Literature Review

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Spring 2025

1 Introduction

Entrepreneurship is a multifaceted landscape, and understanding the reasons and motivations that drive individuals to enter entrepreneurship or begin a venture is one part of the phenomenon. The literature points to differences in motivations for entering entrepreneurship. While some people enter the entrepreneurial landscape based on need, others do so by choice. More specifically, researchers refer to these distinct choices as necessity-driven entrepreneurship and opportunity-driven entrepreneurship [3, 14, 8, 17]. Opportunity-driven entrepreneurs are often "*pulled*" into entrepreneurship [14, 17], motivated by their desire to follow a market opportunity [3] or start a business by choice because they have idle capital to exploit [8]. On the other hand, necessity-driven entrepreneurs are often "*pushed*" into entrepreneurship [14, 8, 17] due to employment barriers and limited access to basic resources [8] and a lack of alternative job opportunities and choices [17]. Oftentimes, necessity-driven entrepreneurs include individuals striving for economic stability as a means of survival and fundamental income generation [3]. Although the dichotomy of the terms has led to criticism about the overly simplified nature of the reasons for entering entrepreneurship (either necessity or opportunity) [17], for this literature review, the terms offer a foundation for exploring the differences between each motivation and how an understanding of an entrepreneur's background can inform the design of generative AI technologies.

Moreover, generative AI has become an increasingly integrated part of workplaces and entrepreneurial practices [9, 23, 11, 12, 6]. While there is limited research on the use of generative AI from the perspectives of entrepreneurs [6, 12], most of the literature on the use of generative AI by entrepreneurs covers AI more broadly, including its benefits in the workplace such as increased productivity [9], the creation of innovative products and services [23], and its potential to effectively design scalable business models [11]. Related to the adoption and use of generative AI, trends in the literature are beginning to highlight the concept of the "*additional labors*" involved when using generative AI tools. Some of these labors include the "*pre-,*" or steps needed for a user to organize and clean inputted data, and "*post-processing,*" or steps needed to take the generative AI outputs and turn them into useful information or artifacts [12]. Additionally, the literature on the opportunities and challenges for gig workers with disabilities also points to the "*invisible labor*" involved for disabled gig workers, including unpaid activities, workarounds for inaccessible applications, and emotional labor, all activities which often go unnoticed [20].

At the same time, with the rise of generative AI, researchers are investigating the need for understanding design guidelines as well as the sociotechnical infrastructure required for building generative AI systems. Some argue that technologies are part of larger systems and that human and social factors are crucial for a sociotechnical system to function and operate [13]. Others highlight key design guidelines for developing generative AI tools such as making clear what the system does and designing for mental models [25, 1]. HCI researchers have also more recently explored how people and communities demonstrate **resilience** amid socio-technical-natural systems [19], the adoption of mandated financial systems [10], and in low-socioeconomic-status environments [24]. Other papers highlight the role of **agency** [4, 22, 18] in the context of generative AI systems, suggesting that it has an important role as we consider the sociotechnical infrastructure of such tools.

Therefore, based on key studies from 27 selected sources, along with patterns, trends, and gaps identified within these papers, this literature review aims to synthesize insights across the literature into three thematic and interconnected areas:

1. The landscape of necessity-driven and opportunity-driven entrepreneurship
2. The additional labors and realities of using generative AI
3. The potential for designing generative AI systems that can foster resilience and agency among entrepreneurs

By exploring literature across these areas, this review seeks to shed light on the unifying factors between entrepreneurs from diverse backgrounds, the ways that generative AI systems can be designed to empower and support an individual's agency and resilience, and the continuous and intentional identification of the additional labors involved in adopting or utilizing generative AI tools.

2 Necessity-driven and Opportunity-driven Entrepreneurship

When asking how entrepreneurs can leverage generative AI systems, investigating entrepreneurs' *motivations* to first engage in entrepreneurship became a key driver for approaching the question. Overall, there is consensus in both the Entrepreneurship and HCI fields that necessity-driven and opportunity-driven entrepreneurship are distinct categories that reflect reasons for entering entrepreneurship. The subsections below detail key studies from both the HCI and Entrepreneurship fields, and unpack definitions for both terms, the experiences and challenges specific to necessity-driven entrepreneurs, and the role digital technologies can play for any entrepreneur.

