Integrating Generative AI into Knowledge-intensive Environments: Insights from Agile Workers

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Abstract: Generative AI (GenAI) is transforming how knowledge-intensive professionals work by generating new content and processing vast amounts of data, impacting knowledge creation. This phenomenon is widely acknowledged by scholars and practitioners, as evidenced by the growing body of literature on the topic. However, research remains in its early stages, and there is a pressing need to deepen our understanding of how these technologies are being adopted in specific contexts. This study addresses this gap by examining how agile practitioners who operate in highly knowledge-intensive environments and are among the earliest adopters of GenAI integrate these tools into their work. We developed a questionnaire including questions about performance, effort, social influence, facilitating conditions, and risks. The survey was distributed among participants at the 2025 edition of the Italian Agile Days, a two-day event that gathers Italian agile professionals. Based on responses from 91 participants, we identified three distinct user clusters: sceptical GenAI explorers, confident adopters, and cautious power users. Our findings contribute to an understanding of how GenAI is being integrated into agile practices and what facilitates or hinders its adoption among these knowledge-intensive professionals. Finally, we discuss implications for how organizations might tailor support, training, and governance to the different clusters to allow more effective and responsible GenAI use.

Keywords: Generative artificial intelligence, Knowledge management, Technology adoption, Agile, Knowledge workers

1. Introduction

Generative AI (GenAI) is deeply and rapidly transforming the landscape of knowledge-intensive work, fundamentally reshaping how professionals create, process, and leverage their cognitive assets. The technology's remarkable ability to generate novel content and analyse vast amounts of data across multiple formats is significantly impacting knowledge creation processes, collaborative workflows, and decision-making practices. This transformative phenomenon has garnered widespread recognition among both scholars and practitioners, as evidenced by the exponentially growing body of literature exploring its multifaceted implications (Purba et al., 2024; Yan et al., 2026). However, despite this burgeoning interest, research remains in its nascent stages, and there is an increasingly pressing need to deepen our understanding of how these powerful technologies are adopted, adapted, and integrated within specific organizational contexts and professional domains (Prasad Agrawal, 2024; Kirchner et al., 2025).

To address this critical knowledge gap, we conducted an empirical investigation into how practitioners working in agile contexts are adopting and utilizing GenAI tools to support their diverse agile-related tasks and activities. Our decision to focus on this professional community is motivated by two compelling, interrelated reasons. First, agile organizations epitomize knowledge-intensive environments, where continuous learning, rapid adaptation, and information sharing are paramount, and agile workers represent knowledge-intensive professionals who consistently engage in complex problem-solving and collaborative knowledge creation (Centobelli et al., 2025). Second, evidence suggests that agile practitioners are positioned among the earliest adopters and most intensive users of GenAI technologies, demonstrating both enthusiasm and sophistication in leveraging these tools within their daily workflows (Wolpers and Bergmann-Gering, 2026).

To this end, we developed a comprehensive questionnaire and strategically distributed it to participants at the 2025 edition of Italian Agile Days. This prominent two-day conference convenes Italian agile professionals, practitioners, and thought leaders from diverse industries and organizational contexts. We got inspired by other surveys examining the specific determinants and barriers influencing GenAI adoption across various professional settings (Kim et al., 2024; Chen et al., 2025; Chou, 2025). We carefully adapted questions to our specific research context and strategically added a risk perception factor, recognizing that perceived risks—including concerns about data privacy, output accuracy, ethical implications, and organizational policies—appear to particularly and significantly influence GenAI adoption decisions and usage patterns (Kim et al., 2024).

This paper presents and discusses preliminary, yet insightful analysis results derived from the collected responses (91 participants), focusing particularly on the emerging theoretical contributions and practical managerial implications of our findings. Our results provide valuable insights into how GenAI is being strategically integrated into agile practices, which specific use cases are emerging as most valuable, and which organizational, technological, and individual factors facilitate or hinder its successful adoption among these knowledge-intensive professionals.

The paper is structured as follows: Section 2 provides the background of the study, while Section 3 outlines the research objectives and methodology. Section 4 presents the results of the study, which are discussed in Section 5. This final section also includes conclusions and addresses the limitations of the study.

