terms of mediation type, because the direct path MA → IT (H8) is non-significant (β = 0.018, p = 0.634), while MA shows significant indirect effects via PE/PU/AT (H15–H19), the influence of MA on IT is best characterized as full mediation through cognitive (PE, PU) and attitudinal (AT) mechanisms. In contrast, SS has strong direct and indirect SS(PE/PU/AT), H1, H14, H16, H18), partial mediation, supportive social environments make it seem doable and helpful, hence Intention, and supportive social environments create Intention directly.

Comparatively, the PU-based channels are the strongest mediators for both exogenous variables (SS: β_indirect via PU = 0.085, H18; MA: β_indirect via PU = 0.092, H19), followed by PE-based channels (SS: 0.083, H14; MA: 0.040, H15) and AT-based channels (SS: 0.037, H16; MA: 0.039, H17). This pattern underscores the centrality of perceived usefulness in transmitting social and technological influences to adoption intention, consistent with the TAM perspective.

Table VII
Indirect effect bootstrap analysis

H14	SS → PE → IT	0.083	0.019	0.047	0.124	Supported
H15	MA → PE → IT	0.04	0.014	0.016	0.071	Supported
H16	SS → AT → IT	0.037	0.013	0.013	0.067	Supported
H17	MA → AT → IT	0.039	0.012	0.018	0.067	Supported
H18	SS → PU → IT	0.085	0.016	0.058	0.119	Supported
H19	MA → PU → IT	0.092	0.017	0.061	0.131	Supported

Note: SS = Social support; MA = AI agent attributes; PE = Perceived Ease of Use; PU = Perceived Usefulness; AT = Attitude toward adopting AI agents; IT = Intention to adopt AI agents.

Total effects

Based on the total effect estimate presented in Table VIII, social support has the greatest effect on entrepreneurs' intention to adopt an AI agent, with a standardized estimate of β = 0.478 (p < 0.001). It shows how important relationships between people and support from the larger community are when it comes to whether someone adopts something or not. Although social support stands out, the attributes of the AI agents also have a significant total effect on adoption intention, β = 0.234 (p < 0.001). And therefore, these design features like adaptability, interactivity, and autonomy would help an entrepreneur with the desire of getting an AI agent in his business. Perceived usefulness (β = 0.284, p < 0.001) and perceived ease of use (β = 0.202, p < 0.001) provide additional direct and mediated contributions to intention, in line with the core propositions of the Technology Acceptance Model regarding performance expectations and effort requirements. Taken together, the pattern of total effects suggests that adoption outcomes in digital entrepreneurship arise from the combined influence of social environments, technological characteristics, and entrepreneurs' cognitive evaluations.

Table VIII
Total effects

Effect path	Effect size	SE	Bias-Corrected 95%CI	Bias-Corrected 95%CI	Bias-Corrected 95%CI
Effect path	Effect size	SE	Lower	Lower	Upper
SS → IT	0.478	0.049	0.375	0.568	0.568
MA → IT	0.234	0.045	0.147	0.325	0.325
PE → IT	0.202	0.038	0.128	0.276	0.276
PU → IT	0.284	0.034	0.217	0.351	0.351

Note: SS = Social support; MA = AI agent attributes; PE = Perceived Ease of Use; PU = Perceived Usefulness; AT = Attitude toward adopting AI agents; IT = Intention to adopt AI agents

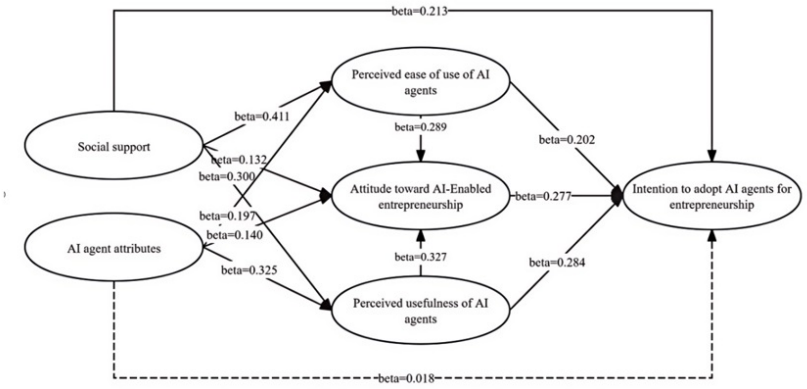


Fig. 4 *Structural model for predicting the intention to adopt AI agents for entrepreneurship*

