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AI Adoption and Knowledge Absorptive Capacity in Start-Ups: The Case of UrBox

Tuan Minh Nguyen
Business School, National Economics University,
207 Giai Phong Road, Hanoi, Vietnam

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Abstract

This study explores how the adoption of artificial intelligence (AI) affects the knowledge absorptive capacity of start-ups, that is, their ability to acquire, assimilate, transform and exploit external knowledge. Using an exploratory single case study of UrBox, a Vietnamese gifting and loyalty start-up, the study draws on semi-structured interviews with the firm's chief executive, technology and financial officers conducted in October 2026, and on internal documents describing an AI-based receipt-processing platform and an AI knowledge service. Interview transcripts and documents were coded deductively against the four dimensions of absorptive capacity and then compared to identify the conditions that shape each effect. The findings indicate that AI turns the acquisition and assimilation of high-volume, standardised external knowledge into fast, scalable routines. According to system documentation, the automated receipt-to-reward path is designed to take under two minutes, although measured performance data were not available. Converting this potential into realised capacity appeared to depend on combining AI output with firm rules, on codifying staff knowledge into governed knowledge bases, and on human review of exceptions and access controls. The evidence does not show whether AI strengthened or weakened employee learning, and part of the improvement may stem from process standardisation rather than AI alone. Five propositions are offered for future testing, together with a discussion of which findings may transfer to other start-ups.

Keywords: artificial intelligence, absorptive capacity, knowledge management, start-ups, case study, Vietnam

1. Introduction

1.1 The Problem

Artificial intelligence (AI), and generative AI in particular, has moved from a specialist technology to an everyday work tool in a very short time. For start-ups, this change matters more than it does for large firms. Start-ups are constrained by size, experience and resources (Freeman et al., 1983), so they depend on knowledge from outside their boundaries to survive and grow (Teece, 2010; Van de Vrande et al., 2009). How well a start-up can recognise, take in and use

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that external knowledge is its absorptive capacity (Cohen & Levinthal, 1990; Zahra & George, 2002).

Absorptive capacity has traditionally been described as path-dependent. It is built slowly through prior related knowledge, R&D investment and the experience of the people inside the firm (Cohen & Levinthal, 1990). Young firms are therefore assumed to start with a structural disadvantage. AI may challenge that assumption. Tools that scan markets, summarise documents, write code and answer questions can perform part of the search, interpretation and codification work that absorptive capacity normally requires from people. Early evidence shows that generative AI raises the productivity of less experienced workers the most, partly by transferring the tacit practices of top performers to novices (Brynjolfsson et al., 2025; Noy & Zhang, 2023). At the same time, scholars warn that substituting human judgement with machine learning can weaken the human learning on which organisational knowledge rests (Balasubramanian et al., 2022; Raisch & Krakowski, 2021).

1.2 Importance of the Problem

Research on AI in innovation management and entrepreneurship has grown quickly (Berente et al., 2021; Chalmers et al., 2021; Haefner et al., 2021; Obschonka & Audretsch, 2020), and information systems research has long linked IT to absorptive capacity (Roberts et al., 2012). Yet little is known about how AI adoption reshapes absorptive capacity inside start-ups, and almost nothing about start-ups in emerging economies such as Vietnam. Studies in Vietnam have examined AI adoption in manufacturing SMEs (Dey et al., 2024) and knowledge capabilities in e-commerce SMEs (Nguyen et al., 2025), but not how AI changes absorptive capacity itself. Existing studies are mostly quantitative surveys of large firms or SMEs (e.g. Abou-Foul et al., 2023), which show associations but not the mechanisms through which AI changes how knowledge is acquired, assimilated, transformed and exploited.

This paper addresses that gap with an exploratory case study of UrBox (To Qua Digital Marketing Joint Stock Company), a Vietnamese gifting and loyalty start-up. A previous case study of UrBox (Nguyen, n.d.) showed how the firm used inbound and outbound open innovation with large partners, and how its founder's experience in large corporations shaped its ability to absorb external technology. The present study returns to the same firm to ask a follow-up question: how does AI adoption affect a start-up's capacity to acquire, assimilate, transform and exploit external knowledge?

