IJNRD.ORG ISSN : 2456-4184

INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG

An International Open Access, Peer-reviewed, Refereed Journal

Generative AI In Creative Industries: Friend Or Foe To Human Artists?

[1]Pushpender Saini, [2]Apoorva Vasishtha

[1]Student, [2] Professor.

[1]JECRC University, Jaipur, Rajasthan, India

Abstract: The invention of generative Artificial Intelligence (AI) technology has dynamically transformed every sector as a result of its ability to independently create text, images, audio, and software code. On the positive side, it broadens creativity, efficiency, and automation in the affected fields such as healthcare, finance, and education. However, it still poses profound ethical, security, and societal problems. Concerns regarding the abuse of generative AI, including misinformation and deepfakes, cybersecurity threats, losing trust in government institutions, and job redundancy is profoundly troubling. Also, issues such as protection of Intellectual Property Rights and absence of bias regulations associated with AI require ethical and regulatory scrutiny. The focus of this paper is generative AI's multifaceted dilemmas, emphasizing its advantages in conjunction with risks. This research aims to solve the question of how generative Artificial Intelligence could be harnessed responsibly to maximize benefits while mitigating negative implications by analyzing its applications, challenges, and governance.

***Index Terms* - Generative AI, Artificial Learning, Generative Intelligence, Deep Adversarial (GANs), Transformer Networks Models, AI Ethics, Misinformation, Deepfakes, Cybersecurity Threats, AI in Healthcare, AI in Creativity, Automation, Intellectual Property Rights, AI Governance, Job Displacement, AI Frameworks, AI-Generated Content, AI Bias, Regulatory.**

I. INTRODUCTION

The technology of Generative Artificial Intelligence (AI) has come forth as an impactful innovation with consequences on healthcare, finance, academics, and even entertainment. By deploying deep learning technologies, these autonomous agents can produce human-like text, images, audio, and code. Unlike traditional AI models that assimilated pre-defined rules and structured data, generative AI employs advanced processors like the Generative Adversarial Networks Transformer-based (GANs) architectures. and These advancements invoke essential dialogue about the consequences that AI brings, such as ethical, security, and socio-political prospects. Whether generative AI advances human imagination or demolishes it, needs discussing. A prime factor of warming up towards adopting generative AI is innovation. AI spearheads revolutionary change in art through the generation of unique visual pieces, music compositions, and prose. In software engineering, AI takes over mundane tasks, optimizes code, and fetches flaws. The healthcare sector's utilization of generative AI speeds up the discovery of drugs, enhances the personalization of treatment, and facilitates better analysis of medical images. Additionally, there has been a rise in efficiency across business functions and customer care services due to the empathetic capability of AI. In spite of the merits, generative AI comes with a set of problems and concerns. One of the foremost issues lies with the potential for misuse such as misinformation, deepfakes, and synthetic media that slowly weaken the trust in public sentiment and has the power to manipulate it. The more realistic the AI content is, the more difficult it becomes to tell what's real and what's fabricated, thus continuing the cycle of deceiving people digitally. Alongside, the automation feature of generative AI also increases the concern of losing profession, especially in content writing, customer handling, and software engineering. The moral concerns regarding AI content such as ownership and blame culture of biased AI models make the adoption harder than it should be. Security concerns posed by generative AI is perhaps the most important side of the argument. Cybercriminals could take advantage of AI models to create sophisticated phishing attacks, automate social engineering schemes, or write malicious code which worsens the cybersecurity problem. And the lack of visibility into how deep learning systems work increases the difficulty to provide accountability and transparency for decisions made by the AI. With the advancement of AI systems, the development of strong policies and ethical guidelines to reduce risks is becoming increasingly necessary.

