
Tacit Knowledge Sharing and Generative AI Chatbots in Fintech Start-ups: A Conceptual Framework

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Abstract

Tacit knowledge — personal, experience-based and resistant to codification — is a strategic resource for innovation, yet sharing it remains difficult because it is informal and context-dependent. The difficulty intensifies in fintech start-ups, which combine flat structures, short product cycles, strict regulatory obligations and high staff turnover. In parallel, generative AI chatbots have introduced a conversational interface between employees and organizational knowledge. This paper develops a conceptual framework specifying how such chatbots shape tacit knowledge sharing among Generation Z employees in fintech start-ups. Following a conceptual-analytical approach based on a purposive review of literature published between 1994 and 2026, the study uses the SECI model as an integrating framework. The analysis indicates that generative chatbots differ most sharply from traditional knowledge management tools in externalization, through staged reflective questioning, and in internalization, through Socratic dialogue and scenario simulation; their contribution to socialization is confined to an expert-finder role that raises the frequency of human encounters without performing the conversion itself. Contrary to a common assumption, recent survey evidence shows that adoption among Generation Z has been accompanied by growing doubt about the cognitive consequences of these tools. The framework therefore incorporates user trust and human validation as moderators, and partial substitution of human interaction as an inhibiting effect. Crucially, it specifies task knowledge intensity as the boundary condition determining whether facilitation or substitution prevails. Eight testable propositions and proposed operationalizations open a path to empirical validation.

Keywords: Generative Artificial Intelligence, Tacit Knowledge Sharing, SECI Model, Generation Z, Fintech ,Start-Ups

1 Introduction

In the contemporary knowledge economy, the capacity to create, share and apply knowledge distinguishes innovative organizations from their competitors. Among the types of organizational knowledge, tacit knowledge — that which resides in experience, intuition, practical skill and mental models — plays an irreplaceable role in innovation and rapid decision-making (Polanyi, 1966; Nonaka, 1994). Yet the very property of tacitness makes sharing one of the hardest challenges in knowledge management: unlike explicit knowledge, tacit knowledge cannot simply be stored in a document or database, and its transfer requires direct interaction, observation and sustained dialogue (Hassanzadeh, 2007).

This problem is sharper in industries characterized by rapid change, short product cycles and heavy dependence on individual expertise. Fintech start-ups are a clear instance of such a setting: flat organizational structures, small cross-functional teams, high staff turnover, and reliance on the specialized technical, regulatory and customer-facing knowledge of key individuals. In such an environment, the departure of one key employee can erase part of the organization's operational memory.

At the same time, the rapid diffusion of generative AI — particularly chatbots built on large language models — has opened a new horizon for rethinking knowledge management processes. Unlike traditional tools focused largely on storing and retrieving explicit knowledge, generative chatbots, by virtue of their conversational nature and capacity to produce context-aware responses, make interaction with tacit knowledge possible at both the elicitation and the absorption stage (Feuerriegel et al., 2024; Kirchner et al., 2025).

The effectiveness of any interactive technology depends, however, on the characteristics of its users. Generation Z, born approximately between 1997 and 2012, reports the highest rate of generative tool use among working generations (Randstad, 2024); yet more recent survey evidence shows that this adoption has been accompanied by a marked rise in doubt about the cognitive consequences of these tools, and that its growth has plateaued (Gallup et al., 2026). This tension between widespread use and eroding trust makes Generation Z not merely an adopting group but one that warrants separate examination.

Research at the intersection of generative AI and knowledge management is growing quickly, and several notable works have used the SECI model as the theoretical lens for this intersection (Sumbal & Amber, 2025; Yan et al., 2026). This literature nevertheless has two shortcomings. First, almost none of these works brings generational differences among users into the analysis. Second, most leave the industrial context unspecified or focus on manufacturing and particular occupational groups (He & Yang, 2025; Kirchner et al., 2025). Beyond this, a theoretical debate is under way as to whether the SECI model is adequate at all for representing knowledge creation in the presence of a generative agent, or whether it requires revision (Böhm & Durst, 2026; Kirchner & Scarso, 2026) — a debate on which applied research in this field has largely declined to take a position.

