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ARCHETYPES OF GENAI USERS: CASE OF GEORGIA

Abstract. We explore how individuals in Georgia engage with generative artificial intelligence (GenAI) by identifying distinct user archetypes based on engagement frequency, the number of tools used, and whether users apply these tools in professional contexts. Drawing on BTU's Quantitative Research on GenAI Users in Georgia, we develop a classification model that captures a wide range of behavioral patterns and reveals six dominant user archetypes that shape the country's evolving AI landscape.

We actively examine how users integrate GenAI into daily routines, either through single-tool specialization or multi-platform flexibility, and whether their use is linked to work or personal exploration. The most prominent archetypes include Power Users, who engage heavily with multiple tools for professional tasks; Dedicated Specialists, who master a single tool for consistent work-related use; and Occasional Explorers, who turn to GenAI casually and infrequently. Additional profiles such as Curious Part-timers, Versatile Performers, and Balanced Professionals reflect intermediate or hybrid usage styles, combining varying levels of frequency, diversity, and purpose.

Our findings reveal strong differences by gender and age. Female users tend to adopt a structured and consistent approach to GenAI, often aligning with archetypes that reflect efficiency, reliability, and tool mastery. Male users more often appear in archetypes marked by either intensive use or sporadic experimentation. Meanwhile, younger users display curiosity-driven behaviors, while older individuals integrate GenAI more strategically into their professional workflows.

This research addresses the current gap in AI user classification by offering an empirically grounded, multidimensional framework. We move beyond narrow definitions and propose a scalable typology relevant to education, policy, and product development. The Georgian case demonstrates how digital societies in transition adopt AI not just as a tool but as a working habit-shaped by professional roles, digital maturity, and socio-demographic factors. These insights support the design of targeted training programs and AI tools adapted to specific user needs and expectations.

Keywords: *Generative Artificial Intelligence, User Archetypes, AI Adoption, Georgia, Digital Behavior, Human-AI Interaction.*

JEL Classification: O30; O33; J24.

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Introduction. The increasing adoption of generative AI (GenAI) tools has sparked considerable academic interest in understanding user behaviors and interaction patterns. Various factors, including user engagement levels, the number of tools utilized, and task-specific applications, play a significant role in shaping the usability and development of GenAI systems. While AI adoption has been widely studied, there is currently no standardized framework to classify GenAI user archetypes, necessitating an empirical approach.

The primary aim of this study is to identify and define archetypes of generative AI (GenAI) users in Georgia. To achieve this, we develop a classification framework based on three key dimensions: user engagement frequency, number of GenAI tools used, and whether these tools are applied for work purposes. The analysis draws on original survey data collected in October 2024 as part of a nationwide quantitative study. Georgia serves as a particularly relevant case due to its high levels of digital connectivity and growing integration of AI tools across sectors. By segmenting users according to their interaction patterns and demographic profiles, this research contributes a structured typology that can inform targeted policy measures, user-centered tool development and digital literacy strategies.

Literature Review. User engagement is a critical factor in the successful adoption and integration of GenAI tools. Kashyap et al. (2024) emphasize that engagement in AI-based environments is driven by human-centered design, cultural sensitivity, and adaptability of AI tools to individual needs. Their study underscores the importance of personalized AI experiences in increasing engagement across diverse populations, especially in regions with varying levels of digital literacy and infrastructure availability. Similarly, Jo (2023) found that personalization and utilitarian benefits are key drivers of engagement with GenAI tools like ChatGPT.

The extent to which users interact with AI tools beyond passive use is a significant determinant of engagement. Riemer and Peter (2024) propose a conceptual framework for understanding GenAI as "style engines" that influence user engagement through adaptation and personalization. Their study highlights that high-engagement users actively shape AI outputs by refining prompts and customizing AI-generated content.

The number and variety of GenAI tools used by an individual play a pivotal role in defining user behavior and expertise. Radcliffe et al. (2025) analyzes AI adoption patterns across multiple domains, illustrating that users who interact with diverse AI applications demonstrate greater technological adaptability and deeper domain-specific expertise. Their findings suggest that tool diversity is positively correlated with long-term AI adoption and professional skill development.

Riemer and Peter (2024) categorize AI adoption into different archetypes based on tool diversity, arguing that generalists use multiple AI platforms for broad applications, while specialists prefer AI tools tailored to specific domains. This approach aligns with recent studies exploring how generative models can simulate diverse user profiles to support behavioral classification. For example, Jenkins et al. (2023) show how GenAI can model early-stage user personas, offering experimental validation for AI-based archetype construction.