1.3 Relevant Scholarship

1.3.1 Absorptive capacity

Cohen and Levinthal (1990) defined absorptive capacity as a firm's ability to recognise the value of new external information, assimilate it and apply it to commercial ends. They stressed that this ability depends on prior related knowledge and is cumulative: firms that invest in learning today find it easier to learn tomorrow. Zahra and George (2002) reconceptualised it as a set of organisational routines with four dimensions: acquisition (identifying and obtaining external

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knowledge that matters to the firm), assimilation (analysing, interpreting and understanding that knowledge), transformation (combining new knowledge with existing knowledge to create new insights) and exploitation (applying the combined knowledge to products, processes and markets).

The first two dimensions form potential absorptive capacity; the last two form realised absorptive capacity. A firm can be good at collecting knowledge but poor at turning it into value, and the ratio between the two is an efficiency measure in its own right (Zahra & George, 2002). Later work added that absorptive capacity is a learning process embedded in exploratory, transformative and exploitative learning (Lane et al., 2006), that recognising the value of new knowledge is a distinct first step shaped by prior knowledge (Todorova & Durisin, 2007), and that organisational mechanisms such as cross-functional interfaces and job rotation drive potential and realised capacity differently (Jansen et al., 2005).

1.3.2 Information technology, AI and absorptive capacity

Information systems research has treated IT as both an antecedent and an enabler of absorptive capacity, for example through knowledge repositories, communication tools and analytics (Roberts et al., 2012). AI differs from earlier IT in one important respect: it does not only store and move knowledge, it also performs cognitive work such as classifying, predicting, summarising and generating content (Berente et al., 2021). This makes AI a potential participant in each absorptive-capacity routine rather than just infrastructure behind it.

Research on AI in innovation management suggests that AI can widen search, speed up idea generation and support decision-making across the innovation process (Haefner et al., 2021). Firms that combine AI technology with complementary human skills and organisational resources build an "AI capability" that is linked to creativity and performance (Mikalef & Gupta, 2021). In a study of 185 US and EU manufacturers, absorptive capacity strengthened the effect of AI capabilities on servitization, suggesting that the two capabilities reinforce each other (Abou-Foul et al., 2023). Field evidence also shows strong productivity effects: in a large customer-support setting, generative AI raised productivity by 15% on average, with the largest gains in both speed and quality for less experienced and lower-skilled workers (Brynjolfsson et al., 2025). Experiments with professional writing tasks (Noy & Zhang, 2023) and with management consultants (Dell'Acqua et al., 2023) show similar gains in speed and quality.

The literature also identifies risks. Raisch and Krakowski (2021) describe an automation-augmentation paradox: automating tasks can save effort but remove the human involvement that drives learning, while augmentation keeps humans in the loop. Balasubramanian et al. (2022) argue that replacing human decisions with machine learning can reduce the diversity and interpretability of organisational knowledge, which may weaken learning over time. Dell'Acqua et al. (2023) add that on tasks outside AI's capabilities, consultants using AI were less likely to reach correct answers, which shows the cost of over-reliance. From a knowledge management perspective, Alavi et al. (2024) argue that generative AI can support knowledge creation, storage, transfer and application, but also brings risks of bias, over-reliance and leakage of sensitive

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information. For absorptive capacity, which depends on prior knowledge held by people, these risks are central.

1.3.3 Leadership and founders

Senior leaders shape absorptive capacity by setting strategic direction, deciding what knowledge to seek and shaping how people interact (Flatten et al., 2015; Volberda et al., 2010; Zahra et al., 2006). The earlier UrBox study found that the founder's experience in large banking and technology firms helped the start-up absorb and commercialise external technology (Nguyen, n.d.). In Vietnamese manufacturing SMEs, leadership has also been found to be the main driver of AI adoption (Dey et al., 2024). AI adoption raises a parallel question: whether founders and managers decide where AI augments people and where it replaces them, and how they protect the knowledge that should stay inside the firm.