2.1 Defining Necessity-driven and Opportunity-driven Entrepreneurship

The term "*necessity entrepreneurship*" (NE) was first introduced in a 2001 report by the Global Entrepreneurship Monitor (GEM) and is presented as entrepreneurial activity driven by survival or lack of employment choices [17]. Individuals who are pushed into entrepreneurship often do so as a result of employment barriers, unexpected life disruptions, poor job satisfaction, and survival strategies [17, 8, 14]. Liñeiro et al. (2024) add that necessity entrepreneurs can be exemplified by individuals who are "*striving for economic stability*" and *"typically embark on new ventures as a means of subsistence and fundamental income generation."* On the other hand, opportunity-entrepreneurship (OE) is typically pursued by individuals who are pulled into entrepreneurship by identifying a business or market gap or potential innovative areas and are driven by the possibility of financial independence, autonomy, or personal fulfillment [3, 17]. Compared to necessity-driven entrepreneurs who may lack access to basic resources, including a stable income, opportunity-driven entrepreneurs often possess idle funds to invest in risky ventures, and more importantly, enter entrepreneurship by choice rather than by necessity [8].

Although NE and OE are often presented simultaneously and in similar conversations within the entrepreneurial landscape, researchers note that this dichotomy has led to the oversimplification of each term, minimizing the complexity of both the decision-making process that individuals embark on when entering entrepreneurship, and the design of policies for both necessity-driven and opportunity-driven entrepreneurs [17]. Furthermore, studies have shown that the two distinct motivations are also reflective of a global divide where it is often believed that NE is more prominent in the Global South, while OE is more closely representative of entrepreneurship in the Global North [17, 8, 3]. However, Hui et al. [8] caution against this belief, indicating that there is a wide range of necessity-driven and opportunity-driven entrepreneurs around different parts of the world. Lastly, in describing both groups, studies have found that the subjective well-being (SWB), defined as the "*affective element in a person's experience*" and exemplified by a person who likes their life, tends to be higher among opportunity-driven entrepreneurs than necessity-driven entrepreneurs [14, 17], underlining the multilayered and complex nature of each category.

2.2 A Deeper Dive Into Necessity-Driven Entrepreneurship

Three key studies provided a deeper analysis of what necessity-driven entrepreneurship entails. The first study by Mueller and Pieperhoff (2023)[17], an integrative and systematic literature review of 252 articles between 1986 and 2022 on necessity entrepreneurship, contributed a multi-level and process-oriented framework to understand necessity entrepreneurship. The framework is structured around four key components, the first one being Applied Theories which includes six theoretical perspectives used to understand NE: 1. Motivational view (focus on individual drivers such as basic needs), 2. Psychological view (well-being, satisfaction, identity), 3. Behavioral view (Theory of Planned Behavior), 4. Capital view (focus on human and social capital), 5. Economic view (connections to macroeconomic conditions and economic growth), and 6. Institutional view (culture, social, and regulatory environments). The second key component of the framework focuses on three Antecedents of NE: Individual Level, Organizational Level, and Environmental Level. The individual level includes low education, family responsibilities, and urgent income as necessity-based factors for entering entrepreneurship. The organizational level covers job loss, poor working conditions, and lack of advancement opportunities, while the environmental level considers discrimination and regional disparities as motivations for NE.

The third component is the Manifestations of NE, which points to different populations and how they engage in necessity entrepreneurship, such as women's entrepreneurship, immigrant and ethnic entrepreneurship, youth and senior entrepreneurship, and informal entrepreneurship. For immigrant entrepreneurship, for instance, studies show that first-generation migrants are often motivated intrinsically (such as economic instability) and pushed into entrepreneurship, while second-generation migrants are motivated more intrinsically, that is, by opportunity, and are often pulled into entrepreneurship. Finally, the fourth component of the framework highlights the outcomes of NE, pointing to mental and physical health, business impact, and economic impact, summarizing that NE typically leads to smaller and less growth-oriented businesses and may contribute less to innovation and job creation in comparison to OE. Overall, this systematic literature review presents a holistic review of necessity entrepreneurship and contributes a process-oriented perspective of the phenomenon, suggesting that it is not a rigid category but one that is fluid and continues to evolve. The paper suggests that recognizing the four key components of the framework, along with the experiences, education, environmental conditions, and barriers of NE, can help individuals transition from necessity- to opportunity-driven entrepreneurship over time.