2. Background

2.1 Agile Professionals as Knowledge Workers and their use of GenAI

Agile methodologies represent a comprehensive suite of project management and product development frameworks specifically designed to enable teams to operate iteratively, collaboratively, and adaptively within dynamic environments characterized by frequently evolving requirements and rapidly changing conditions. While Agile methodologies initially emerged from and were predominantly associated with the software development movement, formally codified through the publication of the Agile Manifesto (Beck et al., 2001). These approaches have increasingly transcended their original domain and gained substantial traction across a diverse array of non-IT sectors (Alam et al., 2017; Ciric et al., 2018).

Contemporary organizational landscapes demonstrate that enterprises confronting complex, ambiguous, and uncertain operational environments are progressively embracing and implementing agile principles as strategic responses to volatility and complexity. Empirical evidence indicates that agile practices have been successfully adopted and deployed across various sectors, supporting critical functions such as product development, continuous process improvement, and large-scale organizational change initiatives (Noleto et al., 2023). Systematic literature reviews substantiate that, agile frameworks, particularly Scrum, can effectively facilitate continuous improvement cycles and foster innovation in non-IT contexts, though such applications frequently necessitate contextual adaptations and modifications, given that the original methodologies were predominantly architected for software development projects with their distinct characteristics and constraints.

Professionals who adopt and implement agile methodologies are typically classified as knowledge workers, since their principal assets and sources of value creation reside in their knowledge, competencies, domain expertise, and advanced problem-solving capabilities rather than physical labour or routine task execution. These individuals typically collaborate within cross-functional teams to conceptualize, develop, and deliver sophisticated solutions to complex organizational challenges. This characteristic profile positions agile practitioners among the earliest and most intensive adopters of GenAI technologies (Wolpers and Bergmann-Gering, 2026). Consequently, agile knowledge workers constitute a particularly compelling and theoretically rich context within which to systematically investigate and analyse the multifaceted factors, mechanisms, and dynamics that influence and shape the adoption patterns of this transformative emerging technology among knowledge-intensive professionals.

2.2 GenAI Adoption

To analyse the factors influencing the use of GenAI by agile workers, we resort to the Unified Theory of Acceptance and Use of Technology (UTAUT) because other authors have already used it as a theoretical framework to investigate the adoption and use of this technology. This widely applied theory explains and predicts individuals' attitudes and intentions to use technology based on their perceptions (Venkatesh et al., 2003). This theory has been the most widely used to investigate the adoption of GenAI across multiple domains, as evidenced by Chen et al. 's (2025) recent literature review on users' attitudes toward GenAI. The adoption and use of a new technology by individuals are affected by four main factors as follows:

- Performance expectancy: refers to the degree to which an individual believes that using new technology will help to improve their job performance. Various studies have proven that this is one of the most influential factors in technology adoption.
- Effort expectancy: refers to the user's perception of the amount of effort required to use new technology. The easier the technology is perceived to be to use, the higher the intention to use it.

- Social influence: refers to social pressures or expectations regarding technology use, including the influence of supervisors, colleagues, organizational culture, etc., on technology acceptance. The higher the social influence, the higher the intention to use.
- Facilitating conditions: refer to the existence of organizational and technical infrastructure that supports the use of technology. Such conditions are deemed crucial for successfully adopting new technology.

Coming back to its use in analysing the determinants of adoption and use of GenAI, it must be preliminarily underlined that most studies have applied this framework to examine the adoption of GenAI in the education (students and educators) domain (Chen et al., 2025) and therefore may not provide very useful indications about items for our study.

As concerns the use of the UTAUT model to investigate the adoption of GenAI in non-educational contexts, the analysis of the still limited literature has highlighted how some scholars have used this model in its original version (Kim et al., 2025; Chou et al., 2025; Tang et al., 2025), while others have preferred to use an expanded version, including additional factors, to take into account some specific aspects of GenAI (Hu et al., 2024; Lee et al., 2024; Xia and Chen, 2024; Kang et al., 2025; Li, 2025; Li et al., 2025).

Among the additional factors, perceived risk, i.e., the potential negative consequences associated with using GenAI, is of particular interest to scholars. This is confirmed by the literature review of Chen et al. (2025), which ranks perceived risk fourth among the top ten independent variables considered in GenAI adoption studies.

3. Data and Methodology

3.1 Participants

For this study, we developed a questionnaire and distributed it to participants at the 2025 edition of Italian Agile Days, a two-day event that gathers Italian agile professionals. The survey was conducted online, and respondents' personal information was anonymized. Only professionals who had used GenAI for business and/or personal purposes were allowed to complete the questionnaire. The aims of the survey and information on the confidentiality of the collected data and their use were included at the beginning of the questionnaire and also illustrated by one of the authors when the survey was presented at the event. Table 1 summarises participants' demographics.

