AI Adoption in Micro and Small Businesses in Almaty, Kazakhstan: An Exploratory Mixed-Methods Study

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Abstract

Artificial intelligence (AI) is increasingly accessible to small firms, yet evidence on adoption by micro and small businesses in Central Asia remains limited. This study examined current AI use, reported benefits, barriers, readiness factors and future intentions among independent businesses in Almaty, Kazakhstan. A cross-sectional exploratory mixed-methods design combined an anonymous Russian-language survey with three short semi-structured interviews. After applying fixed eligibility rules and removing duplicate or ineligible responses, 14 survey responses were retained: four current users and ten non-users. Survey data were analysed descriptively; interviews were paraphrased thematically and kept separate from survey denominators. Four businesses (28.6%) reported purposeful AI use during the previous three months. All four users used AI chat assistants, three used AI daily, and all reported time saving. Three reported lower costs and better quality. Among non-users, insufficient knowledge was the most common barrier (5 of 10), followed by an unconvinced owner or manager (3 of 10). All four users expected to increase AI use, but survey branching left future-intention data missing for non-users. The interviews also suggested that knowledge gaps may discourage initial use and limit deeper adoption. These findings describe only the small convenience sample and do not estimate adoption across Almaty. They nevertheless identify locally relevant patterns for future research and practical support, especially accessible training, local-language tools and low-cost entry points.

Keywords: artificial intelligence; small businesses; technology adoption; Kazakhstan; mixed methods

Contribution/Originality: This study provides exploratory firm-level evidence on AI adoption among micro and small businesses in Almaty, a Central Asian setting rarely represented in the literature. It separates current use, reported benefits, barriers and qualitative context while preserving the limits of a small non-random sample.

1. Introduction

Small and medium-sized enterprises (SME) are a big part of Kazakhstan's economy. From January through June 2024, they produced 38.2% of the country's gross domestic product (GDP) (Bureau of National Statistics, 2024). Almaty is the country's main commercial centre. According to the Bureau of National Statistics, it had 362,345 active SME entities as of 1 July 2026, more than any other city in Kazakhstan (Bureau of National Statistics, 2026).

At the same time, AI tools have become much easier for ordinary users to access than they were a few years ago, so even businesses with few employees can try them; whether small businesses actually do is a different question. In the countries where this has been measured, small firms adopt AI less often than large ones (OECD, 2025a). A 2024 OECD survey of more than 5,000 SMEs in seven developed economies found that 31% were using generative AI (OECD, 2025b).

Kazakhstan treats AI as a national priority. In July 2024, the government approved a Concept for the Development of Artificial Intelligence for 2024–2029, by Decree No. 592 (Government of the Republic of Kazakhstan, 2024). The local academic research available so far follows the policy side rather than the business side. For example, Abdikalikov et al. (2026) study how AI is being added to the state's SME support programmes and to bank credit scoring. Their work shows that AI is taken seriously at the level of state support, but it does not describe how the businesses themselves are using these tools.

There is still limited evidence on how small businesses in Almaty use AI, despite wider access to tools and national policy support. This study therefore asks: what is the current state of AI adoption among micro- and small businesses with one to three locations in Almaty, and what benefits, barriers, readiness factors and future intentions do their owners and managers report?

2. Literature Review

2.1 The adoption gap between small and large firms

The OECD (2025a) gives a useful overview in a discussion paper written for Canada's G7 presidency. In the countries it covers, SMEs adopt AI less often than large firms, and their uptake of AI has also been slower than their uptake of earlier digital technologies, so the small-firm lag is not simply a normal early stage that passes on its own. The paper lists four things a firm needs before adoption becomes realistic: connectivity, data and computing resources, skills, and finance. A second OECD survey (2025b) puts a figure on adoption: out of more than 5,000 SMEs surveyed in seven developed economies in 2024, 31% were using generative AI. This figure should be read with caution rather than treated as a benchmark; it covers generative AI only, not AI tools in general, and it includes a broad range of SME sizes, including firms much larger than those in this study.