Another paper titled "*Making a Living My Way: Necessity-driven Entrepreneurship in Resource-Constrained Communities," [8]*describes the reasons micro-entrepreneurs in Detroit are pushed into entrepreneurship. Among those reasons are unexpected life disruptions, barriers to employment, and most notably, a desire to benefit the community. In addition, the paper outlines how social technologies impact entrepreneurs in resource-constrained environments. Social technology is defined as "*any type of online tool or platform that allows people to communicate, interact, and/or share information or resources with each other.*" Some examples include Facebook, Instagram, Uber, and LinkedIn. Hui et al. (2018) conducted semi-structured interviews with 26 local micro-entrepreneurs in Detroit and observed 7 Detroit-based events related to entrepreneurship. They define micro-entrepreneurs as "*people who own a formal or informal business of less than 5 people, generate income, and regularly interact with locals in their neighborhood.*"

Findings point to the need of necessity-driven entrepreneurs to be in "**control**" over their financial stability, privacy, and day-to-day work. In unstable economic conditions, participants saw entrepreneurship as the "*most resourceful pathway*" to have financial stability and guard against potential disruptions. Some participants saw "odd-jobs" as longer-term employment opportunities rather than temporary solutions. Further, participants described establishing legitimacy around their business *offline* first and then online to bootstrap their customer base in a controlled manner to prioritize their privacy. Findings also indicate that compared to opportunity-driven entrepreneurs, necessity-driven entrepreneurs use social technologies to promote community development over competition, stability over risk taking, privacy over self-promotion, and safety over convenience. Finally, the authors argue that in order to support professional agency among microentrepreneurs in resource-constrained communities, social technologies should 1. Prioritize privacy (*ability to control how one's personal and professional information is presented and shared with others*) and safety (e.g. supporting process of screening customers), 2. Allow for increasing levels of independence (e.g. personal branding and customer base), and 3. Facilitate local engagement (e.g. recommending small group participation with other entrepreneurs for local knowledge-sharing).

While the last paper by Sannon and Cosley (2022) [20] does not directly reference NE, it investigates the experiences and challenges of gig workers with disabilities, specifically focusing on four different types of gig work: ridesharing, delivery, crowdwork, and freelancing. The first author engaged in observational fieldwork (Amazon Flex and Amazon Mechanical Turk) temporarily, and then both authors conducted hour-long semi-structured interviews with 24 gig workers with disabilities. Disabilities included physical disabilities (chronic illnesses and mobility impairments), mental health conditions, and blindness. The researchers investigated the following research questions: How do disabled workers experience working on different gig work platforms? How do characteristics of particular platforms, impairments, and people combine to shape these experiences? What are the risks and opportunities of gig work for disabled workers as compared to traditional workers?

Findings suggest that the low barrier to entry is a main reason why disabled workers do gig work, as participants could start gig work within a short time and did not have challenges such as discrimination during hiring practices and explaining employment gaps. Other reasons included flexibility of time, location, effort, and social interaction. However, this flexibility often came with a cost, such as income constraints based on public benefit laws. It is important to note that while gig work provides disabled workers with opportunities to earn income, participants noted that doing gig work was not their ideal choice, but it was often rooted in their need to sustain themselves with jobs that could match their abilities. The challenges encountered while doing gig work included inaccessible tasks, which would often arise well after participants had invested time and effort in a task, inefficient and costly workarounds such as taking longer for recording and transcribing, and algorithmic evaluation concerns which penalized disabled gig workers for with lower ratings and often put their health at risk. Other challenges include limited control and agency over tasks with multiple dimensions (location, weight, access), power dynamics issues with customers with unaccommodating expectations, privacy and surveillance issues, and tensions with disclosing disabilities.

Recommendations for the design of gig work platforms included: transparency and task selection, control over workflow and adaptable gigs, and supporting preferences vs disclosing disabilities. They also provided additional suggestions for mitigating unfairness, discrimination, and negative interactions, such as institutionalizing vetting inside platforms to charge or ban troublesome customers and make their customer history visible.