3.2 Questionnaire Design and Variables

The survey instrument for this study was developed based on factors from previous literature (see Table 2 for an overview), including questions about performance, effort to use and learn, social influence from others, facilitating conditions in the organization, and technology risks. The items were intentionally limited to 4 per factor to keep the questionnaire short.

The questionnaire consisted of two sections. The first gathered demographic information, as seen in Table 1. The second section focused on the key constructs of the study (Table 2). A 5-point Likert scale was used to measure respondents' agreement with each statement, with values ranging from 1 (strongly disagree) to 5 (strongly agree).

3.3 Analysis Methodology

Given that the adoption and use of GenAI by knowledge workers is a relatively recent phenomenon, and with the aim of conducting a preliminary analysis of the collected data, we decided to perform a cluster analysis to verify whether different usage patterns exist among users of this new technology and, if so, what factors may drive such behaviours. Actually, this methodology seems particularly appropriate for exploratory research, where a new phenomenon is studied.

Specifically, we grouped similar cases using Ward's hierarchical clustering method (Ward, 1963) with factorization. The method starts with each case as its own cluster and repeatedly merges pairs of clusters to make the groups as consistent as possible. The analysis uses squared Euclidean distances to measure similarity between cases (Murtagh and Legendre, 2014). To decide how many clusters to keep, we inspected the dendrogram and selected a three-cluster solution at the point where a clear jump indicated well-separated groups. Clusters were formed from responses to the influencing factor items (4 items per factor, for a total of 20 variables) using the Enginius platform.

Table 1: Sample demographics

Items		Frequency (Percentage)
Gender	Male	72 (79.1%)
	Female	19 (20.9%)
Age	20 -29 years old	12 (13.2%)
	30 – 39 years old	20 (22.0%)
	40 – 49 years old	34 (37.4%)
	50 -59 years old	20 (22.0%)
	60+ years old	5 (5.5%)
Education	High School	23 (25.3%)
	Bachelor Degree	10 (11.0%)
	Master Degree	55 (60.4%)
	PhD	1 (1.1%)
	Other	2 (2.2%)
Job role	Clerk	41 (45.1%)
	Middle Manager	14 (15.4%)
	Manager	14 (15.4%)
	Owner/Shareholder/CEO	11 (12.1%)
	Freelance	8 (8.8%)
	Other	3 (3.3%)
Department/ sector	Production	14 (15.4%)
	Information Systems	33 (36.3%)
	HR	10 (11.0%)
	Sales	4 (4.4%)
	Administration	4 (4.4%)
	R&D	13 (14.3%)
	Marketing	1 (1.1%)
	Purchasing/Logistics	1 (1.1%)
	Consulting	6 (6.6%)
	Other	5 (5.5%)
Industry	Primary	1 (1.1%)
	Manufacturing	24 (26.4%)
	Professional services	46 (50.5%)
	Public Administration	6 (6.6%)
	Logistics	4 (4.4%)
	Finance/Insurance	7 (7.7%)
	Other	3(3.3%)
Company size	< 10 employees	10 (11.0%)
	10 -49 employees	14 (15.4%)
	50 – 249 employees	27 (29.7%)
	250 – 999 employees	12 (13.2%)
	1000 – 4999 employees	22 (24.2%)
	5000+ employees	6 (6.6%)

Items		Frequency (Percentage)
GenAI experience	0 – 6 months	17 (18.4%)
	7 – 12 months	32 (35.2%)
	13 – 18 months	13 (14.3%)
	19 – 24 months	18 (19.8%)
	> 24 months	11 (12.1%)
Most used system	ChatGPT	41 (45.1%)
	Copilot	16 (17.6%)
	Gemini	13 (14.3%)
	Claude	19 (20.9%)
	Perplexity	2 (2.2%)

