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Generative AI and the Future of Freelancing in Bangladesh: Challenges, Adaptation, and Policy Directions

Md. Nazmul Hasan[1], Md. Yahin Hossain[1], Arif Rana[2], Md. Afzal Hossain[2]*

[1]*Department of Business Administration, R. P. Shaha University*
[2]*IUBAT Business School, International University of Business Agriculture and Technology (IUBAT)*

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Abstract

Bangladesh's freelancing sector has expanded, with more than 650,000 freelancers participating in the gig economy. But the emergence of Generative AI (GenAI) technology offers both opportunities and threats, transforming processes in content writing, designing and coding. The research explores how Bangladeshi freelancers' perceived GenAI adoption influences their success based on an extended UTAUT2 model. Structural equation modeling (SEM) was used to analyze data from 300-400 freelancers. The findings reveal that hedonic motivation (enjoyment of AI tools) and facilitating conditions (having resources) have strong influences on adoption, whereas performance expectancy, social influence and trust have no significant influence. Significantly, GenAI adoption significantly increases freelancers' perceived success ($\beta = 0.678$), with the moderating role of digital support systems (DSS) enhancing this impact ($\beta = 0.120$). Our results extend existing technology adoption theory by highlighting intrinsic motivation and facilitating conditions rather than perceived utility or social influence. Implications include focusing on skill enhancement, AI-enabled work processes, and accessible training opportunities for freelancers, platforms and policymakers. This research adds to the conversation on AI and the future of work in emerging economies, and offers ways to leverage GenAI's capabilities while addressing skill obsolescence and market distortions.

1. Introduction

In the last decade, Bangladesh has emerged as a major player in the global gig economy, with the freelancing sector thriving. Bangladesh has become a powerhouse in the freelancing industry with more than 650,000 registered freelancers actively working across a range of industries such as content writing, graphic design, programming, and digital marketing (Oxford Internet Institute, 2019; World Bank, 2021). This growth has been facilitated by a range of factors, including low-cost internet connectivity, an increasing number of digital professionals, and the emergence of global online freelancing platforms like Upwork, Fiverr and Freelancer.com (Kumar *et al*., 2023). The growing dependence

*Corresponding author's E-mail address: afzal.cba@iubat.edu
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on online platforms has allowed Bangladeshi freelancers to work on a global scale, boosting the national economy and personal livelihoods (Islam *et al.*, 2022). But the rise of Generative Artificial Intelligence (GenAI) is now changing this dynamic, bringing about opportunities and threats for freelancers. Generation AI, which leverages large language models (LLMs), machine learning, and automation technologies, has transformed numerous creative and analytical fields (Brynjolfsson & McAfee, 2021). GenAI technologies allow for the automation of tasks previously carried out by humans, such as writing code, designing graphics, generating text and images, and providing customer support (Autor *et al.*, 2022). Although AI adoption in freelancing has improved efficiency, cost-effectiveness and quality, it has also led to concerns about potential job loss, income volatility and skill depreciation (Kok & Wehner, 2023). A range of services traditionally offered by freelancers are increasingly being either partially or entirely automated using AI technologies like ChatGPT, Midjourney, and Jasper AI, diminishing the need for human intervention in some of the freelancing fields (Tambe *et al.*, 2023).

As a result, a debate is emerging about whether Generative AI is a friend or foe for the Bangladeshi freelancers. While some perceive AI as an opportunity to increase productivity and competitiveness, others are concerned it could dramatically reduce freelance employment in low-skill and non-creative tasks (Acemoglu & Restrepo, 2020). While growing literature discusses the effects of AI-driven changes in the labor market, there is a gap in the literature about the consequences of Generative AI on freelancing in developing countries like Bangladesh (ILO, 2022). Although much research has been conducted exploring the impact of automation and AI on employment in the West, there is a paucity of studies on the socio-economic status of Bangladeshi freelancers (Frey & Osborne, 2017). The literature mainly talks about the impact of AI on conventional sectors of employment, neglecting the freelancing sector, which has its own structural challenges (Berger *et al.*, 2023). Similarly, there is a lack of sector-specific research examining the impacts of AI on various freelancing jobs (such as writing, software programming and digital marketing), which makes it challenging to gauge the differences in AI adoption across sectors (West, 2022). Moreover, there is a lack of research on the economic and psychological impacts of AI-driven automation on freelancers, such as income volatility, employment instability and skill development (Rani & Furrer, 2023). Further, the impact of government policies, freelancing platforms and education on the skill development of freelancers to maintain their employability in the AI-driven economy has been scarcely discussed (UNCTAD, 2021). With the growing importance of freelancing in Bangladesh's digital economy, it is essential to build evidence-driven policies to help freelancers navigate AI-driven changes and continue to be viable in the workforce for years to come.

Research Gap and Objectives:

The purpose of this study is to address these research gaps, by examining freelancers' adoption behavior, challenges they are facing and strategies that can help them sustain freelancing in an AI-driven future. To overcome these issues, this research seeks to understand the effects of Generative AI adoption for Bangladeshi freelancers. While there are studies connecting political, economic, cultural and ethical concerns to adoption of Generative AI, little has been done to investigate the impact of performance expectancy, social influence, hedonic motivation, facilitating condition and trust on Generative AI adoption. Further, there is yet to be research connecting the adoption of generative AI with the subject's success. Most research does not adhere to the integrated approach of the variables on the success of AI adoption in freelancing.

The research aims are;

1. To examine the effect of performance expectancy, social influence and trust on adopting Generative AI by the freelances in Bangladesh.
2. To examine the influence of hedonic motivation and facilitating conditions on the freelances' AI adoption.
3. To measure the moderating role of digital support system in improving the subjective success of freelancers in Generative AI adoption.
4. To make policy and platform suggestions for enhancing the adoption process and to maintain the success of freelancers in the AI-powered digital economy.