2.2 What drives adoption

Pinto et al. (2025) examine which factors are associated with AI adoption. Their meta-analysis pools 12 studies with 3,398 respondents; they grouped the factors into technology, organisation and environment, known as the Technology-Organization-Environment (TOE) framework. Seven of the eight factors they tested were significantly related to adoption. The strongest associations were environmental: vendor partnership, competitive pressure and government support. Organisational readiness and management support were also significant, while complexity was not. These findings also point to the importance of organisational readiness and outside support, partly complementing the OECD's four conditions. Two cautions are needed, though. Both the meta-analysis and this cross-sectional survey describe associations with adoption, but neither establishes causation. In addition, the meta-analysis covers organisations of every size, with no studies from Central Asia, so the same pattern cannot be assumed to hold for independent businesses with no more than 100 employees and one to three locations in Almaty, the scope used in this study.

2.3 What blocks adoption

Oldemeyer et al. (2025) focus on barriers to adoption. They reviewed 71 studies using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) method and identified 27 different implementation challenges. The three most frequent were lack of knowledge and skills, cost and the firm's existing digital maturity, followed by data availability, management support and the difficulty of judging return on investment. Trust and privacy are on the list too, but they appeared in fewer of the reviewed studies than knowledge and cost did. This connects to Pinto et al.'s (2025) results from the other side: readiness and outside support are associated with adoption, while lack of knowledge and cost appear as the most common barriers.

2.4 Micro and small firms in an emerging economy

Oldemeyer et al. (2025) cover the broader SME category, including medium-sized firms. García-Vidal et al. (2025) focus specifically on micro and small enterprises. They surveyed 1,200 micro and small enterprises in Ecuador and analysed the 781 that had adopted AI. In their sample, partial adoption was more common than intensive adoption: among microenterprises, 48.3% were partial adopters and only 15.4% were intensive ones. The authors also found a gap between how strategic firms think their AI use is and what it looks like in practice. Among non-adopters, more than 70% said they intend to adopt in the future.

2.5 What firms gain from adoption

On the benefits side, Yesuf and Fields (2025) reviewed 63 articles from 2020 to 2024 and sorted the reported gains into three groups: operational efficiency, such as lower costs and better customer engagement; innovation in processes and products; and better decision-making through predictive analytics. The review also notes that research is concentrated in Europe and North America and that there is a large knowledge gap for SMEs in Africa, Latin America, and Asia. The Ecuador study partly addresses this gap, and this research is an attempt to add evidence from another emerging economy.

2.6 Synthesis and research gap

The literature connects lower AI adoption in small firms with recurring barriers around knowledge, cost and readiness (OECD, 2025a, 2025b; Oldemeyer et al., 2025; Pinto et al., 2025). Reported gains include efficiency, customer-related benefits, innovation and better decisions (Yesuf & Fields, 2025), while García-Vidal et al. (2025) show why adoption depth matters alongside whether a firm uses AI.

However, there is limited firm-level evidence about independent micro and small businesses with one to three locations in Almaty. Much of the literature covers larger SMEs, developed economies or manufacturing. The closest emerging-economy study concerns Ecuador, while the Kazakhstan study examines state support rather than firms' own use (Abdikalikov et al., 2026). This study adds a small convenience survey and three interviews to the extant literature. The comparisons concern broad patterns, not population estimates or directly equivalent percentages.

2.7 Definition of micro and small enterprises

Most of the literature reviewed above uses the broader term SME, which includes both small and medium-sized businesses. Since some of these studies include firms that are much larger than the businesses covered in this project, the study is focused more narrowly on micro and small businesses in Almaty.

Kazakhstan's business-size rules refer to average annual employee numbers and income (Republic of Kazakhstan, 2015, Art. 24). Since annual income was not collected, employee count was used as a practical size measure.

The number of locations was also recorded. Businesses with one to three locations formed the primary sample; businesses with four or more were excluded from it. Location count is used only as part of the study design and is not part of the official definition of business size.

Broader SME studies are still useful for comparison because they examine similar questions about AI adoption, barriers, benefits, readiness, and future intentions. However, where business sizes or measures differ, the findings are compared mainly as general patterns rather than as directly comparable percentages.

3. Methodology

3.1 Study design and participants

This cross-sectional descriptive mixed-methods study combined an anonymous online survey with three in-person interviews. The survey provided descriptive quantitative evidence, and the interviews added qualitative context. The design can describe reported patterns and associations, but cannot establish causation.