II. LITERATURE REVIEW.

Digital labor platforms for microwork:

Microwork DLPs connect clients (task requesters) and workers through an open call to trade completion of bite-sized microtasks for a small payment (Horton & Chilton, 2010). These digital platforms allow Internet users worldwide to find microwork that was previously unavailable to them, while enabling employers to access on-demand labor power globally. Apart from monetary rewards, microwork on DLPs provides workers with a channel to acquire knowledge and to practice relevant skills such as writing, typing, information retrieval, and data processing. The conduct of micro working is characterized by autonomy, skill variety, and task simplification (Kaufmann et al., 2011). Focusing on microworkers' motivations, prior studies have examined factors driving individuals' participation, including making money, improving skills, entertainment, and making an impact (Deng et al., 2016; Ipeirotis, 2008; Kaufmann et al., 2011). DLPs such as MTurk seem to provide extremely temporal flexibility, giving workers full control over how to spend each hour and minute on a platform. Individuals were attracted to the autonomy in making their own decisions on "what," International Journal of Information Management 79 (2024) 102823 "when," "where" regarding micro working, and the flexibility to perform the small tasks during spare time and get paid seamlessly online (Deng & Joshi, 2016).

Individual labor supply theory:

The theory of individual labor supply has its roots in the neoclassical model of labor supply that explains an individual's choices in allocating time for work and leisure, which are the primary sources of individual utility (Heckman, 1993). To estimate the amount of time spent on work, the neoclassical theory of individual labor supply posits that the individual chooses the optimal number of work hours to maximize utility given the trade-off between work and leisure. The key factors that affect the individual labor supply decision revolve around the wage rate offered and the individual's preferences for work and leisure, which may vary with the wage rate. The dynamics between wage rate and labor supply, i.e., the wage elasticity of the labor supply, are regulated by substitution and income effects (Boppart & Krusell, 2020). As the wage rate increases, the opportunity cost of leisure rises accordingly, so that the individual is willing to substitute more work hours for leisure hours, which is known as the substitution effect. An increase in the wage rate also leads to the income effect, which may motivate the individual to consume more leisure and work fewer hours. For workers aiming at a target income, such a target serves as a reference goal that regulates workers' labor supply in a dynamic manner (Camerer et al., 1997; Hsiaw, 2013). As the income gets close to the target level, an increase in the wage rate can demotivate the individual from working.

Use of Artificial Intelligence Technology:

Major users of heavy forklifts include wood mills, steel works, and ports. These users typically regard heavy forklifts as critical for their operations. Hence, forklift functioning and predictable high uptime are prioritized over unit cost caused by unscheduled downtime that often produces costly operational Well-scheduled maintenance disturbances. servicing and repair sessions helps ensure high uptime and proper functioning of forklifts. Each forklift truck provided by both Beta and Gamma is monitored by the manufacturer's service support information system and an assigned technician. This system continuously receives information from hundreds of sensors in each truck. This data enables real-time monitoring and diagnosis of each individual forklift. Depending on each truck's condition, the service system proposes customized service schedules for the truck's user and technician. The information systems assign one or two service technicians and provide them with service information, such as the truck model and its configuration in terms of International Journal of Information Management 79 (2024) 102836 the engine, gearbox, and so on. Crucially, this information includes current and past service and error code for the truck. These codes reflect truck parameters that may deviate from some standard and may require repairs or maintenance such as oil changes or new gearboxes. In more than 50 per cent of cases, truck information includes multiple codes, sometimes as many as 100 individual codes. A major challenge for a service technician is to interpret the meaning of any specific combination of codes provided by the information system because different combinations indicate different truck conditions with different service and repair needs. Service technicians need extensive experience of truck servicing to interpret a combination of codes correctly.

How generative AIs work:

AI algorithms are created by training mathematical, probabilistic structures, called artificial neural networks, with training data that embody the kinds of patterns the network is supposed to inherit (or "learn"). This process results in what is commonly known as an AI model. Once trained, e.g. on large numbers of photos, the AI model can recognize in a new piece of data (e.g. a photo it has not been seen before) with a high degree of probability patterns of the same kind. This works precisely because the artificial neural network does not store content but appropriates likenesses (the new photo 'looks like' the kind of data it has been trained on). Interestingly this process can be reversed. Instead of using these patterns for recognition, they can be used to generate new content. This is the domain of generative AIs, a class of systems that, through their ability to discern, encode and represent underlying patterns, structures, and associations within their training data (Bengio et al., 2013), are capable of creating new and diverse content, such as text, images, audio, or video, depending on the type of training data (Goodfellow et al., 2016).