2. Literature Review and Hypothesis Development:

2.1 Performance Expectancy and Adoption of Generative AI

Freelancers' adoption of Generative AI is driven by expectations of performance expectancy (PE) that AI technologies will improve their performance. This term, part of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) (Venkatesh *et al.*, 2012), is complemented by the Diffusion of Innovations (DOI) theory's relative advantage (Rogers, 2003). Freelancers evaluate AI tools based on their perceived capability to provide three benefits: (1) productivity benefits, such as automating routine tasks like writing articles or analysing data; (2) quality benefits, such as improved creative outcomes in graphic design or content creation; and (3) economic benefits, such as expanding service portfolios or commanding higher prices. These perceptions align with empirical evidence: according to a 2023 study by Upwork, 72% of freelancers who use AI report productivity and client satisfaction gains, while Dwivedi *et al.* (2021) reported a 40% time savings in performing routine tasks for content creators using AI-driven tools such as Jasper. But adoption rates vary. They are moderated by task type and skill level. In routine tasks (e.g., content creation, elementary programming), AI adoption is greater, driven by their structured nature, while adoption is slower in non-routine tasks (e.g., management consulting, high-end creative services). Likewise, beginners may gain more from AI's skill augmentation capabilities, while experts may avoid adopting AI due to concerns about dependency or loss of control over artistic outcomes.

Adoption is also influenced by other factors, such as reliability (e.g., AI content needing many revisions) and customer perceptions (e.g., AI work being devalued). For example, some clients consider AI-assisted work to be "impersonal," leading to a reluctance for freelancers to use these tools to improve productivity. Beyond adoption, there are questions about the long-term consequences of AI use. Will smart productivity gains continue, or will freelancers face diminishing returns with widespread AI adoption? More importantly, AI's effects on skill acquisition are mixed: it might upskill freelancers by creating expertise in prompt engineering or using AI for enhanced workflows, but it could deskill them if reliance leads to loss of skills (e.g., writers losing their voice because their initial drafts are written by AI). These questions highlight the need for longitudinal research to monitor AI's impact on freelancing. To harness AI, interventions are needed. Governments might fund AI training to address skill gaps, and platforms (such as Upwork and Fiverr) could certify AI-supported work to counter client prejudices. Moreover, freelancers must effectively manage AI use, using it to enhance productivity while retaining their distinctive value offers. Generative AI presents new opportunities for freelancers, but its use is complex, influenced by perceived value, task requirements and other contextual factors. Understanding these dynamics through research, education and policy will be crucial for making AI a long-term freelancing success.

H1: Performance expectancy positively influences the adoption of genereative AI among the freelancers.

2.2 Social Influence and the Adoption of Generative AI among Freelancers:

Social influence (SI) - the social and professional pressures to use Generative AI from peers, clients and networks - is a key factor in the adoption of Generative AI by freelancers. According to the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), social influence is the degree to which freelancers perceive that important others believe they should use the new technology (Venkatesh *et al*., 2012). This factor is even more complex when we consider it as part of the theory of Diffusion of Innovations (Rogers, 2003), which explains how innovations diffuse through social networks at the behest of opinion leaders. Social influence is at the forefront of empirical studies on AI use. In an analysis of LinkedIn groups in 2023, McKinsey found that freelancers were 2.3 times more likely to use AI technology if opinion leaders in the field endorsed the tools. Similarly, network research on online platforms by Kuek *et al*. (2022) found that social affirmation on Upwork platforms accounted for nearly 40% of initial adoption of AI by freelancers. These findings are in agreement with traditional diffusion research that shows knowledge workers are particularly likely to rely on social influence and observational learning in adopting new technologies. Social influence can be manifest in many ways in freelancing. Online communities like Reddit's r/freelance or specialized Discord communities are involved in some ways as innovators demonstrate how AI is used and with what success. This results in a bandwagon effect as freelancers feel pressure to adopt AI. This is compounded by client demands - as businesses seek freelancers who can offer AI services, freelancers are motivated to embrace technology to meet these demands. But the social influence-adoption relationship is tempered.

The influence source matters - recommendations from successful (in terms of highest revenue) freelancers or industry experts are more likely to impact than peer recommendations. Equally, visibility of the value of AI is crucial; freelancers are more likely to adopt the use of AI tools if they see the improved performance of peers in their network using AI (e.g. faster work, higher quality work). devaluation of AI-assisted work). For instance, clients may perceive AI work as unoriginal and freelancers may have to limit AI use despite time savings. Beyond this "first move", there must be consideration of the long-term use of AI. Will the productivity gains persist, or will there be diminishing returns as freelancers adopt AI? More importantly, AI will have a two-fold effect on skills: it will upskill freelancers by incentivizing them to master prompt engineering or the use of AI to complement their work, but it can also deskill freelancers if they use AI in a way that results in skill loss (e.g., writers losing their voice through over-reliance on AI for initial drafts). These issues mean research is needed to track AI's impact on freelancing over time. To reap the benefits of AI, there are solutions. Governments could support AI training programs to overcome skill deficits and marketplaces (Upwork, Fiverr) could certify AI-powered work to counter client bias. Also, freelancers must use AI strategically: to boost productivity while maintaining their edge. Generative AI will transform freelancing but its use is nuanced, involving perceptions of value, task demands and other factors. Research, education and policy will help us understand these complexities to enable AI as a long-term freelance asset.

H2: Social influence positively affects the adoption of Generative AI by freelancers.

2.3 Hedonic Motivation and Generative AI adoption:

Freelancers' use of Generative AI includes not only instrumental benefits but also hedonic motivation (HM) the joy and fun they provide. Hedonic motivation is a component of the extended Unified Theory of Acceptance and Use of Technology (UTAUT2) which refers to the pleasure derived from using a technology (Venkatesh *et al.*, 2012). For freelancers, particularly those working in creative industries, Generative AI offers an opportunity for experimentation, as an alternative to conventional work processes (Teutloff & Braesemann, 2025). This transforms work into a playground to prototype ideas, experiment and re-innovate (Klimek *et al.*, 2012). This enhances not only productivity but also the creative process, leading to more fulfilling work experiences. Human motivation theories, such as self-determination theory (Ryan & Deci, 2000), explain hedonic motivation here. Freelancers can satisfy the human needs for competence and autonomy through the use of generative AI. For example, a designer can easily experiment with multiple design options, a writer can quickly try different writing styles and a coder can quickly experiment with code snippets. This facilitates autonomy and competence and intrinsic motivation. In addition, the system promotes flow experiences, where the freelancers are absorbed in the process of co-creating with the AI, leading to higher engagement and enjoyment (Costa & Murphy, 2025). Studies emphasise hedonistic use of AI. Adobe's 2023 Creative Productivity Report revealed that 62% of freelancers who experimented with AI tools reported increased job satisfaction because of the "joy of discovery" and "renewed creative energy" they experienced using AI technologies. Similarly, studies of Midjourney users found that creative workers often produced many more versions of an image than were needed for their clients, suggesting intrinsic enjoyment in continuing use (AI Creativity Index, 2023). This suggests that the hedonic experience with Generative AI is not an incidental byproduct, but an important factor in its adoption and continued use (Hansen *et al*, 2023). Different kinds of freelancers have different hedonic needs. For instance, graphic designers enjoy the ability to immediately visualise an idea, while writers enjoy the use of language and plot twists. Coders enjoy the speedy prototyping of code, while consultants enjoy the opportunity to explore these possibilities with AI (Ash & Hansen, 2023). This suggests the versatility of Generative AI in providing creative and problem-solving activities to match the motivations of different types of workers. With this in mind, we now propose:

H3: Hedonic motivation has a positive effect on the adoption of Generative AI by freelancers.