Eligible businesses operated in Almaty, had 100 employees or fewer and one to three locations, and made their own technology decisions independently of a chain or franchise. Respondents had to be owners, co-owners, managers or genuine decision-makers. Employee count was a practical size indicator, not a complete legal classification, because income was not collected (Section 2.7). The broad employee categories prevented a reliable separate analysis of micro and small businesses.

3.2 Survey and recruitment

The Russian-language Google Forms survey was designed to take about five minutes and used mainly multiple-choice and checkbox questions, with limited free-text options. After a plain definition of an AI tool, a yes/no question measured purposeful AI use for work during the previous three months. Users and non-users then followed different branches.

The questions covered frequency and routine integration of AI use, tools and tasks, reported benefits, barriers, who used AI within the business, language, paid/free tool use and support needs. Benefit and barrier options drew on Yesuf and Fields (2025) and Oldemeyer et al. (2025), respectively; the support question drew on the OECD's four conditions (OECD, 2025a). García-Vidal et al. (2025) informed the depth-of-use and future-intention questions. Their study assessed adoption across business functions; this survey measured frequency and routine integration separately. Future intentions concerned increased use over the following 12 months. The support and intention questions were intended for both groups, but only current users had recorded answers. Missing non-user responses were not treated as negative answers or filled in.

Recruitment used non-random convenience sampling. Recruitment channels were not recorded in the response dataset, so the contribution of each route could not be calculated.

3.3 Interviews

I conducted three in-person semi-structured interviews with a transport/logistics manager, an IT owner, and a café owner. I recruited them directly in person during data collection. The interviews explored AI use or non-use, perceived benefits, barriers, support needs and future use where relevant.

Interview accounts were grouped into themes and paraphrased. Without verbatim transcripts, no formal transcript coding or direct quotations were used. These qualitative cases were kept outside the survey totals.

3.4 Data analysis and ethics

Responses were exported from Google Forms to Google Sheets. Exact duplicates and responses failing the eligibility rules were excluded before analysis; the screening flow is reported in Table 1. The main analysis used 14 eligible responses. A broader sensitivity calculation was kept separate and is reported in Section 6.

Cleaned data were analysed using counts and percentages, with subgroup denominators stated explicitly. Multi-select benefits and barriers were ranked by frequency, and support preferences were summarised in the same way. Frequency and routine integration were kept as separate measures of adoption depth. Application areas were counted, and a narrower generative-AI rate was calculated from the tool checklist. Small sector groups were treated descriptively, without inferring sector effects. Python was used to generate and check the final counts, figures and tables.

Survey and interview evidence were analysed separately and brought together in the Discussion. The TOE framework from Pinto et al. (2025) guided interpretation of barriers and readiness there; results retained the original survey categories. Comparisons with international studies concerned themes and categories, not directly equivalent percentages, because populations and AI measures differed.

The survey began with consent information and instructed those who did not consent to leave the form. The response sheet stored no names, business names or contact details. It also had no separate field recording consent, so consent could not be independently verified from the sheet. Respondents were informed that anonymous answers could not be withdrawn after submission. Interviews were reported without identifying details.

4. Results

4.1 Sample and response screening

The survey produced 26 submissions. Applying the eligibility and duplicate rules left 14 responses for the main analysis: four AI users and ten non-users (Table 1). All survey results below refer to these 14 responses or to the stated user and non-user subgroups; the three interviews are reported separately. Role exclusions comprised a corporate lawyer, an employee responsible for digital or operational work, and an unclear free-text response. One exact duplicate was removed among otherwise eligible records; another duplicate was already excluded by the employee rule.