The present paper aims to address this gap by offering a conceptual framework that explains the role of generative chatbots in each of the four SECI processes, in the context of tacit knowledge sharing among Generation Z employees in fintech start-ups. The central research question is: through which mechanisms can generative AI chatbots facilitate the four knowledge conversion

processes in tacit knowledge sharing among Generation Z employees in fintech start-ups, and under what conditions is that facilitation weakened or reversed? The remainder of the paper reviews the theoretical foundations, sets out the conceptual method, presents the proposed framework together with eight research propositions, and closes with discussion, limitations and directions for future research.

2 Theoretical Background

2.1 Tacit and explicit knowledge

Organizational knowledge has long been classified into two categories: explicit knowledge, which is structured and codifiable in documents and written procedures; and tacit knowledge, which is personal and context-bound, rooted in experience, practical skill and mental models, and difficult to articulate (Nonaka, 1994). The origin of this distinction lies with Polanyi, who emphasized the inexpressible dimension of knowing in his well-known claim that we know more than we can tell (Polanyi, 1966). Tacit knowledge itself divides into a technical dimension, comprising practical skills, and a cognitive dimension, comprising mental models and beliefs. Its strategic importance follows from the fact that, unlike explicit knowledge, which is readily imitated, the sticky and context-bound nature of tacit knowledge makes it a more durable source of competitive advantage.

It is essential to note that in Polanyi's reading, tacit knowledge is not merely knowledge that has yet to be articulated; part of it is inherently inexpressible. This distinction has a direct implication for any claim about technology's capacity to elicit tacit knowledge, and the boundaries of the proposed framework are set accordingly in Section 4.

2.2 The SECI model, the concept of ba, and its critics

One of the most influential theoretical frameworks for explaining organizational knowledge creation is the SECI model, introduced by Nonaka (1994) and subsequently by Nonaka and Takeuchi (1995). The model rests on a spiral interaction between tacit and explicit knowledge across four processes: socialization, the conversion of tacit to tacit knowledge through direct interaction and shared experience; externalization, the conversion of tacit to explicit knowledge through the articulation of concepts, metaphors and models, regarded as the most difficult and pivotal stage; combination, the synthesis and rearrangement of fragments of explicit knowledge into new configurations; and internalization, the absorption of codified knowledge into individual skill through learning by doing.

Nonaka and Konno (1998) later added the concept of ba: the shared physical, virtual or mental context within which knowledge conversion alone becomes possible (Nonaka & Konno, 1998; Nonaka et al., 2000). This concept is of central importance to the present discussion, because the key question about generative chatbots is not whether they produce text, but whether they can constitute a shared context for knowledge conversion. Recent research has pursued precisely this question (He et al., 2026).

The SECI model has not, however, been immune to criticism. Gourlay (2006) argues that the empirical evidence supporting the model's four processes is weak, and that the notion of converting tacit into explicit knowledge rests on a contestable interpretation of Polanyi. This critique requires that the use of SECI in the present study be understood not as settled law but as an organizing framework conditional on empirical testing. A further response is available and is

adopted here: the propositions below are formulated at the behavioral level — documentation intention, volume of recorded documentation, performance in scenario-based tasks — rather than at the ontological level of conversion itself. These variables remain observable regardless of how the interpretive dispute over Polanyi is resolved.

2.3 Generative AI and enterprise chatbots

Generative AI denotes a class of computational technologies that produce novel and meaningful content on the basis of training data (Feuerriegel et al., 2024). With the development of large language models, enterprise chatbots have shifted from rule-based question-answering tools to conversational, context-aware assistants. This shift has drawn the attention of knowledge management researchers to the potential of these technologies for facilitating knowledge creation and sharing (He & Yang, 2025; Kirchner et al., 2025).