1.4 Conceptual Framework and Research Questions

Combining these streams, this study treats AI adoption as acting on each absorptive-capacity dimension through two opposing channels. The amplifying channel extends the reach, speed and scale of knowledge work. The eroding channel reduces the human learning and prior knowledge that future absorption depends on. Because the study is exploratory, it does not test hypotheses. Instead, it addresses two research questions: (RQ1) in which absorptive-capacity dimensions does AI participate at UrBox, and how; and (RQ2) which organisational conditions shape whether AI's contribution remains at the level of potential capacity or becomes realised capacity. Figure 1 summarises the framework as refined through the case analysis; the propositions it labels (P1 to P5) are developed and linked to the evidence in Section 4.1.

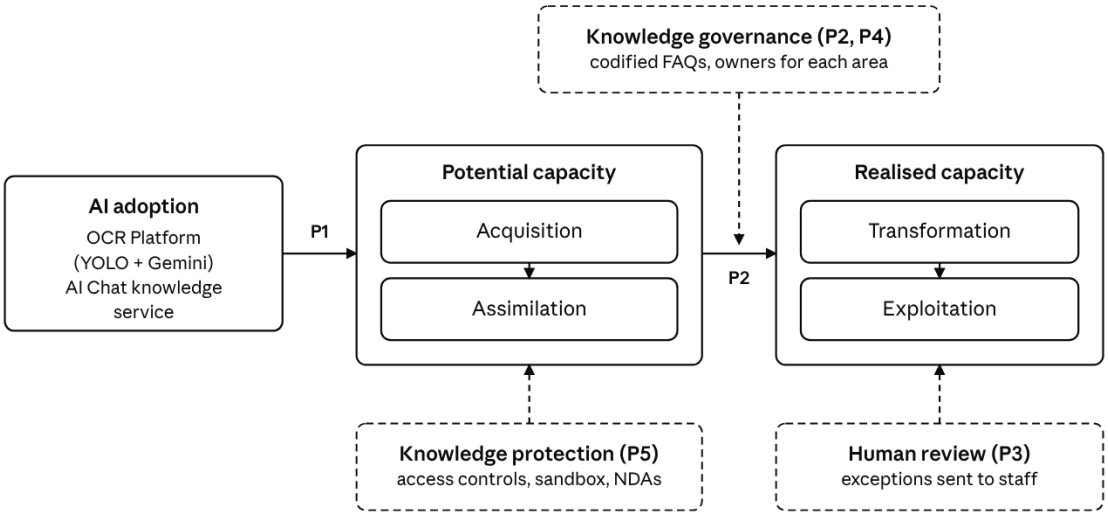

Figure 1. Conceptual framework of AI adoption and absorptive capacity

Note. Solid arrows show direct effects; dashed boxes show the conditions that shape them. P1 to P5 refer to the propositions in Section 4.1. Source: the author.

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The paper makes three contributions. First, it maps AI use onto each of the four dimensions of absorptive capacity. Second, it extends the earlier finding on founder experience by examining how leadership and governance shape AI-enabled knowledge absorption. Third, it develops testable propositions for future quantitative research, while separating what the case shows from what remains to be tested.

2. Method

2.1 Research Design

The study uses an exploratory, single-case design. This design suits a "how" question about a contemporary phenomenon that the researcher cannot control and on which theory is still emerging (Eisenhardt, 1989; Yin, 2003). UrBox was selected purposively for three reasons. It is a technology start-up whose business depends on external knowledge from partners, merchants and clients. It had adopted AI in two production systems at the time of the study. And a previous case study of the same firm provides a baseline, so the study can show how the firm's knowledge routines have changed rather than describe them at one point in time.