2.3 Digital Technologies: Opening Avenues Related to Entrepreneurship

While most papers in this section describe the dynamic nature of necessity-driven and opportunity-driven entrepreneurship, the paper "*Digital Entrepreneurship: Toward a Digital Technology Perspective of Entrepreneurship,*" [18] invites further reflection on how digital technologies may disrupt, reinforce, or reconfigure necessity and opportunity entrepreneurship. In particular, Nambisan (2017) argues that digital technologies have transformed the nature of entrepreneurial uncertainty, agency, and outcomes by introducing more fluid and distributed forms of entrepreneurial activity, that is, when and where entrepreneurship happens and the evolutions of products and services. Nambisan proposes that digital entrepreneurship is characterized by "less bounded" outcomes and a "less predefined locus of entrepreneurial agency," where acknowledging that various goals, motivations, and capabilities exist becomes critical, as well as understanding that value creation is spread across networks of actors including users, platforms, and infrastructures (e.g. crowdsourcing platforms).

This shift can be connected to the assumptions about who can become an entrepreneur and how opportunities are presented to different groups in digitally mediated environments. For instance, platforms like crowdfunding sites, social media, and makerspaces allow new actors, including those with limited capital or formal business training, to participate in entrepreneurial ecosystems. Drawing from the less bounded perspective proposed by the paper, digital technologies have the potential to lower barriers to entry, enabling necessity-driven entrepreneurs to start ventures in ways that may not have been possible before. At the same time, however, digital infrastructures can introduce new challenges and Nambisan's work opens up key questions for researchers and designers. For instance, do digital platforms truly lead to the "*democratization of entrepreneurship,*" or do they simply reconfigure access in ways that continue to favor opportunity-driven entrepreneurs? Particularly, how might generative AI systems support the experiences or exacerbate the challenges for necessity-driven vs opportunity-driven entrepreneurs? The following section will explore the latter in more detail, spefically unveiling the additional labors of using generative AI.

3 Additional Labors of Using Generative AI

As digital technologies, in particular, generative AI tools become increasingly present in entrepreneurship, their promise of "simplicity" often masks the complex forms of labor required to use them effectively [12]. Drawing inspiration from Avle et al.'s work on the "*Additional Labors of the Entrepreneurial Self,*" [2], in this section I explore three dimensions of the additional or invisible labor involved when using generative AI: (1) the multiple skills required to effectively engage with generative AI, (2) the conceptual ambiguity around AI's role as a collaborator, agent, or tool, and (3) the regular experimental and iterative work entrepreneurs must take on to meaningfully adopt these technologies.

3.1 Additional Labors and Skills Required for Effective GenAI Use

Avle et al. [2] argue that while life in low-income cities is already entrepreneurial due to people resorting to multiple jobs and gigs to make ends meet, there are *additional labors* that are often invisible but critical to communities in resource-constrained environments. Through ethnographic case studies in a city in the Global South, Accra, and a city in the Global North, Detroit, researchers investigated how participants acquired digital skills throughout their entrepreneurship journeys and found that necessity-driven entrepreneurs take on the labor of continual *self-upgrading*. This includes teaching themselves new tools, managing multiple digital identities, traveling long distances to attend trainings, events, and workshops, and keeping up with shifting platform features, all while managing income-generating activities. For some entrepreneurs in Accra, traveling long distances was not an issue; however, traveling short distances in a "demanding landscape" of informal public transportation and unreliable address systems introduced additional labors of planning for transportation issues and spending time asking community members for event location details, taking away from their limited time and resources. Additional labors included technology awareness and maintenance — some entrepreneurs had to purchase affordable smartphones due to limited capital, but eventually had to pay for fixes related to poor device quality, revealing how labor is not simply technical but also deeply contextual. The paper suggests that to reduce the burden of entrepreneurial efforts in low-resource contexts, researchers and designers should (1) orient toward group-based support systems, (2) help to sustain tech repair and maintenance ecologies, and (3) support opportunities for surviving and thriving, all relevant in the context of designing generative AI systems that can proactively support necessity-driven entrepreneurs, acknowledging their motivations for income-generation and minimizing the additional labors involved (including access to training information) in using generative AI for personal and business growth. Finally, as the authors put it, the "*costs to getting up to the same level, for one's entrepreneurial dreams to come true, are quite different*" for necessity-driven entrepreneurs than opportunity-driven entrepreneurs. Intentionally seeking these differences is a first step for unpacking the additional labors of generative AI use.