Table 2: Questionnaire's items

Factor	Items	References
Performance Expectancy (PE)	PE1: The use of GenAI in an agile context contributes to increasing the efficiency of activities	Kim et al. (2025)
	PE2: The use of GenAI in an agile context contributes to increasing the quality of activities	Cao & Peng (2024)
	PE3: The use of GenAI in an agile context contributes to solving complex problems	
	PE4: The use of GenAI in an agile context contributes to generating innovative ideas	
Effort Expectancy (EE)	EE1: GenAI is simple to use	Kim et al. (2025)
	EE2: GenAI doesn't take long to become an advanced user	Cao & Peng (2024)
	EE3: GenAI can meet the many needs of its users	
	EE4: GenAI integrates well with my current work methods	
Social Influence (SI)	SI1: The use of GenAI in an agile context is encouraged by my supervisor	Kim et al. (2025)
	SI2: The use of GenAI in an agile context is positively evaluated by my colleagues	Chen et al. (2025)
	SI3: The use of GenAI in an agile context is widely adopted within my team/organization	
	SI4: The use of GenAI in an agile context is widely adopted among my company's competitors	
Facilitating Conditions (FC)	FC1: GenAI is compatible with the technology systems currently in use at my organization	Kim et al. (2025)
	FC2: My organization is providing sufficient training, technical support, and assistance regarding the use of GenAI	
	FC3: I can easily find help from colleagues if I encounter difficulties using GenAI	
	FC4: My organization has sufficient resources to equip itself with advanced GenAI systems	
Perceived Risk (PR)	PR1: I am very concerned that daily use of GenAI could reduce my creative capabilities	Cao & Peng (2024)
	PR2: I am very concerned that daily use of GenAI could reduce collaboration with colleagues	Chen et al. (2025)
	PR3: I am very concerned that GenAI could produce unreliable content	Li et al. (2025)
	PR4: I am very concerned about the potential negative consequences in terms of ethics and confidentiality of business information resulting from the use of GenAI	

4. Findings

Our analysis revealed three clusters. Table 3 summarises the results of the cluster analysis. For each variable, the mean values in the overall dataset and in each cluster are shown.

Table 3: Overview of the 3 clusters

Factor	Overall Population (N=91)	Cluster 1 (N=20)	Cluster 2 (N=38)	Cluster 3 (N=33)
PE1	4.13	3.60	4.16	4.42
PE2	3.62	3.10	3.53	4.03
PE3	3.53	2.80	3.53	3.97
PE4	3.63	3.10	3.74	3.82
EE1	3.70	3.55	3.63	3.88
EE2	3.34	3.05	3.32	3.55
EE3	4.11	3.90	4.24	4.09
EE4	4.19	3.60	4.37	4.33
SI1	3.69	2.65	3.95	4.03
SI2	4.13	3.55	4.47	4.09
SI3	3.84	2.80	4.13	4.12
SI4	3.86	3.45	3.76	4.21
FC1	3.86	2.80	4.03	4.30
FC2	3.29	2.50	3.21	3.85
FC3	3.68	2.55	3.84	4.18
FC4	3.60	2.60	3.82	3.97
PR1	2.86	3.05	2.05	3.67
PR2	2.55	2.40	1.92	3.36
PR3	4.20	4.35	3.92	4.42
PR4	3.76	3.80	3.21	4.36

Table 4 presents the demographic values (see Table 1) assumed by the three clusters, excluding descriptors with low presence. We could not find any differences in age, gender or months of using GenAI, but we did find differences in the sector and education in which participants work. These factors are shown in Table 4.

Table 4: Demographic factors in each cluster

	Population	Cluster 1	Cluster 2	Cluster 3
Age	43.2	43.1	42.5	43.9
Gender	0.791	0.700	0.868	0.758
Education	2.33	2.70	2.21	2.24
Months of using GenAI	16.8	17.3	16.9	16.3
Information Systems	36.3%	25.0%	28.9%	51.5%
Production	15.4%	15.0%	13.2%	18.2%
R&D	14.3%	5.0%	23.7%	9.1%
HR	11.0%	25.0%	13.2%	0.0%
Clerk	45.1%	35.0%	47.4%	48.5%
Mid Manager	15.4%	20.0%	7.9%	21.2%
Manager	15.4%	20.0%	15.8%	12.1%
Freelance	8.8%	10.0%	10.5%	6.1%
Owner/Shareholder/CEO	12.1%	15.0%	13.2%	9.1%
Manufacturing	26.4%	40.0%	23.7%	21.2%
Professional Services	50.5%	50.0%	50.0%	51.5%
Public Administration	6.6%	0.0%	5.3%	12.1%

	Population	Cluster 1	Cluster 2	Cluster 3
Logistics	4.4%	5.0%	2.6%	6.1%
Finance/Insurance	7.7%	5.0%	13.2%	3.0%

Based on the results from the cluster analysis in Tables 3 and 4, we can describe the three clusters as “sceptical explorers”, “confident adopters” and “cautious power users” (see Table 5).