2.2 Case Setting

UrBox is a Vietnamese digital gifting and loyalty platform that supplies electronic gifts and reward solutions to banks, insurers and other corporate clients, as well as reward flows inside client campaigns (Nguyen, n.d.). The firm adopted AI in 2025, following a decision by its chief executive officer. At the time of data collection, AI was used in two systems: an OCR Platform that turns consumer purchase receipts into campaign rewards, and an AI Chat knowledge service built on standardised product and legal answers.

2.3 Participants and Sampling

Informants were selected purposively as the three executives directly responsible for deciding on, building and overseeing the risks of AI at UrBox (Table 1). The chief executive officer (CEO) made the adoption decision; the chief technology officer (CTO) is responsible for the systems in which AI is used; and the chief financial officer (CFO) oversees financial and data-security risk. This sampling targets the people best placed to explain why and how AI was adopted. Its main drawback is that it does not capture the experience of employees who use the OCR Platform and AI Chat in daily work; this limitation is discussed in Section 4.5.

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Table 1. Profile of the informants

Informant	Role in AI adoption	Relevant experience	Interview date	Duration	Mode
CEO (founder)	Took the 2025 decision to adopt AI; sets strategic direction	Founder of UrBox; 15 years of professional experience, including banking (VPBank) and technology platforms (Grab Vietnam) (Nguyen, n.d.)	October 2026	About 120 minutes	In person
CTO	Responsible for the OCR Platform, AI Chat and partner API integration	16 years of experience in technology roles	October 2026	About 120 minutes	In person
CFO	Oversees financial risk, compensation of erroneous rewards and data-security concerns	15 years of experience in finance roles	October 2026	About 120 minutes	In person

Note. Informants are identified by role. Interviews were conducted in Vietnamese, in person, and audio-recorded.

2.4 Data Sources

Two sources of data were used. First, semi-structured interviews followed a three-part protocol. The first part asked general questions about AI adoption: which tools, since when, in which functions and who decided. The second part asked, for each dimension of absorptive capacity, how AI had changed the way the firm finds, interprets, combines and applies external knowledge, with a request for concrete examples. The final part asked about drawbacks: tasks where AI reduced learning, errors, knowledge-security concerns and how leaders responded. Each interview was conducted in person, lasted about two hours and was audio-recorded and transcribed verbatim by the author, giving about six hours of recorded material.

Second, four internal documents were analysed (Table 2). Documents were used to check and complement interview accounts, because they record practices, targets and known risks in a form that does not depend on informants' recollection.

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Table 2. Internal documents analysed

Document	Main content	Used for
OCR Platform technical documentation	Process flow, component processing times, manual review targets, known risks	Acquisition, assimilation, exploitation; processing-time targets; risks
AI Chat product FAQ	41 standardised questions in five topic groups; channels; review responsibility	Transformation, exploitation; knowledge governance
Legal FAQ	Standard positions on contracts, payments, vouchers, personal data and NDAs; escalation boundaries	Acquisition, transformation; knowledge governance
API-Loyalty project procedures	Partner integration flow, sandbox testing, acceptance, go-live, security controls	Assimilation of partner knowledge; knowledge protection

2.5 Data Analysis

The data were analysed through deductive thematic analysis (Braun & Clarke, 2006; Miles et al., 2014) in five steps, carried out manually by the author.

1) Preparation. All interview transcripts and the four documents were read in full. Every passage that described an AI use, a human task linked to it, a risk or a control was extracted as a unit of analysis and labelled with its source.
2) First-cycle coding. Each unit describing an AI use was assigned to one of the four dimensions of absorptive capacity using the codebook in Table 3, which was derived from Zahra and George (2002).
3) Second-cycle coding. Each unit was then coded for whether it extends the reach, speed or scale of knowledge work (amplifying) or reduces human involvement in judgement (potentially eroding), and for the organisational condition involved: human review, knowledge governance, knowledge protection or leadership decision.
4) Triangulation. Interview statements were compared with the documents. Practices recorded in documents were treated as observed evidence; statements found only in interviews were treated as informants' perceptions and are reported as such.
5) Interpretation. The coded evidence was compared with the earlier UrBox case and with prior studies to develop propositions (Eisenhardt, 1989). Section 4.1 separates the observed evidence behind each proposition from the author's interpretation.

