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Beyond Adoption: A Dynamic Model Of Generative Ai User Archetypes In Information System Development Teams

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BEYOND ADOPTION: A DYNAMIC MODEL OF GENERATIVE AI USER ARCHETYPES IN INFORMATION SYSTEM TEAMS

Completed Research Paper

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Abstract

Generative Artificial Intelligence (GenAI) is rapidly transforming Information Systems Development (ISD), yet traditional binary adoption models fail to capture its complex, open-ended nature. To understand how ISD professionals integrate these tools, we conducted an exploratory qualitative case study at a telecommunications and software company, applying the Job Characteristics Model (JCM) and the social perspective on ISD. Our analysis identifies a framework of dynamic GenAI user archetypes driven by perceived value and depth of engagement: the Disengaged Sceptic, Cautious User, Frustrated Strategist, and Productive Optimiser. With our study, we contribute to the ISD community with an extended theoretical perspective on post-adoptive GenAI use. Additionally, we equip ISD professionals with guidelines to scale GenAI sustainably within ISD teams through targeted, non-linear interventions.

Keywords: GenAI Adoption, Individual Adoption, Adoption Archetypes, Information Systems Development (ISD), Social Perspective

1 Introduction

The public release of Generative Artificial Intelligence (GenAI) models marks a fundamental transformation in knowledge work. This transformation is especially evident in Information Systems Development (ISD), a domain that demands a complex interplay of cognitive, technical, and collaborative expertise. ISD work requires broad domain knowledge, detailed expertise in data structures and processing logic, and a methodical understanding of effective software development practices (Iivari et al., 2004). Such multifaceted work is typically performed by ISD teams composed of programmers, analysts, testers, and project managers collaborating to produce software artefacts (Sawyer et al., 2010; Walz et al., 1993).

GenAI has the potential to fundamentally change ISD work by supporting developers across various tasks. Tools such as GitHub Copilot[1] can assist in code generation (Nguyen-Duc et al., 2023), debugging (Ziegler et al., 2022), documentation (Noy & Zhang, 2023), and refactoring (Nguyen-Duc et al., 2023), thus enabling developers to reuse knowledge, accelerate problem-solving, and reduce cognitive load (Bouschery et al., 2023; Ozkaya, 2023). Current research further shows that GenAI transforms not only single ISD activities but has broader implications on collaborative practices and work systems in ISD

[1] https://github.com/features/copilot

practices (Bruhin, 2024). Providers of GenAI tools report substantial productivity gains (Dakhel et al., 2023; Kalliamvakou, 2024), suggesting benefits across multiple stages of the ISD lifecycle. Despite initial scepticism regarding hallucinations, bias, fairness, and copyright concerns (Dwivedi et al., 2023; Feuerriegel et al., 2024), many organizations have proceeded with large-scale deployments, motivated by these reported efficiency benefits.

Early research on GenAI in ISD has primarily examined the effects of GenAI tools on developer productivity (Bruhin et al., 2024; Brynjolfsson et al., 2023; Li et al., 2024; Peng et al., 2023) and code quality (Dakhel et al., 2023; Dell'Acqua, McFowland, et al., 2023). Empirical findings show that GenAI-supported ISD professionals can complete tasks faster, make fewer errors, and deliver higher-quality outputs (Nguyen-Duc et al., 2023; Ziegler et al., 2022; Noy & Zhang, 2023). This focus aligns with broader ISD research that frames GenAI as productivity-enhancing digital technology (Berente et al., 2021; Feuerriegel et al., 2024).

Simultaneously, organizations are starting to report that actual GenAI usage lags expectations and that many GenAI projects are failing to deliver on their promised business value. A study on enterprise GenAI implementation found that while many organizations have piloted GenAI, 95% are getting "zero return," with only 5% of custom enterprise GenAI tools successfully reaching production (Challapally et al., 2025). While GenAI tools such as GitHub Copilot are widely adopted, reports indicate they primarily enhance individual productivity, not indicating robust insights on overall performance gains. This highlights a significant gap between initial investment in tools and their sustained, productive integration into core workflows.

Information Systems (IS) literature has a rich tradition of examining technology adoption, evolving through distinct theoretical phases. Traditionally, early models, such as TAM (Davis, 1989) and UTAUT (Venkatesh et al., 2003, 2016), viewed adoption primarily as a single, distinct event – a binary decision of whether to accept a new system. Post-adoptive use frameworks (Jasperson et al., 2005; Orlikowski, 1996) expanded this perspective by tracking usage frequency over time. Scholars have increasingly argued for a theoretical shift beyond mere behavioural adoption toward understanding effective technology use (Burton-Jones & Grange, 2013) – specifically, how individuals adaptively leverage a technology to achieve high task performance.

GenAI, however, disrupts this paradigm by introducing a new layer of complexity. Since GenAI tools operate probabilistically (Hamid, 2024) and require iterative, conversational prompting (Morris et al., 2023), their integration goes beyond both binary acceptance and mere usage frequency. Instead, it demands a constant, task-by-task decision of whether and how to apply the tool, resulting in highly fluctuating value generation for the organization. Therefore, the focus must shift to measuring how individuals continually harness GenAI's unique characteristics to realize these high-performance outcomes. To unlock the full potential of GenAI tools for organizational value creation, it is important to analyse this dynamic, continuous evolution.

Therefore, we pose the following research question:

RQ: *How do distinct user archetypes emerge within ISD teams during enterprise GenAI adoption and what dynamic paths describe their transition toward productive use?*

To answer this question, we conducted an exploratory, theory-building qualitative case study at a large telecommunications and software development firm. Based on 20 semi-structured interviews with ISD professionals, we applied inductive coding to derive patterns of the initial GenAI adoption and continuous usage patterns. This analysis led to the development of a 2x2 framework of GenAI User Archetypes, *Disengaged Sceptic*, *Cautious User*, *Frustrated Strategist*, and *Productive Optimiser*, capturing how individuals differ in their initial adoption with GenAI tools and how these individual adoption paths evolve.