Table 1. Response screening and primary sample

Screening stage	Removed	Remaining
All submissions	—	26
More than 100 employees	3	23
No independent technology decisions	4	19
Exact duplicate	1	18
Four or more locations	1	17
Role mismatch or ambiguity	3	14

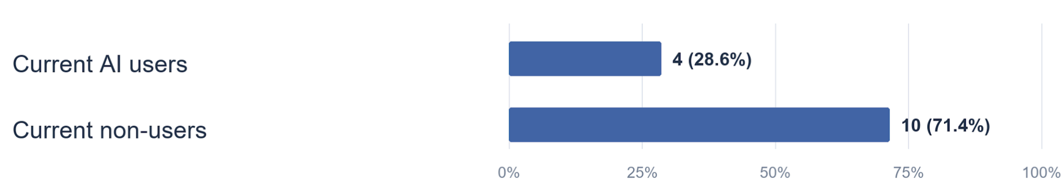
The 14 included businesses were small in practical terms. Ten had one location, three had two and one had three. Four respondents described a one-person business, eight reported 2–10 employees and two reported 10–50 employees. Twelve respondents were owners or co-owners, while two were managers or decision-makers. Nine businesses had operated for more than ten years, four for one to three years and one for less than a year. Five worked mainly in person, five combined online and in-person work, and four worked mainly online.

The sample covered several sectors, but was not balanced. Retail was the largest group with four businesses. Three selected "Other," including one that specified cleaning services and two that did not add a description. Two were in IT or software. Manufacturing, tourism, transport and logistics, café or food service, and beauty services each contributed one response. These small sector counts are descriptive only.

4.2 Current AI adoption

Four of the 14 businesses (28.6%) reported purposeful AI use during the previous three months; the other ten reported no use (Figure 1).

Figure 1. AI adoption in the primary analytical sample (n = 14).



Of the four AI users, three used AI daily, while one had tried it only once or twice. Their answers about integration covered four levels: experimenting, occasional use without a routine, use as a routine tool, and use as an important part of the business. Each level was selected by one user.

4.3 How AI was used

AI chat assistants were the only tool category selected by all four users. Translation tools, customer-service chatbots, design or image/video tools, and AI functions in business software were each selected by one user. Tool and task questions allowed multiple responses.

Advertising and marketing was the most common task, selected by three users. Two selected writing, editing or translation, two selected images, design or video, and two selected analysis, reports or documents. Technology consulting and chatbot development were each reported by one.

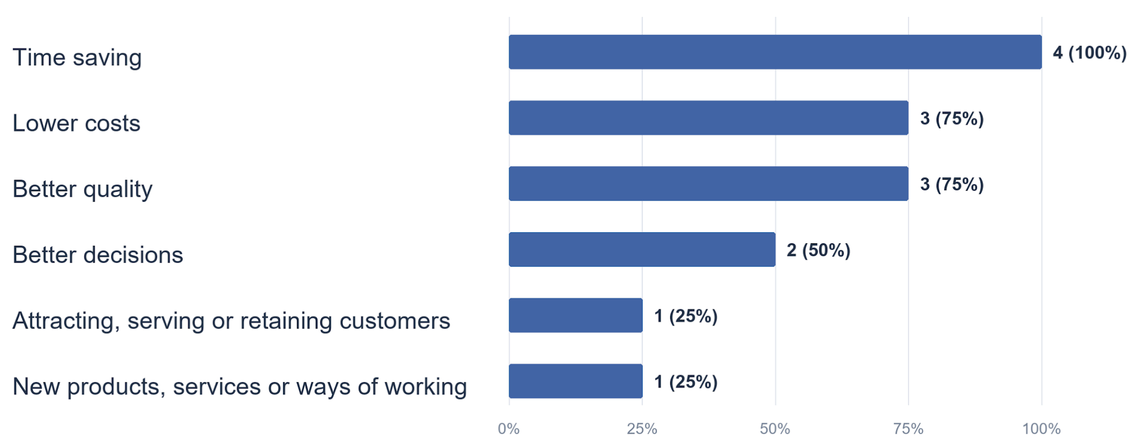
One user selected one application area, two selected three, and one selected four. The narrower generative-AI count was also 4/14 (28.6%), since every user selected a chat assistant.

Three users worked mainly in Russian and one in English. In two businesses only the owner used AI; in the other two, the owner and employees used it. All four used at least one paid tool: two combined paid and free tools, and two used paid tools only.

4.4 Reported benefits

Time saving was the only benefit reported by every current user. Lower costs and better quality followed, while customer-related gains and innovation were less commonly selected (Figure 2). These are perceived benefits, not independently measured changes in performance.