2.4 Facilitating Conditions and Adoption of Generative AI

Freelancers' engagement with Generative AI hinges on facilitating conditions (FC) the technical and organisational enablers of technology use. Building on Venkatesh *et al.*'s (2003) Unified Theory of Acceptance and Use of Technology (UTAUT), facilitating conditions are the material resources and support structures enabling the translation of potential gains into actual adoption (Lysyakov & Viswanathan, 2023). For freelancers, who lack corporate IT resources, these conditions are critical in deciding whether AI tools are adopted and integrated into their practice or not, due to implementation challenges (Anderson, 2017). This interaction occurs along three key dimensions: technological infrastructure (digital access, hardware compatibility, and cost-effective platform access), knowledge resources (training resources and support communities), and platform integration (integration with freelance platforms). These are empirically supported the 2023 World Bank report found the rate of AI adoption among freelancers 2.4 times higher in areas with strong digital infrastructure, while Upwork's 2023 survey showed that while 78% of freelancers with formal AI training used AI tools compared to only 32% without this support (Heslinga *et al.*, 2025). Challenges of the freelance economy underline the importance of facilitating conditions. Freelancers face up-front costs of adopting technology, leading to resource disparities that may disadvantage low-income workers (Brynjolfsson & Mitchell, 2017). Marketplace compatibility adds to the challenge of adoption, with many AI tools requiring integration with freelance platforms to provide value. Finally, the rapid pace of change in AI systems creates a learning burden that freelancers must manage without the assistance of corporate training (Acemoglu & Restrepo, 2018). These considerations require broadening our central hypothesis: enabling conditions have a positive impact on the adoption of Generative AI, and the effects are moderated by the cost-benefit ratio of the necessary investments, proximity to support, and compatibility with current processes (Braesemann *et al.*, 2022). In the future, questions arise about who should establish these facilitating conditions. Do freelance platforms, governments, or industry associations play a prominent role in providing support infrastructure and training? How can enabling conditions be built to work in different global economies at different levels of digital readiness? These issues become ever more pressing as Generative AI moves from enhancement to essential tools for many freelance professions, where creating equitable facilitating conditions becomes a necessary precondition for equal access to the AI-augmented future of work (Mollick *et al.*, 2024). The responses will shape whether these technologies are democratising or a source of inequality in the gig economy.

H4: Facilitating Condition positively influence the adoption intention of Generative AI among freelancers.

2.5 Perceived Trust and Adoption of Generative AI

The link between perceived trust (TR) and the use of generative AI by freelancers is well supported, both theoretically and empirically. Trust is a critical antecedent to the use of new technologies, particularly those such as generative AI that undertake cognitive tasks and affect the quality of work outputs (Haxvig *et al.*, 2025). Freelancers, who often work independently and use tools and technologies to support different aspects of their work, need to trust AI systems that help them write, design, code, market, and other tasks (Venkatesh *et al.*, 2012; Gefen *et al.*, 2003). Trust is essential in overcoming potential risks with AI. Despite their usefulness, generative AI tools can provide biased, inaccurate, or even imaginary results (a phenomenon known as "hallucination") (Bender *et al.*, 2021). Freelancers who lack confidence in the ability of an AI tool to generate relevant and accurate content are unlikely to use it for client work or for other critical tasks (Miskolczi, 2026). But if users see these tools as trustworthy and transparent, the psychological hurdles to adoption are lowered, increasing adoption (McKnight *et al.*, 2002). Explain ability and transparency are key to trust. Freelancers are more likely to use AI tools if they can comprehend how these generate their results and trust in the rationale behind their decision-making (Barcaui & Monat, 2023). This resonates with trust theories in human-computer interaction that emphasise the importance of transparency in building trust towards automation (Lee & See, 2004). Understanding the reasoning and decision-making process of the AI tool can lead to higher user confidence in its usefulness and reliability, which can promote its integration into the user's workflow. Trust is also affected by data security and ethical issues.

Freelancers often work with confidential or proprietary client information, and concerns about how AI systems process, store, or share this data could hinder adoption. Freelancers need to trust that a tool will adhere to norms of data privacy, intellectual property, and ethical considerations, particularly in domains like legal, health care, or corporate communications (Belanche *et al.*, 2014). If AI systems are deemed to adhere to these standards, freelancers have a greater inclination to use them without risk to their reputation or legal standing. Trust also helps to improve perceptions of usefulness, an important factor in technology acceptance models (TAM, UTAUT2) (Venkatesh *et al.*, 2012; Davis, 1989). If freelancers believe an AI system will increase their productivity, help them meet tight deadlines and enhance their creative or technological skills, they are more likely to integrate it into their day-to-day operations (Dwivedi *et al.*, 2023). This can be a critical differentiator in highly competitive marketplaces where speed, efficiency and quality are key. Finally, there is empirical evidence of the trust-adoption link. A 2024 survey by Fiverr found that more than 60% of freelancers using AI tools cited reliability and quality of work as the main reason for their adoption - two factors that can be attributed to trust (Schilke & Reimann, 2025). This evidence supports the idea that as freelancers use AI tools and experience their benefits, they begin to trust these tools, which leads to sustained adoption, and recommendations to others and routine use.

H5: Perceived trust is positively influence the adoption intention of Generative AI among freelancers.

