Working with Generative AI: We need more African Voices, Real African Voices

ABSTRACT

Generative AI has taken the world by storm, appearing to be more usable than previous generations of AI. We describe the findings of a qualitative study of Small and Medium Businesses in Kenya and Nigeria who were using generative AI tools in their everyday work. We found that AI tools were used to support both mundane and creative work and provided both organisational and individual benefits. Participants adopted a number of methods to navigate the strengths and weaknesses of different tools and comparing the output of multiple tools was common. Additionally, our findings suggest that whilst to some extent rhetorics around the democratisation of AI might hold true, these tools did not well support or represent African languages, identities or locales and were understood by participants to embody Western biases. We propose that regional bias should be explicitly called out to encourage researchers to focus on these concerns.

CCS Concepts: • **Empirical–Qualitative:** → ethnography • workplace studies • qualitative user studies

KEYWORDS: Generative AI, workplace studies, Africa

1 INTRODUCTION

In the last two years, generative AI tools such as ChatGPT, BingChat, Bard, Midjourney and DALL_E have become widely available. The new generation of generative AI models (GPT4, LLAMA, etc.) and the tools built on top of them are widely predicted to be transformational because of their ability to process and produce human-like language and generate new content. Their natural language interfaces, combined with the current pricing models, make these new tools much more accessible than previous generations of AI and this is reflected in both the media reaction and their widespread uptake and use around the world [2, 9, 118].

These early versions of generative AI tools reduce the barriers to AI adoption because they are available to anyone with internet access for no or relatively low-cost, enabling people to experiment with them easily and cheaply. Equally importantly, their natural language input and 'human-like' output make them easily usable by a wide population, as no special programming skills or high GPUs are needed by the end user. As such they have the potential to democratize AI [e.g.[47, 59]]. Seger et al [114] discussed four types of AI democratization – democratising use, development, profits and governance. In this paper, we examine whether generative AI can be said to be democratising AI use.

There has been widespread public discourse on how generative AI might impact the workplace [1, 10, 39]. CSCW has a long history of understanding workplace technology deployments, revealing how the situated use of workplace technologies often differs from intended uses [3, 98, 119], and what the implications of this are for workplace technology design and for the future of work [98, 119]. As a discipline, CSCW is ideally positioned to look beyond the hype and examine the situated use of generative AI technologies, which show great promise, but are in their early stages of workplace deployment. Such an understanding can be used to help determine the future research directions needed if we are to build technologies which make work better, or to borrow from Kittur et al [79] if we are to build the future workplaces, we would wish our children to work in. What makes the current situation exciting is that we still have everything to play with. New tools, interfaces and interaction mechanisms are being created and deployed right now and the full shape of how generative AI technologies – with all their promises and limitations - will be deployed in the workplace has yet to be fully defined.

In this paper we report on a study which aimed to understand the real-world, workplace use of generative AI technologies by Small and Medium Businesses (SMBs) in Kenya and Nigeria[1]. The SMBs in this study used a range of generative AI tools including text, image and speech generation and speech synthesis tools. We provide

1 A note on the research site. The research site happens to be in the Global South, not as part of some HCI4D or ICTD initiative, but simply because that is as legitimate a site for understanding workplace technology deployment and use as any other. Technology has global reach and should be understood from a diversity of perspectives and situated use cases. If we are striving to be part of a movement to create equitable and beneficial futures of work for everyone, there is much we can learn from one another. Finally, workplace technology use in the Global South is rather understudied outside of the (many wonderful) HCI4D and ICTD initiatives.

a picture of where generative AI works for these SMBs, what challenges they face in using it, and we begin to get a sense of how it might transform work. In addition, our findings speak to the question of whether generative AI can be said to be democratizing workplace AI for small businesses in the Global South.

Our contributions include

1) Augmenting the small but growing set of empirical studies of generative AI in the workplace, by providing a rich description of how participants use generative AI tools at work. We explicate the methods that participants used to navigate the strengths and weaknesses of the different AI tools on the market. In addition, this paper adds to the diversity of perspectives on this topic by examining generative AI use by SMBs in Africa.
2) We illustrate how these tools are currently mostly being used to support expertise, but we also highlight cases where they are used to substitute for expertise.
3) We advance discussion about whether generative AI is a force for the democratisation of AI use. The very use of these tools at work by small businesses in Kenya and Nigeria, as well as their reported organisational and individual benefits, speaks to the democratisation of AI in some senses. However, our data revealed stark examples of how generative AI fails in African contexts. This goes well beyond failures to support African languages and impacts businesses day to day operations.
4) We add to the small but important body of research examining model performance in global contexts and call for the recognition of regional bias. Whole continents and their knowledge are severely underrepresented in these models and tools. We hope that making regional bias an explicit category of bias will draw attention to the need for more research in this space.

2 LITERATURE

2.1 Working with Generative AI

Recent studies on generative AI explore its wide-ranging impacts, applications, and ethical dilemmas across numerous domains, including academia, creative industries, and professional environments [21, 26, 29, 37, 55, 56, 68, 88, 94, 103, 121, 132]. Scholars are particularly interested in the potential of tools to enhance productivity and creativity, while also grappling with their limitations regarding accuracy, privacy, and ethical concerns [53, 86, 102, 112, 130]. Despite the varied applications of generative AI, a recurring theme emerges: the need to balance its capabilities with the challenges it introduces.

In academic settings, for instance, generative AI tools have been widely adopted for tasks such as academic writing and literature reviews [16, 84, 132]. These tools offer significant benefits, especially for non-native English speakers, by simplifying complex writing tasks and aiding in the generation of adaptable teaching materials [117, 131]. However, alongside these benefits are concerns about the biases embedded within AI-generated outputs, the risk of diminished ownership over academic work, and broader ethical considerations [14, 40, 74, 86]. These challenges are amplified in contexts with less robust digital infrastructures, raising questions about the equitable distribution of AI's benefits.

In creative industries, particularly in game design and visual arts, generative AI plays an increasingly prominent role [26, 30, 56, 60, 88, 134]. Many professionals find value in using AI tools to experiment with new ideas and iterate on creative concepts more quickly. However, these same professionals express deep concerns about the potential erosion of human creativity. The fear that AI-generated content could homogenize art, diminish the uniqueness of human expression, or commodify artistic labor underscores the tension between technological innovation and the preservation of individual artistic agency [15, 22, 66, 137]. This dilemma is particularly acute for marginalized artists, who worry that their work may be appropriated without proper acknowledgment or compensation [46].

A further challenge arises when considering the social implications of generative AI. Studies reveal that in specific contexts, such as communication support for autistic workers, generative AI can serve as a powerful tool [69]. Yet, the limitations of AI models in representing diverse experiences and identities, particularly in text-to-image systems, raise important ethical questions. These systems often perpetuate societal stereotypes, reinforcing problematic depictions of marginalized groups, including people with disabilities [86]. Such concerns extend beyond creative and professional spaces to the broader societal implications of deploying AI tools without adequately addressing their biases and limitations.

As generative AI continues to be integrated into professional workflows, it is often positioned as a solution to streamline routine tasks and enhance productivity [27, 83, 91]. In fields like customer service and software development, AI tools such as GitHub Copilot have been shown to significantly accelerate task completion [35, 65, 104]. However, these gains are not without trade-offs. Studies indicate that while AI can enhance the speed and quantity of work, it can also compromise quality, as seen in the case of code generated by Copilot, which often required human intervention to correct errors [35, 64]. The balance between efficiency and accuracy remains a critical consideration in determining the value of AI tools in professional contexts.