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Table 3. Codebook used in the analysis

Code	Definition	Example indicator in the data
Acquisition	Identifying and obtaining external knowledge	AI capturing information from receipts; compilation of external legal guidance
Assimilation	Analysing and interpreting external knowledge	AI extracting fields from receipts; partner integration testing
Transformation	Combining external knowledge with internal knowledge	Matching extracted data with campaign rules; matching cases with standard legal positions
Exploitation	Applying knowledge to products, services or processes	Issuing rewards; answering customers across channels
Amplifying	Extending reach, speed, scale or consistency	Processing-time targets; consistent answers across channels
Potentially eroding	Reducing human judgement or learning	Automated decisions without human review
Conditions	Human review; knowledge governance; knowledge protection; leadership decision	Review queues; FAQ ownership; sandbox and access controls; adoption decision

Interview quotes were translated from Vietnamese into English by the author. Two limitations of the procedure should be noted: coding was performed by a single coder, and the case description was not reviewed by the informants before submission.

3. Results

3.1 AI Adoption at UrBox

UrBox uses AI mainly in two systems. The OCR Platform supports client campaigns in which consumers submit purchase receipts to claim rewards. It combines two models: YOLO, an object-detection model that recognises the bill type and retailer, and Gemini, a large language model that extracts the fields needed to assess the receipt. The AI Chat service draws on a product FAQ of 41 questions in five topic groups and on a legal FAQ, and is designed to give consistent answers across the app, website, hotline, Zalo and email. Table 4 maps each use to the four dimensions of absorptive capacity.

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Table 4. AI-supported practices at UrBox mapped to the dimensions of absorptive capacity

Dimension	**AI-supported practice at UrBox**	**External knowledge source**	**Human role**
Acquisition	YOLO identifies receipt type and retailer; legal FAQ compiles contracts, policies and legal guidance	Retailers, consumers, legal environment	Legal curates sources
Assimilation	Gemini extracts retailer, purchase time and order value; partner integration flows tested in sandbox	Receipts, API partners	Engineers and partners validate integrations
Transformation	Extracted data checked against campaign rules; legal answers combine partner situations with default positions	Campaign clients, customers, partners	Legal sets positions and escalation limits
Exploitation	Automated e-voucher issuance; AI Chat answers across app, website, hotline, Zalo and email	Consumers, customers	Customer Service reviews unclear cases

Note. Based on the internal documents in Table 2 and the interviews.

3.2 Acquisition: Capturing External Knowledge at Scale

Each receipt carries information from a retailer and a consumer purchase, in formats that vary by retailer. According to the OCR Platform documentation, YOLO first recognises the bill type and retailer, so that the platform can select the right layout and prompt before extraction. Acquisition thus becomes a routine whose capacity depends on campaign volume rather than on the number of staff handling receipts.

The legal FAQ shows a second form of acquisition. It compiles template contracts, internal policies, operating procedures and current legal guidance into one source, covering contracts, payments, vouchers, personal data and NDA terms. Here AI does not search for new knowledge itself, but the AI Chat service gives the firm a reason and a structure to collect it in one place. The CTO linked AI to acquisition at the individual level:

> *"AI is becoming a tool that creates significant value for the business, especially in information technology, enabling developers to easily keep up with and apply the most advanced technologies." (CTO)*

This statement is an informant's perception; the documents analysed do not record how developers use AI.

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3.3 Assimilation: Interpreting What Is Acquired

Gemini interprets each receipt by extracting the required fields, such as retailer, purchase time and order value. This is assimilation in Zahra and George's (2002) sense: raw external information is turned into a form the firm can analyse.