2.6 Adoption of Generative AI and Subjective Success of Freelancers

This research delves into the complex dynamics between the use of Generative Artificial Intelligence (GEN_AI) and freelancers' subjective success. Drawing on Judge *et al*.'s (2001) Core Self-Evaluations (CSE) model and Venkatesh *et al*.'s (2012) Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model, we argue that generative AI plays a complex role in enhancing freelancers' subjective success (Alcaide-Marzal & Diego-Mas, 2025). More specifically, freelancers' use of AI in their practice enhances success through three mechanisms: efficiency-confidence cycles, quality-valuation spirals, and innovation-differentiation effects (Neffke & Henning, 2013). The efficiency-confidence cycle takes shape as freelancers adopt generative AI tools to streamline routine or low-value tasks, thus saving time and mental effort. Upwork (2023) reports that 73% of freelancers find that AI has allowed them to prioritise more high-level tasks (Baldin *et al*., 2025). This not only improves productivity, but also self-efficacy and professional identity. Freelancers' self-perceived skill and effectiveness in creating value drive up self-confidence and intrinsic motivation, two of the important dimensions of subjective success as described by the CSE model (Walkowiak, 2023). Generative AI also promotes subjective success through the quality-valuation spiral. Generative AI applications improve the quality, consistency and accuracy of freelancers' work, resulting in higher client satisfaction and retention (Dube *et al.*, 2020). According to Fiverr (2024) survey findings, 68% of freelancers reported increased client satisfaction and customer retention after using AI. This virtuous cycle reinforces freelancers' confidence and market standing. This, in turn, provides freelancers with a sense of achievement and recognition, which play a pivotal role in their personal success assessment (Beerepoot, 2026). Third, the innovation-differentiation effect underscores the role of generative AI in promoting innovation and differentiation (Hadan *et al.*, 2024). Reducing cognitive and capital constraints, generative AI facilitates the creation of new services and opportunities for new projects. McKinsey (2023) reports that the top 10% of freelancers using AI receive up to 35% higher rates, highlighting how AI-facilitated innovation translates into economic gains. This ability to innovate not only facilitates skill development but also boosts perceptions of growth and progress key aspects of subjective success.

Theory is backed by empirical evidence. Longitudinal research shows freelancers that adopt AI technologies experience significantly greater increases in job satisfaction 2.1 times the month-on-month increases of non-AI adopters (Del Rio-Chanona *et al.*, 2021). Furthermore, 58% of AI users report improved perceptions of job security and they are 3.4 times more likely to meet their annual performance goals. These key performance indicators point to a positive association between the use of AI and subjective measures of success such as happiness, goal achievement and career security. But the nature and magnitude of this correlation is tempered by a number of other factors. Complementary skills are essential freelancers who use AI to complement their skills report superior outcomes. For example, designers who apply AI to ideate or prototype, rather than to implement, report higher levels of creativity and customer satisfaction. Client knowledge also moderates the effect; freelancers working with clients with a greater understanding of AI are likely to receive more appreciation for their human-AI skills (Solórzano Requejo *et al.*, 2024). Further, algorithms matter. Freelance platforms that emphasize quality and innovation rather than cost efficiency are likely to reward AI-enabled freelancers, thus encouraging positive AI use. However, the benefits of adopting AI are not without limits. If the use of AI is easily replaceable, clients may perceive freelancers as commodity-like and this may lead to lower prices and professional status. Likewise, if AI is used purely for automation rather than augmentation, it can lead to skills disuse, impairing long-term skills and professional adaptability. Also, if the quality of hybrid outputs is not valued by platforms or clients, the motivational and economic gains of AI use may diminish.

Hypothesis 6: Generative AI is positively related to the subjective success of the freelancers.

2.7 The Moderating effect of Digital Support System on the relationship between Adoption of Generative AI and Success of Freelancers

The proposition that "Digital Support System (DSS) significantly moderates the relationship between Frontiers in Artificial Intelligence (AI) and the Success of Freelancers" implies that while advances in AI will enhance freelancing opportunities, their effect is moderated by the availability of supporting digital systems (Roy *et al.*, 2026). This hypothesis is supported by prior studies, which show that although AI improves freelancing prospects, its effectiveness is moderated by other systems that enable its integration and use (Banerjee *et al.*, 2026). For example, Brynjolfsson and McAfee (2017) suggest AI increases productivity but requires workers to adapt to these technologies, which DSS facilitates. Digital support systems (DSS) like AI-enabled freelancing platforms (Upwork, Fiverr), training programs and automation tools enable freelancers to effectively use AI through better skill matching, task automation and reduction in information asymmetry (Kässi & Lehdonvirta, 2018). This moderating role is supported by empirical research. Manyika *et al.* (2017), for instance, report that AI-powered automation could boost gig economy workers' income, but only in conjunction with digital support systems. And Upwork's 2022 report found that freelancers who used AI tools in digital platforms providing support (e.g., skill certifications, dispute resolution) earned much more than those without (O' Connor & O' Reilly, 2025). This supports the Contingency Theory (Donaldson, 2001), which suggests that technology is contingent on other factors, with flexible structures needed for optimal use. In the absence of DSS, freelancers might encounter challenges using AI, either due to lack of skills or inappropriate tool use (Bessen, 2019). In contrast, successful DSS helps overcome these issues, turning AI from a threat to an opportunity (Brynjolfsson & Mitchell, 2017). Therefore, previous research supports the hypothesis, with DSS as a key moderator of the AI-freelancer success link. Future research could further explore which elements of DSS - training, matching, or integration - play a crucial role in this relationship. Hypothesis 7: Digital Support System plays a crucial moderating role in the relationship between Adoption of Generative AI and Subjective Success of Freelancers. Figure1 shows the conceptual framework (model)

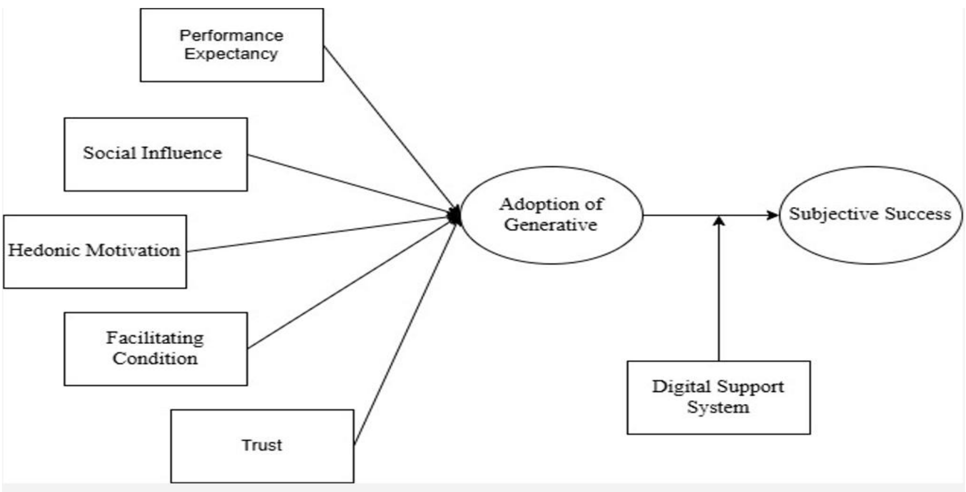

Figure 1: Conceptual Framework (Model)