Furthermore, research suggests that AI tool ecosystems shape user preferences. Siau and Liu (2023) highlight that users who engage with multiple GenAI platforms often develop a preference for those offering better user interfaces, seamless integration with existing workflows, and higher degrees of customization. This aligns with Kashyap et al. (2024), who identify accessibility and interoperability as crucial factors in AI tool adoption.

The increasing **integration of GenAI in professional environments** has significantly impacted workplace productivity and the nature of job functions across various industries. Joshi (2024) examines how GenAI enhances workforce innovation and national competitiveness, emphasizing its role in automating repetitive tasks and improving workforce agility. The study underscores that AI-powered automation supports knowledge workers by reducing cognitive load and enabling them to focus on strategic tasks.

Generative AI is also transforming content creation and knowledge work. Dorta-González et al. (2024) investigate the use of GenAI in research environments, highlighting its impact on knowledge generation, citation analysis, and literature synthesis. Their findings suggest that AI-assisted researchers experience increased efficiency but must navigate ethical challenges related to content originality.

In financial and compliance sectors, Agarwal et al. (2024) analyze how banks utilize generative AI to manage risk assessment and regulatory compliance. Their research shows that AI enhances fraud detection, automates reporting, and streamlines decision-making processes. However, they emphasize the necessity for regulatory oversight to ensure transparency and mitigate AI-related biases.

Another key aspect of AI in the workplace is its effect on teamwork and collaboration. Krishnasamy and Lee (2024) explore how AI-powered chatbots impact workplace dynamics, emphasizing that while AI enhances productivity, its impact on collaborative work remains complex. Their research suggests that AI adoption can lead to reduced face-to-face interactions, which may influence organizational culture and team cohesion.

Despite the growing body of literature on AI engagement, tool diversity, and professional applications, there remains a **significant research gap in the classification of GenAI user archetypes**. Existing studies primarily focus on individual aspects of AI adoption rather than offering a comprehensive framework that categorizes users based on their interaction patterns. Without such a framework, it is challenging to develop targeted AI literacy programs, optimize AI tool usability, or formulate policies that address the distinct needs of different user groups.

Several studies have explored AI archetypes, but they remain fragmented in scope. Affsprung (2023) notes that many existing classification efforts implicitly reflect assumptions about the "ideal" AI user, shaped by policy and regulatory expectations rather than empirical diversity of behaviors. This suggests that user archetypes are not only empirical categories but also socially constructed narratives. Böhm and Graser (2023) present a preliminary classification of AI user behaviors based on experimental studies, but their work lacks a standardized taxonomy. Riemer and Peter (2024) conceptualize AI user archetypes through style adaptation models, yet their study does not extend beyond creative and content-driven AI applications.

More structured attempts at AI archetype classification exist in specific industries. For instance, Dorta-González et al. (2024) analyze AI adoption among researchers, identifying categories such as AI-assisted authors, AI-native researchers, and AI-averse academics. Similarly, Wong (2024) evaluates AI archetypes in higher education, distinguishing between AI-integrated learners, AI-enhanced instructors, and AI-reliant administrators. Other works highlight the role of AI archetypes in structured environments such as banking (Agarwal et al., 2024), education (Dogan & Medvidović, 2023), and health services (Gimpel et al., 2024).

Non-academic Research conducted by Slack's Workforce Lab and published in September 2024 identified five distinct archetypes of generative AI (GenAI) users in the workplace, based on a global survey of over 14,000 employees across 14 countries. These archetypes - Leaders, Skeptics, Pragmatists, Resistors, and Supporters – reflect varying levels of engagement, trust, and experience with GenAI. Notably, "Leaders" are confident and proactive adopters, while "Skeptics" and "Resistors" exhibit low trust and limited use. This segmentation offers valuable insights into how user attitudes influence AI adoption patterns in professional environments (Salesforce 2024).

While suggested academic studies suggest domain-specific AI user types, they do not propose a unified framework applicable across industries or user demographics. By addressing this research gap, our study contributes to both the theoretical understanding of GenAI user behavior and the development of a practical framework for AI system personalization.

Research Methodology. This study evaluates GenAI user archetypes in Georgia based on three key factors discussed in literature: user engagement, the number of GenAI tools used, and whether the tool is used for work purposes. The classification framework follows established academic literature, which will be outlined in a dedicated table within the text. Given the three factors and their respective categorical options, three levels of engagement (active, moderate, infrequent), three levels of tool usage (one, two, or three or more tools), and two work-related statuses (using for work, not using for work) □ we identified and calculated the shares of 18 distinct user archetypes (3 × 3 × 2) (Table 1).