In examining the adoption of generative AI, it becomes clear that these tools do not operate in a vacuum. Their integration into workflows often highlights existing inequalities, particularly in access to technology and the distribution of its benefits. For instance, while generative AI has been shown to improve productivity for novice workers, more experienced employees report little to no gains [80]. Moreover, in regions such as the Global South, where digital infrastructure and technological access may be limited, generative AI can exacerbate existing divides. Journalists in Africa, for example, have reported mixed experiences with ChatGPT, using the tool primarily to organize information but finding that it often reproduces Western stereotypes and inaccuracies, particularly in coverage of African countries [51]. This not only raises concerns about the reliability of AI outputs but also underscores the importance of cultural representation and contextual sensitivity in AI systems.

2.2 Representation and Bias in Generative AI Models

Concerns about representation and bias in AI models have been longstanding, particularly in fields like Natural Language Processing (NLP) and Fairness, Accountability, Transparency, and Ethics in AI (FATE). Generative AI models, which produce text, images, and other content, are susceptible to various forms of bias that can result in outputs that are inaccurate, stereotyped, or harmful. Extant studies evaluate the impacts of the data divide on AI performance [45, 46, 48, 49, 51, 52], investigates biases present in these models [77, 92, 135] , identifies the limitations of current models [36, 44, 108, 138], and proposes methods to mitigate bias [64]. These efforts have emphasized the complexity of addressing biases in generative AI, particularly as biases often stem from multiple sources within the model development process.

Biases in AI models often originate in the data used to train these systems. Datasets reflect the subjective perspectives and values of their creators, leading to the overrepresentation of dominant groups and the underrepresentation or misrepresentation of marginalized communities [19, 109]. In addition, bias arises from training methodologies, including feature selection, labeling practices, and the underlying design choices embedded in models. The social risks posed by these biases are significant, as they can perpetuate discrimination, reinforce societal inequalities, and create "hermetic beliefs," where AI systems amplify pre-existing biases [135]. These biases manifest in various ways, including demographic biases, cultural stereotypes, and linguistic biases, and extend to temporal, confirmation, ideological, and political biases [41]. Collectively, these biases contribute to the perpetuation of harmful content, the exclusion of marginalized communities from the benefits of AI, and the overall reduction in the utility of AI models for diverse populations [19, 45, 109, 135] . Research shows that these biases have particularly far-reaching consequences. For instance, generative AI models trained predominantly on English-language data often exclude speakers of non-standard dialects and sociolects, further widening the gap between dominant groups and underrepresented communities [36, 81] . Despite advances in generative AI, such as GPT-4's improved performance in processing mid- and low-resource languages, the models remain far from achieving parity with English, highlighting the persistent inequalities in linguistic representation [8]. These linguistic disparities, combined with other biases in generative AI, affect users' ability to fully engage with and benefit from these systems.

The underrepresentation of non-Western perspectives in generative AI models is an ongoing issue. Most research on AI bias has centered on Global North contexts, with comparatively little attention paid to how these biases impact users in the Global South. A notable exception is the work by Alenichev and Grietens [12], who attempted to use AI image generation to challenge stereotypes of "suffering African children" and the "white savior" trope in global health imagery. However, their efforts were stymied by the model's inability to break free from entrenched global narratives. Similarly, Qadri et al. [106] found that generative AI models continued to reproduce the "outsider's gaze" in their depictions of South Asian culture, reinforcing cultural biases rooted in colonial perspectives. These studies underscore the difficulty of achieving truly equitable representation in generative AI, particularly in the context of global power dynamics.

Mitigating these biases has proven challenging. Kumar et al. [81] outline strategies for detecting and addressing the harms caused by biased generative AI models. These include toxicity detection, curating balanced training datasets, and developing novel data pipelines that prioritize fairness and inclusiveness. The authors emphasize the need for a multidisciplinary approach to tackle the inherent complexities of bias in AI, calling for collaboration across fields to develop more transparent and responsible AI systems [41]. Raji et al. [109] further propose alternative evaluation techniques, such as adversarial testing and behavioral analysis, to uncover hidden biases and assess how generative AI models perform in diverse contexts. Some countries have even begun large-scale efforts to collect data in low-resource languages, with the goal of creating more representative training sets for future AI models [11]. Despite these initiatives, the literature indicates that more work is needed to establish robust safeguards that can effectively mitigate bias in generative AI [36]. The current body of research on bias in generative AI has largely been confined to experiments and the use of artificially constructed datasets [7] . While these studies have been instrumental in identifying various types of bias, they do not fully capture how these biases play out in real-world applications. In the field of Human-Computer Interaction (HCI) and Computer-Supported Cooperative Work (CSCW), where the situated nature of technology use is a central concern, this gap in knowledge is particularly significant. Research in NLP has shown that generative AI models frequently misrepresent culture, but these studies rarely examine how cultural biases manifest in everyday use, especially in non-Western contexts. For example, while much attention has been paid to gender and occupational biases [38], there remains speculation about whether these biases meaningfully impact business applications of AI in regions like Kenya and Nigeria, or if they primarily produce more abstract harms.

Given the widespread use of generative AI in everyday tasks, especially in the context of small- and medium-sized businesses (SMBs), there is a pressing need to move beyond benchmarking studies and experimental evaluations. These models, now available to the public, are used by a wide range of users, including those in Global South contexts where biases may have more pronounced social and economic consequences. By investigating how generative AI models are used in practice, particularly in SMBs in Kenya and Nigeria, this paper aims to explore how underlying biases in the training data affect the real-world experiences of users. In doing so, we can begin to understand the full extent of AI's societal impact.

As the literature suggests, there is a growing recognition of the limitations of current approaches to studying bias in generative AI. This survey of over 90 research papers on culture and large language models (LLMs) demonstrates the need to move beyond treating culture as a dataset that can be measured through proxies like language or values and assessed through decontextualized benchmarks [7]. To understand how specific user groups experience AI within their unique cultural contexts, researchers must engage in participatory design with diverse communities and consider the long-term societal and cultural impacts of AI [ibid]. Incorporating qualitative methods and theoretical frameworks from HCI, CSCW, and anthropology can provide a more nuanced understanding of how cultural factors shape the user experience of LLMs [7]. By adopting such approaches, future research can advance the development of truly inclusive AI models that account for the diverse needs and values of users in both the Global North and Global South [ibid].

2.3 AI and the Digital Divide

The digital divide broadly refers to the disparities in access to digital technologies, including internet connectivity, digital literacy, and technological infrastructure [62, 128]. These disparities often reflect broader socioeconomic inequalities, leaving marginalized communities with limited access to the benefits that digital technologies can provide [20]. Within the context of AI, the digital divide manifests in what is often referred to as the "data divide." This data divide highlights the fact that the vast majority of training data for large AI models comes from the

English-speaking Global North, raising concerns about the inclusivity and fairness of AI systems across diverse global contexts [78, 115, 123].

Generative AI, which has gained increasing attention for its capacity to produce human-like text, images, and other content, is often portrayed as a tool that could democratize access to advanced technologies, particularly in regions with historically limited access to AI [28, 122]. However, the extent to which generative AI can bridge—or further exacerbate—the digital divide remains an open question. Some researchers have suggested that while generative AI may introduce new opportunities, it also risks replicating and reinforcing the existing inequalities associated with the digital divide [34].