At the same time, the properties of this technology also generate risks that carry additional weight in the fintech context: the production of incorrect answers delivered in a confident register, bias arising from training data, and the confidentiality of financial and customer data. Chen et al. (2026) show that employees' perceptions of the intelligence and humanness of these tools have a positive effect on knowledge sharing intention through AI self-efficacy, but that perceived skill threat can attenuate this relationship — a finding indicating that the effect of this technology on knowledge sharing is neither unidirectional nor assured.

2.4 The intersection of generative AI and SECI: three competing streams

A review of the literature suggests that existing research at this intersection can be grouped into three streams. The first treats generative AI as a powerful instrument in the service of the four SECI processes and seeks to specify its application in each quadrant of the model; Sumbal and Amber (2025), focusing on ChatGPT, and Yan et al. (2026), in a systematic review of 82 articles yielding five propositions on the multifaceted role of AI, belong to this category.

The second stream regards generative AI not as a tool but as a new actor in the knowledge creation process, and therefore calls for revision of the SECI model itself. Böhm and Durst (2026) propose an alternative model termed GRAI, and Kirchner and Scarso (2026) advance the AKI model, in which machine-generated knowledge constitutes a distinct type of knowledge. The third stream assembles empirical evidence on the actual effect of these tools on the four processes; Kirchner et al. (2025), studying software developers, showed that knowledge exchange among colleagues is partially, though not wholly, displaced by interaction with generative AI, and in a follow-up study measured the effect of these tools on all four knowledge creation processes (Kirchner et al., 2026).

The present study deliberately positions itself in the first stream and retains SECI as an organizing framework, because its question concerns the role of the chatbot as an interface mediating interaction among employees, rather than the ontological status of machine-generated knowledge. As discussed in Section 5, however, if the second stream's claim regarding the agency of generative AI is confirmed, the scope of validity of the present framework will be correspondingly narrowed.

2.5 Generation Z in the workplace: the adoption paradox

Generation Z is the first cohort to have grown up with digital technologies and conversational interfaces, and it reports the highest rate of weekly AI tool use in the workplace (Randstad, 2024).

Interpreting this datum nevertheless requires caution: in the same survey, Millennials surpassed Generation Z in proficiency with these tools. Generation Z's lead therefore lies in frequency of use, not necessarily in mastery.

More recent evidence paints a more complicated picture. A survey of 1,572 respondents aged 14 to 29 indicates that growth in AI adoption within this cohort has plateaued, that enthusiasm has fallen markedly, and that close to half of employed respondents (48 percent) believe the risks of the technology in the workplace outweigh its benefits; the principal concern relates to its effect on deep learning and critical thinking (Gallup et al., 2026). This tension between widespread use and eroding trust has a direct implication for the proposed framework and is formalized in Proposition 5.

It must further be acknowledged that the very concept of generation as an explanatory variable is contested, since generational effects are frequently confounded with age and period effects. In this paper, Generation Z is used not as a biological category but as a marker for a cluster of shared technological experiences — principally fluency with conversational interfaces and a preference for informal communication. Accordingly, and departing from much of the generational literature, the propositions below name these mechanisms directly rather than resting on cohort membership as such; cohort labels are retained only as empirical markers. Testing them, as proposed in Section 6, requires cross-generational comparative designs.

2.6 Fintech start-ups as the research context

Fintech start-ups — young organizations operating at the intersection of technology and financial services — constitute a suitable context for studying tacit knowledge sharing for several reasons. First, their activities are strongly knowledge-intensive, spanning technical, regulatory and financial domains. Cojoianu et al. (2021), analyzing 3,081 fintech ventures across 226 OECD regions, show that the emergence and financing of these firms depends primarily on the surrounding stock of IT knowledge and the productivity of the skilled IT workforce rather than on capital availability, underlining that the critical resource in this sector is human expertise. Second, a flat and informal structure grounds communication more in direct interaction than in documentation. Third, the workforce is predominantly young, with a substantial share of Generation Z. Fourth, the rapid pace of product change leaves insufficient opportunity for complete codification of knowledge, so that departures of key staff carry a correspondingly high risk of knowledge loss.