Figure 4 shows that social support from family, friends, mentors, and policy institutions is the most prominent external resource influencing entrepreneurs' evaluation of AI agents, particularly in shaping perceived ease of use and perceived usefulness. In contrast, the impact of AI-agent attributes is relatively weak, but these design features are still significantly positively correlated with entrepreneurs' technological cognition (Peng et al., 2024). The structural model does not show a significant direct impact of AI-agent attributes on adoption intention, a pattern that may be related to China's unique institutional and market context. In China, many entrepreneurs are inexperienced and have poor knowledge about the functions of AI agents, and thus, the functional attributes are not very predictive of adoption intention (Duong et al., 2024; Li et al., 2022).

On the other hand, social support has more impact as Generation Y entrepreneurs in China seem to respond more to interpersonal and community signals. Their entrepreneurial choices are frequently formed in the larger social environment, making them more open to relational cues (S. He et al., 2023).

Meanwhile, the strength of technology-related perceptions as predictors of both attitudes and intentions to adopt is mirrored in findings of other studies of AI-enabled e-commerce and virtual assistant technologies (Lopes et al., 2024; Pathak & Bansal, 2025). And these results highlight how entrepreneurs' minds process and evaluate smart systems.

But it still holds the most extensive and powerful impact in the eyes of the whole effect, social support. And so this means something really: rather than just trying to increase the amount of complexity in functional terms of AI agents, policy design, and ecosystem stakeholders need to be thinking about investing more into supporting these kinds of mechanisms. Emotional encouragement, informational resources, hands-on help, and the validation of peers or mentors can all play important roles in reducing the perceived effort, increasing the perceived usefulness, and developing favorable attitudes. These kinds of support can be combined so that the potential of the AI techs will become a long-term entrepreneurship.

Discussion

A study on how social support and AI-agent attributes affect the intention of Generation Y entrepreneurs in Beijing to use intelligent systems in their businesses is conducted, using this as a whole to study.

From the findings, we know social support has a great effect. It will directly increase PEOU, PU, attitude, and adoption intention, and finally get the biggest total effect on entrepreneurs' willingness to use AI agents. Compared with this, although the AI-agent characteristics such as autonomy, adaptability, and interactivity have a positive effect on the formation of core TAM belief, they have no significant effect on intention. Which means that good systems can probably help it be usable and practical for people (important!), but the ecosystem-level support – those touchpoints with real people who offer emotional assurances, handy informational nudges, and motivating little boosts – is really what gets them to go from feeling good about it to using it. We could see it even more evidently in Beijing, where there were lots of opportunities, but the entry was rather high.

On the other hand, the core TAM holds up strong. Both PEOU and PU positively influence attitude, and all three constructs—PEOU, PU, and attitude—significantly predict entrepreneurs' intention to adopt AI agents in digital commerce settings. Mediation tests further show that external antecedents operate through these TAM. The absence of a direct path to intention path alongside sizable indirect effects implies that a "cognitive–attitudinal mechanism" that PEOU/PU shapes attitude, which together drive intention, dominates entrepreneurial adoption of AI agents.

Theoretical implications

This study advances the theoretical understanding of AI-enabled entrepreneurship by simultaneously incorporating two types of external antecedents—social support and AI-agent attributes—into the Technology Acceptance Model (TAM) and clarifying their different pathways to adoption intention.