A recent study focusing on the adoption of ChatGPT, illustrates how patterns of interest and use reflect pre-existing digital divides in the United States. The study found that interest in ChatGPT was geographically clustered, with higher rates of usage on the West Coast and lower rates in regions like the Gulf Coast and Appalachia. These spatial differences were strongly associated with socioeconomic factors, with education emerging as the most significant predictor of interest in ChatGPT, even when controlling for other variables such as income, race, and industry makeup. This suggests that generative AI, rather than leveling the playing field, could further entrench existing educational inequalities, especially in communities where access to quality education is already limited [34].

Further compounding these concerns, researchers argue that generative AI has the potential to exacerbate existing inequalities in sectors like education and healthcare. In the context of education, for example, AI-powered learning tools could widen the digital divide if access to these tools is not distributed equitably. Students from underprivileged backgrounds, who may lack access to reliable internet or devices capable of running AI applications, could be left behind, thereby deepening educational inequalities [28]. In healthcare, similar patterns could emerge, with AI-driven healthcare services offering the potential for improved diagnostics and treatment in well-resourced settings, while under-resourced communities may struggle to access these advancements. The potential for generative AI to widen socioeconomic disparities underscores the need for policies aimed at ensuring equitable access to these technologies [18, 95].

The risks posed by the digital divide are not limited to access alone; the broader structural barriers to digital infrastructure can also hinder the productive use of AI technologies. A study examining the impact of generative AI in Latin America and the Caribbean found that while the risk of job automation due to AI is relatively small, the lack of digital infrastructure in the region is a significant obstacle to realizing the potential productivity gains from generative AI [50]. Approximately 30% to 40% of employment in the region is exposed to generative AI in some capacity, yet only a small fraction of jobs—between 2% and 5%—are at risk of full automation. More jobs (8% to 12%) stand to benefit from AI augmentation, where AI assists rather than replaces human workers. However, the study highlights that the region's lack of access to digital technologies, such as computers and high-speed internet, prevents workers from leveraging AI's full potential. Without addressing these infrastructural gaps, the region risks exacerbating existing inequalities and failing to capture the economic benefits associated with generative AI.

In light of these findings, this paper interrogates the question of whether generative AI is truly democratizing access to advanced technologies in the Global South or whether it is perpetuating existing divides. While technology holds the promise of opening new opportunities, particularly in under-resourced regions, the persistence of the digital divide in access to infrastructure, education, and technological literacy suggests that generative AI may not be the great equalizer it is often portrayed to be. Addressing these divides will require not only technological advancements but also targeted policies that ensure equitable access and utilization of AI technologies across diverse socioeconomic contexts.

3. METHODOLOGY

We conducted 21 semi-structured interviews with 27 participants (8 females, 19 males) from 21 small and medium-sized businesses (SMBs) in Kenya and Nigeria between July and October 2023. This approach provided in-depth insights into the use of Generative AI in these regions. Semi-structured interviews are commonly used in HCI and CSCW research due to their flexibility, allowing the exploration of key themes while following a general framework [24, 71]. One interview was conducted in a group format, involving seven participants from different legal departments within a law firm—specifically, a partner, a business development lead, three trainee associates, an intern, and a trainee advocate. Group interviews can be effective in eliciting a range of opinions and perspectives from multiple stakeholders [43].

The interviews focused on four key themes: AI discovery and tools, AI impacts, AI skills, and AI vision. Participants were asked to share their experiences regarding how they find, experiment with, and use AI tools. We also explored the benefits and challenges they encountered, the skills they needed to use AI effectively, and their expectations and concerns about the future of work with AI. Additionally, we probed issues of trust, privacy, security, and ethics, which are particularly significant for SMBs in developing countries. These organizations often face unique challenges, such as limited infrastructure, regulatory gaps, and lower levels of AI awareness compared to those in more developed nations [97].

3.1 Participants

To capture diverse perspectives, we recruited participants from a wide range of professional fields, including law, design, creative writing, real estate, finance, outdoor recreation, retail and wholesale, software development, fashion design, business development, marketing, supply chain, journalism, training, and telecommunications. The aim was to reflect a balance between frontline workers and knowledge-based professionals, providing a comprehensive view across different roles (details in Table 1).

Table 1: Table of participants and the generative AI tools they use

Participant ID	Job sector	Title	Country	Generative AI tools used
RP13	Architectural Design	Product Designer	Kenya	Leonardo.ai, Adobe Firefly ChatGPT, Midjourney BrieflyAI
RP14	Outdoor recreation	Guide	Kenya	Google Bard ChatGPT
RP15	Retail	CEO	Kenya	Runway Canva Descript BrowseAI, Naming Magic ChatGPT
RP16	Retail	Managing Director	Kenya	ChatGPT
RP17	Legal Service	Partner	Kenya	ChatGPT, Bing Chat Midjourney
RP17A	Legal Service	Head of Business Development	Kenya	
RP17B	Legal Service	Trainee Associate	Kenya	
RP17C	Legal Service	Associate	Kenya	
RP17D	Legal Service	Intern	Kenya	
RP17E	Legal Service	Trainee Advocate	Kenya	
RP17F	Legal Service	Associate	Kenya	
RP18	Printing & Design	Research and Development Lead	Kenya	Photoshop Beta, Adobe Firefly Midjourney ChatGPT
RP19	Creative Writing	CEO/Founder	Kenya	ChatGPT

				Canva
RP20	Outdoor Recreation	CEO	Kenya	ChatGPT Canva
RP21	Real estate	Founder/Director	Kenya	ChatGPT
RP22	Imports and distribution of Goods	Sales and Marketing Lead	Kenya	ChatGPT DALL-E
RP23	Financial Services	Operations Manager	Kenya	ChatGPT
RP24	IT	CEO/Founder	Kenya	ChatGPT Leornado.ai Stable Diffusion ElevenLabs Midjourney
RP25	IT	Software Engineer	Nigeria	ChatGPT Bing Synthesia Pictoria
RP26	Clothing & Fashion Design	CEO	Nigeria	ChatGPT
RP27	Business Development	Founder	Nigeria	ChatGPT
RP28	Digital Marketing	CEO	Nigeria	ChatGPT MidJourney Google Bard
RP29	Financial Services	Lead Consultant	Nigeria	ChatGPT
RP30	General contract & supplies	Partner	Nigeria	ChatGPT Google Bard Bing Chat
RP31	Multimedia Journalist	COO	Nigeria	ChatGPT
RP32	Power Sector	Lead Trainer	Nigeria	ChatGPT Google Bard Bing Chat
RP33	Telecommunication	CEO	Nigeria	ChatGPT Leornado.ai MidJourney Blue Willow

Participants were recruited through a combination of convenience [17, 57] and snowball sampling methods [113, 127]. Recruitment flyers were shared via social media and personal networks. Informed written and verbal consent was obtained from all participants prior to the interviews. To accommodate individual preferences and accessibility needs, we offered the option to participate remotely (via phone or video call) or in person. Ultimately, three interviews were conducted remotely using Microsoft Teams, while the remaining 18 took place either at the participants' SMB workplaces or the researcher's office, based on the participants' preferences. As a token of appreciation for their time and contributions, participants were compensated with shopping vouchers.

Interviews lasted between 60 and 90 minutes. During the sessions, participants were encouraged to showcase examples of work involving Generative AI. The interviews, conducted in English, were transcribed using HeyMarvin [58]. The analysis, primarily inductive, was led by the authors. While HeyMarvin was employed to assist lightly in organizing notes and tagging key interview sections, the primary analysis involved a thorough review of each interview to identify recurring themes. Quotes relating to specific themes were extracted and analyzed collectively to gain a deeper understanding.