Cluster 1 “sceptical explorers” see fewer benefits from using AI in their work than the other clusters, and have more concerns. Cluster 1 employees have higher levels of education than people in the other two clusters. In particular, it consists of employees working in HR or as middle managers, who need to make decisions about people (e.g., about hiring, firing, evaluations), so they might be more concerned about AI hallucinations that could lead them to wrong decisions. Furthermore, the cluster has more manufacturing employees who might face compliance and procedural constraints, and thus have less autonomy to make free decisions in their daily work. As IT and R&D employees are underrepresented in the cluster, it does not have many technical experts who can more easily understand how GenAI works.

Cluster 2 “confident adopters” gain higher efficiency when using GenAI at work. They are mainly knowledge workers (R&D, Finance, Clerks, and Freelancers), who can use GenAI to get support in routine tasks or standardized processes in finance. These tasks are not directly connected to people's responsibilities, which might cause them to be less concerned about GenAI.

In Cluster 3 are “cautious power users”, which contains more IT, public administration, and logistics. Especially IT people are capable of using AI and are aware of risks. People working in public administration can use GenAI well for their work; however, they need to be cautious users when decisions about people have to be made.

Table 5: Clusters description

Cluster 1: Sceptical explorers	Cluster 2: Confident adopters	Cluster 3: Cautious power users
20 people (22% of the sample) See fewer benefits from GenAI use Feel the least supported when using GenAI, e.g., by training and help from colleagues Have concerns about their GenAI use above average overrepresented people from HR and manufacturing, middle managers Underrepresented IT and R&D	38 people (42% of the sample) Have a supportive environment when using GenAI, e.g., most help from colleagues and supervisor support Have the lowest concerns toward GenAI use Gain from GenAI use, e.g., higher efficiency Overrepresented people from R&D, finance, clerks, and freelancers	33 people (36% of the sample) Perceive the highest benefits: efficiency, quality, can solve complex problems the best, ... have the highest support at their workplace (helping colleagues, most training, ...) have the greatest concerns about GenAI use Overrepresented IT, public administration, and purchasing logistics

A closer examination of the demographic profiles reveals further nuance. The sceptical explorers (Cluster 1) are dominated by HR professionals (25%) and manufacturing workers (40%), whose roles involve people-related decisions and compliance constraints where AI errors carry serious consequences. This explains their high risk concern scores (PR3=4.35, PR4=3.80). Counterintuitively, this cluster has the highest education level (2.70), suggesting that more educated users critically evaluate AI limitations rather than uncritically embracing the technology. The underrepresentation of IT and R&D workers (5%) means the cluster also lacks internal advocates who could model effective GenAI use. The confident adopters (Cluster 2) are primarily R&D (23.7%), finance (13.2%), and clerical workers (47.4%), whose tasks are routine and standardized, making AI errors easy to detect and consequences manageable. This explains the lowest risk scores across the sample (PR1=2.05, PR2=1.92). The cautious power users (Cluster 3) present the most theoretically interesting profile. IT professionals dominate (51.5%), and despite reporting the highest perceived benefits (PE1=4.42), they also show the highest risk concerns (PR4=4.36). This challenges the assumption that technical familiarity reduces risk perception; instead, deeper technical knowledge appears to heighten awareness of GenAI's failure modes such as hallucinations and data leakage.