The mechanics of generative AI:

Unlike conventional AI models that underpin bespoke AIs, trained to accomplish a particular organizational task, generative AIs such as ChatGPT, Google Gemini, Claude, DALL-E or Midjourney, are based on large, task-agnostic models called foundation models (e.g. Feuerriegeletal., 2023). Foundation models are "trained on broad data (generally using self-supervision at scale) that can be adapted (e.g., fine-tuned) to a wide range of downstream tasks" (Bommasani, 2021), without specif-ically or explicitly being trained to do so. This renders these generative AIs to be general AI,2 with applicability in a range of task contexts.

Text generation: large language models (LLM) and transformers

Large language models (LLMs), like GPT (Generative Pre-trained Transformer), work by leveraging the above-described deep learning techniques to encode (or"learn") from training data fine-grained patterns, which are in turn used to generate new text. GPT is pre-trained on a massive corpus of textual data from various sources (such as the Internet) to encode the probabilistic relationships between words and phrases during the (generally unsupervised, or self-supervised) training process (Radford et al., 2018). It is important to distinguish between the LLM, or foundation model, and the actual AI system or concrete applications that make use of the model, as Fig. 1 illustrates. While it is technically possible to prompt the LLM directly, users will typically interact with applications that make use of a systems layer that provides the interface atop the foundation model. For example, in OpenAI's case a second layer of training imbues the system with its human-like conversation abilities, which constitutes ChatGPT.

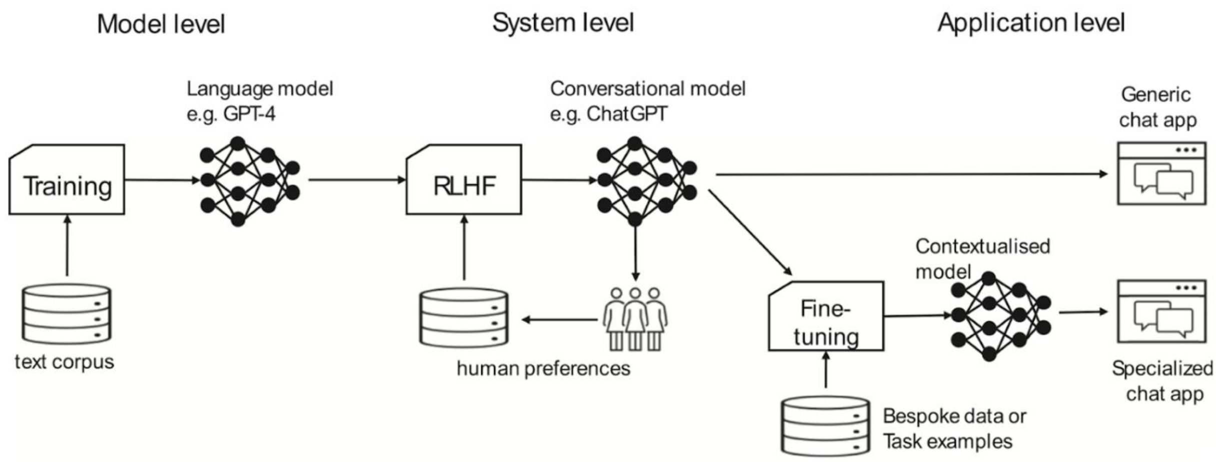


Fig. 1. Large-language model architecture (figure own, with input from (Feuerriegel et al., 2023)).

In sum, text-generation AIs have the following defining characteristics:

- Large language model (LLM) refers to the base model that encodes nuanced language patterns from a large corpus of training data, trained using self-supervised learning,