4 FINDINGS

Participants used a range of generative AI tools, including text and text-to-image generation, generative AI search, AI-augmented design tools, and, in one case, speech generation (Table 1). They learned about these tools through various channels such as news reports, search engines, social media, and personal networks. While participants were early adopters, they were not uniformly technical. Some identified as "techies," while others distanced themselves from such expertise. Regardless, all were eager to enhance both personal and business effectiveness through these tools. They utilized podcasts, YouTube, TikTok videos, and network connections to acquire skills for using generative AI. ChatGPT stood out as notably easy to learn and use, especially compared to more complex tools like Midjourney.

In the following sections, we will explore the nuanced ways in which generative AI was used.

4.1 What Generative AI is Used For

We found that SMBs employed generative AI in both creative and mundane work. Creative work refers to "productive activity involving originality, resourcefulness, and self-expression. It is varied, challenging, non-routine, and engaging" [96, pg. 386]. In contrast, mundane work consists of practical, routine, or banal tasks that still need to be done [32, 76]. Creative work is not confined to creative industries—any job can involve creativity. Drafting a specialized contract for a client is as much an act of creativity as generating images for a new product. Similarly, every role includes some level of mundane work [76].

4.1.1 AI in Creative Work. Generative AI tools were widely used across industries for ideation and inspiration. For example, IT_CEO[2] and Architect_Designer used ChatGPT to generate ideas for brand names. Architect_Designer generated ideas for names relevant to their client's country with which the team were unfamiliar. It is not just designers and creatives who use Generative AI for idea generation, Retail_CEO used it to name his business. Law_Advocate described how he used text generation tools for inspiration when stuck "*if you have creative block and you just can't think of that clause [...] I use it as just to trigger my mind and then I'll probably rephrase the entire clause*". BusDev_CEO used ChatGPT to help generate talking points for their radio show targeting local entrepreneurs. They would use ChatGPT to help generate "*some simple topics that will resonate with my listeners*". Once they had these ideas, they would find real case studies from the local Hausa speaking community to illustrate them. They explained how "*Before, I used to find it difficult to get an idea that would align with our local entrepreneurs*".

Image generation systems were also used to inspire new concepts and designs, as Logistics_SalesLead said "*when I'm thinking outside the box, yes. [...] I have asked DALL-E to give me an image of a wine bottle in a crooked shape. Like funky, fun*".

Generative AI reduced the time needed to generate ideas, helped in unfamiliar contexts, and in overcoming creative block. Architect_Designer described how before "*we would manually kind of like bounce off ideas of each other*" and arriving at ten strong ideas would take two or three sessions whereas now they achieved the same results in one.

Participants used Generative AI to support content creation for a broad range of activities. Image, speech and text generation systems were used to create presentations and pitches, including concept notes and business proposals; educational material, including coaching videos and multiple-choice questions for tests. The use of Generative AI in content creation work may be more or less creative. At the more creative end, it supports the user in creating new content – where generative AI is used to co-create or co-generate - although nonetheless the user has to carefully craft their inputs to get the AI to produce the right sort of output [85, 129]. For example, PowerSector_LeadTrainer (training) explained how they used ChatGPT to generate training content: "*I outlined all the areas I want relating to protection to maintenance, to operations, health and safety environment, blah. blah. I outlined everything and it actually generated the twenty-five questions based on these respective areas. I*

[2] In this study, participants are labeled by combining their industry and job title (e.g., Law_Advocate, Recreation_Guide).

even asked it to provide their respective answers for each question and it did". At the more mundane end of content creation, generative AI is used to create variations on, or tidy up, existing content.

SMBs also used Generative AI to support search and research. AI enhanced search was preferred over web search because of how it distills the information and "*helps us get context very quickly and it's easy to assimilate*" (Architect_Designer). While SMBs were concerned at times by how the trustworthy AI output could be this was less of a concern for exploratory research and creative content than those looking for factual output (see section 4.2).

In most of the examples above Generative AI complements, rather than replacing, professional expertise and is integrated into existing workstreams. For example, it is their knowledge of the topics they wish to cover which enables PowerSector_LeadTrainer to craft the prompt and get new forms of content; BusDev_CEO uses their knowledge of their listeners combined with inspiration from ChatGPT to generate fresh radio content; Logistics_SalesLead has ideas in her head which she uses image generation tools to make manifest. Architect_Designer sums it up well "*we already know sort of what we are looking for. We're just using the AI to help us get there*".

However, generative AI is sometimes used instead of professional expertise. For example, Contract&Supplies_Partner describes how they used AI tools when writing a joint proposal:

"*We actively participated in it, from the very beginning to the end. It's an area that we have no deep experience or understanding of, but with the use of, this, what do you call it, AI tools, what we're able to contribute in the course of the work went far far beyond what many other people that have even the experience in the area were able to contribute*".

This is an interesting example as it is not clear from the interviews alone whether this is a positive use of Generative AI, enabling the team to rapidly gain expertise and make valuable contributions to the project. Alternatively, it might be a concerning use of AI – given the propensity of AI for fabrication and the difficulty of spotting this if you do not have the expertise. It also raises questions around the potential of Generative AI to devalue expertise.

4.1.2 AI in Mundane Work. Participants used Generative AI to reduce the burden of and improve productivity in mundane work, including writing communications, information management, planning and troubleshooting. A common use of generative AI was crafting emails to help articulate polite professional communication with little extra effort. This includes condensing wordy communication, correcting the English, and adding professional tone. As Logistics_SalesLead, who's dyslexic explains, "*I use a lot of AI or ChatGPT to answer most of my emails because I feel that it really gives me an edge of being very professional using very, very good English*". Several participants described how it helped with more difficult communication such as "*how do I tell my client he's four months late now to this to pay his fees and I don't want to sound rude*?" (LegalService_Advocate). Participants use text generation to reduce the miscommunication common in emails [49, 84] without spending additional time. The output still needs to be corrected however and made "*to sound like me*" Logistics_SalesLead.

Generative AI was also used for information management, including meeting notes, summarizing information for easier consumption, and structuring content, as well as planning, i.e. creating checklists or project plans. RP25 (software engineering) described how ChatGPT helped with troubleshooting "when I had the bugs, I was on it for like four hours trying to locate where the bug was and the solution for it. If not because of the ChatGPT I would have spent maybe three or four days looking for the exact bugs. So, with ChatGPT it located the exact bugs within a twinkle of an eye".

4.2 Methods of use

The findings from our study highlight five distinct methods by which small and medium-sized businesses (SMBs) in Africa utilised generative AI tools, while navigating their limitations and strengths.

4.2.1 Combining Outputs from Multiple Generative AI Platforms. Several participants described switching between multiple generative AI platforms to take advantage of each tool's unique capabilities, labelled by one as "cross-carpeting3". "*I don't use one single... AI tool. I do what is called cross-carpeting and I will check from here to this one and to the other one*." (participant working in general contracting and supplies). This strategy allowed users to combine the strengths of different platforms while compensating for their respective weaknesses. For example, one user might rely on ChatGPT for content creation while turning to Bing Chat for more up-to-date or multimedia-rich responses. A consultant in financial services shared, "*If this tool is giving me wrong, I go to another tool... I'm using three tools, and I give all the three tools the same prompt*." A power trainer described how "*where there are differences or similarities, I now coined it to what I think will fit better for my trainers*." By blending outputs from multiple tools, users could tailor AI-generated content to meet their specific needs, ultimately enhancing their productivity and outcomes.