Assimilation of partner knowledge remains largely human-led. In API-Loyalty projects, partners describe their intended integration flow and gift type, then take part in sandbox testing, acceptance, production configuration and go-live validation. The documents do not show AI being used in this process. The contrast suggests that UrBox applies AI where external knowledge is high-volume and standardised, and keeps people in charge where it is complex and relationship-specific.

3.4 Transformation: Combining External Knowledge with Firm Rules

In both systems, AI output becomes useful only when combined with knowledge UrBox already holds. Extracted receipt data is checked against campaign rules, such as the qualifying value, eligible product and validity period, to decide whether a reward should be issued. In the legal service, a customer's or partner's situation is matched against UrBox's approved default positions, which reduces inconsistent answers and flags cases that still need Legal. The CEO framed this as a change in how the firm converts knowledge:

> *"AI greatly increases employees' capacity to absorb knowledge, especially tacit knowledge, and allows the company to convert this knowledge into explicit knowledge at a cost and effort many times lower than before." (CEO)*

The FAQs offer documentary support for part of this view. The judgement of Legal and Customer Service staff is written down as standardised answers and escalation limits that both people and AI can use, which matches the externalisation of tacit knowledge described by Nonaka and Takeuchi (1995) and the argument that generative AI can support the knowledge-creation cycle (Sumbal & Amber, 2025). The claim that this happens at a much lower cost than before, however, is the CEO's assessment and was not measured.

3.5 Exploitation: Applying Knowledge Commercially

The clearest efficiency indicator comes from the OCR Platform. Its documentation states that the automated "happy path" from receipt to reward is designed to take under two minutes, compared with manual handling that, according to the same documentation, could take hours. Table 5 shows the documented time of each step. These are design targets; measured processing times were not available to the study.

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Table 5. Documented processing times of the OCR Platform

Step	Documented time
Receipt upload	under 5 seconds
YOLO detection	under 5 seconds
Gemini extraction	about 10-25 seconds
Automated validation	under 10 seconds
Manual review (if needed)	target under 4 business hours
Reward disbursement after approval	under 5 minutes

Note. Source: OCR Platform technical documentation.

Valid receipts lead to an e-voucher or reward delivered by SMS, app or campaign flow, while unclear cases go to a Customer Service agent who checks and corrects the extracted data. On the service side, the AI Chat product FAQ is intended to reduce Customer Service workload by answering routine questions consistently across channels. The records do not quantify time saved, ticket reduction, conversion, revenue, cost savings or return on investment attributable to AI.

3.6 Risks, Governance and the Role of Leadership

The OCR Platform documentation and the FAQs identify five risks: AI may extract an incorrect SKU, leading to duplicate or incorrect rewards; the system cannot reliably detect software-edited receipts or receipts re-photographed from another screen; incorrect approvals may require compensating the customer; FAQ answers may fall out of date relative to actual operating procedures; and legal answers touch on personal-data protection, data-processing agreements, confidentiality and NDAs. The CFO described security as the central concern:

> *"AI brings a lot of value, but security remains a serious concern that needs to be considered. Granting AI uncontrolled permissions could cause the business to leak information and expose its trade secrets." (CFO)*

UrBox responds through three documented mechanisms. First, human-in-the-loop review: Customer Service agents handle exceptions and correct AI-extracted data. Second, knowledge governance: Legal owns the standard answers and escalation limits, and Customer Service leads quarterly FAQ reviews with Product and Partnership, while staff are expected to escalate legal cases rather than make their own commitments. Third, security controls: API projects require sandbox acceptance before production, and production connections use a public key and IP allowlisting.

These mechanisms also show how leadership operates after AI adoption. In the earlier case, the founder personally brokered external knowledge, drawing on his experience in large banks and technology firms to negotiate with partners (Nguyen, n.d.). In the AI context, the founder's role appears in the 2025 adoption decision, while day-to-day control of AI-related knowledge is assigned to functions: Legal decides what the AI Chat may say on legal matters, Customer

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Service decides when FAQ content is updated, Customer Service agents decide on unclear receipts, and Engineering decides when a partner connection may go live. At least two of these routines, the AI Chat FAQ review and the OCR review queue, exist because of the AI systems. The documents do not record when the other routines were introduced, so the study cannot establish that all of them followed AI adoption.