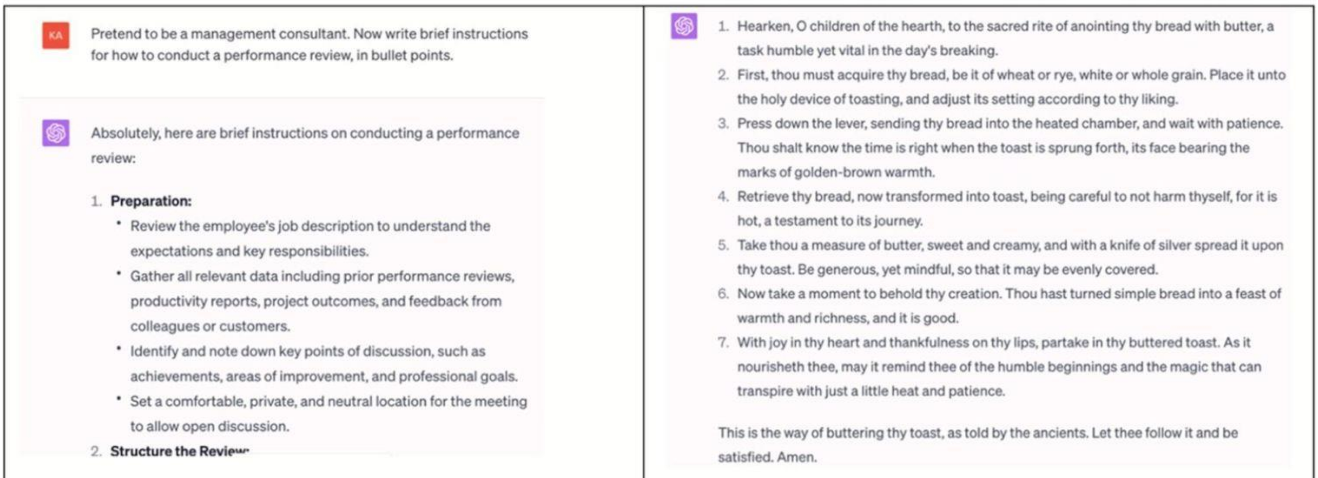
- LLMs are turned into conversational systems through fine-tuning with reinforcement learning from human feedback (RLHF), which encodes additional human conversational styles,
- This process results in general purpose chatbot apps, such as ChatGPT, Gemini or Claude,
- Further fine-tuning can be used to create task-specific generative AI applications.

Styles in generative AI:

In art and film, a style is defined as a distinctive and recognizable way in which an artifact is made (Gombrich, 1968), expressed in the (audio-)visual characteristics or features of an artwork or film that can be attributed to a particular artist/maker, culture, period, or movement, and thus permits recognition and grouping of said artifacts (Fernie, 1995). Style encompasses a wide range of aspects, including composition, color, lighting, texture, camera angles, editing techniques, pacing, dialogue, and storytelling. It is a way of expressing a unique perspective or approach to a subject matter, which can help distinguish the works of different creators or movements in each medium. Styles are a known topic in the context of AI generally and generative AI specifically. Research in computer science has demonstrated in much detail that artificial neural networks underpinning generative AI excel at encoding styles (Radford et al., 2015). For example, it has been shown that it is possible to distil a style from one object to transfer it to and blend with the content of another (e.g. Gatys et al., 2016, Huang & Belongie, 2017). Styles are also a much-discussed topic in the context of prompt engineering, the art of instructing generative AI models to produce specific kinds of content (e.g. Scharth, 2023), whereby prompts contain keywords to deliberately evoke styles. As such, for GPT,'styles' in a narrow sense refer to writing styles, such as formal, informal, poetic, academic, or journalistic styles, or different genres such as letters, tables, scripts, conversations, or even computer code. As GPT is trained on a massive corpus of text from various sources, it teaches us to identify and reproduce these styles. When prompted, GPT can generate text in a specific style or apply a style to a text submitted to it, such as organizing text into a table.

Working with style engines– some examples:

Understanding generative AIs as 'style engines' repositions our interaction with these systems towards creative writing, visual work, conversation and generally expansive interactions, rather than the retrieval of information or seeking answers to factual questions. In its most basic form this amounts to applying a style to an existing piece of content, by uploading a text or an image to a generative AI system to manipulate it. For example, this includes shortening, summarizing or cleaning up texts (applying conciseness as a style), turning text into bullet points, tabling it (see Fig. 2a), or changing its tone, such as turning it from academic to more casual writing. For images this might include simple touch-ups, the transformation of the image using a particular artistic style (e.g. turning a pop star into a Pixar character, see Fig. 2b3), or the adding of new visual elements, all of which conceptually amount to evoking the overlay of styles by the generative AI model.



(a) management consultant instructions for performance reviewing in bullet points

(b) buttering toast instructions in the style of the King James bible

Fig. 2.

Complementing common conceptions of generative AI with styles:

Understanding generative AI as style engines resolves this surprise. It also opens the door to understand, again surprisingly against traditional computing expectations, why generative AI is good at tasks that are commonly associated with inherently human abilities, such as creativity (Hubert et al., 2024), conversation and persuasion (Salvi et al., 2024), negotiation (Bianchi et al., 2024), or creating empathetic-sounding text (Ayers et al., 2023).