4.2.2 Situated Adaptive Scaffolding with Generative AI Tools. SMBs often adapted generative AI tools to support their unique work contexts. Users constructed adaptive workarounds that allowed them to complete tasks more efficiently and produce high-quality outputs. This process, which we refer to as situated adaptive scaffolding, involved three key strategies:

a) Augmented Prompting with External Tools: Users employed plugins like AIPRM for ChatGPT to refine their prompts, personalizing AI outputs to make them more "human-like." In this context, "human-like" refers to content that feels crafted by a person, steering clear of common AI markers such as repetitive phrasing or overly formal language. One telecom vendor noted, "*Honestly, most of [the content generated by ChatGPT] is not human-like content... that's why we emphasize the use of AIPRM*." This sentiment underscores the need for tools that bridge the gap between AI-generated outputs and genuinely human-sounding text, adding a natural touch that conceals typical signs of AI authorship.

b) Curated Conversational Workspaces: Through ongoing dialogue with AI tools, users establish a back-and-forth dialogue with the Generative AI tool, providing information and requesting improvements to content clarity. In effect SMBs were using these named sessions as internal knowledge bases - which they built up through continued interaction. These then acted as repositories for task-specific knowledge that participants subsequently used to generate output like proposals, emails, and concept notes tailored to their company's needs.

c) Conversational Scaffolding for Complex Inquiry: For some users, formulating effective prompts was a challenge, especially for complex inquiries. To overcome this, participants engaged AI tools in meta-level conversations, asking questions like, "*What is the best way to ask ChatGPT... so that we can get a high-quality output*?" (PowerSector_LeadTrainer). By doing so, they learned how to craft more effective prompts for complex tasks.

4.2.3 Maintaining Originality and Avoiding Plagiarism. Concerns about the recognizability of AI-generated content led some participants to edit and personalize outputs to maintain originality. For instance, a business development service provider emphasized, "*I make sure that I add my own diction, my own choice of words to edit the content I generate using ChatGPT to my own standard to the extent that it will be difficult, if not impossible for people to know*" Similarly, a power trainer explained that they customized their AI-generated training materials to address concerns around plagiarism and intellectual property. These strategies demonstrate users' awareness of the potential risks associated with over-reliance on generative AI tools and their efforts to ensure their work retained an authentic, personal touch.

4.2.4 Critical Evaluation and Fact-Checking: Mitigating Mistrust. A recurrent theme among participants was the need for critical evaluation and fact-checking of AI-generated content. Users expressed caution, acknowledging that AI outputs were not always reliable. As one digital marketer and copywriter noted, "*If I feel like I don't trust this, I have to go back and do the manual method of research... then I will use it.*" This lack of

[3] The word "cross-carpeting," used by our respondent in this context, refers to a common political term within Nigerian political lexicon, describing the act of politicians switching party affiliation (i.e. from one Party to another). In this case, the respondent used the term to illustrate how they navigate and utilize different generative AI platforms to enact their work.

trust often prompted users to cross-reference information from AI tools with other sources, such as Google or industry websites.

Participants also emphasized accountability in ensuring the final outputs met their quality standards. A telecom vendor explained, "*You really have to check the content and make sure it's aligned with what you want to achieve*." This practice triangulating AI-generated information through external verification highlights the critical role of user oversight in the generative AI process.

4.2.5 Prompt Engineering and Refinement. Effective use of generative AI requires users to develop and refine prompts iteratively. Many participants described prompt engineering as an ongoing, user-centered process. One digital marketer illustrated this by describing how they created a series of Facebook posts: "*If I don't like [the response], then I add another prompt to modify the previous response until the response is okay for me*." This iterative design process involved increasing the specificity of prompts to guide AI tools toward desired outputs. Participants tailored their instructions to generate content in specific formats, such as blog posts or marketing strategies, and included key details to ensure relevance. Users played an active role in evaluating and refining the outputs, ensuring alignment with their goals.

In summary, participating SMBs adopted diverse and adaptive strategies to integrate generative AI tools into their workflows. Whether by combining outputs from multiple platforms, employing conversational scaffolding, or refining prompts, these users creatively harnessed the power of AI. However, issues of trust and the need for critical evaluation remained central to their use of AI, emphasizing the importance of user oversight in achieving high-quality outputs.

4.3 Benefits of use

In exploring the motivations behind the adoption of generative AI among SMBs, our participants highlighted several key organizational and individual benefits. These benefits can be broadly categorized into two areas: organizational benefits, which include timesaving, efficiency, innovation, adaptability, and reduced labour costs, and personal benefits, such as enhanced knowledge, client satisfaction, and personal growth.

4.3.1 Organizational Benefits. The predominant organizational benefits of generative AI usage were related to increased efficiency and time savings. Many participants described how AI tools allowed them to streamline both creative and mundane tasks, significantly reducing the time spent on ideation and execution. For example, a FinancialServices_LeadConsultant noted that generative AI "*Increases the speed of my work… things that would normally take two hours, with these tools I can do in thirty minutes… or maximum forty minutes*." This sentiment was echoed by a copywriter (DigitalMarketing_CEO), who stated, "*Normally to write like two thousand words for a blog post, it will take you two to three days. But with AI, I can sit here and have three blog posts in a day*."

Even participants from industries that bill by the hour expressed how generative AI presented the possibility in the future of freeing them from mundane work to focus on more strategic and creative endeavours. A lawyer (LegalServices_Partner) explained how they would like to be able to use Generative AI for document reviews in small cases (they already used proprietary machine learning tools for large cases, but it was too costly for use in small cases): "*We could have spent that fifteen hour on important things. Once the AI had given us the report, we'd be thinking creatively now as we have the time, we have the budget, we can manage this*." This was not possible at the moment, as the lawyers were using general purpose generative AI tools and so could only use them with non-proprietary data. However, they see the potential of generative AI for smaller tasks, provided the tools are confidential, affordable, and localized to specific legal frameworks, such as Kenyan law.

In addition to efficiency, innovation and adaptability were other frequently cited advantages of generative AI adoption. Participants felt they could stay ahead of competitors by rapidly adopting and adapting new tools. As a vendor in telecom services says "*By staying at the forefront of AI advancement, we are better equipped… we can change rapidly, we can scale quickly… and do things quickly and efficiently*."

4.3.2 Personal Benefits. On an individual level, participants described how generative AI enhanced their knowledge, allowed them to exceed client expectations, and drove their professional and personal development. Contract&Supplies_Partner emphasized how generative AI contributed to deeper insights, stating, "*It increases* *the depth of my knowledge in certain issues.*" He elaborated on his perception that generative AI enables faster access to up-to-date information from multiple sources, which he feels overcomes the limitations of traditional literature searches. He explained, "*In a normal search, you may end up getting information that was three years old, two years old… but this one you can get something that was validated a day before*." This suggests a belief in generative AI's capability to provide more timely data, even though actual information retrieval can vary based on the AI's training data and access to recent sources.

Several participants also highlighted how the time saved through generative AI enhanced their reputations for promptness and reliability. PowerSector_LeadTrainer shared, "*Somebody will request for something from you, expecting it in three days, and they get it in three hours… they see you as someone who is actually prompt with good time management*". This efficiency not only enhanced client loyalty but also helped participants build a competitive edge in their respective industries. For example, Contract&Supplies_Partner recounted how he and his colleagues' outperformed competitors by using generative AI to draft a service-level agreement that was subsequently adopted, humorously noting, "*We are even now joking among ourselves that we are calling ourselves barristers, courtesy of ChatGPT*."