Our study draws on two complementary theoretical lenses. First, we adopt a social perspective on ISD (Sawyer et al., 2010), which conceptualizes ISD practices as a socio-technical process of collaboration, negotiation, and sensemaking. Second, we integrate the Job Characteristics Model (JCM) (Hackman & Oldham, 1974) to capture how GenAI influences individual work design. By altering job attributes such as autonomy, skill variety, and feedback, GenAI can enrich or constrain work depending on how individuals interpret and appropriate its capabilities. Integrating these two theoretical perspectives on ISD allows us to conceptualize GenAI adoption as simultaneously a cognitive and a social process, shaped by personal perceptions of work enrichment and collective interaction dynamics within teams.

The study contributes to the ISD community by 1) extending post-adoptive use literature by identifying four distinct user adoption archetypes in voluntary GenAI adoption paths of enterprise GenAI tools, 2) giving empirical insights into how the JCM framework is influenced by GenAI use and 3) contributing to a dynamic perspective on technology adoption.

For practitioners, the framework provides ISD managers with an analytical lens to recognise and support distinct user states instead of treating GenAI adoption as a homogeneous evolution in the organisation. Tailoring interventions to each archetype can help organizations scale GenAI responsibly and foster more sustainable human-AI collaboration.

2 Theoretical Background

2.1 GenAI in Information Systems Development (ISD)

GenAI refers to a class of Artificial Intelligence (AI) models, most prominently Large Language Models (LLMs), capable of generating new and meaningful content, such as text, software code, and audio (Feuerriegel et al., 2024). In this study, we use the term *AI* as an umbrella concept. *GenAI* refers to AI systems capable of producing novel content, and *LLMs* represent a subset of GenAI focused specifically on text-based generation. Within ISD, GenAI tools are increasingly embedded across the Software Development Lifecycle (SDLC), in agile processes known as the DevOps[2] lifecycle, shaping how knowledge is created, shared, and applied. GenAI tools differ fundamentally from other digital technologies by performing human-like cognitive tasks, continuously learning from data, and eventually reshaping work practices and organizational structures (Benbya et al., 2024; Bruhin, 2024).

GenAI tools such as GitHub Copilot represent this trend by supporting developers in code generation (Nguyen-Duc et al., 2023), debugging (Ziegler et al., 2022), documentation (Noy & Zhang, 2023), and refactoring (Nguyen-Duc et al., 2023). Through these capabilities, GenAI tools assists ISD in reusing existing knowledge, accelerating problem-solving, and reducing cognitive load (Bouschery et al., 2023; Ozkaya, 2023). Current studies indicate substantial productivity gains associated with these tools (Dakhel et al., 2023; Kalliamvakou, 2024), suggesting benefits across multiple SDLC phases.

Despite concerns about hallucinations, bias, fairness, and copyright issues (Dwivedi et al., 2023; Feuerriegel et al., 2024), organizations continue to expand GenAI deployments, driven by expectations of productivity and efficiency improvements. This growing integration indicates that GenAI is not just a productivity enhancer but can act as a collaborative partner that reconfigures how ISD teams coordinate, make decisions, and conduct core ISD work (Ulfsnes et al., 2024).

GenAI can be classified as a workplace technology, yet it differs fundamentally from traditional workplace technologies through two unique characteristics: *inscrutability* and *open-endedness*. These characteristics shape adoption, governance, and use, and correspond closely to the tensions around transparency, learning, and human–machine interaction as discussed by Benbya et al. (2021).

Inscrutability. GenAI models are inherently opaque. Unlike conventional ISD tools, whose decision logic can be inspected and validated, GenAI operates as a probabilistic generative process that resists straightforward explanation (Wang et al., 2024). Non-determinism, arising from sampling procedures and hardware-level numerical variation (e.g., top-k/top-p sampling; Ouyang et al. (2025) limits predictability and reproducibility, thereby making testing and governance more difficult (Ganguli et al., 2022).

Open-endedness. GenAI tools provide unrestricted natural-language interfaces that enable broad, exploratory interaction (Brown et al., 2020). This broad and loosely defined input–output space encourages creative use but also creates uncertainty about appropriate application. This uncertainty

[2] https://devops.com/

reflects common tensions in AI-supported organizational processes, such as balancing automation with human support and machine logic with human judgment (Benbya et al., 2024). ISD professionals have to navigate when and how to rely on GenAI, calibrate trust, and develop new forms of skill and reflection (Stray et al., 2025). As a result, GenAI can simultaneously empower and challenge ISD professionals, due to its broader shifts in expertise, coordination, and authority observed when AI is incorporated into organizational processes (Ganguli et al., 2022; Rodon Modol & Eaton, 2021; Benbya et al., 2021).

2.2 From Binary Adoption to Evolutionary Adoption Paths

The unique characteristics of GenAI in ISD (*inscrutability* and *open-endedness*) disrupt traditional views of technology adoption. In mandatory technology adoption settings, users are forced to align with a standardized system, such as integrating Microsoft Teams organization-wide while making it impossible for employees to use applications they have used before for video conferencing (such as Zoom). Even in traditional voluntary contexts, adoption is typically viewed as a binary event or tracked merely through usage frequency. With GenAI, however, the voluntary decision to adopt is only the starting point. Because the tool acts as a highly flexible cognitive collaborator rather than a rigid workflow system, identical voluntary adoption decisions can lead to drastically different depths of engagement and highly fluctuating task performance. Achieving effective use requires constant task-by-task integration rather than a one-time alignment. To understand this shift, we propose a socio-cognitive lens that blends two theoretical perspectives.