Kotturi et al. [12] reinforce this point in their study with entrepreneurs from a local entrepreneurial hub in Wilkingsburg, PA, where the local entrepreneurs learned about generative AI platforms through co-designed workshops. Using a community-driven approach, the researchers and community members outlined three workshop goals: meeting entrepreneurs where they are, focusing on hands-on work, and prioritizing a network of trust. This work emphasizes that beneath the "veneer of simplicity" presented by interfaces like ChatGPT lies a complex "laundry list of operational skills," needed beyond prompt engineering including browser literacy, password management, file type conversion, image editing and graphic design, knowledge of cloud and local storage, keyboard shortcuts, and more. Entrepreneurs needed to not only craft effective prompts but also contextualize AI outputs, assess their quality, and iteratively refine them to meet business-specific needs. These forms of labor often required communal scaffolding and trust-building, especially when entrepreneurs lacked formal training or prior exposure to AI tools. This paper importantly highlights the pre- and post-processing steps required for entrepreneurs to not only use generative AI effectively, but to obtain value from these tools especially as it related to their business needs and goals. Additionally, one of the main contributions of this paper was the encouragement of non-use of generative AI based on the entrepreneurs' experiences, business needs, and concerns such as intellectual property and inauthenticity, which in itself can lead to the additional labor of identifying whether using generative AI or not is the right direction.

Finally, to add to the complexity of engaging with generative AI, Long and Magerko's work on AI literacy [16] define AI literacy as a *"set of competencies that enables individuals to critically* *evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace".* The paper proposes a framework which identifies key knowledge areas such as distinguishing between technological artifacts that use and do not use AI, identifying problem types that AI excels at and does not excel at, and identifying key ethical issues surrounding AI (i.e. privacy, employment, misinformation, ethical decision making, biases, transparency), and other core competencies. These competencies are especially important for entrepreneurs, who are often encouraged to adopt AI for productivity and innovation but are rarely offered the foundational tools to fully grasp the technology's benefits and limitations. Entrepreneurs, particularly those with less access to formal technical training, may face an additional labor: being expected to innovate with AI to remain competitive, while simultaneously navigating the behind-the-scences of how the systems work and whether they provide value or not.

3.2 Ambiguity in the Role of Generative AI (and the Literal Invisible Labor of Generative AI)

Another dimension of the additional labor of using generative AI, especially as it relates to necessity-driven (or opportunity-driven entrepreneurs) is the interpretive work required to position generative AI within one's business. More specifically, is AI a collaborator, a tool, or something more ambiguous? While the metaphor of "human-AI collaboration" has become increasingly common, Sarkar (2023) [21] argues that while the term is well-intentioned, it is misleading and takes away credit from the humans and labor behind these systems. Instead, the author proposes viewing AI as a tool or an instrument, claiming that it is more accurate and fairer. The author writes about AI's data annotation industry or 'back office,' stating that in the 'tool' model of credit assignment, the labor sharing and credit assignment are fairly transparent. For instance, the programmer gets credited for writing code and the designer gets credited for using Photoshop. However, since AI systems have a third party, the data labeler, the global industry has responded to the growing need for labelled training data (Scale AI and Amazon Mechanical Turk) by relying on labor from poor countries in the Global South such as India, Venezuela, and Kenya. As an example, Time magazine discovered that ChatGPT relied on toxicity filters trained by Kenyan workers paid less than $2 per hour, leaving many of them with lasting mental health issues. Furthermore, AI developers view workers as "corrupt", "lazy", and "non-compliant," and focus on improving data quality or output rather than engaging with the field workers. While data labeling is often portrayed as an opportunity for "social inclusion and mobility" there is little mobility for the workers in the Global South. Sarkar advocates for viewing AI as a tool and suggests that the push to continue viewing AI as a collaborator may root from humans having a "preoccupation with privileging intelligence that resembles their own" and also points to the need of questioning whether AI truly resembles human intelligence. On the topic of the additional labors of generative AI, this paper, along with findings from Zhang (2023) [26], who documents how the global AI supply chain relies on undercompensated labor from data annotators often in marginalized regions such as western China, take a literal conceptualization of the invisible labor embedded in generative AI systems. Furthermore, when coupled with the additional obstacles that necessity-driven entrepreneurs overcome to use generative AI, the understanding of the working conditions of data annotators may present an even more complex decision for entrepreneurs looking to adopt these technologies in their business endeavors. A key question here is whether these insights will deviate an entrepreneur's decision of using generative AI and whose responsibility it is to inform communities about the invisible labor behind the design and maintenance of generative AI systems.