These personal benefits extended beyond efficiency and knowledge acquisition to broader themes of adaptability and growth. BusinessDev_Founder summarized the transformative potential of AI, stating, "*It is changing many things, so you either use it to help yourself, or you don't use it and spend most of your time doing it yourself… or spending your money on others who are possibly using it to do the job.*"

4.4 Challenges of Generative AI in the Workplace

Despite the benefits described, using Generative AI at work poses a number of challenges, particularly for small- and medium-sized businesses (SMBs) operating in diverse environments such as those in Africa. The key concerns raised by participants in this study revolve around the limitations of free tools, concerns regarding data privacy and security, the impact of AI "hallucinations" on trust, and the performance of generative AI systems in African contexts. Each of these challenges contributes to a complex landscape of AI use, where utility is balanced with caution and critical reflection on AI's capabilities, limitations, and implications for business practice.

4.4.1 The Limitations of Free Tools and Concerns About Data. By and large SMBs were using the free version of tools, with the one common exception being Midjourney, which was considered to produce professional quality images. As IT_CEO explained

"*[Midjourney] produces images that are close to reality [which] means that we can use them in our work as opposed to other engines […] where you you can clearly tell that they're AI generated images*".

This shows that SMBs, who are very price conscious, are willing to pay for tools which produce high enough quality output. However, as discussed above, currently they have to engage in a lot of extra work to make these tools work for them, which is more justifiable when using free versions. During the study participants expressed a growing interest in exploring premium LLM tools often for reasons of speed and access to increased features. As General contract and supplies_partner says "*And I begin to think the best way to get more is by paying. [rather than using multiple different tools and collating information]*".

In addition to performance issues, there was a prevalent concern about how free versions handle data. Participants were certainly aware and concerned that their data might be used in ways they were not entirely clear about, especially for model training purposes. To work around this, participants described being selective about the types of data they input into AI systems. As one respondent (Import_Sales&Marketting) stated,

"*ChatGPT hasn't given us a reason to have any concerns. It's not like the information that we fed it, we'll find it, somewhere. So far, we haven't seen such a case […]. And also, it's because the data that we feed it is very basic […] Kindly draft an email to John requesting a meeting stating that you're grateful" as opposed to, "our critical data [e.g. monthly sales figures], we don't give it.*"

Participants employed strategies such as using synonyms to protect confidential information or avoiding the use of AI tools for business-critical data. For instance, a CEO in one of the creative writing platforms in Kenya explained that while he would find ChatGPT useful for reviewing his customers writing, he refrains because "*that's someone else's idea. I don't know. I'm not so sure about the back end of Chat GPT, to be honest.*" This reflects a broader sentiment about the systems' handling of sensitive or proprietary information.

Participants also questioned what constitutes fair use of their data. Some participants saw the use of their data as a potential trade-off for use of free versions of the tools. Although an operation manager in one of the financial service sector expressed frustration that AI might use her data without attribution: "*They're taken to their advantage and yeah, yeah, without giving me credit for it.*" However, in the context of paid versions, this is not considered fair use. However, participants are aware of the need for training data to improve model performance. IT_CEO described the situation as a "*tricky balance because AI only becomes better if you feed it more data*" and suggested a profit-sharing model where models could be trained on customer data to improve, but customers would also benefit from this directly. Participants also questioned the sourcing of images used in AI outputs and the ownership of intellectual property in generated content.

4.4.2 The Impact of Fabrication on Use and Trust. A defining characteristic of generative AI systems is their propensity to fabricate, aka hallucination, producing outputs that are plausible but incorrect. Participants were reflective about the accuracy of the AI outputs, for example, OutdoorRecreation_CEO explains, "*The last prompt I made was I was writing a piece on […] how much e-bikes are transforming the space of cycling in Kenya […] it was really accurate.*" However, they recognized the need for human oversight informed by their experience with search, as Printing_ResearchLead explained,

"*It's not the gospel truth. It's yeah, it's just a tool that's giving you information. It's just like as good as a search engine, when you type something in the search engine, and it gives you the results, it's up to you to pick up that information and trust how much of it is true and how much of it is not*."

However, inaccuracies and fabricated citations were damaging to trust. Achitect_Designer noted that recent experiences with ChatGPT had led them to question its credibility: "*Of late, we've had instances where ChatGPT has given us less than accurate information, and we're beginning to, you know, question its credibility*." The inability to trace answers back to credible sources exacerbates this mistrust. As a sales and marketing lead in the imports and goods distribution sector pointed, "*Your answer is not wrong, but your source, your reference […] is so wrong it's nonexistent*" going on to say "*I don't understand how you can have all this information. but not have reference points*".

Whilst participants understand the need to assess system output, its usefulness in information gathering is determined by how accurate its output is and the production of non-existent references or fabricated information erodes participants' trust in the system, just as the production of accurate content can build trust. As noted elsewhere [72, 82, 126] the disconnect between the AI's apparent confidence in its responses and the accuracy of those responses underpins concerns about the reliability of generative AI systems. In particular it puts the burden of fact-checking and accuracy on the user. This might be reasonable for expert users who are more likely to be able to identify fabricated output but is likely to be more problematic for novice users. Some of our participants did not use it for factual research, as CreativeWriting_CEO illustrates "*I don't use it mostly for facts […] for research I use Google.*". However, other participants appreciated the summarization function of generative AI in search, and this, combined with the generative AI response being placed at the top of the search results, encourages users towards generative AI as a search tool.

Fabricated output does not result in a complete breakdown in trust, as users rationalize about why they might get a particular answer and what that means for the use of the tool. Trust in Generative AI, as everywhere, is situated. It is not binary, rather it is tied into the task and context. Many users had adopted a "*copilot model*" of interaction with generative AI, wherein AI outputs are iteratively refined and verified. Telecommunications_CEO described this process:

"*The content may not be a hundred percent accurate. OK, so yeah, you really have to check the content and make sure it's aligned with what you want to achieve, otherwise you will be taken by surprise.*"

4.4.3 Doing Business in Africa – Generative AI Performance in Context. Some of the most notable findings from this research related to how the performance of generative AI breaks down frequently in African business settings. In this section we elaborate on how generative AI performs in the African context. It is important to note that participants were not specifically asked about performance on matters relating to Africa, rather these surfaced naturally, typically when participants were asked about where generative AI did not work well for them. Participants found difficulties producing appropriate and relevant content in all forms of generative AI, spanning text, image and speech systems.

Both Kenya and Nigeria are countries with rich and diverse cultures and languages. As a consequence, participants often wanted generative AI output to reflect this context, for example, where they were producing content for their local market. At times generative AI was successfully used to produce local content. For example, IT_CEO highlighted how a Nigerian creative had employed generative AI to generate "*images of old Africans and the fashion on the runway*" illustrating the potential of AI in producing content that resonates with local cultural contexts. Further several of the businesses in our study operated across multiple African countries and wanted to use generative AI to help navigate these cultural and contextual boundaries. However, despite this wish only one business reported a successful use. Achitect_Designer leveraged ChatGPT to suggest culturally and linguistically relevant names for a client in another African country, explaining, "*I used it to suggest names… related to the language of that country… which we as Kenyans aren't familiar with*". We can see that generative AI can certainly be used to generate content appropriate to African settings, however, these examples were few and far between (and one was not about the interviewees own use but them reporting someone else's use).

However, the system's successes were counterbalanced by numerous failures. Generative AI often produced inaccurate or misleading outputs in African contexts, particularly when dealing with local languages and cultural knowledge. We describe four categories of failures found in our data.