First, we draw on the social perspective of ISD (Sawyer et al., 2010) to provide the context for the study. An individual's adoption path is shaped by GenAI's perceived impact on both their personal JCM dimensions and their social boundary-spanning roles. ISD teams operate simultaneously on internal and external fronts: internally through coordination, informal communication, and shared problem-solving, and externally through boundary-spanning activities such as information gathering, coordination with other units, and managing stakeholder expectations. Within this dual-front system, GenAI emerges as a new non-human actor that can reconfigure established work patterns and facilitate learning and information exchange, while also introducing new dependencies and coordination challenges.

Second, the Job Characteristics Model (JCM) (Hackman & Oldham, 1974). The JCM is a foundational work design theory (DeVaro et al., 2007) positing that work should be structured to include core features that foster motivation and satisfaction (Hackman & Oldham, 1974). These five core dimensions are: (1) *Skill Variety*, the degree of complexity and variety in a task; (2) *Task Identit*y, the degree to which an employee is responsible for a whole, identifiable piece of work; (3) *Task Significance*, the job's impact on the lives of others; (4) *Autonomy*, the freedom and independence to schedule and perform work (Morgeson & Humphrey, 2006); and (5) *Feedback*, the clear information an employee receives about their performance (Hackman & Oldham, 1974). These dimensions combine to create critical psychological states, such as 'experienced meaningfulness of work' (Humphrey et al., 2007).

GenAI is expected to enrich jobs by automating routine tasks, freeing team members for more complex work and thus increasing these JCM dimensions. While the JCM traditionally frames technologies as potential sources of job enrichment (increasing autonomy, skill variety, and significance by automating routine tasks), the integration of GenAI can alternatively lead to job enlargement. Job enlargement occurs when a technology expands the sheer volume of tasks, such as constantly verifying unpredictable AI outputs or meticulously reverse-engineering prompts, without elevating the meaningfulness or autonomy of the work. This distinction between job enrichment and job enlargement provides a vital explanatory mechanism for understanding how individuals transition between, or become stuck within, specific usage states depending on how effectively teams and organizations integrate GenAI into their socio-technical systems.

3 Methodology

To explore these emergent individual adoption patterns and paths of enterprise GenAI use, we employed an exploratory, theory-building qualitative case study approach (Eisenhardt, 1989; Eisenhardt & Graebner, 2007). This approach is ideal for approaching our research question, that aims to answer "how" and "why" a new phenomenon (in our case individual GenAI adoption) is unfolding within a complex, real-world social context (an ISD team). The case refers to a leading Swiss telecommunications and IT provider (referred to as "TeleComp"). TeleComp serves as a revelatory case (Yin et al., 2018) due to its advanced technological environment and its active, ongoing process of exploring with GenAI adoption, which provides rich, in-depth data. Our insights are built on a rich qualitative dataset, drawn from 20 semi-structured interviews with employees and leaders within ISD teams.

3.1 Data Collection

Our data collection strategy was designed to ensure triangulation (Yin et al., 2018) by capturing multiple, complementary perspectives on the adoption phenomenon: the managerial/strategic view, the "ground-truth" user experience, and the formal organizational context. The data set consists of 20 semi-structured qualitative interviews with ISD professionals within TeleComp's software development core (see Table 1 for an overview of participants, their roles, and their archetype matching).

All participants were selected based on having 6 to 18 months of baseline experience with GenAI tools. Although they all met this initial criterion, their actual depth of engagement at the time of the interview varied significantly, reflecting their individual adoption journeys. The emergence of the *Disengaged Sceptic* archetype therefore does not contradict our inclusion criteria. These participants were not recruited as non-users; rather, they are individuals who initially experimented actively with the technology. However, due to a perceived tool-task misfit or a lack of realized value, they subsequently reduced their engagement to a minimum over time. The selected roles ranged from on-the-ground DevOps Engineers (e.g., I1, I3, I5, I8), Product Owner & Platform Architects (e.g., I9, I20), to senior leadership like Tribe Chiefs (I16) and Heads of DevOps@Software (I18, I19). These interviews, lasting between 32 and 61 minutes, were conducted via MS Teams[3], transcribed, and manually checked for accuracy by two independent researchers.

To contextualize the participants' use of GenAI, it is crucial to understand the diverse nature, difficulty, and complexity of the tasks performed within the ISD teams. Participants' daily responsibilities range from highly structured, routine tasks (e.g., writing boilerplate code, generating standard documentation, and writing unit tests) to unstructured, highly complex cognitive tasks (e.g., architectural design, complex cross-system debugging, and aligning business logic with technical constraints). This spectrum of task complexity is essential for interpreting the archetypes, as the utility and necessary cognitive involvement with GenAI tools vary drastically depending on whether a developer is automating a low-complexity routine or seeking assistance for a high-complexity architectural problem.

To capture the diversity of individual experiences and attitudes, the interview guide included a set of open-ended, exploratory questions that encouraged participants to reflect on their personal engagement with GenAI tools. Exemplary questions included: *"How deeply and in what specific ways do you engage with GenAI tools in your daily work?"*, *"For which types of tasks or activities do you rely on them, and how much cognitive effort goes into verifying or adapting the outputs?"*, *"How useful or meaningful do you find these tools for your role?"*, and *"How has your perception of GenAI changed over time?"* These questions were designed to surface both the behavioral and perceptual dimensions of adoption. Specifically, they aimed to capture how actively and critically participants interacted with GenAI (depth of engagement) alongside how they evaluated its relevance and added value (perceived value). This dual focus became critical for identifying the key analytical dimensions underlying our archetype framework.