First, this study reveals the path asymmetry between the two types of antecedents. Compared to previous AI-acceptance research, which mainly emphasized the cognitive chain from Perceived Ease Of Use (PEOU) and Perceived Usefulness (PU) to attitude and then to intention (Lu et al., 2025; Yi & Choi, 2023), this study finds that:

Social support has both a direct impact on adoption intention and an indirect impact through PEOU, PU, and attitude;AI-agent attributes, on the other hand, only indirectly affect intention through TAM beliefs.

This result repositions social support from an ”external motivating factor” to a ”key force in belief formation.” Emotional, informational, instrumental resources, and evaluative support can reduce entrepreneurs’ perceived effort, making them more likely to perceive value, rather than simply creating normative pressure (Davis & Granić, 2024).

Secondly, this study clarifies the conceptual role of AI-agent capabilities in TAM. The results show that attributes such as interactivity and adaptability are more like cognitive catalysts that promote cognitive change, rather than direct triggers that drive behavior. Natural interactive experiences and seamless integration into the entrepreneurial process can first reduce perceived effort and increase instrumental value, then drive changes in attitude and intention. This also helps explain why the direct relationship between system attributes and adoption intention often shows inconsistencies in digital commerce research. Within Beijing’s high-opportunity, high-barrier (data, skills, compliance requirements) ecosystem, the conditions under which different paths function become clearer: when entrepreneurs have limited resources and high uncertainty, ecosystem support can accelerate adoption decisions; while when AI’s interpretability and onboarding structure are more complete, the impact of design attributes is more pronounced.

Third, this study further enriches the explanation of the impact of social support on TAM beliefs from the perspectives of need satisfaction and stress buffering. Evidence from motivational psychology suggests that supportive relationships can enhance an individual’s autonomy, competitiveness, and relatedness, thereby improving evaluative judgment and exploratory behavior (Messmann et al., 2022; Vansteenkiste et al., 2020). From the perspective of technology adoption, it stands to reason that positive emotional states will lower our estimates of required effort and increase our sense of confidence in our own abilities, thus improving our sense of PEOU and making the performance-related benefits of PU more apparent. At the same time, social support can also reduce perceived stress levels, which prevents the stress from consuming our cognitive resources for learning and evaluation. Users would have more steady and similar opinions about using new technology (Acoba, 2024; Jam et al., 2025).

In addition to this, more recent research that is using social support theory in conjunction with the technology acceptance model also shows that a supportive environment can help contribute to ongoing improvements in the level of perceived usability, as well as improvements in the perceived usefulness of a technology (Aldraiweesh & Alturki, 2025; Alshammari & Alkhwaldi, 2025). In entrepreneurial terms, it points to stuff like mentorship, building capabilities, or places where safe experimenting with AI might make that social assistance feel really helpful and wanted, kind of.

Moreover, the present study identifies significant boundary circumstances for the extended TAM framework. Findings suggest that the effect of social support is high at the beginning of an entrepreneurship or if the algorithm that leads to the behavior of the AI agent is not open. On the other hand, the effects of AI-agent features show up most when the systems provide unambiguous feedback and understandable outputs (Glikson & Woolley, 2020; Shin et al., 2022).

This revelation makes it evident that the surroundings of the TAM are operating. Specifically, social support works through a relational and emotional pathway, and AI-agent features work through a design-oriented cognitive pathway. Thus, TAM goes beyond the original focus on individual cognition, becoming a socially embedded and design-aware framework for understanding AI adoption (S. He et al., 2023).

Practical implications

We suggest that practical strategies would benefit from efforts to both strengthen social support and improve the quality of intelligent tool design.

Entrepreneurs, the news is that cultivating and sustaining a good digital network is more of a sideline than a resource. Take part in the online entrepreneur community, get involved in peer learning and mentorship, and then you can have all these shared out and out there within a collaborative space, making those challenges to learn some AI tools much easier. And the interactions offer us some use case reality, and the emotional reassurance from that helps overcome some of the wariness we have towards using new technologies. Entrepreneurs who engage actively, interact, and engage in shared knowledge and trust will find that they might see as trusted, useful, manageable helper AI’s.