Limited African language support. Participants found that their languages were not well supported. For example, MultimediaJournalist_COO said

"*I asked something in Hausa language and it gave me something else so I felt it is not understanding the language. Not that it doesn't know. It doesn't have some sense of the content. If I should ask the same question in English Do you get what I'm saying? It will be able to give me those answers*"

Participants wanted generative AI to support their work across languages for example DigitalMarketing_CEO was writing ad copy and explained

"*I don't know the name of spices in Hausa despite me being Hausa at least like the words skip out of my head and I wanted to like just rush back to ChatGPT and ask what is umm spices and it give me like Kununwuta*".

However, this was not possible and where LLMs were used for translations to African languages they were poor "*I find it very hard to even comprehend what it is saying in terms of its translation pattern*" MultimediaJournalist_COO. There are around 88 million Hausa speakers. Even in the positive example above where Achitect_Designer was using generative AI to help with name generation in another language, the system was prone to errors. As Achitect_Designer explained, "*GPT told us in the local language this word means this. But upon further inquisition, we found that those were not actually facts*."

Whilst the limited language support is a well-known problem of LLMs [5, 87, 124], the challenges of using generative AI in African contexts go well beyond language.

Limited geographic localization. Generative AI also lacks sufficiently localized content, impacting participants ability to generate the content they desired. For example, a general contractor and supplier described how he might want information about the products in a particular market.

"Sometimes I will ask something about KANO. but I will not get enough information about KANO […] Like to see Kwari market in Kano. or Sabon Gari market in Kano. So, the information I will get. Is it will be scanty"

At other times, the AI will produce content, but it might be fabricated as an associate lawyer explained:

"So I went deep into traditional African culture and asked it what is the Genesis version of the Meru people […] The first version, I'm also from that tribe so I knew it was wrong, so I went back again 'that is wrong, give me the correct one'. It went in again and gave me a different version. So which point do you believe? Story (a)

which was the initial question, or story (b) which the only difference I said is that's wrong, give me another version and another version appeared?"

Image systems too, suffered from a similar lack of localization, producing inaccurate content, as OutdoorRecreation_CEO described of an image prompt for hiking "*In the landscape there's not much coherence because it was not even African – there was snow!*" Achitect_Designer confirmed "*Sometimes it doesn't really understand [the] African nuances that you're trying to prompt it*".

Misrepresentation of African Identities was another reported concern. For example, image systems often generated poor quality images of Africans, as CEO of an outdoor recreation company describes prompting an image system for "*a black man sliding in a hike*" which produced unusable output because "*if you look at the black person's face you can't really say this is real black, you know. So either they have a black face and white man's hair*". Similarly, DigitalMarketing_CEO described trying to generate an image of a Nigerian girl, but the result resembled "*an Irish girl*" with features that did not align with those of Nigerians.

Speech-based AI systems were also found lacking in their ability to recognize and generate African accents. Achitect_Designer described how transcription systems often misinterpret local words, altering the entire context of conversations. Similarly, IT_CEO noted that AI-generated voices tended to default to "*a white woman or a white man*" with no representation of African voices: "*I want to hear the voice of a Yoruba woman or, Igbo woman or, a Kenyan woman […] We need more representation*." This challenge even extends to voice cloning, as the same participant lamented that the coning system gave her a British accent, which "*takes away from my originality, which is I am not British, I am Kenyan*" (IT_CEO).

Western bias. Finally, the systems were found to have a strong and evident Western bias by our participants, one which they encountered in their everyday work. Participants attributed this to the belief that these systems were primarily developed by individuals from "*the West*". As Design_CEO rather starkly explains:

"*Because I think because ChatGPT was invented by white men, so the information it has, most be moved from that European people or these white men than Africans. This is what I have just conceived in my mind. It cannot be true, but I conceived it because mostly whenever ChatGPT has to give you the information about someone, unless if you have specified, ChatGPT usually gives the names of this European maybe because they are more educated than black people or something like this. But whenever I have to narrow him (ChatGPT) to the Africans, I have to specify that I need Africans information or African names of this*"

Here we can see that it is not that the systems do not have that information in them, just that it is not readily surfaced without extensive prompting. This resulted in immense frustration, Design_CEO shared that when ChatGPT was consulted for role models in his field, it defaulted to examples of white men, ignoring the contributions of Black men. He expressed frustration at having to ask repeatedly for African names: "*I sometimes ask him (ChatGPT), 'You have been mentioning this white man? What about Black men*?'"

Participants experienced generative AI as "*really Americanised*" (LegalService_Associate), reinforcing Western perspectives even when African data is incorporated into these systems. As he puts it, "*Because of the heavy reliance on datasets from the West, only the Western perspective is embodied in the system*." This dynamic is particularly evident when generative AI is tasked with referencing African legal or cultural information, as the systems tend to default to non-African sources or frameworks. The associate lawyer shared frustration with AI's inability to accurately respond to questions about Kenyan law, instead referencing U.S. legal systems: "*They'll reference the people in the US, which is insane because we have Kenyan authors. We've also done the actual work*."

Impact. As we have shown, the poor performance of generative AI in African contexts, not only impacts AI's accuracy but also its usability for African businesses. CreativeWriting_CEO, who runs a platform for African writers, saw potential in AI's ability to assist with writing but was skeptical about its capacity to reflect "*African ways of knowing*." As noted by IT_CEO, "*Most of these tools don't have African voices or African perspectives or even African names*." The lack of diversity in the AI industry was cited as a major obstacle to creating systems that genuinely serve African interests. Overcoming this challenge, as Achitect_Designer pointed out, will be key to leveraging AI "*for the betterment of humanity and the democratization of skills and basically empowering people*".

5 DISCUSSIONS

In this paper we outlined the findings of a study about how small and medium businesses in Kenya and Nigeria used generative AI technologies at work. This research provides insights into how different aspects of generative AI are playing out in practice, as well as speaking to questions around the democratization of AI.

Our study shows the many ways in which generative AI is being deployed in both creative and mundane work, showing that, even in these early stages of deployment, it is already a valued workplace tool. Businesses in our study used a wide range of generative AI tools, including text generation, image generation, meeting assistants and speech and video generation tools. The versatility of text and image generation make them particularly powerful workplace tools. Whilst SMBs were excited about how these tools positively impacted on their productivity, their knowledge and their reputations, they put in considerable work to get the best out of these tools. Participants employed a variety of methods to navigate the strengths and weaknesses of different tools, including 'cross-carpeting', meta prompting, using add-ons and personalising output for their audiences. So far generative AI has not fundamentally changed the way in which work gets done but was made at home [111] within existing practice, knowledge, and ways of working. Unlike both customer support [27] and GitHub Copilot [65, 104, 136], the Generative AI tools used were not fine-tuned for specific types of work. That such tools already improve productivity is promising.

5.1 Tools for experts or instead of expertise?

Previous research found that generative AI could improve productivity at work [104], [5], however this may come with a quality trade-off [65, 136] [46, 61, 67, 110]. By and large, in this study participants were using AI to support and complement their professional expertise. Participants used generative AI to facilitate and reduce the burden of aspects of both creative and mundane work – whether to inspire new ideas in less time or to wordsmith everyday or tricky emails. Participants wanted to free up more time for work which maximised their expertise. Technology which reduces the burden of, for example, document work has long been a wish of workers worldwide (e.g. nurses [75] and local government workers [93]. However, until now most workplace technologies have only increased this work (see for example, [25, 105]. The possibility of addressing this is one of the most promising aspects of generative AI.