Alongside these, regulatory requirements and the confidentiality of financial data make this a setting in which validating AI output is not a marginal concern but a binding condition. Gelashvili-Luik et al. (2026), in a case study of a global fintech organization, find that knowledge trust and cross-functional alignment operate as ongoing preconditions for reliable AI use, and that mediating roles linking technical and business functions are central to how AI-enabled knowledge management develops. Both findings speak directly to the moderators specified in Section 4.5 and to the expert-finder mechanism of Proposition 1.

2.7 The research gap and the position of this paper

Taken together, the reviewed literature reveals a clear gap. Applying the SECI model to explain the role of generative AI is not itself a novel undertaking and has an emerging track record. What is absent from that record is the simultaneous entry of two elements into the analysis: first, the characteristics of the user group viewed through a generational lens, and second, a specific

industrial context in which the requirement of human validation is imposed on the process from outside. The contribution of this paper lies not in introducing the link between generative AI and SECI, but in conditioning that link on the characteristics of user and context — and, more specifically, in identifying the boundary condition under which the same technological affordance switches from facilitating to displacing human knowledge exchange. In MacInnis's (2011) classification of conceptual contributions, this work combines delineation with an element of differentiation.

3 Methods

This study falls into the category of conceptual papers and adopts an analytical, library-based approach. Conceptual papers, unlike empirical research, seek to generate new theoretical insight by combining concepts and findings previously examined in isolation, rather than testing hypotheses with field data (MacInnis, 2011). Because of the conceptual nature of the study, sections concerning statistical population, data collection instruments and statistical analysis are not applicable.

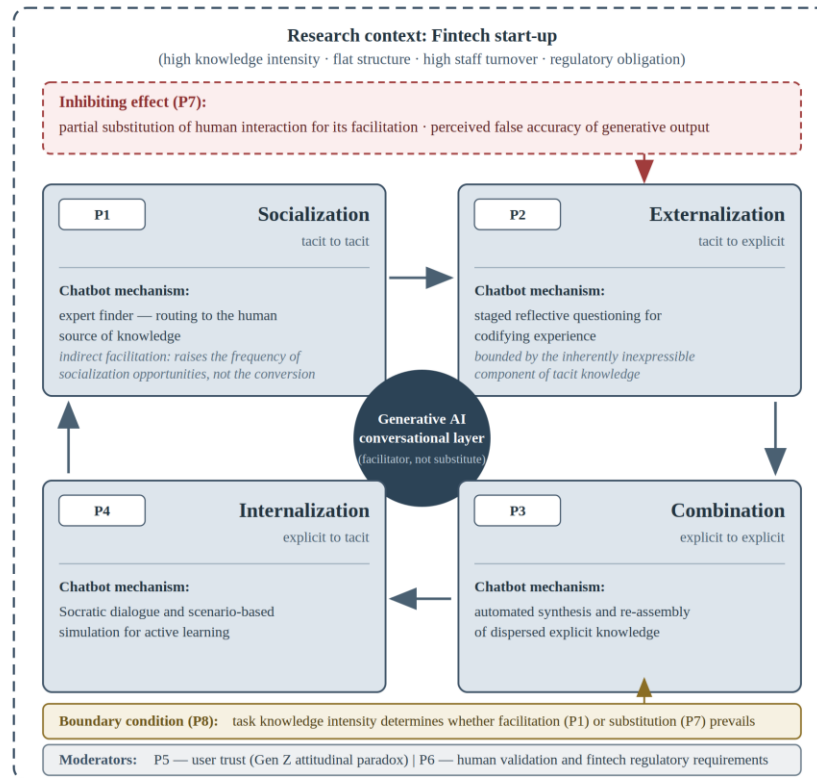
The review was purposive and narrative rather than systematic, and is presented as such; it was conducted in three steps against explicit criteria. In the first step, a targeted search was carried out in Scopus, Web of Science and Google Scholar, combining the keywords “generative AI”, “large language model” and “chatbot” with “knowledge management”, “tacit knowledge”, “SECI” and “Generation Z”. The time span was set from 1994, the year of Nonaka's foundational article, to mid-2026. The inclusion criterion was publication in peer-reviewed journals or scholarly books together with direct relevance to knowledge conversion; sources without a connection to the organizational context were excluded. In addition to scholarly sources, two reputable survey reports on Generation Z behavior were included to supply contextual data.