For developers and tech providers, it is evidence of the value of making AI systems that are easy to learn, transparent in logic, and flexible to various entrepreneurial workflows. And thus, is it merely that a system gets its job done, or is it that a system explains why it does a job

as well as it does, how well it is able to integrate with what we use, and how simple it makes it to change when required by entrepreneurs? Programmers need to stress iterative testing with genuine people, make the getting-started experiences simple and understandable, and clearly show performance results - possibly through easy-to-use pictures. Offering different levels of custom automation, clear reasons for system actions, and the choice to have a human oversee are all very good at raising both PU and PEOU with entrepreneurial users.

For policymakers, institutions, and others, showing the big role social support plays shows how much we should make places and spaces where it's okay for people to play and to use AI with the people they know. Government-backed programs can fund incubators and accelerators that do hands-on AI training, set up a system for helping new AI users learn from experienced ones, and give small grants for taking small risks. And at the same time, it will be very necessary for the clarity of the regulatory framework on data safety, fairness, and the accountability of algorithms that can reduce ambiguity and make entrepreneurs believe that using responsible AI is encouraged and supported.

Teachers and teachers, from the conclusions of this, it is concluded that AI education needs to give attention to attitude education, peer cooperation. Courses that mix hands-on AI projects and planned thinking alongside groups are better for making long-term, good ideas about clever machines. Activities like we do co-designing with an AI-powered business model activity, share out our project results with each other, and give each other peer feedback, so students start perceiving AI instead of it being some magical black box kind of a thing, more like a trustworthy decision maker sidekick kind of a thing.

In short, promoting the use of AI agents in digital entrepreneurship needs the cooperation of the ecosystem. Entrepreneurs build emotionally and informationally supportive communities, developers improve the usability and trust of systems, policymakers can set up enabling conditions through institutions and regulation, and educators can teach founders-in-training how to interact with intelligent technologies. When these efforts line up, AI agents are more apt to spur innovation, improve competitiveness, and permit more sustainable kinds of digital entrepreneurship.

Conclusion

In this study, the key factors influencing entrepreneurs' adoption of AI agents in a digital business setting are explored, with a focus on the roles of social support, system design attributes, and cognitive–attitudinal pathways from TAM. From the empirical evidence, it is found that the interpersonal and community support and the positive attitudes towards the functionality and usability of the AI agents can increase the entrepreneurs' Perceived Usefulness (PU), Perceived Ease Of Use (PEOU), and attitude towards AI. Psychological mechanisms, therefore, also increase the probability that AI agents will be adopted by entrepreneurs.

Theoretically, this research contributes by adding social and technological elements to the TAM framework in the literature and validating TAM in emerging contexts of entrepreneurial activity with AI. Practically speaking, it provides doable recommendations to players in the game who are founders of enterprises, technology creators, platform masters, and lawmakers, all of whom would like to play a role in the smart linking of smartgizmos and business.

However, we must read them along with some restrictions, which also give hints for further research. Firstly, it's just sampling Generation Y entrepreneurs in Beijing, so that could limit how generalizable the results are for other ages, other geographical areas, and other industries. Future studies could also use this model elsewhere (domestically and internationally) to have a greater generalizability to this study.

Second, it is based on cross-sectional self-report data that can be prone to common method bias, and does not support causal claims. In the future, we hope it would be good if future research did longitudinal studies, collected more sources of data, or added behavioral measures and business success indicators to enhance our measurement and analysis.

Finally, although the model focuses on the central cognitive variables—i.e., social support, AI-agent design features, and TAM constructs – it is still possible to investigate moderating conditions. Future works might also take into account the role of things like organizational cultures, technology infrastructure, or policies surrounding things. If we did qualitative research, we would have a greater idea of what the entrepreneurs use AI tools for on a day-to-day basis. And they'd both deepen the theoretical grounding of using AI. And give us even more contextually-grounded, actionable tips on how to build inclusive, sustainable digital entrepreneurship ecosystems.

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