Interviewee Code	ISD role of interviewees	Experience with GenAI tools (name of tools & approx. duration of use)	Interview duration in minutes	Primary GenAI Archetype based on Analysis

[3] https://teams.live.com/

I1	DevOps Engineer/SOSA	GitHub Copilot, ChatGPT (approx. 12-18 months)	42	Disengaged Sceptic
I2	Release Train Engineer	ChatGPT, Internal Chatbot (approx. 6-12 months)	35	Cautious User
I3	DevOps Engineer	GitHub Copilot, ChatGPT (approx. 12-18 months)	34	Disengaged Sceptic
I4	Leader for Teams Development	ChatGPT, MS Copilot (approx. 12 months)	35	Cautious User
I5	DevOps Engineer	GitHub Copilot, Cursor (approx. 10 months)	46	Cautious User
I6	DevOps Engineer	GitHub Copilot, ChatGPT (approx. 12 months)	61	Frustrated Strategist
I7	Leader for Teams	ChatGPT (approx. 6 months)	42	Frustrated Strategist
I8	DevOps Engineer	GitHub Copilot, ChatGPT, Claude (approx. 12-18 months)	35	Disengaged Sceptic
I9	Product Owner & Platform Architect	ChatGPT, MS Copilot (approx. 6-12 months)	34	Cautious User
I10	Release Train Engineer	GitHub Copilot, ChatGPT, Internal Tools (approx. 18 months)	53	Cautious User
I11	Senior DevOps Engineer	ChatGPT (for planning/docs) (approx. 12 months)	42	Frustrated Strategist
I12	Product Manager	Internal Tools, ChatGPT (cautious use) (approx. 6 months)	35	Productive Optimiser
I13	Data Governance Manager	GitHub Copilot, ChatGPT (approx. 12 months)	34	Cautious User
I14	Software Test Engineer	GitHub Copilot (approx. 10 months)	35	Frustrated Strategist
I15	DevOps Engineer	ChatGPT, MS Copilot, Internal Tools (approx. 18 months)	46	Productive Optimiser
I16	Tribe Chief	GitHub Copilot, ChatGPT (approx. 12-18 months)	61	Productive Optimiser
I17	DevOps Engineer	GitHub Copilot, ChatGPT, Internal Tools (approx. 12 months)	44	Productive Optimiser
I18	Head of DevOps@Software	ChatGPT, MS Copilot (approx. 12 months)	36	Productive Optimiser
I19	Head of DevOps@Software	ChatGPT, MS Copilot, Internal Chatbot (approx. 18 months)	32	Productive Optimiser
I20	Platform Architect	GitHub Copilot, Perplexity (approx. 12-18 months)	45	Productive Optimiser

Table 1. Overview of interview participants (own illustration).

3.2 Data Analysis

Our data analysis followed a systematic, three-stage qualitative coding process (open, axial, and thematic coding; see Figure 1, following Saldaña, 2013). This approach enabled us to move inductively from descriptive observations of participants' statements toward the higher-order conceptual and theoretical insights that underpin our findings.

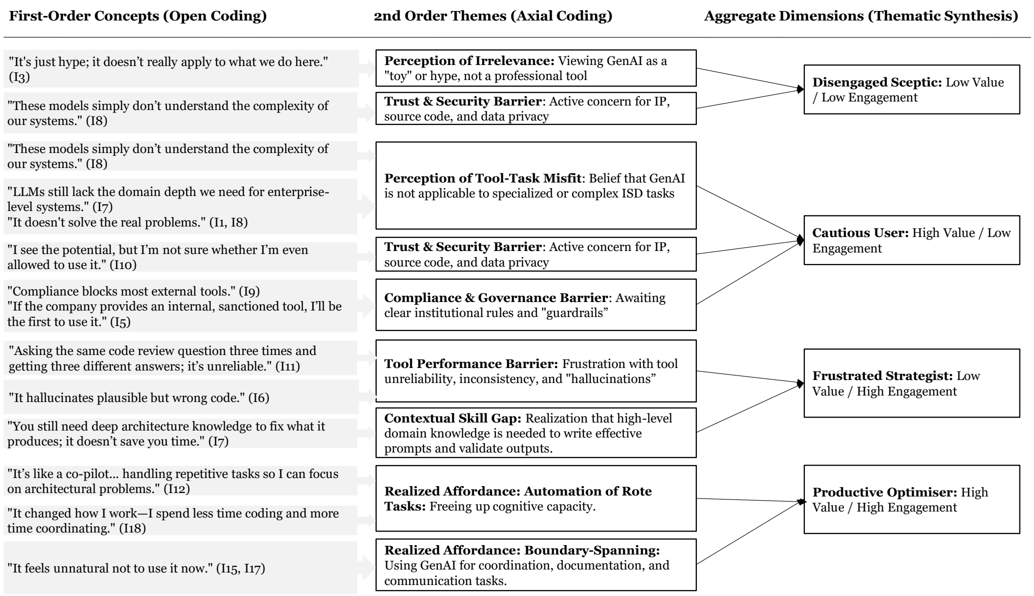

Figure 1. Data Structure of the Coding Process (own illustration).

In the *first stage*, open coding was conducted on the full set of interviews. This phase focused on identifying granular, descriptive codes that captured the participants' own words and immediate concerns. These "ground-truth" statements reflected participants' lived experiences and perceptions (e.g., *"worried about source code," "it hallucinates," "it's just hype"*). The purpose of this stage was to remain close to the data and avoid premature abstraction, ensuring that emerging categories were firmly grounded in the participants' discourse.