In the second step, the key findings of each domain were integrated and mapped onto the SECI model as the unifying framework, in order to identify the probable role of generative chatbots in each of the four conversion processes. In the third step, eight research propositions were derived from this integration: four addressing the facilitating mechanisms in each quadrant, two addressing moderators, one addressing a potential inhibiting effect, and one specifying the boundary condition that determines which of the two prevails. The rationale for deliberately including an inhibiting proposition is set out in Section 4.7.

4 Results: The Proposed Conceptual Framework

The proposed framework positions the generative AI chatbot as a conversational layer at the center of the SECI knowledge spiral, facilitating each of the four conversion processes differently, conditional on the characteristics of Generation Z users and the fintech context. Fig. 1 presents an overview of the framework.

Figure 1: The proposed conceptual framework of generative AI chatbot interaction with the four SECI processes



Source: authors' own elaboration

As Fig. 1 shows, the generative chatbot operates not as a substitute for human interaction but as a facilitating interface across the four quadrants of the model, while the upper band represents the potential inhibiting effect, the lower gold band the boundary condition, and the bottom band the framework's moderators. Each of these roles is elaborated below.

4.1 Socialization: the chatbot as expert finder

Socialization, which traditionally occurs through face-to-face interaction and shared experience, appears at first sight least compatible with text-based technologies. In fintech start-ups with flat and often distributed structures, however, generative chatbots can perform the role of expert finder: by analyzing the organization's prior question-and-answer patterns, they can direct a new employee to the individual or team holding the relevant specialized knowledge, and thereby create the conditions for human interaction to occur.

Precision is required here. By Nonaka's definition, socialization is a tacit-to-tacit conversion effected through shared experience. An expert finder does not participate in that conversion; it raises the frequency of the encounters within which the conversion may take place. Proposition 1 is therefore a claim about the antecedents of socialization opportunity rather than about the conversion process itself, and it should be read and tested as such.

Proposition 1: In fintech start-ups with flat organizational structures, deploying generative chatbots in an expert-finder role increases the frequency of socialization encounters between newer employees and colleagues holding relevant tacit knowledge.

4.2 Externalization: reflective questioning and the codification of experiential knowledge

Externalization — the articulation of tacit knowledge in intelligible language and concepts — is traditionally the most difficult stage of the SECI model, because many holders of specialized knowledge struggle to give structured expression to their experience and intuition. Through staged reflective questioning, the provision of guided input options with scope for free response, and adaptive feedback, generative chatbots can facilitate this process (Sumbal & Amber, 2025). For users fluent in conversational, informal interaction, this modality is likely to provoke less psychological resistance than completing formal documentation templates.

Consistent with Section 2.1, this proposition is confined to that portion of tacit knowledge which is in principle amenable to linguistic expression; inexpressible motor skills and perceptual intuition fall outside the scope of this mechanism.

Proposition 2: The greater an employee's fluency with conversational interfaces and preference for informal communication — attributes observed with higher frequency among Generation Z — the stronger the effect of chatbot-mediated reflective questioning on the intention to externalize and document experiential knowledge, relative to traditional documentation tools.