3.7 Evidence on Employee Learning

The data contain no direct evidence on whether AI strengthened, maintained or weakened employee learning. No interviews were held with employees who use the OCR Platform or AI Chat, and the documents do not record training, error trends or changes in staff skills. The only statements on learning are the CEO's and CTO's perceptions reported above. The eroding channel of the framework is therefore not observed in this case, and neither is its absence.

4. Discussion

4.1 Propositions and Supporting Evidence

The case suggests that AI does not raise absorptive capacity as a whole. It changes each dimension in a different way, and its effect appears to depend on how the firm keeps people involved and governs the knowledge AI uses. Table 6 links each proposition to the observed evidence and states where the proposition goes beyond that evidence.

Table 6. Propositions, observed evidence and interpretation

Proposition	**Observed evidence (source)**	**Interpretation beyond the evidence**
P1. AI adoption increases a start-up's potential absorptive capacity mainly for external knowledge that is high-volume and standardised; for complex, relationship-specific knowledge, absorption remains human-led.	AI used for receipt detection and extraction (OCR documentation); no AI in partner API integration (API-Loyalty procedures)	That the same pattern holds in other start-ups and knowledge types
P2. AI adoption strengthens realised absorptive capacity when the firm codifies tacit knowledge into governed knowledge bases, and the effect weakens when that knowledge is not maintained.	Standard answers in product and legal FAQs; quarterly review responsibility (FAQ documents); CEO statement on codification (interview)	That codification increases realised capacity, and that the cost of codification fell; neither was measured

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Proposition	Observed evidence (source)	Interpretation beyond the evidence
P3. Combining automation of routine cases with human review of exceptions preserves the human learning that future absorptive capacity depends on.	Automated happy path and Customer Service review of unclear cases (OCR documentation)	That review of exceptions preserves learning; no evidence on employee learning was collected
P4. As start-ups adopt AI, the leadership role in absorptive capacity shifts from supplying knowledge to designing governance routines, and clear governance positively moderates the effect of AI on realised capacity.	CEO adoption decision (interview); functional ownership of FAQs, escalation, review and partner access (documents); founder-led absorption in the earlier case (Nguyen, n.d.)	That the shift was caused by AI adoption, and the moderating effect
P5. AI adoption increases a start-up's need for knowledge-protection mechanisms, and firms that pair AI with access controls can absorb partner knowledge without weakening their appropriability.	CFO concern about uncontrolled AI permissions (interview); sandbox, public key and IP allowlisting (API-Loyalty procedures)	That protection mechanisms preserve appropriability

P1 rests on the clearest evidence. Before AI, external knowledge carried by receipts entered UrBox only through manual work; with YOLO and Gemini, it is designed to be captured and interpreted in seconds, so potential absorptive capacity can grow with transaction volume rather than headcount. This partly offsets the liability of smallness described in the earlier UrBox study. P2 is supported by documented practices but its causal claim is not. The FAQs show that staff judgement is codified and owned; whether this increases realised capacity, and whether AI made codification cheaper, remain to be tested.

P3 should be read with particular caution. UrBox automates the happy path and sends unclear cases to people, a design that resembles the augmentation side of Raisch and Krakowski's (2021) paradox and may limit the eroding effect that Balasubramanian et al. (2022) warn about. Keeping people responsible for exceptions may also guard against the over-reliance seen when AI is used on tasks beyond its capabilities (Dell'Acqua et al., 2023). However, the case provides no evidence that employees' learning has been preserved or improved; P3 is therefore a proposition derived from theory and from the design of the review process, not a finding.

P4 is supported by concrete examples of functional ownership (Section 3.6), but the timing of several routines is not documented. P5 is supported by the CFO's concern and by the

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documented controls, consistent with the earlier finding that UrBox protects its core technology while staying open to partners and with the knowledge-leakage risks noted by Alavi et al. (2024).