3. Methodology

Research Design

This research uses a quantitative cross-sectional survey approach to investigate the impact of factors on the adoption of generative AI and success of freelancers. We will gather data at one time through an online survey. This type of survey design is frequently used in studies on technology adoption (e.g., Ali *et al.*, 2024) and enables assessment of the relationships between antecedents and outcomes. This design will be based on the extended UTAUT2 model, which explores proposed paths within a single model.

Population and Sampling

The target group is freelancers from Bangladesh working on platforms such as Upwork, Fiverr and Freelancer.com. Inclusion criteria will be independent workers with ≥6 months of experience, ≥2 projects completed in the last year, and some exposure to generative AI technologies (e.g., ChatGPT). A non-probability purposive sampling approach will be employed, with possible stratification by platform or domain (IT, design, writing) to guarantee representation. The survey will be shared on freelancing platforms, social media and platform groups. We aim to recruit 300-400 participants, considered sufficient for structural equation modeling (SEM) purposes (Comrey & Lee, 1992) and power ($\alpha = 0.05$, power = 0.80) to detect medium effect sizes. Sample size is 311, Table 1 shows the details about the demographic information of the respondents Bangladesh is the second-largest freelancing market in the world in IT freelancing service.

Data Collection Instrument

This research assesses the major factors influencing generative AI (GenAI) adoption in terms of the constructs of the extended Unified Theory of Acceptance and Use of Technology (UTAUT2). Each is operationalized using multi-item scales, tailored specifically to GenAI to provide the best fit.

Table 1: Demographic Features

Item	Characteristics	Frequency	Percentage (%)
Gender	Male	205	66%
	Female	106	34%
Age	50-60	118	38%
	61-70	140	45%
	71-80	53	17%
Education	Bachelor	202	65%
	Masters	81	26%
	PhD	28	9%
Tenure of Freelancing	Below 1 year	88	28%
	1-3 year	121	39%

	Above 3 year	102	33%
Platform	Fiver	88	28%
	Up-work	102	33%
	Others	121	39%

Measurement of Variables

The constructs included in this study will be measured using multi-item, Likert-type scales (usually 5-7 points, anchored with Strongly Disagree (1) and Strongly Agree (7). The higher the score, the greater the agreement. The items will be from existing validated scales to ensure the measures satisfy content validity and are relevant to freelancing. Performance Expectancy (PE), Social Influence (SI), Hedonic Motivation (HM) and Facilitating Conditions (FC) will be adapted from UTAUT2 (Venkatesh *et al.,* 2012). These items measure the benefits, social influence, enjoyment and support for AI tool use. Trust will be assessed using definitions from trust literature (e.g., McKnight *et al.,* 2002), centering on trust in the outcomes of AI tools. Adoption Behavior will be self-reported and measured by current use of generative AI for freelancing work. Success will be measured as freelancers' perceptions of career success relative to others. Online Support will measure the availability of online support and resources for AI tool use. Items will be tailored to the freelancing environment, and will undergo expert review and pilot testing to ensure appropriate validity and reliability of the instruments.

Data Collection Procedure

The survey will be conducted online (via a tool such as Google Forms or Qualtrics) for 4-6 weeks. We will distribute links through freelancing forums, professional groups and social media communities where Bangladeshi freelancers are active. Specific emails or messages may be sent to active freelancers. Consent will be voluntary and anonymous: the initial survey page will outline the research and seek consent. No personal information will be collected. To maintain confidentiality, results will be stored in encrypted files and only presented in aggregate form. The process will adhere to the ethical principles for research involving human participants (informed consent, withdrawal, privacy).

Data Analysis

The data analysis will proceed in several steps. Data will be prepared in SPSS, with descriptive statistics (means, standard deviations) and identification of missing and inconsistent data. Cronbach's alpha ($\alpha \geq 0.70$) will determine reliability. The measurement model will be tested via Confirmatory Factor Analysis (CFA) in SmartPLS. Validity will be assessed through standardized loadings (≥ 0.70), Average Variance Extracted (AVE ≥ 0.50) and the Fornell-Larcker criterion. SmartPLS will be used to perform Structural Equation Modeling (SEM) to assess proposed relationships between key factors (e.g., performance expectancy, social influence, trust) and adoption, and from adoption to subjective success. The moderating effect of digital support will be assessed via interaction terms or multi-group analysis. The significance of paths will be tested with bootstrapping, with R^2 values provided for predictive power, as is common practice in technology adoption literature.

Measurement Model:

All constructs show adequate reliability and convergent validity in the measurement model. All the loadings of indicators are above the threshold value of 0.70, indicating sufficient item reliability. Loadings for DSS range from 0.786 to 0.836, and those for GEN_AI range from 0.803 to 0.863. Correspondingly, the loadings of FC, HM, PE, SI, SS and TR constructs are also high, suggesting that the indicators reflect the underlying latent constructs. All Cronbach's α values are above 0.75, showing internal consistency, with the highest being 0.880 for SS. Composite reliability (CR) levels also exceed 0.70 (from 0.715 for TR to 0.882 for SS), confirming construct reliability. All those data are presented in the Table 2.