4.3 Combination: synthesis and rearrangement of dispersed explicit knowledge

The combination stage, previously carried out largely through databases and document management systems, has been transformed by the capacity of generative AI to summarize and synthesize large volumes of text (He & Yang, 2025). In fintech start-ups, explicit knowledge is typically dispersed across heterogeneous formats including technical documentation, regulatory reports, team correspondence and meeting notes. By reassembling these sources into coherent, context-sensitive responses, generative chatbots can reduce the cognitive load of knowledge search, particularly for newer employees.

Proposition 3: The capacity of generative chatbots to synthesize dispersed organizational explicit knowledge increases the speed with which employees obtain combined knowledge relevant to their tasks.

4.4 Internalization: Socratic dialogue and scenario-based learning

Internalization — the absorption of explicit knowledge into individual skill — ordinarily occurs through learning by doing. At this stage, generative chatbots can act as conversational tutors: instead of supplying an answer directly, they can guide the employee toward active discovery through Socratically styled directed questions and simulated scenarios, such as a simulated conversation with a dissatisfied customer or the analysis of a case suspected of financial fraud. This modality aligns with the principles of experiential learning and, in contextual terms, allows high-stakes situations to be rehearsed without incurring real cost.

Proposition 4: Deploying generative chatbots with a Socratic dialogue and scenario-simulation approach increases the effective internalization of organizational explicit knowledge relative to non-interactive instructional methods.

4.5 Moderators: user trust and human validation

The framework treats the effectiveness of the above mechanisms as conditional on two distinct moderating factors, which are stated separately because they operate through different pathways and can be tested independently.

The first is the level of user trust. As set out in Section 2.5, Generation Z attitudes toward generative AI are divided and shifting, and declining trust can render even well-designed mechanisms inert.

Proposition 5: The relationship between generative chatbot use and the effectiveness of the four SECI processes is moderated by the level of employee trust in AI, such that the facilitating effect weakens as trust declines.

The second is the presence of human validation mechanisms. The knowledge intensity and regulatory requirements of the fintech sector demand that chatbot output be validated under human supervision before it is relied upon organizationally.

Proposition 6: The presence of established human validation procedures moderates the relationship between generative chatbot use and the effectiveness of the four SECI processes, most strongly in the combination and internalization quadrants, where organizational reliance on generated output is highest.

These two moderators are not independent. The presence of a transparent validation procedure can itself rebuild user trust — a claim that is mediational rather than moderating in form. The framework flags this pathway explicitly as a corollary requiring separate modeling, rather than folding it into the moderation propositions, since conflating the two would misspecify the relationship in any subsequent structural model.

4.6 The inhibiting effect

Empirical evidence indicates that interaction with generative AI displaces part of the knowledge exchange between colleagues (Kirchner et al., 2025; Kirchner et al., 2026). In the socialization quadrant, this substitution stands in direct tension with the mechanism assumed in Proposition 1: a chatbot that supplies an answer immediately removes the incentive to consult an expert colleague.

Two further bodies of evidence, absent from most SECI-based treatments, reinforce this concern. Lee et al. (2025), surveying 319 knowledge workers across 936 real instances of generative AI use, found that higher confidence in the AI predicted less enacted critical thinking. Gerlich (2025), in a mixed-method study of 666 participants, found a significant negative association between frequent AI tool use and critical thinking, mediated by cognitive offloading — with the effect most pronounced among the youngest participants. This last finding is directly germane to the present framework: it suggests that the inhibiting effect may be strongest precisely in the cohort under study, and it converges with Generation Z's own reported anxiety about the erosion of critical thinking (Gallup et al., 2026). Compounding this, the confident register of generative output can produce a perception of false accuracy and deter verification — a risk with immediate consequences in the fintech regulatory domain.