However, it is important to note the limitations inherent in these systems, which generate new content based on patterns and structures within existing datasets and the prompts they are given. Fabrications, whether plausible but untrue text or mixed-up images, are inherent to their generative nature. They go hand-in-hand with positive traits such as producing human-like content. Generative AI output can also miss important information [70] and produce low-quality, generalized content, depending on how it is prompted [90]. Our participants had built up a practical understanding of the generative nature of AI and how it works without necessarily understanding it technically. Like previous research into developers [23], participants built this knowledge through use and experimentation and played around with prompt engineering to produce the output they desired. Seeing how the system performed on the topics of their expertise, whether e-bikes or the Meru people, helped users determine its strengths and weaknesses. Of course, it is much easier to spot errors in our own areas of expertise, so fabrication can be less of an issue there. Luckily much of what we do in the workplace does tend to fall within our areas of expertise.

Natural language interaction with Generative AI helps build practical understandings of appropriate business use and establish appropriate levels of trust [133]. Whilst inaccurate output erodes trust to some extent, it does not do so wholly, and participants continued to use Generative AI. Instead, participants deployed a collection of methods for working around the limitations of these tools. The generative nature of AI comes into its own when inspiring creativity. Brainstorming typically includes the philosophy of 'no bad ideas' and is well supported by generative AI. For mundane work it was mostly used to generate new versions of existing content, which largely mitigates against fabrication. It was in factual research and work involving African contexts (see below) that the generative nature of AI became most problematic.

Whatever the work, participants agreed the onus was on the user to check and refine the output, which was rarely taken as is. However, we also are beginning to see other uses where generative AI was being used instead of expertise. In particular, Contract&Supplies_Partner were able to contribute extensively to a joint proposal in an area they did not have a deep understanding of. It is not possible to know from the interviews if this is a worrying use of AI, but it does hint at how generative AI might change the role of professional expertise. Given the tendency to fabricate such uses merit further investigation.

5.2 Democratisation of AI Use

The ready use of generative AI technologies at work by these small business in Kenya and Nigeria speaks to the democratisation of AI use. Most of the participants were not technology experts, and were employed by or owners of small businesses and start-ups, yet they were able to deploy powerful AI functionality in their work. Previously, only larger businesses, or businesses with the resources for a machine learning team, were easily able to deploy AI. Only the lawyers in our study previously used AI tools and these were expensive proprietary tools reserved for large cases.

Generative AI has the capacity to enhance both organizational and individual capabilities, and as such offers transformative possibilities for SMBs. These tools are already reshaping the digital landscape in Africa, challenging the narrative that the continent is being "left behind" in technological innovation. It is important to include such narratives of real-world technology use in our disciplinary dialogue because it provides a useful counterpoint to papers focused on technology for development. Whilst technology for development is an important research area, it is equally important also to understand the technology use and needs of everyday businesses. By examining the use of generative AI tools by businesses in Kenya and Nigeria, we encountered a set of stark examples showing the limits of democratisation with current generative AI models and technologies. That is, for all these technologies might be said to democratise AI by making it more accessible and available, the underlying models, and the technologies built upon them, have a number of limitations which impact their relevance and usefulness for African business contexts.

For example, even major African languages such as Hausa are poorly supported. There are over 1,000 languages spoken on the continent, including more than 75 languages that each have over a million speakers. The vast majority of these have limited support in AI systems [8, 63, 101]. Whilst models such as GPT4 have vastly improved “language understanding” of some mid-resource African languages [100], language production lags behind, and many languages remain poorly supported overall. Generative AIs limitations in respect to African languages is the most researched and least surprising of the local/contextual challenges surfaced. We already knew that AI has a language problem, but what our data highlighted – being focused on real business use cases - is that equally importantly, AI has a ‘knowledge’ problem. Text, image and speech AI systems often failed to meet business needs for processing and creating content reflective of African contexts. We found examples of Western bias, limited geographic localization and the misrepresentation of African identities. When considering these findings, it is worth remembering that we did not ask participants to surface such examples, rather they were surfaced naturally when discussing the challenges they faced using generative AI. That almost all of the challenges raised related to the African context, is revealing.

The diversity of languages, cultures, and contexts across the African continent pose specific challenges for generative AI systems, most of which are developed and trained predominantly on data from the Global North. Taking image models for example, participants experiences suggest that these models do not adequately reflect African facial features, cultural aesthetics, or landscapes, a finding which extends the work of [107]. This compounds the inherent challenges of image generation, which tends to produce something of a mishmash of elements in response to any prompt, such as the commonly seen extra limbs and nonsensical image components.

The inability to adequately represent African contexts and cultures is likely to stem from imbalances in the training data; how the training methods are designed and applied; and the difficulty of surfacing data within the models but which sits at the tail of the data distribution [73, 89]. If left unaddressed, the combination of inequitable language and knowledge support is likely to compound existing systemic inequalities.

5.3 The data divide

Whilst access was, and remains, an important issue when it comes to the digital divide, this paper reinforces recent concerns about AI introducing new divides. In this research the data divide came clearly to the fore – that is, the consequences of the lack of representativeness and equivalence in the training data and processes such as labelling, reinforcement learning (e.g. RLHF), etc. Other research is needed to examine the other AI divides such as those around compute and the socioeconomic conditions around who gets to create, deploy and benefit from AI [123].

Our study builds on Gondwe [51], to show how the data divide plays out in the everyday work of SMBs in Africa. There is appetite, and business cases, for using generative AI to understand, create content, conduct research for, and evaluate content across African cultures and contexts. However, the lack of diversity in these tools emerged as a serious and frequent concern, with generative AI generating false, poor or unrealistic content for African contexts across all modalities. This went beyond the stereotyping found in [51] and included contextually confused images, inability to process or produce diverse accents, and generating text which prioritises 'Western' ways of thinking. All of which impacts usability and trust. Whilst all the examples are troubling, the prioritisation of 'Western' ways of thinking is perhaps the most worrying, given its likely invisibility to those outside of African contexts. Clearly there is much work to be done. This is a matter of concern to both the authors and the participants themselves who worry that if not solved these tools will recreate systemic inequalities "*We are continuing that cycle, which really has to be broken because our future generations cannot go through the same problems, you know, that we've gone through*" (IT_CEO).

5.4 Making regional bias explicit

Whilst the lack of representation in AI models has been widely studied, the research has tended to focus on demographic biases, such as gender, occupational gender [38, 44, 48, 52, 54, 77, 92, 116, 120, 125] and racial biases [31]. This study adds to the small but important body of research examining model performance in global contexts [13, 51, 107]. Given the underrepresentation of research in this space, we propose adding an additional category, that of **regional bias**, to the existing categories of bias commonly examined in Generative AI research [42]. Regional bias goes beyond demographic biases like race, although it will be compounded by them [33]: whole continents and their knowledge are severely underrepresented, and this comes through clearly in use. By making this category of bias explicit, we hope to draw the attention of fairness researchers and the AI industry to its importance and therefore to the business of redress. Currently regional bias only surfaces in passing reference outside of language communities, who aim to evaluate and address the poor multi-lingual representation of these models [e.g. [6, 8, 99]]. Whilst this is important and necessary work, addressing regional bias will require additional work, if we are to go some way to solving AI's knowledge problem. We hope this paper, alongside Qadri et al. [107] and Alenichev and Grietens [13] will bring this issue to the forefront of generative AI research. Given the situated nature of workplace AI use, we join the call for more globally diverse researchers, and more African voices [4], at the front and centre of AI research.

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