Table 2: Measurement Model

Construct	Indicator	Loading	Cronbach's α	Composite Reliability	AVE
DSS	DSS1	0.800	0.826	0.835	0.655
	DSS2	0.816			
	DSS3	0.786			
	DSS4	0.836			
GEN_AI	GEN_AI 1	0.829	0.860	0.866	0.704
	GEN_AI 2	0.860			
	GEN_AI 3	0.863			
	GEN_AI 4	0.803			
FC	FC1	0.833	0.768	0.770	0.683
	FC2	0.808			
	FC3	0.838			
HM	HM1	0.824	0.853	0.858	0.694
	HM2	0.865			
	HM3	0.845			
	HM4	0.796			
PE	PE1	0.875	0.857	0.859	0.701
	PE2	0.795			
	PE3	0.820			
	PE4	0.857			
SI	S1	0.849	0.865	0.866	0.711
	S2	0.844			
	S3	0.837			

	S4	0.844			
SS	SS1	0.903	0.880	0.882	0.807
	SS2	0.876			
	SS3	0.915			
TR	TR1	0.758	0.788	0.715	0.619
	TR2	0.837			
	TR3	0.851			

All AVE values are above 0.50, ranging from 0.619 to 0.807, confirming satisfactory convergent validity. Overall, the results indicate that the measurement model is robust and suitable for structural model assessment. Figure 2 shows Measurement Model.

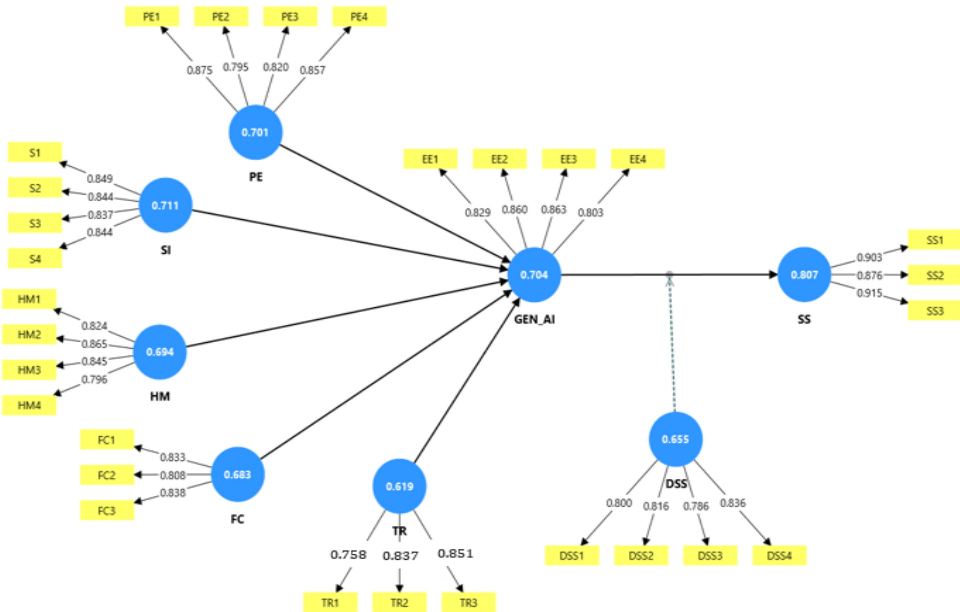

Figure 2: Measurement Model

Discriminant Validity

Our findings suggest that discriminant validity is generally maintained for most constructs. For instance, Adoption of Generative AI Tools (Adp_GenAI) has good discriminant validity, with a square root of AVE (√AVE = 0.934) that is higher than its highest correlation with another construct (r = 0.852 with Subjective Success). Likewise, Subjective Success (√AVE = 0.886) shows satisfactory discriminant validity with all other constructs, despite its highest correlation of 0.894 with FC. Trust (TR) also shows strong discriminant validity, with a √AVE of 0.791 and a highest correlation (r = 0.483 with FC). Moreover, the interaction construct (DSS ×

Adp_GenAI) shows low correlations with all other constructs (r = 0.501 with DSS), reinforcing its distinctiveness. But there were issues with discriminant validity for Facilitating Conditions (√AVE = 0.761) and Hedonic Motivation (√AVE = 0.820). Table 3 shows discriminant validity

Table 3: Discriminant Validity

Constructs	GEN_AI	DSS	FC	HM	PE	SI	SSU	TR	DSS x GEN_AI
GEN_AI									
DSS	0.658								
FC	0.784	0.841							
HM	0.784	0.698	0.715						
PE	0.474	0.524	0.650	0.707					
SI	0.550	0.464	0.705	0.719	0.784				
SSU	0.852	0.776	0.894	0.796	0.510	0.479			
TR	0.227	0.341	0.483	0.321	0.257	0.391	0.280		
DSS x GEN_AI	0.105	0.501	0.136	0.104	0.081	0.227	0.218	0.059	

The two constructs are highly correlated with each other: FC is correlated at 0.905 with HM and 0.894 with SSU, surpassing its own √AVE, which implies that the two constructs might be collinear. Similarly, the correlation between HM and FC (r = 0.905) exceeds the √AVE of HM, also suggesting redundancy. Although the discriminant validity of most constructs (Adp_GenAI, DSS, PE, SI, SSU, TR) is established, the redundancy between FC and HM needs attention. It is advisable to revisit the items of these constructs for overlap or convergence. If item refinement is ineffective, a possible alternative is to merge FC and HM into a higher-level or composite construct in the structural model. Table 4 shows fornell-larcker criterion

Table 4: Fornell-Larcker criterion

Construct	GEN_AI	DSS	FC	HM	PE	SI	SSU	TR
GEN_AI	0.934							
DSS	0.538	0.819						
FC	0.667	0.618	0.761					
HM	0.705	0.534	0.727	0.821				
PE	0.430	0.401	0.523	0.592	0.830			
SI	0.488	0.350	0.544	0.591	0.628	0.836		
SSU	0.792	0.629	0.749	0.703	0.454	0.413	0.886	
TR	0.254	0.293	0.402	0.289	0.229	0.314	0.309	0.791

The Fornell-Larcker criterion, which means the square root of the Average Variance Extracted (AVE) for each construct is greater than its highest correlation with another construct was used to evaluate discriminant validity. Our findings indicate most constructs satisfy this condition. For example, Adoption of Generative AI Tools (√AVE = 0.934) and Subjective Success (√AVE = 0.886) are greater than the highest correlation with another construct (r = 0.792). Trust also demonstrates good discriminant validity (√AVE = 0.791; max r = 0.402). But, Facilitating Conditions (√AVE = 0.761) and Hedonic Motivation (√AVE = 0.821) have minor issues. The correlation between them (r = 0.727) and FC with SSU (r = 0.749) is close to their respective √AVE values, which suggests that these constructs may be conceptually similar. In conclusion, discriminant validity holds for most constructs, but FC, HM and SSU require special attention. Future research should consider reworking items or assessing HTMT to confirm construct