In the second stage, we moved toward axial coding, in line with Strauss & Corbin (1998) recommendations for connecting initial codes around conceptual axes. Here, related initial codes were clustered to form broader, interpretive categories. For instance, codes such as *"worried about source code," "is this allowed?"* and *"not sure it's accurate"* were grouped under the higher-level axial category Trust and Security Barriers. This phase served to organize the dataset into a set of meaningful clusters that highlighted relationships between users' perceptions, behaviours, and contextual factors.

During the axial and thematic coding phases, the Social Perspective on ISD (Sawyer et al., 2010) and the JCM (Hackman & Oldham, 1974) were explicitly applied as sensitizing concepts. Rather than merely summarizing quotes, we systematically interrogated the emerging data clusters against these theoretical lenses. For example, when analysing a participant's frustration, we mapped their statements against JCM dimensions, specifically looking for expressions of diminished autonomy or lack of reliable feedback. Similarly, for the social perspective, we coded how GenAI usage influenced informal communication and boundary-spanning activities within the team. This theory-driven interpretation allowed us to explain the underlying mechanisms of the archetypes rather than just describing user behaviour.

The identification of our two analytical axes emerged directly from this exploratory process. From the outset, the data collection was designed to uncover differentiated patterns of GenAI adoption among ISD professionals rather than treating the sample as homogeneous. During coding, it became increasingly evident that participants varied significantly across two core dimensions that jointly capture their orientation toward the technology: *Depth of GenAI Engagement* (which encompasses both frequency of use and cognitive involvement, distinguishing active, critical verification from passive, routine reliance) and *Perceived Value of GenAI Use* (reflecting how meaningful and valuable they found the tools for their specific work). The interplay between these dimensions proved to be a defining feature shaping their overall approach. For instance, some users interacted with the tools on a deeper, highly cognitive level (e.g., critically verifying outputs, actively debugging hallucinated code, and continually adapting prompts) but perceived limited value. Others saw high potential but restricted their engagement to a shallow level (e.g., recognising strategic benefits but limiting usage to infrequent, low stakes queries due to governance concerns). These recurring contrasts solidified Depth of GenAI Engagement and Perceived Value of GenAI Use as the structuring axes for differentiating the emergent adoption archetypes.

The *final stage* involved a thematic synthesis (Braun & Clarke, 2006), in which the axial codes were refined and abstracted into the overarching theoretical themes that constitute the paper's main contribution. At this stage, we integrated the axial codes corresponding to distinct user orientations to form the four archetypes: (1) the *Disengaged Sceptic*, (2) the *Cautious User*, (3) the *Frustrated Strategist*, and (4) the *Productive Optimiser*. This synthesis also illustrated the barriers and dynamic paths associated with each archetype, explaining how users navigate between states of adoption and resistance.

To ensure methodological transparency and illustrate how our empirical data supports all four quadrants of the model, each interviewee was mapped to their primary archetype based on our qualitative analysis following the interviews (Table 1).

4 Findings

Our analysis reveals that members of ISD teams do not adopt GenAI in a uniform or linear manner and that it can change over time depending on how they are influenced by the organization. In our data set, there emerged four different archetypes of GenAI use: (1) the D*isengaged Sceptic*, (2) the *Cautious User*, (3) the *Frustrated Strategist*, and (4) the *Productive Optimiser*. Figure 2 presents the identified archetypes and their relative positions within the 2x2 framework.

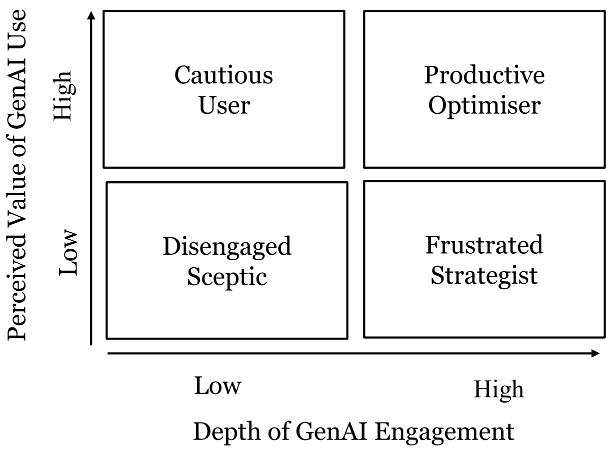

Figure 2. The four identified GenAI User Archetypes (own illustration).

4.1 The Disengaged Sceptic (Low Value, Low Engagement)

The first archetype, the Disengaged Sceptic, is characterized by low perceived value and a minimal, shallow depth of engagement with GenAI tools. Members of this group view GenAI as peripheral or irrelevant to their specific professional context, leading to infrequent and cognitively passive interactions. As one DevOps Engineer explained, *"It's just hype; it doesn't really apply to what we do here"* (I3), while another noted, *"These models simply don't understand the complexity of our systems"* (I8). Such scepticism is not necessarily rooted in hostility but in a pragmatic assessment of tool–task misfit. Team leaders echoed this sentiment; one participant reflected that *"LLMs still lack the domain depth we need for enterprise-level systems"* (I7). For these individuals, the absence of compelling, credible examples of GenAI's practical benefits reinforces disengagement. As I1 and I8 observed, current implementations *"don't solve the real problems"* and therefore fail to justify deeper cognitive investment or exploration. From a JCM perspective, the Disengaged Sceptic sees little enrichment of their core job dimensions. From a social perspective, GenAI appears to offer no meaningful support to their internal or boundary-spanning coordination, which further reduces their motivation to engage with the tools beyond a superficial level.