Table 1. Factors and options for GenAI user archetypes

Factor	Options		
User Engagement	Active	Moderate	Infrequent
Number of using GenAI tools	1 Tool	2 Tools	3+ Tools
Work Purposes	Using it for Work	Not Using for Work	

The data for this study was obtained from BTU's Quantitative Research on GenAI Users in Georgia, conducted in October 2024. A structured survey was administered using a snowball sampling approach, resulting in 489 responses. The questionnaire comprised 15 questions, including checkboxes, open-ended responses, and optional questions. Data collection occurred between September 25 and October 13, 2024. After filtering out

Table 2. Research-Related Survey Questions

Question from Survey	Response Options from Questionnaire	Which factor is related to this question	Converting methods
How frequently do you use GenAI tools?	Every day/almost every day Several times a week Several times a month Once a month Less frequently	User Engagement	“Every day/almost every day” is converted to “Active” “Several times a week “is converted to “Moderate” “Several times a month”, “once a month” and “less frequently” is converted to “Infrequent”
How do you typically use GenAI tools?	For learning, For work, For personal use (entertainment, information searching, etc.)	Work Purposes	If the option “For work” is checked it is converted to “Using it for Work” Otherwise, it is converted to “Not Using for Work”
Which AI tools do you use for image, video, or audio generation?	ChatGPT Claude Microsoft Copilot Gemini Other (specify)	Number of using GenAI tools	The total number of tools from both questions are calculated. If the number is 3 or more, it is converted to “3+”
Which AI tools do you use for text generation?	Midjourney DALL-E Adobe Firefly Stable Diffusion Leonardo AI Runway Synthesia AIVA Amper Other (specify)		

responses that did not specify the use of particular GenAI tools, 460 valid responses remained for analysis. The dataset had already been compiled and processed before being used for this academic study. The data was weighted according to gender distribution derived from website traffic data of major GenAI tools, which indicated a 60% female and 40% male split. No further adjustments were made due to limited demographic data. Among the 460 respondents, 271 were under 30 years old, and 189 were 30 or older. Additionally, 283 respondents were employed, while 181 were students, including those who also had employment.

The classification of users was carried out by cross-referencing the three factors across the valid dataset, allowing for a quantitative assessment of the prevalence of each archetype. The findings contribute to a deeper understanding of the composition of GenAI users in Georgia and provide insights into patterns of adoption and professional application.

The following questions were included in the survey to collect data for the research (see Table 2). These questions provided the basis for identifying user engagement levels, tool usage diversity, and work-related application patterns.

Main Results. From the 18 possible archetype combinations, six stood out as having the highest shares, collectively representing 62.4% of the sample (see Table 3). These dominant archetypes were categorized and named according to their distinct characteristics.

Among the most prevalent were the ‘Power User’ and ‘Occasional Explorer’. The ‘Power User’ is someone who engages daily with multiple tools for work, making them highly dependent on GenAI for efficiency and productivity. In contrast, the ‘Occasional Explorer’ interacts with GenAI infrequently, typically using a single tool for non-work purposes, representing a casual and need-based approach to AI.

Other significant archetypes include the ‘Dedicated Specialist,’ who focuses deeply on one tool for work, and the ‘Curious Part-timer,’ who explores GenAI sporadically but does not integrate it into daily routines. The ‘Versatile Performer’ balances specialization and adaptability by efficiently employing two tools for work-related tasks. Lastly, the ‘Balanced

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Professional' consistently integrates a single GenAI tool into their workflow but without excessive dependence.

These six archetypes illustrate varying levels of engagement, specialization, and tool reliance. While some users exhibit high dependency and frequent interaction, others adopt a more exploratory or occasional approach to AI adoption.

To better understand how GenAI adoption differs by gender, we examined the distribution of these six dominant archetypes among male and female users. The findings indicate notable differences in engagement patterns and specialization. Power Users and Occasional Explorers are more common among male users, whereas Dedicated Specialists, Balanced Professionals, and Versatile Performers are more prevalent among female users. This suggests that while male users tend to either engage heavily with multiple tools or use GenAI sporadically, female users are more likely to integrate GenAI into specific, structured workflows.

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The gender distribution of the six key archetypes is as follows in Table 4.

These findings reveal significant distinctions in how men and women engage with GenAI tools. Women tend to integrate GenAI into their workflows with a greater degree of consistency and structure, while men exhibit more variation in their usage patterns, either engaging in intensive tool use or using GenAI sporadically.