Expanding on whether AI should be seen as a collaborator or tool, Gupta (2024) [6] encourages entrepreneurs to treat generative AI as a knowledge collaborator, meaning a source of exploratory hypotheses rather than a decision-making authority. This emphasizes the importance of maintaining a critical view, where entrepreneurs have control over AI-generated outputs. Similarly, Satyanarayan and Jones (2024) [22] call for viewing generative AI systems as agents capable of taking initiative and shaping outcomes. They argue that rather than viewing generative AI as a static tool, users should understand these systems as culturally creative agents that not only perform tasks but also shape human behavior, decisions, and relationships.

3.3 Ongoing Experimentation and Labor of Integrating Generative AI

Finally, the process of adopting generative AI is not a seamless or straightforward implementation, but a continuous activity based on regular experimentation. In his study, Gupta [6] empirically validates a generative AI adoption model to understand the factors that influence generative AI adoption among entrepreneurs. The three-staged process includes: the **pre-perception and perception stage** where entrepreneurs gradually explore the technology's potential (influenced by social factors, domain experience, technology experience, system quality, training and support, interaction convenience, and anthropomorphism), the **assessment stage** where entrepreneurs utilize generative AI for more complex tasks (influenced by perceived usefulness, perceived ease of use, and perceived enjoyment, together generating emotions towards the technology), and the **outcome stage** where critical decisions on the use of genAI are made (i.e. adoption of tech, use of human expertise, or switch to alternative technologies).

Findings from 482 surveys with entrepreneurs analyzed using the Partial Least Squares Structural Equation Model (PLS-SEM), technique demonstrate that social factors, domain experience, technology experience, system quality, training and support, interaction convenience, and anthropomorphism are all correlated with perceived usefulness, perceived ease of use, and perceived enjoyment of generative AI among entrepreneurs. Similarly, the statistical values demonstrate that perceived usefulness, perceived ease of use, and perceived enjoyment are all correlated with positive emotions. Finally, positive emotions are correlated with switching intentions. Based on these findings, Gupta argues that entrepreneurs are more likely to think the same way about technology if others in their social circle also find it valuable (social factors), reflecting similar findings in Kotturi et al.'s work [12]. He also claims that entrepreneurs who have industry knowledge as well as awareness of generative AI are in a unique position to use the tool for financial growth and that having familiarity with the tool (and other technologies) provides the confidence to experiment with new technologies like generative AI. Additionally, Gupta states that entrepreneurs are more likely to adopt new technologies that stand out in terms of quality, performance, accuracy, maintainability, and accessibility, but that experimentation is required to understand how the tool can meet their business needs. Finally, the author states that the decision-making process (adoption model) is heavily influenced by the emotional connection to the technology, meaning the positive and favorable feelings that show up for entrepreneurs when using generative AI. Gupta's work highlights how integrating generative AI can be a process that is deeply labor-intensive as entrepreneurs navigate through the three different stages which can be considered additional labor for necessity-entrepreneurs who don't have ample time to experiment as they strive to maintain income stability in their day-to-day operations.