4.2 The Cautious User (High Value, Low Engagement)

In contrast, the Cautious User recognises GenAI's potential value but maintains a shallow depth of engagement due to trust, compliance, or security concerns. These participants often articulate ambivalence, acknowledging the promise of efficiency while remaining hesitant to invest deep cognitive effort or integrate the tools into critical workflows. *"I see the potential, but I'm not sure whether I'm even allowed to use it"*, remarked a Release Train Engineer (I10). A similar concern was raised by a Platform Architect, who pointed out that *"we could automate documentation, but compliance blocks most external tools"* (I9). For I2 and I13, both working in governance-related roles, uncertainty about data exposure and intellectual property created significant hesitation. Their position is therefore not one of rejection but of careful restraint; their engagement remains superficial, restricted to safe, low-stakes queries while awaiting clearer institutional guidance. As I5 mentioned, *"If the company provides an internal, sanctioned tool, I'll be the first to use it."* These findings suggest that organizational trust and explicit policy frameworks are decisive enablers for this group to move toward deeper cognitive involvement.

4.3 The Frustrated Strategist (Low Value, High Engagement)

A different dynamic emerges among the Frustrated Strategists, who demonstrate a deep, active cognitive engagement with GenAI, but experience only limited perceived value. Unlike passive users, Frustrated Strategists do not merely accept AI outputs; they engage critically with the tool. They tend to be early adopters, technically competent, and willing to invest significant cognitive effort into structuring complex prompts and actively verifying or debugging generated code. However, they express frustration with the inconsistency and immaturity of current GenAI systems. One Senior DevOps Engineer described the experience as *"asking the same code review question three times and getting three different answers (...), it's unreliable"* (I11). Likewise, I6 commented that "it hallucinates plausible but wrong code", highlighting a lack of trust in the tool's stability. The frustration is compounded by the heavy cognitive load required to interpret or correct AI-generated outputs. As I7 explained, *"You still need deep architecture knowledge to fix what it produces; it doesn't save you time unless you already know the answer."* The Tribe Chief (I16) described this phase as one of "Disillusionment" – a sober realization that GenAI requires intense cognitive oversight rather than providing seamless integration.

Nevertheless, as *Frustrated Strategists* continue to engage deeply, they position themselves as informal boundary spanners whose critical verification generates organizational learning about GenAI's strengths and weaknesses. From a theoretical perspective rooted in the JCM, the frustration of this archetype is driven by the manifestation of job enlargement rather than job enrichment. Because of the inherent inscrutability of GenAI models, technically competent users experience their work expanding horizontally, so they must endlessly verify outputs, correct hallucinated code, and reverse-engineer prompt logic. The lack of reliable feedback from the tool actively diminishes their experienced autonomy. This theoretical distinction explains the mechanism of their frustration: their deep engagement expands their task volume (enlargement) but fails to elevate their core job dimensions (enrichment).

4.4 The Productive Optimiser (High Value, High Engagement)

The fourth archetype, the Productive Optimiser, represents a mature stage of adoption in which high perceived value aligns with a deep, strategic depth of engagement. For these individuals, GenAI has become an integral, reliable partner in daily work. Rather than mindless reliance, their engagement is characterized by strategic augmentation: they know precisely when to delegate routine tasks and how to critically evaluate the system's output. *"It's like a co-pilot"*, explained a project manager (I12), *"handling repetitive tasks so I can focus on architectural problems."* Similarly, a senior software leader remarked that *"it takes care of the boilerplate, so I can spend time on business logic and integration"*

(I19). These participants report that GenAI allows them to reallocate cognitive effort from routine coding to strategic problem-solving, enhancing autonomy and job satisfaction. I15 and I17 highlighted that consistent exposure, and organizational endorsement had normalized their deep integration of the tool to the point where *"it feels unnatural not to use it."* From a social view on ISD, Productive Optimisers leverage GenAI tools to support internal coordination and external boundary-spanning activities, strengthening their role as integrators. As I18 succinctly summarized, *"It* [TeleComp's Internal GPT and GitHub Copilot] *changed how I work, I would say, I spend less time coding and more time coordinating."*

4.5 The Dynamics of Individual Adoption

A central contribution of our research lies in introducing a dynamic model instead of a static, one-time understanding of enterprise GenAI adoption. The four identified archetypes capture dynamic states that individuals navigate through as their experiences with GenAI, organizational support, and technological maturity evolve. Adoption is therefore best understood as an ongoing, adaptive learning process that unfolds within a socio-technical context. Users frequently shift between archetypes, and these transitions are shaped by social influence, institutional conditions, and the perceived alignment of GenAI with daily work practices.

While our model outlines predominant pathways toward productive optimization (as illustrated in Figure 3), these transitions are not strictly teleological or linear. The dynamic nature of GenAI adoption means reverse transitions are highly plausible and frequently triggered by external organizational or technological shifts. For example, a *Productive Optimiser* might revert to a *Cautious User* if a new corporate data leak scandal introduces restrictive governance policies. Similarly, a *Productive Optimiser* could regress into a *Frustrated Strategist* if an enterprise software update introduces severe bugs or increases AI hallucinations. Acknowledging this non-linearity adds necessary theoretical nuance, demonstrating that human-AI collaboration requires continuous adaptation rather than simply reaching a final, static end-state.

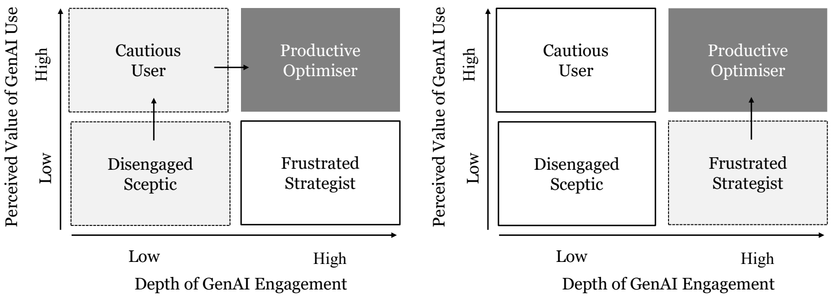

Figure 3. Predominant Transition Paths Between Archetypes.