Figure 2. Reported benefits among current AI users (n = 4). Multiple responses were allowed.

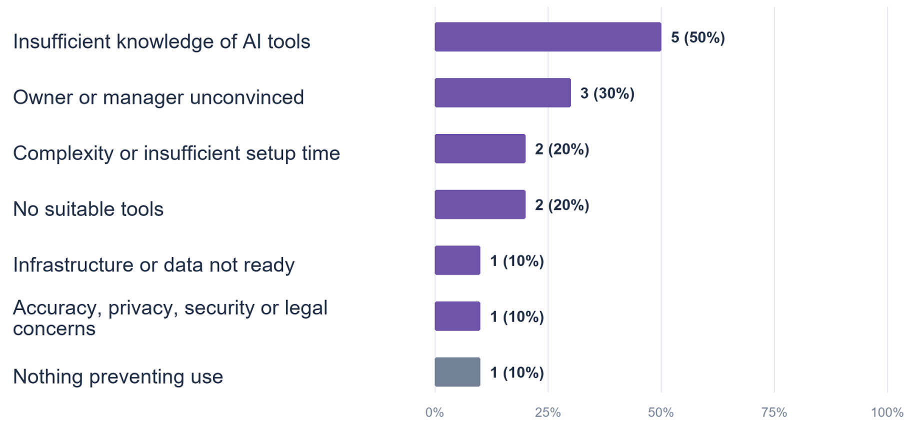


Two users rated AI as “extremely useful”, one as “very useful” and one as “moderately useful”. None selected a low-usefulness category.

4.5 Barriers to adoption and deeper use

Insufficient knowledge was the most frequently selected barrier among non-users, followed by the owner or manager being unconvinced that AI was needed (Figure 3). One respondent reported that nothing was preventing use.

Figure 3. Reported barriers among current non-users (n = 10). Multiple responses were allowed.



All ten non-users said they had never tried AI. The primary findings therefore concern non-adoption before trial, not discontinuation.

Users answered a separate question about barriers to deeper use. Two selected insufficient knowledge and two selected accuracy, privacy, security or legal concerns. One selected complexity or lack of setup time, while one reported no barrier. These categories could overlap.

4.6 Support, readiness and future intentions

Only the four current users had completed support and future-intention fields. Cheaper or free tools, better Russian- or Kazakh-language tools, and simple information or training with Kazakhstan business examples were each selected by two users. None selected external implementation support.

All four users were “likely” or “very likely” to increase AI use over the next 12 months, with two in each category. All ten non-users’ support and intention cells were blank. Their intentions cannot be inferred from these missing responses. Table 2 summarises the main quantitative findings and their denominators.

Table 2. Main quantitative findings

Measure	Count (%)	Base
Current AI adoption	4 (28.6%)	Primary sample, n = 14
Daily AI use	3 (75%)	AI users, n = 4
AI chat assistant use	4 (100%)	AI users, n = 4
At least one paid tool	4 (100%)	AI users, n = 4
Reported time saving	4 (100%)	AI users, n = 4
Reported lower costs	3 (75%)	AI users, n = 4
Reported better quality	3 (75%)	AI users, n = 4
Knowledge barrier	5 (50%)	Non-users, n = 10
Owner or manager unconvinced	3 (30%)	Non-users, n = 10
Knowledge barrier to deeper use	2 (50%)	AI users, n = 4
Likely to increase use	2 (50%)	AI users, n = 4
Very likely to increase use	2 (50%)	AI users, n = 4

4.7 Interview findings

The three interviews added detail to the survey findings. The transport and logistics manager ran a one-location business with 2–10 employees and had never tried AI, mainly because of limited knowledge about available tools. The café owner also had one location and 2–10 employees and had never tried AI. Alongside limited knowledge, this owner mentioned expected cost, uncertain return on investment, complexity and the time needed to learn and set up tools.

The IT owner used AI daily in Russian, with both paid and free tools used by the owner and several employees. The account covered writing, advertising, chatbots, chat assistants and AI-enabled business software. The owner reported saving time, reducing costs and making better decisions, and was very likely to increase use. Even so, the business's adoption was still described as experimental. Limited knowledge of available tools remained a barrier to deeper use, and the owner wanted straightforward training, examples from similar Kazakhstan businesses and better Russian-language options.