5. Discussion and Conclusion

This study provides early empirical insights into how knowledge-intensive professionals working in agile contexts adopt and use GenAI in their daily tasks. Based on a survey of 91 practitioners at the Italian Agile Days 2025, we identify three distinct user clusters: sceptical explorers, confident adopters, and cautious power users, each characterized by different levels of engagement, perceived benefits, effort expectancy, social influence, and risk awareness. These findings show that GenAI adoption in agile environments is not uniform but unfolds through diverse sense-making processes, competence levels, and perceptions of value. The distribution of roles across clusters highlights how occupational context shapes adoption. Notably, Cluster 3 challenges a common assumption: rather than technical expertise reducing risk concern, IT professionals' deeper understanding of GenAI's failure modes, hallucinations, data leakage, output unreliability appears to heighten their caution, suggesting that capability and critical scrutiny co-evolve. Sceptical explorers are concentrated in HR, middle management, and manufacturing, where responsibility for people-related decisions and procedural constraints increase concerns and reduce the perceived benefits of GenAI. In contrast, confident adopters are primarily knowledge workers in R&D, finance, and freelance roles, where GenAI is used to support routine and standardized tasks, enabling efficiency gains with fewer concerns. Cautious power users illustrate how technical capability and work context interact, while their roles enable effective use of GenAI, their awareness of risks leads to a more critical and cautious engagement. These findings highlight a central tension between organizational support and risk perception. While training, collaboration, and enabling conditions can facilitate movement from scepticism to more confident use, increased experience does not eliminate perceived risks. Most UTAUT-based studies implicitly assume a linear adoption trajectory, where increased experience and organizational support progressively reduce barriers and lead to more confident use (Venkatesh et al., 2003; Bagozzi, 2007; Kim et al., 2024). Our findings challenge this assumption. While Cluster 2 broadly fits this pattern, Cluster 3 demonstrates that higher technical capability does not reduce risk concern but intensifies it. This suggests that GenAI adoption is better understood as a branching process shaped by occupational context and domain expertise, rather than a single pathway toward confident use (Kim and Kim, 2026). This aligns with prior research indicating that experienced users adopt more critical evaluation practices (Kirchner et al., 2025) and that perceived risk remains a persistent factor in GenAI use (Kim and Kim, 2026). It also contributes to research on human–AI collaboration by showing that effective use of GenAI depends not only on technical capability but also on users' ability to interpret, question, and validate AI-generated outputs (Jarrahi et al., 2023).

These findings suggest that organizations should move beyond one-size-fits-all adoption strategies and instead design differentiated support mechanisms that account for users' roles, experience levels, and evolving perceptions of risk. As GenAI becomes increasingly embedded in knowledge work, understanding these nuanced adoption dynamics will be critical to realizing its potential while mitigating its limitations.

5.1 Academic and Managerial Implications

From a theoretical perspective, our study contributes to the literature on AI adoption in knowledge-intensive contexts by offering an empirically grounded typology of GenAI user groups within agile work. Practically, our findings indicate that organizations may need to tailor support strategies to the specific needs and concerns of each cluster to facilitate effective and responsible GenAI use.

In the first cluster with sceptical explorers, organizations should better support these employees by providing sufficient training about how they can successfully employ GenAI for benefitting their work, validating the results, and changing their sceptical to cautious usage behaviour.

The confident adopters in the second cluster who regularly use GenAI for their work could benefit from scaling up, for example, by creating a prompt library with standard prompts they can use to optimize their daily tasks with GenAI and gain more benefits than only efficiency. Furthermore, they could support employees in cluster 1 to get more familiar with GenAI and understand the pitfalls.

Lastly, the cautious power users in cluster 3 could evaluate different GenAI tools to give advice to the organization and help with drafting organizational policies for GenAI use. The employees working in IT in this cluster might be able to help with fact-checking processes, so that employees can better check that the generated AI-content is correct.

5.2 Future Research Directions

Future work should collect data from more agile professionals, which would enable the validation of the three-user-cluster model. Since GenAI tools evolve rapidly, longitudinal research is needed to understand how perceptions, adoption levels, and user clusters shift over time. Building on our clusters, researchers could design and test interventions, such as onboarding programmes, peer learning, or GenAI-risk awareness workshops, to examine their effectiveness in supporting effective and responsible GenAI use.

5.3 Limitations

This study presents several limitations. First, data were collected exclusively from participants at the Italian Agile Days 2025, which limits the generalizability of the findings to other cultural and professional contexts. Second, only professionals who had already used GenAI were eligible to participate, introducing a self-selection bias that excludes non-users who might exhibit different adoption patterns. Third, the cross-sectional design captures perceptions at a single point in time, making it impossible to observe how adoption behaviours and risk perceptions evolve over time. Finally, the three-cluster solution is exploratory in nature and based on a relatively small sample of 91 participants; future confirmatory studies with larger and more diverse samples are needed to validate and refine it.

Ethics Declaration: All participants gave their informed consent before participating in our study. We did not require ethical clearance for the research described in this paper.

AI Declaration: We used GenAI to revise and correct the written text.

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