4.2 Alternative Explanations

Several improvements observed in the case may not be due to AI alone. First, process standardisation plays a large role: the receipt-to-reward flow relies on predefined campaign rules, and the automated validation step is rule-based rather than AI-based. Second, software integration with SMS, app and campaign flows, rather than AI, determines how quickly a reward reaches the consumer. Third, the FAQs are a knowledge management practice that could exist without AI; AI Chat makes them more visible and more frequently used, but the codification itself is a human activity. In the OCR process, the AI-specific steps (detection and extraction) account for up to about 30 seconds of the documented two-minute target. A fair interpretation is that AI enables a redesigned process, and that the efficiency of that process comes from AI, standardisation and integration together. Finally, because the evidence comes from senior managers and internal documents, accounts may present AI implementation more favourably than independent measurement would.

4.3 Generalisability

As a single case, the study aims at analytic rather than statistical generalisation (Yin, 2003). Some findings are likely to be relevant to other start-ups: the use of AI for high-volume, standardised external knowledge; the dependence of realised capacity on codified and maintained knowledge; the need for human review of exceptions; and the need for access controls when AI handles partner or customer data. Other features are specific to UrBox. Its business model processes large numbers of similar transactions, such as receipts and vouchers, which suits AI-based acquisition; start-ups whose external knowledge is mainly tacit, relational or research-based may see smaller gains. UrBox's founder has prior experience in large banks and technology firms, which may have shaped both the adoption decision and the governance design. The firm operates in Vietnam, where customer communication runs through local channels such as Zalo and where personal data protection rules shape what AI may process. Findings on governance and protection are therefore most transferable to start-ups that handle client or consumer data under comparable regulation.

4.4 Theoretical and Practical Implications

The study extends absorptive-capacity theory by treating AI as a participant in each absorptive-capacity routine, not only as infrastructure, and by suggesting that AI acts mainly on potential capacity while realised capacity depends on governance. It also extends the earlier UrBox case by showing how a start-up's ability to absorb external knowledge may change when part of the cognitive work moves to machines.

For practitioners, the case suggests four actions. Start-up founders should decide which tasks AI augments and which it automates, and protect the tasks where staff build core knowledge. Firms should capture what AI-assisted work produces in a shared knowledge base with clear owners

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and review cycles. Start-ups working with large partners should add AI-specific rules on confidential data to partnership and non-disclosure agreements. Firms should also measure actual processing times, error rates and staff learning after AI adoption, rather than rely on design targets.

4.5 Limitations and Future Research

The study has several limitations. The empirical basis is narrow: three senior managers and four internal documents, without the perspectives of employees who use the OCR Platform and AI Chat. The data on efficiency are design targets rather than measured outcomes. There is no direct evidence on employee learning, so the eroding channel remains untested. Coding was performed by a single coder, and the case description was not reviewed by informants. Future research should interview or survey frontline users of AI systems, collect system log data on processing times and error rates, and follow firms over time to see whether gains in potential capacity turn into realised capacity or erode prior knowledge. The propositions can be tested with survey data from Vietnamese start-ups and SMEs, using established absorptive-capacity scales (Flatten et al., 2011) and AI-capability measures (Mikalef & Gupta, 2021).

5. Conclusion

This study examined how AI adoption affects absorptive capacity in a Vietnamese start-up. At UrBox, AI turns the acquisition and assimilation of high-volume external knowledge into fast, scalable routines, while realised capacity appears to depend on combining AI output with firm rules and codified staff knowledge. The firm limits the risks of AI through human review of exceptions, functional knowledge governance and access controls. Compared with the earlier UrBox study, knowledge absorption now appears to rely less on the founder's personal experience and more on designed routines. These conclusions are exploratory: they rest on a single case, on management accounts and on documented targets, and are offered as propositions for further testing rather than as established effects.

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