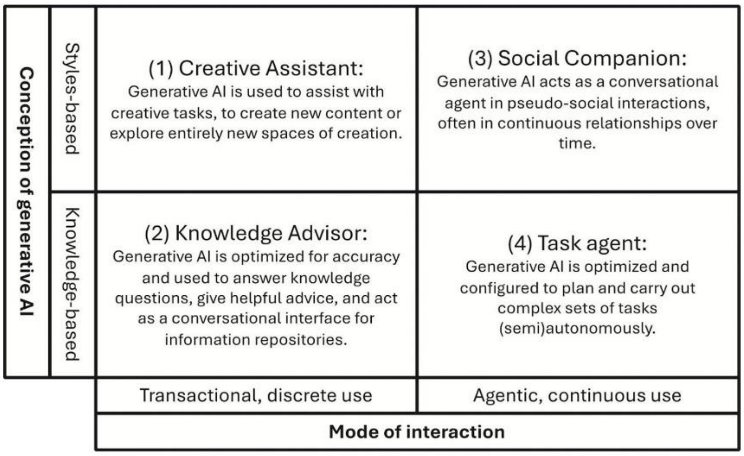


Fig. 3.

III. RESEARCH METHOD

1. Data collection

We selected MTurk as the sample site for our empirical study, as it is a general-purpose microwork DLP with a representative range of microtasks (Hara et al., 2018), such as relevance evaluation, data digitalization, audio transcription, and image labelling. Such simple microtasks on MTurk are referred to as "human intelligence tasks" (HITs). Workers on MTurk choose from available HITs and complete them in exchange for small payments. We administered our survey as a HIT, offering each respondent one dollar for completing the survey HIT on MTurk. A total of 347 workers clicked the survey link and 306 completed responses were collected.

2. Measurements:

The measurements of the constructs in the research model include items adapted from previously validated

measurement scales with wordings modified for the microwork DLP context, along with self- developed items asking factual questions related to microwork behavior and wages on MTurk (see Supplementary Appendix A for the measurement items). Additionally, we collected demographic information as control variables: age, gender, country, education, employment status, and tenure (in months) on MTurk (see the descriptive statistics in Table 1). Some of the variables were coded as dummy variables: gender (1=male, 0=female), employment status (1=fully employed, 0=not fully employed), and country (1=India, 0=not India). Below we present the measurements in detail. Microwork Motivations Based on the previously validated Work Preference Inventory (WPI) (Amabile et al., 1994), we measured monetary rewards and enjoyment as extrinsic and intrinsic motivations. Microtime structure is measured by the Time Structure Scale (Bond & Feather, 1988; Feather & Bond, 1983), which was adapted to the Descriptive statistics of sample demographics.

Demographic variable	Level	Frequency	Percentage (%)
Gender	Male	185	60.46
	Female	121	39.54
Country	USA	117	38.24
	India	176	57.52
	Other	13	4.25
Age	< =19	6	1.96
	20-29	150	49.02
	30-39	91	29.74
	40-49	30	9.80
	50-59	21	6.86
	> =60	8	2.61
Education	High school	45	14.71
	Vocational / Technical school	21	6.86
	Undergraduate	156	50.98
	Master / Postgraduate	84	27.45
Employment status	Full-time job	158	51.63
	Part-time job & Not a student	45	14.71
	Unemployed & Not a student	47	15.36
	Part-time student	16	5.23
	Full-time student	40	13.07
Most frequent HIT type	Information gathering	38	12.42
	Data verification / clean-up	41	13.40
	Photo / video processing	31	10.13
	Data processing	32	10.46
	Filling out surveys	154	50.33
	Other	10	3.27
Tenure on MTurk	< = 12 months	142	46.41
	13 - 24 months	105	34.31
	25 - 36 months	42	13.73
	37 - 48 months	11	3.59
	49 - 60 months	5	1.63
	> 60 months	1	0.33

Fig. 4.