Insufficient knowledge was mentioned in all three accounts, including that of the daily user. These interview observations are considered separately from the survey counts.

5. Discussion

Overall, the adopters generally reported AI as useful, while most participating businesses had never tried it. Chat assistants and content or marketing tasks were common among users, but daily use did not always mean that AI was well established in the business.

The interviews help explain why knowledge appears as a barrier among both groups. Knowing how to start and knowing how to develop existing use may require different kinds of support. That distinction is worth investigating, but the study's account of readiness remains incomplete because support preferences and future intentions were recorded only for users.

5.1 An uneven early-adoption picture

Only four of the 14 businesses used AI, but even within this small group, use meant different things. Three used it daily, while only two described it as a routine tool or an important part of their work. Frequency alone therefore gives an incomplete picture. A person may use a chat assistant every day while still experimenting with how it fits into the business.

García-Vidal et al. (2025) also found partial or uneven adoption, although they measured it across value-chain functions rather than through frequency and routine. Their percentages cannot be compared directly with these results. What the studies share is a reason to look beyond the yes/no adoption question: businesses that use AI can differ in how far that use has developed.

The sample's 28.6% adoption figure is close to the OECD's 30.7%, but that closeness is not evidence of a match. The OECD surveyed more than 5,000 SMEs in seven countries, included larger firms and asked a different question about generative AI (OECD, 2025b). Here, the measure was purposeful use of any AI tool in the previous three months, based on a convenience sample of 14 businesses.

5.2 Accessible tools as an entry point

Chat assistants were the one tool category shared by all four adopters. Marketing, writing and document work give owners and employees tasks on which they can try these tools without building a separate technical system. That makes chat assistants a plausible entry point, though the survey did not ask why respondents chose them.

The operational and customer-facing uses described by Yesuf and Fields (2025) help place these tasks in context. Use was not limited to basic chat, however. The IT interview also described chatbots and AI-enabled business software, alongside the more familiar writing and advertising tasks.

Both businesses in the IT/software category were users, while none of the four retail businesses were. With such small, non-random groups, this is a descriptive difference to investigate in a larger, balanced sample, not evidence of a sector effect.

5.3 Time saving was the clearest reported benefit

All four users reported saving time. Lower costs and better quality were common too, and the IT owner described helping with decisions. These are the kinds of benefits discussed by Yesuf and Fields (2025). The study records users' assessments of those benefits; it did not check working hours, costs or quality against business records.

The IT owner's account is useful here because daily use and reported benefits sat alongside the description of adoption as experimental. AI did not have to be fully integrated for the owner to find it helpful.

5.4 Knowledge as a Barrier: Distinguishing Entry from Expansion

Insufficient knowledge was reported on both sides of adoption. All ten survey non-users had never tried AI, and knowledge was their most common barrier. The next was the owner or manager being unconvinced that AI was needed. Taken together, these answers point to questions about both how to use a tool and whether it is worth trying. They fit Pinto et al.'s (2025) discussion of organisational readiness and management support, without establishing either as a cause of non-adoption.

The interviews make the difference between these stages clearer. Neither the transport/logistics manager nor the café owner had tried AI, and both mentioned insufficient knowledge. The daily IT user mentioned it too, but as a problem for deeper use. For the two non-users, the gap concerned getting started. For the IT owner, it concerned what to do next. These accounts are the basis for the two-stage interpretation, rather than evidence that the survey measured two distinct types of knowledge.

Knowledge and skills were also prominent in Oldemeyer et al. (2025). Their review focused on manufacturing SMEs, while this sample covered several sectors, so the relevance of barriers linked to industrial data may differ. The three interviews give this broad category a more specific meaning, but are too few to establish how often either kind of gap occurs. A later survey could ask separately about awareness of tools, practical skills, and confidence in checking outputs.

Several barriers could operate together. The café owner, for example, connected limited knowledge with expected cost, uncertain return and lack of time. In TOE terms, the accounts cover organisational readiness, such as knowledge and management support, as well as technological concerns about tool suitability, setup and infrastructure. Affordable tools and locally relevant learning resources concern the external support environment. These groups help organise the answers, but are not tested causes. The survey also combined accuracy, privacy, security and legal concerns in one option, so those concerns cannot be ranked separately.