Proposition 7: The greater the availability of immediate chatbot answers, the lower the likelihood that employees consult expert colleagues to obtain tacit knowledge — an effect that attenuates the facilitation assumed in Proposition 1 and that is amplified by cognitive offloading.

4.7 The boundary condition: task knowledge intensity

A framework that predicts only positive effects is effectively unfalsifiable and therefore of little value. Proposition 7 addresses this by admitting an inhibiting effect. Yet a framework that predicts both a positive and a negative sign for the same relationship without specifying which prevails is no better off: it accommodates any outcome. The framework therefore specifies the condition that determines the net sign.

That condition is the knowledge intensity of the task — the share of specialized, contextual and regulatory judgment required to complete it. Where a task is low in knowledge intensity, comprising procedural or regulatory questions with determinate answers, the chatbot's immediate response is an adequate substitute for consulting a colleague, and the substitution effect prevails. Where a task is high in knowledge intensity, requiring contextual judgment that the model cannot supply, the chatbot's answer is insufficient on its own; its principal value then lies in identifying the appropriate human expert, and the facilitation effect prevails. This distinction parallels the difference between delegating retrieval and delegating judgment, and it makes the framework's two competing predictions separately falsifiable.

Proposition 8: Task knowledge intensity moderates the relative strength of the facilitating effect (P1) and the substitution effect (P7), such that substitution prevails in low-knowledge-intensity tasks and facilitation prevails in high-knowledge-intensity tasks.

Tab. 1 summarizes the eight propositions together with the associated process, principal mechanism and direction of effect; Tab. 2 proposes operationalizations of the key constructs for future empirical research.

Table 1: Summary of the research propositions of the proposed conceptual framework

Proposition	SECI process	Principal chatbot mechanism	Direction of effect
P1	Socialization	Expert finder; routing to the human source of knowledge	Indirect facilitation
P2	Externalization	Staged reflective questioning for codifying experience	Direct facilitation
P3	Combination	Automated synthesis and rearrangement of dispersed explicit knowledge	Direct facilitation

Proposition	SECI process	Principal chatbot mechanism	Direction of effect
P4	Internalization	Socratic dialogue and scenario simulation for active learning	Direct facilitation
P5	Whole model	User trust in AI	Moderator
P6	Whole model (strongest in C and I)	Human validation procedures	Moderator
P7	Socialization and externalization	Partial substitution of human interaction; cognitive offloading; perceived false accuracy	Inhibiting
P8	P1 versus P7	Task knowledge intensity	Boundary condition

Source: authors' own elaboration

Table 2: Proposed operationalization of the framework's key constructs for future empirical research

Construct	Proposed operational definition	Proposed measurement basis
Generative chatbot use	Frequency and breadth of work-related use of the organizational conversational assistant	Self-reported weekly frequency alongside system usage logs
Externalization intention	Intention and behavior of recording personal experience as retrievable text	Knowledge sharing intention scale (Bock et al., 2005), complemented by volume of documentation recorded
Effective internalization	Capacity to apply organizational explicit knowledge in a novel work situation	Scenario-based assessment administered pre- and post-intervention
Trust in AI	Belief in the reliability and accuracy of generative assistant output	Trust in Automated Systems scale (Jian et al., 2000)
Human validation	Existence of a review procedure prior to organizational reliance on output	Organization-level measure based on procedural documentation
Task knowledge intensity	Share of specialized and regulatory judgment required to perform the task	Task classification combined with expert assessment

Source: authors' own elaboration

5 Discussion

The framework presented in this conceptual study both aligns with and departs from the emerging literature. Consistent with the systematic review of Yan et al. (2026) and with the work of Sumbal and Amber (2025), the present framework identifies the greatest transformative potential of

generative AI in the externalization and internalization stages — precisely those stages traditionally regarded as the most difficult parts of tacit knowledge conversion. This finding is also aligned with the results of Kirchner et al. (2025), who showed that interaction with generative AI complements knowledge exchange among colleagues without wholly replacing it.