The 2024 report from Microsoft's research initiative on AI and productivity explores how productivity gains are associated with LLM-powered productivity tools like Microsoft Copilot [9]. Drawing from more than a dozen studies conducted by Microsoft researchers that focus on generative AI in the workplace, the authors note that while generative AI can increase productivity, its benefits are dependent on contextual factors such as an individual's role, domain, and support infrastructure. They also highlight that early adopters often face cognitive overload when first using these tools and that productivity gains depend on a period of extended acclimation, experimentation, and refinement, indicating a less visible labor that may not be as easily achievable by necessity-driven entrepreneurs. The researchers also introduced the concept of "AI Power Users," defined as "*individuals reporting being familiar with generative AI, using it at work at least several times a week, and saving more than 30 minutes a day by using it,*" noting that regular experimentation with AI emerged as the most significant predictor of an AI power user. Insights from this report challenge the assumption that AI automatically reduces labor; instead, it often reconfigures or hides additional labors involved in the integration of these tools, placing high demands on entrepreneurs to quickly adapt these tools for productivity and benefits, all while managing numerous contextual and invisible labors.

Lastly, Kostis et al. (2024) [11] frame generative AI as a mechanism for "*learning-by-conversing*," where entrepreneurs engage in iterative dialogue with AI systems to test, refine, and generate business ideas. Learning-by-conversing involves both reflexive (hypothesis-generating) and confirmatory (validation-seeking) learning modes, depending on entrepreneurs' experience levels. For instance, novice entrepreneurs often rely on reflexive learning, using GenAI to explore unfamiliar concepts, navigate jargon, and investigate foundational questions. This requires significant time and cognitive effort to make sense of navigating a new digital domain. In contrast, experienced entrepreneurs use confirmatory learning to validate ideas or streamline known tasks, often critically assessing outputs and refining interactions. This work highlighting that GenAI adoption demands continuous interpretive, evaluative, and strategic labor which may also vary from necessity-driven to opportunity-driven entrepreneurs.

4 Considerations for Designing Generative AI Systems: A Closer Look at Resilience and Agency

I previously described the landscape of necessity-driven entrepreneurship and the additional and invisible labor involved when interacting with generative AI tools. In this section, I will detail how building generative AI systems that meaningfully support entrepreneurs, especially those motivated by necessity, requires design practices that go beyond common usability practices and guidelines. This includes perspectives on 1. designing for user agency, 2. designing for resilience in constrained environments, and 3. suggestions on how existing design guidelines require reflective approaches that are human-centered and foster agency and resilience.

4.1 Understanding User Agency in the Context of AI

Generative AI systems are often perceived and presented as intelligent partners; however, they risk undermining human autonomy when not carefully designed. Several of the selected sources argued for protecting a user's agency when using generative AI tools [4, 22, 25]. Fanni et al. (2020) [4], for instance, present **human agency** as "*the ability of users to make informed autonomous decisions regarding AI systems.*" Fanni et al. propose a distinction between *passive* human agency, where AI diminishes control and where humans may be largely excluded from AI-driven (human-out-of-the-loop), and *active* human agency, which emphasizes human involvement and oversight (human-in-the-loop). Ultimately, the paper argues that AI systems should support **active agency** where users have the ability to interrogate, modify, or reject AI use and suggestions. They suggest that human agency is closely linked to the idea of empowerment as it enables social processes that help users gain control over their lives, which are "*mediated by digital technologies.*" Furthermore, the authors indicate that user empowerment depends on the knowledge of how mechanisms operate, from what premise, and one's capabilities to change these systems.

On the other hand, Satyanarayan and Jones [22] approach agency from the perspective of generative AI, calling for a shift to re-conceptualizing *AI's intelligence* from competence (or task completion and success) to **agency**, or as they define it, "*its capacity to meaningfully act.*" The paper argues that generative AI is moving from information processing toward meaning-making forms, and such a shift requires a reorientation of how people use generative AI as active agents (as opposed to inanimate objects). They also propose that design is best understood as the **delegation of constrained agency**, where designers intentionally shape what AI can and cannot do on behalf of users. They highlight that through the delegation of agency, independent agents (i.e. people) become co-agents (where the human and generative AI system are the co-agents), and an arrangement of roles with corresponding responsibilities and goals is established. For example, the user may take on compositional agency such as crafting a prompt, while the generative AI tool takes on an interpretive agency (generating or evaluating a response). The authors argue that over time, these roles can reverse or blend depending on the task, trust, and system design. In summary, Satyanarayan and Jones argue that interacting with generative AI is a shared and negotiated process rather than a linear exchange of inputs and outputs. Through delegation of agency, co-agents are both accountable for the progress and interpretation of their actions, and this shared agency can either empower or constrain the human user depending on how designers delegate forms of agency to generative AI systems. When designers decide how much control or autonomy a generative AI system has, they are shaping not only system behavior but also the relational and potential interactions between humans and generative AI tools. In the context of necessity-driven entrepreneurs, the concept of co-agents may open up conversations about the responsibility of generative AI tools to meaningfully act and provide value for entrepreneurs who participate in entrepreneurship by necessity. For designers, an understanding of their agency, the delegated agency to the generative AI system, and the delegated agency to the human can support the design of generative AI systems that help necessity-driven entrepreneurs make informed, context-sensitive, and time-sensitive decisions whether it is for income generation, survival, or to minimize existing additional or hidden labors.