5.5 Readiness and support

The IT owner asked for straightforward training and examples from similar businesses in Kazakhstan. The survey users' preferences also concerned practical learning resources, cost and local-language access. The requests for affordable tools and practical training reflect the finance and skills conditions in OECD (2025a) and the readiness framework discussed by Pinto et al. (2025).

Guidance based on familiar business tasks may be worth testing, especially if it explains cost and risk in locally useful languages. But the café account is a reminder that knowing how a tool works may not be enough. The owner also needs a reason to spend time trying it. This small study can identify a possible approach to support, not justify a city-wide programme.

All four adopters intended to increase use, which fits their positive usefulness ratings. Whether non-users wanted to begin is still unanswered. Their intention fields were blank, and the Ecuadorian findings on future adoption (García-Vidal et al., 2025) cannot substitute for responses from these businesses.

6. Limitations

The small convenience sample limits what can be concluded beyond the participating businesses. There were only 14 responses, and changing one adoption answer would shift the percentage by 7.1 points. Sector groups were also small and uneven. Businesses willing or available to respond may differ in their interest in technology or digital access from those that did not take part, but the direction and size of that selection bias are unknown. The study therefore cannot estimate adoption across Almaty or explain the observed differences between sectors. A separate sensitivity calculation, applying only the employee, independent decision-making and duplicate rules, included 18 responses: six users and 12 non-users (33.3%). This broader group did not apply the location-count and respondent-role boundaries and was not used for the main results.

There is also uncertainty about who the responses represent. The sheet had no dedicated city field, so the Almaty scope depends on recruitment context. Ambiguous or mismatched roles were excluded, but without anonymous business identifiers, it was not possible to confirm whether similar, non-identical submissions came from different businesses. Exact duplicates were removed; test records could not be reliably identified. The absence of contact details also prevented follow-up verification through the response sheet. Future studies could record consent explicitly and invite participants to provide optional contact details in a separate, securely stored file, with a stated retention and deletion schedule. Broad employee bands added a separate problem: the 10–50 category crosses the planned micro/small boundary, and no annual income data were collected. The businesses could only be analysed as a combined group screened at no more than 100 employees, not as verified legal size categories.

The answers describe respondents’ understanding of their own AI use. Some may have interpreted AI differently or overlooked occasional use, and reported benefits were not checked against records. Without before-and-after measures, the study cannot establish performance changes. Its cross-sectional design also cannot show that a reported barrier caused non-adoption. Differences in definitions and samples also limit comparisons with earlier research, as discussed in Sections 3.4 and 5.1.

The missing non-user responses leave part of the original research question unanswered. All ten had blank support and future-intention fields. These were not treated as negative answers, and no values were imputed. The paper can describe what existing users wanted and whether they expected to increase use, but not what would help non-users or whether they intended to begin. This also prevents a comparison of intentions between the two groups.

The three interviews add explanations that the checkboxes alone could not provide, but they do not show how common an explanation is. Verbatim transcripts were unavailable, so the accounts were paraphrased rather than quoted or analysed word by word. They could not be linked reliably to individual survey records and were kept outside the survey totals.

7. Conclusion

Four of the 14 businesses used AI. Their use centred on chat assistants, and they reported practical benefits, especially time saving, even when AI was not yet well integrated into the business. All ten non-users said they had never tried it. Adoption in this sample was, therefore, uneven both between businesses and in how established their use had become.

Insufficient knowledge was the most visible recurring barrier. The interviews suggest that it can concern knowing how to begin for a non-user and knowing how to develop use for an existing user. Among current users, support preferences centred on cheaper tools, local-language access, and practical training or examples from businesses in Kazakhstan. All four adopters intended to increase use, but non-users’ future intentions cannot be determined because their responses were missing.

These results cannot be generalised to all Almaty businesses. A useful next step would be to follow a larger, more balanced group of users and non-users over time, asking both groups about their intentions and specific knowledge gaps. That would help test whether the different needs described in these interviews remain visible as businesses begin or expand AI use.

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