3. Data analysis:

Given that all constructs were measured by the survey data, we examined common method bias using Harman's single factor test (Harman, 1976), which posits that common method bias presents if a single factor accounts for more than 50 % of the variance of all constructs. In our study, the variance explained by one factor is 24.4 % thus, common method bias is not a serious concern. To test multicollinearity, we further calculated the variance inflation factor (VIF) values for predictors and control variables. The results are VIF values between 1.04 and 2.08 (see Supplementary Appendix B), below the threshold of 3.3 (Kock & Lynn, 2012), suggesting that the data are not subject to multicollinearity. We then conducted descriptive and correlation analyses of all constructs and present the results in Table 2. Among all 11 constructs, three atent constructs related to microwork motivations, i.e., monetary reward, enjoyment, and microtime structure, were measured by multiple reflective items, whereas the remaining were measured by single items because of their factual nature. Through the confirmatory factor analysis of the three microwork motivations, we calculated their average variance extracted (AVE) and composite reliability (CR), as presented in Table 2 with the squared roots of AVEs in the diagonals. The values of AVEs exceed 0.5 and those of CRs are greater than 0.7, indicating convergent validity and reliability at an adequate level (Shrestha, 2021). The square roots of the AVEs of the three constructs are greater than their correlations with any other constructs, suggesting the discriminant validity of the multi-item constructs (Fornell & Larcker, 1981). The values of AVEs and CRs of the remaining single-item constructs are one by default.

3.1.Discretionary Access Control:

The results of the hierarchical regression analysis are presented in Table 3. The predictive powers of the independent variables on the microwork labor supply differ between the macro (i.e., weekly hours) and micro (i.e., minutes per task) level. Among the three microwork motivations, while the motivation for monetary rewards has a positive effect on the microwork labor supply at the macro level, enjoyment has no significant impact. The negative relationship between microtime structure and the labor supply is significant at both the macro and micro levels. Microworkers' perceiving microwork as work exerts a positive effect on weekly hours of microworking, whereas target earners spend less time per task than those without an earnings target. Thus, the results support H1a, H3a, and H4a, but do not support H2a, H5a, H6a, and H7a. Regarding microwork wages, the positive relationship between the motivation for monetary rewards and weekly wages is crowded out by the effect of the perception of microwork as work, yet the motivation for monetary rewards is negatively associated with hourly wages. Neither enjoyment nor microtime structure affects microwork wages. The positive effect of work perception and the negative effect of leisure perception are significant for weekly wages but not hourly wages.

3.2.Theoretical contributions and implications

Drawing upon individual labor supply theory (Hsiaw, 2013; Lazear, 1991; Sharif, 2000), this study integrates the neoclassical economic factors with psychological factors to predict the microwork labor supply and wages. Our study advances IM research on DLPs in three ways. First, the limited impact of microworkers' motivations on their labor supply and wages and the co-existence of work- and leisure-oriented attitudes toward microworking suggest relaxing the assumption about the nature of the labor supplied to DPLs, which is presumably regarded as the online counterpart of the labor supply in traditional workplaces. There has been a longstanding debate on the nature of DLP participants, who are neither employees nor traditionally defined independent contractors, freelancers, or the self-employed (Kuhn & Maleki, 2017). Such a controversy brings about the ambiguity in the appropriateness of applying IM theories stemming from traditional workforces to DLPs. Assuming laborers on DLPs are workers, prior studies on IM activities on DLPs (Bakici, 2020; Nwafor et al., 2022) have primarily adopted motivational and social-psychological perspectives to explain online laborers' (dis) continuance intention.

3.3.Implications for practice

This study offers practical insights for various stakeholders involved in microworking, including microworkers,
requesters, and DLP operators. For microworkers, the negative association between the motivation for monetary rewards and hourly wages shows that microworkers who are more driven by making money are more likely to earn a lower hourly wage, inferring a more precarious working condition for extrinsically motivated workers and rendering them more susceptible to exploitation by low-paying microwork. Microworkers are encouraged to keep track of their wage rates, through which they can adjust their labor supply decisions or work strategies to avoid microworking at an undesirable wage rate.