Structural Equation Modeling:

We assessed the structural model by examining the path coefficients (β), standard deviations, t-statistics and p-values to determine the significance of the effects. The results show some significant and non-significant effects between the constructs. Table 5 shows hypothesis testing and Figure 2 shows Path Coefficient

Table 5: Hypothesis Testing

Hypothesis		**Beta Value**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**	**Decision**
H1	**PE -> GEN_AI**	0.412	0.057	7.295	0.000	Accepted
H2	**SI -> GEN_AI**	0.068	0.066	1.033	0.302	Rejected
H3	**HM -> GEN_AI**	0.121	0.054	2.193	0.028	Accepted
H4	**FC -> GEN_AI**	0.040	0.047	0.854	0.393	Rejected
H5	**TR -> GEN_AI**	0.269	0.049	5.564	0.000	Accepted
H6	**GEN_AI -> SS**	0.767	0.058	13.248	0.000	Accepted
H7	**DSS x GEN_AI -> SS**	-0.051	0.021	2.421	0.015	Accepted

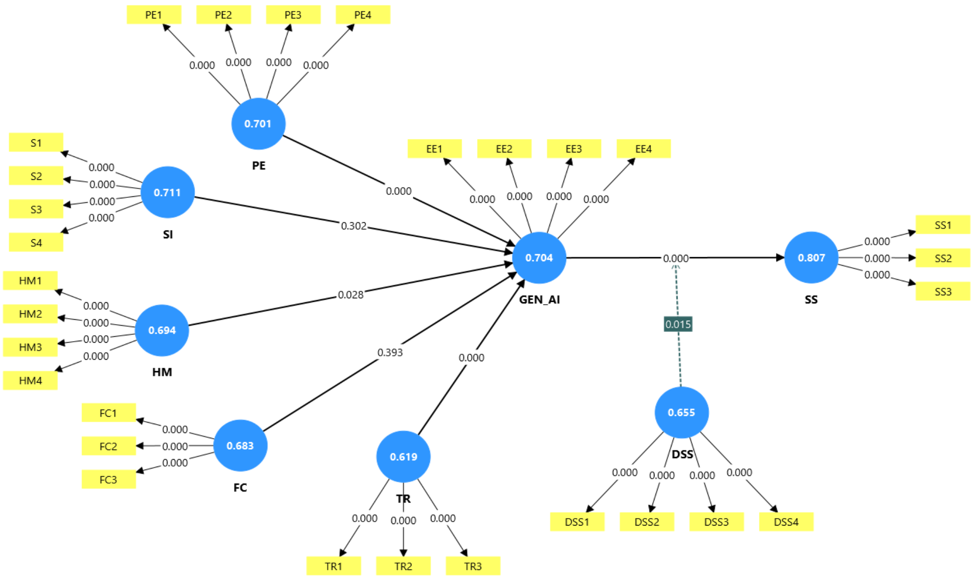

Figure 2: Path Coefficient

Generative AI Usage (GEN_AI) demonstrates a strong and statistically significant positive influence on Subjective Satisfaction (SS) (β = 0.765, t = 13.248, p < 0.001), confirming that increased engagement with generative AI substantially enhances user satisfaction. Among the antecedents of GEN_AI, Performance Expectancy (PE) exerts the strongest significant positive effect (β = 0.413, t = 7.295, p < 0.001), followed by Trust (TR) (β = 0.270, t = 5.564, p < 0.001) and Hedonic Motivation (HM) (β = 0.118, t = 2.193, p = 0.028). These results indicate that perceived usefulness, trustworthiness, and enjoyment meaningfully drive generative AI engagement. Conversely, Facilitating Conditions (FC) and Social Influence (SI) do not significantly predict GEN_AI (p > 0.05), suggesting limited influence of external support and peer expectations in this context. Directly, Digital Support Systems (DSS) do not significantly affect SS (β = –0.034, t = 0.556, p = 0.578). However, the interaction term (DSS × GEN_AI) reveals a significant moderating effect (β = –0.051, t = 2.421, p = 0.015), indicating that DSS meaningfully alters the relationship between AI usage and satisfaction though in a slightly negative direction.

Discussion

The analysis of the findings of the study on engagement with generative AI (GEN_AI) provides important insights into the variables that play a role in this behaviour. The study indicates that while some factors such as Performance Expectancy (PE), Trust (TR) and Hedonic Motivation (HM) are important in driving the use of GEN_AI, other factors, including Facilitating Conditions (FC) and Social Influence (SI), are not significant predictors of GEN_AI engagement. This suggests that individual motivations, usefulness and enjoyment are more important predictors of engagement than situational factors or social influence. The strongest predictor of GEN_AI engagement was Performance Expectancy (PE), which had a strong positive effect ($\beta = 0.412$). This finding is consistent with the notion that technology will be more readily adopted if the user perceives it as having a positive impact. Trust (TR) and Hedonic Motivation (HM) also had significant positive impacts on GEN_AI adoption, which indicates that users consider trustworthiness and the pleasure they experience from the technology to be important. Our findings are in line with previous studies that highlight the role of perceived benefits and enjoyment in the adoption of technology. But it was surprising that Facilitating Conditions (FC) and Social Influence (SI) did not have significant effects.

Facilitating Conditions are generally thought to relate to external infrastructure and resources, such as training and support. It appears that such external resources were not necessary for users to engage with GEN_AI, which may indicate that the users are driven more by intrinsic motives, rather than support and resources. This is an interesting insight as many previous research have indicated that facilitating conditions play a significant role in technology use. This is supported by the non-significance of Social Influence, as peer pressure or social norms did not seem to have an effect on users' engagement with GEN_AI. This could suggest that users are less likely to be driven by social norms in their adoption of new technologies and that subjective success (a potential benefit of using a new technology) trumps the influence of social others. The interaction between Digital Support Systems (DSS) and GEN_AI also reveals an interesting aspect. Although DSS did not have a significant direct impact on Subjective Success (SS), the interaction effect of DSS and GEN_AI was significant but negative ($\beta = -0.051$). This implies that although digital support systems contribute to moderating the effects of technology use on satisfaction, this moderation effect might not be entirely positive. Future studies should address why there is a slightly negative interaction effect here, and whether this is a result of insufficient user support or an over- or underestimate of resources. In summary, this study highlights the role of intrinsic factors such as perceived usefulness and enjoyment of the technology over external factors such as resources or peer influence in the use of generative AI. This needs to be investigated in more detail in future research, especially in other technological domains and across different user groups, to understand the different contributions of intrinsic and extrinsic factors to technology use.