The principal distinction of the present framework lies in three points. First, in contrast to prior studies focused either on particular occupational groups or on manufacturing industries (He & Yang, 2025; Kirchner et al., 2025), this framework brings the user-characteristic and the fintech industrial context into the model simultaneously — a combination that gains importance in light of the findings of Chen et al. (2026) concerning the role of self-efficacy and perceived skill threat, since these psychological factors may manifest differently across user groups. Second, unlike most optimistic applications of SECI, this framework incorporates an inhibiting proposition and thereby increases its own falsifiability. The moderators it specifies are, moreover, not merely stipulated: Gelashvili-Luik et al. (2026) identify knowledge trust and human mediating roles as recurring preconditions for reliable AI-enabled knowledge management in a fintech setting, which is precisely what Propositions 5 and 6 formalize as testable moderating relationships. Third, and most consequentially, it does not leave the resulting tension unresolved: Proposition 8 specifies the condition under which facilitation or substitution prevails, converting a pair of opposing predictions into a single testable contingency claim.

Theoretically, the framework reopens the question of *ba*: if knowledge conversion is possible only within a shared context (Nonaka & Konno, 1998; Nonaka et al., 2000), the key question becomes whether a conversational interface can constitute such a context or merely accelerates access to explicit knowledge (He et al., 2026). The position of this paper is that a generative chatbot can provide an effective context in the combination and internalization quadrants, but does not substitute for human *ba* in the socialization quadrant. Accepting this position is conditional on generative AI being treated as a tool rather than an actor; should the claims of Böhm and Durst (2026) and Kirchner and Scarso (2026) regarding the necessity of revising the SECI model be confirmed, the scope of validity of the present framework will be narrowed. Empirically testing these two competing positions is itself a valuable line of research.

From a practical standpoint, managers of fintech start-ups are advised to build distinct mechanisms into organizational knowledge chatbots for each SECI process, rather than adopting a uniform approach: expert-finder capability for socialization, reflective questioning for externalization, automated synthesis for combination, and scenario-based design for internalization. In light of Propositions 7 and 8, it is further recommended that systems be designed to refer users to an expert colleague, rather than supplying a final answer, precisely in questions that rest on specialized judgment — a design rule that follows directly from the boundary condition rather than from general caution. Maintaining human validation procedures in sensitive regulatory and financial domains, and making those procedures transparent to users, is both a governance requirement and a mechanism for rebuilding trust.

6 Conclusion

This paper has developed a conceptual framework specifying how generative AI chatbots shape tacit knowledge sharing among Generation Z employees in fintech start-ups, using the SECI model as an integrating lens. Its contribution is to condition the generative AI–SECI link on user and contextual characteristics, and to identify task knowledge intensity as the boundary condition

under which the same conversational affordance switches from facilitating human knowledge exchange to displacing it.

Several limitations must be acknowledged. First, the wholly conceptual nature of the framework means that the proposed relationships still require data-driven validation. Second, the survey evidence cited on Generation Z was gathered predominantly in a North American context, and approximately 44 percent of that sample comprised school-age respondents rather than employees; generalization to other cultural contexts, and to working populations specifically, requires caution and locally grounded research. Third, the focus on the fintech context may limit the generalizability of the findings to other knowledge-intensive industries. Fourth, the rapid pace of change in these technologies requires that the framework be revisited periodically.

On this basis, future research is invited to test the eight propositions through quantitative designs such as surveys with structural equation modeling, or qualitative designs such as comparative case studies across start-ups at differing levels of maturity. Proposition 8 in particular lends itself to experimental testing, since task knowledge intensity can be manipulated directly. Cross-generational comparative designs should also be employed, in order to establish whether the identified mechanisms are distinctive to Generation Z or generalize to other cohorts.

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