Table 3. Popular archetypes of GenAI users

Archetype name	Archetype share in total users	Archetype description	Factors		
			User Engagement	Number of using GenAI tools	Work Purposes
Occasional Explorer	12.5%	Uses GenAI rarely, typically less than once a week. Relies on a single tool, primarily for other use rather than work purposes. This archetype represents casual users who explore AI capabilities only when they need specific information.	Infrequent	1 Tool	Not Using for Work
Dedicated Specialist	11.8%	A daily user of GenAI, focusing on a single tool to maximize efficiency for work. This archetype represents individuals who master one tool for specific, consistent tasks.	Active	1 Tool	Using it for Work
Power User	10.9%	Engages with GenAI tools daily, leveraging multiple tools (3 or more) for work-related tasks. Highly dependent on GenAI for productivity and decision-making, this archetype exemplifies the heavy and skilled user.	Active	3+ Tools	Using it for Work
Curious Part-timer	9.6%	Uses GenAI a few times a week, relying on a single tool mainly for other uses rather than work. This archetype reflects individuals who explore GenAI occasionally to satisfy curiosity or personal needs	Moderate	1 Tool	Not Using for Work
Versatile Performer	9.0%	Uses GenAI daily and efficiently employs two tools for work. This archetype reflects adaptable professionals who strike a balance between versatility and specialization.	Active	2 Tools	Using it for Work
Balanced Professional	8.6%	Engages with GenAI a few times weekly, focusing on a single tool for work. This archetype represents individuals who integrate GenAI into their workflow without heavy reliance.	Moderate	1 Tool	Using it for Work

Table 4. Popular archetypes of GenAI users by gender

Archetype name	Archetype share in users for each gender group	
	Male	Female
Dedicated Specialist	9.5%	13.4%
Versatile Performer	5.3%	11.5%
Balanced Professional	4.2%	11.5%
Occasional Explorer	16.8%	9.6%
Power User	13.7%	9.0%
Curious Part-timer	11.6%	8.2%

Table 5. Popular archetypes of GenAI users by age groups

Archetype name	Archetype share in users for each gender group	
	Under 30	30+
Dedicated Specialist	15.8%	5.8%
Versatile Performer	11.7%	5.3%
Balanced Professional	9.2%	14.3%
Occasional Explorer	7.9%	19.9%
Power User	7.7%	10.4%
Curious Part-timer	7.6%	11.8%

Dedicated Specialists, who focus on a single tool for daily work, show a strong presence among female users. This suggests that women prefer to develop expertise in a limited set of tools, ensuring efficiency and mastery within a specific domain. Similarly, Balanced Professionals and Versatile Performers □ who integrate one or two tools into their work without excessive dependence □ are also more common among women. This highlights a strategic and methodical approach to GenAI engagement among female users, balancing reliability with adaptability.

Conversely, men exhibit a dual tendency in GenAI adoption. A significant proportion of male users fall into the Power User category, indicating a higher level of engagement with multiple tools for work. This implies that male users who incorporate GenAI into their workflow tend to do so at an advanced level, utilizing a diverse array of tools to optimize productivity. At the same time, men are also more frequently found in the Occasional Explorer category, using GenAI tools infrequently and primarily for non-work purposes. This suggests a more experimental or interest-driven approach to AI adoption among male users, contrasting with the structured engagement observed among female users.

Curious Part-timers, who use GenAI occasionally but do not integrate it into daily workflows, also show a slightly higher share among men. This indicates that some male users explore AI without fully incorporating it into their routine work processes. The data suggests that male users either immerse themselves deeply in GenAI for professional purposes or engage with it sporadically, whereas female users maintain a more balanced and methodical relationship with AI tools.

To further understand GenAI adoption, we examined how different age groups engage with technology. The analysis reveals significant differences between users under 30 and those aged 30 and above (see Table 5).

Younger users (under 30) are more likely to be Occasional Explorers (15.8%) and Curious Part-timers (11.7%). This suggests that many younger individuals use GenAI tools on a casual basis, often for personal interest rather than work. These users may be experimenting with GenAI without integrating it into their daily routines.

Conversely, older users (30+) are more likely to be Dedicated Specialists (19.9%) and Balanced Professionals (10.4%). This indicates that users in this age group tend to develop expertise in one tool and use it consistently for work. Versatile Performers, who employ two tools for work-related tasks, also have a stronger presence in the older demographic (11.8%).

Power Users, who engage with multiple tools daily for work, are more common among the older group (14.3%) than younger

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users (9.2%). This suggests that experienced professionals are more likely to integrate multiple AI tools into their workflows, optimizing productivity and efficiency.