Variable	AVE	CR	Mean	SD	1	2	3	4	5	6	7	8	9	10	11
1. Monetary reward	0.58	0.78	5.70	0.95	***0.77***										
2. Enjoyment	0.68	0.87	5.25	1.23	0.11	***0.83***									
3. Microtime structure	0.58	0.77	5.19	1.21	0.10	0.59	***0.76***								
4. Microwork as work	1.00	1.00	5.39	1.44	0.34	0.17	0.03	1.00							
5. Microwork as leisure	1.00	1.00	4.41	1.76	-0.02	0.37	0.44	-0.10	1.00						
6. Reservation wage	1.00	1.00	0.50	3.23	0.08	-0.02	0.01	0.01	-0.01	1.00					
7. Earnings target	1.00	1.00	0.49	0.50	0.33	-0.06	-0.02	0.13	-0.05	0.13	1.00				
8. Weekly hours	1.00	1.00	20.93	14.83	0.25	0.11	-0.06	0.38	-0.08	0.04	0.09	1.00			
9. Minutes per task	1.00	1.00	14.48	11.45	0.01	0.04	-0.13	-0.01	-0.06	-0.10	-0.13	-0.10	1.00		
10. Weekly wage	1.00	1.00	41.51	45.43	0.17	-0.11	-0.06	0.12	-0.18	0.13	0.29	0.32	-0.19	1.00	
11. Hourly wage	1.00	1.00	2.70	3.83	-0.10	-0.18	-0.07	-0.09	-0.08	0.02	0.08	-0.26	-0.05	0.46	1.00

Notes: Diagonal elements are the squared roots of AVEs of reflective constructs; off-diagonal elements are correlations among latent constructs. AVE: average variance extracted; CR: composite reliability; SD: standard deviation.

IV. CONCLUSION

Our analysis is grounded in the surprising insight that generative AI, due to its fundamentally different technical characteristics, fails to comply with traditional expectations of computing in terms of reliability, accuracy and veracity. At the same time, and equally surprising, generative AI excels at many tasks that are associated with uniquely human abilities, such as creativity, persuasion, or negotiation. We put forward the notion of styles as a foundational characteristic describing the nature of generative AI. We argue that, when understood as style engines, the capabilities of generative AIs can be appropriately conceptualized as complementing traditional computing. Our analysis culminated in putting forward a framework of archetypes of generative AI applications that makes use of the complementing nature of a styles- based understanding and a more traditional knowledge-based understanding. Our analysis leads us to derive implications for future research, and for practice and policymaking.

References

[1] Ferrara, E. (2024). GenAI against humanity: Nefarious applications of generative artificial intelligence and large language models. *Journal of Computational Social Science*, *7*(1), 549-569.

[2] Blain, L. (2024). GPT-4 is 82% more persuasive than humans, and AIs can now read emotions. *Newatlas. Technology. Available at: https://newatlas. com/technology/gpt-persuasion-manipulation*.

[3] MIGUEL, X. O. ARTIFICIAL INTELLIGENCE. LEGAL FRAMEWORK AND EFFECTS ON THE ECONOMY.

[4] Bishop, C. (2024). Composite AI: Uniting Generative AI and Neuro-symbolic AI for Transparent and Accurate AI Decision Making. The AI Journal**.**

[5] Eve, O. (2024). The rise of AI companions: Your new AI friend. WonderShare. Retrieved from https://democreator.wondershare.com/ai-friend/best-virtual-ai-friend-a pps-you-should-try.html.

[6] Ramesh, A., Pavlov, M., Goh, G., Gray, S., Voss, C., Radford, A., ... & Sutskever, I. (2021, July). Zero-shot text-to-image generation. In *International conference on machine learning* (pp. 8821-8831). Pmlr.

[7] Raza, M. M., Venkatesh, K. P., & Kvedar, J. C. (2024). Generative AI and large language models in health care: pathways to implementation. *npj Digital Medicine*, *7*(1), 62.

[8] Reisner, A. (2024). The flaw that could ruin generative AI. *The Atlantic*, *11*.

[9] Li, J., Yuan, Y., & Zhang, Z. (2024). Enhancing llm factual accuracy with rag to counter hallucinations: A case study on domain-specific queries in private knowledge-bases. *arXiv preprint arXiv:2403.10446*.

[10] Barzel, Y., & McDonald, R. J. (1973). Assets, subsistence, and the supply curve of labor. *The American economic review*, *63*(4), 621-633.

[11] Bieber, F., & Moggia, J. (2021). Risk shifts in the gig economy: The normative case for an insurance scheme against the effects of precarious work. *Journal of Political Philosophy*, *29*(3), 281-304.