4.5.1 Path 1: From Disengaged Sceptic to Productive Optimiser

The first trajectory, from the user archetypes *Disengaged Sceptic* to *Productive Optimiser*, captures how individuals evolve from initial scepticism to confident, productive use. This path is defined less by technical skill than by overcoming social and organizational barriers related to relevance and trust. At the outset, Disengaged Sceptics perceive a fundamental tool-task misfit. They view GenAI as "*a hype"* (e.g., I3) and irrelevant to their specific, often highly complex, professional context. As one engineer noted, *"These models simply don't understand the complexity of our systems"* (I8), while a team lead (I7) reflected that *"LLMs still lack the domain depth we need."* For this group, the perceived value is low because they have not encountered a credible use case that solves a tangible problem. The transition from *Disengaged Sceptic* to *Cautious User* begins when this relevance barrier is overcome. Our data shows this rarely occurs through formal, top-down managerial mandates. Instead, the shift is driven by the internal social system of the ISD team (Kirsch, 1996; Walz et al., 1993). Relevance is established through social proof and "informal communication" (Sawyer et al., 2010). As one team lead (I7) recalled, *"Seeing what colleagues achieved with prompt libraries made me rethink my stance,"* while a release train engineer (I10) added, *"Peer examples changed my view more than any formal training"*. This social sensemaking is critical: when a Sceptic sees a peer solve a familiar problem, their perception shifts from "no value" to "potential value," moving them into the Cautious User archetype. The subsequent and most critical shift, from *Cautious User* to *Productive Optimiser*, is contingent upon overcoming the trust barrier. *Cautious Users* are defined by their ambivalence; they now see the tool's potential but are organizationally constrained. They describe themselves as "*waiting for permission"* (I5, I9) and are blocked by legitimate concerns for data governance and intellectual property. As a Data Governance Manager (I13) and Release Train Engineer (I2) noted, uncertainty about data exposure is a significant inhibitor. This final transition is, therefore, a governance solution. It is unlocked by "*confidence-building measures"* and the introduction of *"clear institutional guardrails"* and, most importantly, *"secure, internally approved GenAI tools."* The act of organizational sanctioning resolves the user's role conflict. As one engineer (I5) explained, "*Once we had a company-approved tool, I started using it daily."* Similarly, the data governance manager (I13) emphasized that *"transparent data-handling rules finally made it feel safe."* In this trajectory, institutional trust is the pivotal enabler that reconciles individual enthusiasm with organizational responsibility, finally unlocking the user to pursue the JCM benefits (autonomy, skill variety) of the *Productive Optimiser*.

4.5.2 Path 2: From Frustrated Strategist to Productive Optimiser

A second major trajectory, from *Frustrated Strategists* to *Productive Optimisers*, describes users who already engage frequently with GenAI but derive limited value due to inconsistent or unreliable performance. This path is not about building trust but about closing the gap between the promise of GenAI and its performance in practice. Often, *Frustrated Strategists* are blocked by significant technical and contextual barriers. These types of users occupy an intermediary stage where experience and experimentation coexist with disappointment. These users are often technically competent and curious, but they are let down by the tool's immaturity. A Senior DevOps Engineer (I11) described the experience as *"asking the same code review question three times and getting three different answers – it's unreliable". "This is more than a simple tool failure; it is a socio-technical breakdown that disrupts a critical internal social process of the ISD team; the code review".* Other interviewees echoed this, noting the tool *"hallucinates plausible but wrong code"* (I6) or, as the Tribe Chief (I16) aptly termed it, a phase of *"Disillusionment."* This frustration is compounded by the realization that the tool increases, rather than decreases, cognitive load. As one leader (I7) explained, "*You still need deep architecture knowledge to fix what it produces; it doesn't save you time unless you already know the answer."* Moving from frustration to productivity requires overcoming specific technical and contextual barriers. Technically, the transition is catalysed by deep integration into established development environments. Frustration diminishes when GenAI evolves from a standalone, disconnected interface (e.g., a separate browser window) into a context-aware plugin directly embedded within the IDE[4]. This deep integration lowers the cognitive barrier for providing contextual data and allows for seamless, real-time code verification. Several participants (I6, I11) noted that improvements in GitHub Copilot and its deep integration were what *"finally made outputs stable enough for production."* Thus we learnt that when the tool becomes more reliable, the socio-technical tension can be resolved, and perceived value begins to rise. Contextually, the transition requires a fundamental shift in the user's mental model and continuous learning. Users must learn to stop treating GenAI as an infallible 'oracle' that produces finished products, and instead engage with it as a conversational 'co-pilot' (Burton-Jones & Grange, 2013). This learning process is highly social; participants noted that observing peers structure complex prompts or use iterative 'chain-of-thought' techniques was crucial. By learning to supply the necessary architectural context and mastering iterative refinement, these users move from experiencing job enlargement (correcting errors) to job enrichment (strategic augmentation). As I8 put it, *"The difference between frustration and mastery is knowing how to ask."* This is more than just "prompt engineering"; it is about

[4] IDE = Integrated Development Environment: An IDE is a software application that provides a comprehensive set of features for software development. Popular examples include NetBeans, Eclipse, IntelliJ, and Visual Studio.

the user providing the necessary context. This transition represents the evolution from a *"coder"* to a true "*software engineer,"* one who supplies the *"broad knowledge of the intended domain*" (Iivari et al., 2004) that the tool requires. The Tribe Chief (I16) captured this perfectly: *"a software engineer with architectural insight benefits far more than someone who just copies prompts."*

5 Discussion

Our study advances both theoretical understanding and managerial practice in the domain of technology adoption within ISD teams. By conceptualizing GenAI adoption as a dynamic, deeply cognitive, and individual-centric process rather than a monolithic event, this paper provides an empirically grounded framework that captures the evolving, heterogeneous nature of human–AI interaction in contemporary ISD contexts.