Younger users often interact with GenAI in an informal, exploratory manner, while older users integrate these tools into their work more systematically. These trends highlight the evolving role of AI across different career stages and levels of professional experience. This suggests that experienced professionals are more likely to integrate multiple AI tools into their workflows, optimizing productivity and efficiency.

Conclusion. This study set out to **develop a typology of GenAI users in Georgia** by analyzing how frequently they engage with GenAI tools, the number of tools they use, and whether these tools are applied for work purposes. Drawing on **survey data collected in 2024**, we created an empirically grounded classification framework that identifies distinct user archetypes. Based on this classification, several key findings emerged that highlight how GenAI is adopted and integrated across different user groups:

Firstly, **six dominant user archetypes were identified**, covering **over 60%** of all GenAI users in Georgia. These were named based on their behavioral patterns and include: Power Users, Dedicated Specialists, Occasional Explorers, Versatile Performers, Curious Part-timers, and Balanced Professionals.

Secondly, **structured and consistent engagement** with GenAI is more common among **older users and female professionals**. In contrast, younger users and male **professionals** demonstrate more varied patterns of use from high-intensity multi-tool reliance to occasional and exploratory interactions.

Thirdly, **professionals who integrate GenAI into their work tend to focus on efficiency by specializing in one or two tools**. These users typically represent archetypes such as Dedicated Specialists or Balanced Professionals. Meanwhile, casual or interest-driven users more often younger and male are concentrated in exploratory categories such as Curious Part-timers or Occasional Explorers.

The typology presented in this study offers practical insights for researchers, educators and policy makers. Understanding how GenAI usage varies across user types can support the design of targeted digital skills programs, personalized tools and inclusive AI adoption strategies. Future research should explore how these archetypes evolve as GenAI becomes more embedded in everyday professional and personal life.

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АРХЕТИПИ КОРИСТУВАЧІВ GENAI: ПРИКЛАД ГРУЗІЇ

Ми досліджуємо, як індивіди в Грузії взаємодіють з генеративним штучним інтелектом (GenAI), визначаючи різні архетипи користувачів на основі частоти взаємодії, кількості використовуваних інструментів і того, чи застосовують користувачі ці інструменти в професійному контексті. Спираючись на кількісне дослідження BTU щодо користувачів GenAI в Грузії, ми розробили класифікаційну модель, яка охоплює широкий спектр поведінкових моделей і виявляє шість домінуючих архетипів користувачів, які формують ландшафт штучного інтелекту, що розвивається в країні.

Ми активно досліджуємо, як користувачі інтегрують GenAI у повсякденне життя - через спеціалізацію на одному інструменті чи багатоплатформну гнучкість - і чи пов›язане їхнє використання з роботою або особистими дослідженнями. Найпомітніші архетипи включають досвідчених користувачів, які інтенсивно працюють з декількома інструментами для виконання професійних завдань; спеціалістів, які опановують один інструмент для постійного використання в роботі; і випадкових дослідників, які звертаються до GenAI випадково і нечасто. Додаткові профілі, такі як «Допитливі сумісники», «Універсальні виконавці» та «Збалансовані професіонали», відображають проміжні або гібридні стилі використання, що поєднують різні рівні частоти, різноманітності та цілей.

Наші результати свідчать про значні відмінності залежно від статі та віку. Жінки-користувачки, як правило, застосовують структурований і послідовний підхід до GenAI, часто узгоджуючи його з архетипами, що відображають ефективність, надійність і майстерність володіння інструментами. Користувачі-чоловіки частіше демонструють архетипи, що характеризуються або інтенсивним використанням, або спорадичним експериментуванням. Тим часом, молоді користувачі демонструють поведінку, зумовлену допитливістю, тоді як старші люди інтегрують GenAI у свої професійні робочі процеси більш стратегічно.

Це дослідження заповнює існуючу прогалину в класифікації користувачів ШІ, пропонуючи емпірично обґрунтовану багатовимірну структуру. Ми виходимо за межі вузьких визначень і пропонуємо масштабовану типологію, що стосується освіти, політики та розробки продуктів. Кейс Грузії демонструє, як цифрові суспільства на перехідному етапі приймають ШІ не просто як інструмент, а як робочу звичку, сформовану професійними ролями, цифровою зрілістю та соціально-демографічними факторами. Ці знання допомагають розробляти цільові навчальні програми та інструменти штучного інтелекту, адаптовані до конкретних потреб та очікувань користувачів.

Ключові слова: *генеративний штучний інтелект, архетипи користувачів, впровадження ШІ, Грузія, цифрова поведінка, взаємодія людини та ШІ.*

JEL Classification: O30; O33; J24.

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