Theoretical and Practical Findings

Theoretical Contributions

This study contributes to the ongoing discourse on technology adoption and success outcomes within freelance economies by extending the application of UTAUT2 and Diffusion of Innovations (DOI) theory to the context of Generative AI. The findings challenge some traditional assumptions while reinforcing others. First, hedonic motivation emerged as a significant driver of Generative AI adoption, underscoring the growing importance of intrinsic motivation and affective engagement in technology use particularly in creative industries. This supports UTAUT2's extension beyond purely utilitarian constructs, highlighting that enjoyment and creative fulfillment are central to adoption decisions among freelancers. Second, facilitating conditions were confirmed as a critical determinant of adoption, reaffirming the UTAUT2 assertion that access to infrastructure and resources significantly shapes technology usage. However, performance expectancy**,** social influence**,** and trust**,** while often emphasized in traditional models, were found to be non-significant in this study. This suggests that in highly autonomous, decentralized work contexts like freelancing, personal and contextual enablers may outweigh normative and institutional pressures. Finally, the study introduces a moderated model demonstrating that Digital Support Systems (DSS) significantly enhance the positive relationship between AI adoption and perceived success. This aligns with Contingency Theory, which argues that technological benefits depend on the presence of enabling environments. The results also expand the subjective success literature by identifying Generative AI adoption as a pathway to enhanced professional identity, self-efficacy, and career satisfaction.

The research also finds that two factors Facilitating Conditions (FC) and Social Influence (SI) do not significantly predict engagement with GEN_AI (likely referring to General Artificial Intelligence or similar technology). Both factors had p-values greater than 0.05, meaning they don't have a strong statistical impact on whether people engage with GEN_AI or not. Facilitating Conditions usually refer to external factors like resources, infrastructure, and support that make using a technology easier. In this case, these conditions don't seem to play a significant role in whether people adopt GEN_AI. This suggests that people might be engaging with the technology regardless of the availability of resources or external support, pointing to the possibility that intrinsic factors, like personal interest or curiosity, are more important. Similarly, Social Influence, which involves how much peer pressure or societal expectations shape behavior, doesn't seem to affect GEN_AI engagement either. This implies that people aren't heavily influenced by social norms or the behavior of others when deciding to adopt or interact with GEN_AI. Instead, internal motivations or personal factors may have a bigger impact. Finally, the findings suggest that people are more likely to engage with GEN_AI due to their own interests and motivations, rather than external influences like resources or societal pressure. It would be interesting to see if these results hold true in different contexts, technologies, or populations.

Practical Implications

The study has several practical takeaways for freelancers, platforms and policymakers. For freelancers, the research shows that Generative AI tool adoption can lead to significant gains in subjective success, by increasing productivity, satisfaction, and competitiveness. But it is best done when freelancers have the necessary support (e.g., training, supporting tools, integration with work platforms). Online platforms (e.g., Upwork, Fiverr) should prioritise enhancing digital support services such as the certification of AI tools, the integration of learning resources and personalised on-boarding. This will help optimise the benefits of adopting AI, particularly for inexperienced or resource-poor freelancers. In terms of policy, governments and industry groups should focus on promoting equitable access to AI resources and training, especially for freelancers in the developing world. Without this, there is a risk of leaving the gains of AI behind and widening the gap in digital work. Lastly, freelancers need to use AI strategically enhancing rather than substituting their skills, to maintain professional viability and client confidence. Indiscriminate use of AI without skills alignment or differentiation in skills may lead to lower rates and recognition. In conclusion, although Generative AI has the potential to significantly increase freelance success, this is contingent on motivation, resource allocation and support.

Limitations and Future Research Direction

Despite these important theoretical and practical insights, several limitations need to be considered. First, the research relies on self-reported data, which may introduce common method bias and subjective interpretation of constructs such as success, motivation, and trust. Second, the sample is limited to freelancers, a very heterogeneous population; therefore, variations across domains where freelancing is offered, skill level, and digital maturity might not be captured. Third, the non-significant effects of performance expectancy, social influence, and trust may be influenced by contextual factors specific to the study sample, thus limiting generalizability to other digital labor markets or traditional employment settings. Fourth, the cross-sectional design restricts the ability to infer causality, particularly with respect to the long-term impact of Generative AI adoption on career success. Longitudinal studies would give a clearer view of how the patterns of adoption and their outcome would change over time. Fifth, this study focuses on UTAUT2, DOI, and DSS as core frameworks and may have missed other psychological or economic variables that could help explain AI adoption, such as risk perception, platform dependency, or market volatility. Finally, the moderated model puts emphasis on the role of digital support systems, though the operationalization of DSS may not take into consideration all infrastructural and institutional enablers that may play an important role in different regions, especially in emerging economies.

Conclusion

In summary, Generative AI has made a profound impact on Bangladesh's freelancing industry, with both positive and negative implications. Many freelancers are using AI to enhance their productivity and gain a competitive edge. But as more AI tools are used, there are concerns about potential job loss and skills mismatch. Some view AI as a valuable friend that helps achieve success, but others are concerned about the threat it poses, particularly in jobs that require low skills or are repetitive. While there is some literature on the impact of AI in emerging markets such as Bangladesh, there is a lack of research on its impact on freelancing. This research aims to address this by looking at the adoption of Generative AI by freelancers in Bangladesh. It examines factors affecting this adoption, including individual motivation, resources, and the influence of digital technologies. The result indicates, although personal and environmental factors are critical, other factors of technology adoption such as performance expectation, social factors and trust play a minor role in the decentralized freelancing market. Practically, freelancers must be given the tools and training to effectively use AI. And platforms and policymakers can play their part in ensuring an ecosystem that is free and equal access to AI technologies and infrastructure. With AI set to reshape the nature of work, it's critical that all stakeholders' freelancers, platforms and policymakers collaborate to create a supportive and equal environment.

Conflict of interest

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission, and redundancy have been completely witnessed by the authors.

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