5.1 Theoretical Implications

This study contributes to ISD theory in three significant ways. *First*, this study extends the perspective on technology adoption by positioning GenAI use firmly within the "Technology-in-Practice" (Orlikowski, 2000) and post-adoptive behaviour literature (Jasperson et al., 2005) in voluntary adoption contexts. Rather than merely confirming that adoption is heterogeneous, a well-established fact in IS literature, our framework demonstrates how the specific affordances of GenAI (namely, its *inscrutability* and *open-endedness*) drive these specific user archetypes. Because GenAI operates as an open-ended cognitive collaborator rather than a deterministic tool, it forces users to continuously negotiate their depth of engagement toward effective use. This explains why traditional models that focus solely on the binary decision to adopt fail to capture the fragmented, highly individualized ways in which ISD professionals enact GenAI in practice. *Second*, this study provides empirical insights into how the JCM framework is influenced by GenAI use, effectively extending work design theory in IS. By moving beyond a descriptive application of the JCM, our findings elucidate the mechanisms behind archetype transitions. Specifically, we demonstrate that for the *Frustrated Strategist*, the misaligned integration of GenAI triggers job enlargement (expanding task volume through constant output verification and error correction) rather than the intended job enrichment (elevating autonomy and skill variety). The positive impacts on JCM dimensions (Hackman & Oldham, 1974) are therefore not an automatic affordance of GenAI. Achieving true job enrichment is a contingent process that requires overcoming the technical and contextual barriers that keep users trapped in deep, yet frustrating, engagement. *Third*, our study contributes a dynamic, non-linear perspective on technology adoption, moving beyond static "status quo" typologies. The identification of transition paths reframes adoption as a fluid, ongoing journey. Importantly, this progression is not strictly teleological. Our model acknowledges the reality of reverse transitions: a *Productive Optimiser* might revert to a *Cautious User* if new governance or data security scandals emerge, or they may become a *Frustrated Strategist* if an enterprise software update introduces severe hallucinations. This non-linearity provides a robust theoretical lens to understand how individuals navigate states of engagement over time.

5.2 Practical Recommendations

For practitioners, particularly ISD leaders, this study highlights that GenAI adoption cannot be managed as a uniform organizational rollout. Instead, it must be approached as the coordination of multiple, concurrent individual journeys defined by varying levels of perceived value and depth of engagement. To address the *Disengaged Sceptic*, ISD leaders should focus on demonstrating relevance through concrete, domain-specific examples and peer-led success stories. Internal roadshows and practical showcases can create cognitive resonance, encouraging them to move past shallow engagement. For *Cautious Users*, the priority lies in building institutional trust. Providing officially sanctioned, secure GenAI environments, alongside clear communication about data governance, reduces uncertainty. Transparency and organizational endorsement act as enablers for these users to safely deepen their cognitive engagement. *Frustrated Strategists* require a dual intervention: technical and developmental. Enhancing tool integration can alleviate technical frustration, while skill-building initiatives focused on contextual reasoning, prompt architecture, and critical evaluation of AI outputs can bridge the knowledge gap. Transforming their deep, exhausting engagement into productive collaboration is strategically vital, as they already possess the drive to champion GenAI-enabled workflows. Finally, *Productive Optimisers* represent the ideal state of deep, strategic engagement. Empowering these users with experimental freedom and recognition helps sustain motivation. They should act as “peer leaders,” facilitating informal mentoring and cross-role knowledge transfer, thereby accelerating collective learning at scale.

5.3 Limitations and Future Research

This study has two major limitations that open avenues for future research. *First*, the findings stem from a single case within a telecommunications and software development company. While the case offers strong theoretical insight, the identified archetypes and transition paths can vary across contexts. Comparative studies could test and refine the framework under different cultural conditions and governance structures. *Second,* while this paper claims to present a dynamic model with specific transition paths, the study relies on cross-sectional data derived from single point-in-time interviews. The dynamics and transitions in our model are inferred from retrospective accounts. It is important to acknowledge that these transitions represent retrospective reconstructions by the users, rather than longitudinally observed behaviours. Future longitudinal studies are needed to systematically track these behavioral shifts over time, empirically validate the non-linear reverse transitions proposed in our model, and observe how tool habitualization affects these pathways.

6 Conclusion

This study advances the understanding of GenAI adoption in ISD by conceptualizing it as an individual, deeply cognitive, and dynamic process rather than a uniform organizational event. Building on the JCM and the social perspective on ISD, we identified a 2x2 framework structured around two emergent dimensions: Perceived Value and Depth of Engagement. This yields four distinct GenAI user archetypes: the *Disengaged Sceptic*, the *Cautious User,* the *Frustrated Strategist*, and the *Productive Optimiser*.

Our research contributes to the ISD community by: (1) extending post-adoptive use literature by illustrating how GenAI's unique affordances drive heterogeneous engagement; (2) explaining archetype transitions through the theoretical mechanism of job enlargement versus job enrichment; and (3) providing a dynamic, non-linear perspective on continuous technology adoption. For practitioners, this framework provides ISD leaders with a diagnostic lens to recognise distinct user states, allowing them to tailor interventions that move teams from shallow or frustrating interactions toward deep, sustainable human–AI collaboration.

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