4.2 The Relationship between Resilience and Technology in Uncertain and Adverse Environments

Resilience has surged as a topic of interest within the HCI and CSCW communities [24, 19, 10, **?**]. This section outlines key studies on the topic of resilience and how individuals in different contexts, including in low-income communities, socio-technical-natural systems, and within a community health infrastructure in rural areas, have demonstrated resilience in their use of technologies.

Vyas and Dillahunt (2017) [24] describe resilience as *"patterns of positive adaptation in the context of past or present adversity, which is one class of phenomena observed in human lives."* They utilized a strengths-based approach, which focuses on people's strengths, capabilities, and expertise, to collaborate with a community care center in a metropolitan city in Australia to investigate how resilience is manifested in the lives of people from low socioeconomic status and how technology can play a role in supporting resilience. The researchers engaged in field visits at the food relief community drop-ins to speak with community members about their experiences and conducted interviews with 14 participants. Their findings were structured as 1. resilience in everyday lives 2. a spirited nature of resilience, and 3. a social and care-focused process. Resilience was demonstrated in the participants' everyday lives and activities including budgeting, cooking, and traveling. For instance, being economical was central to their daily lives as they sought for cheaper alternatives in supermarkets, shopped at second-hand stores, and made arrangements for cheaper travel options. Furthermore, participants often relied on online resources to learn about healthy behaviors as well as keep track of finances via online banking, which were integral daily activities that reflected resilient behaviors. Regarding the spirited nature of resilience, researchers found that despite adversaries, people demonstrated the willingness to learn and come out on the other side. For instance, some participants went to the community center to learn new skills, others relied on teaching and informing the community, and one accessed state resources for their personal needs such as learning software to gather evidence for a legal battle. Many participants also reflected the spirited nature of resilience by having a positive outlook on restarting a new life after difficult life events. Finally, findings point to how participants relied on sharing resources and splitting costs to help one another. This included sharing meals, Wi-Fi, carpooling, etc. to make ends meet. Beyond sharing resources and costs, participants showed great care and compassion for each others' situations.

In the context of HCI and CSCW, findings highlight the use of technology such as information and communication technologies being used for generating more income and obtaining access to tools and resources. The authors argue that while the use of technology is beneficial for people of low socioeconomic status (SES), social and non-digital activities such as bartering and negotiating with lenders are also beneficial in supporting the everyday lives of people of low SES. They also argue that leveraging the use of a nuanced strength-based approach based on everyday routines can shed light on the individual and evolving acts of resilience, which in turn, can inform designers how to best support efforts to help people of low SES. In the context of necessity-driven entrepreneurship, understanding the everyday activities and acts of resilience that necessity-driven entrepreneurs engage in can enable designers to build generative AI systems that support an entrepreneur's daily activities, or equally and perhaps more importantly, such understanding can reveal the non-digital activities that are just as essential.

Another paper on resilience by Karusala et al. (2019) [10], further demonstrates the complexity of resilience as it is shaped by intersectional identities and local constraints, which influence how people utilize their assets and adapt technologies. This work takes an assets-based approach within a community health infrastructure in a rural county, southwest Kenya. Through the lens of intersectionality the researchers examined 1. how the Ministry of Health (MoH) and other non-government health organizations pay the health workers through digital payments as opposed to previous cash payments (and how workers responded to the mandated change), and 2. how do the workers' assets, constraints, and backgrounds shape their response to change and adversity.

Through 15 semi-structured interviews and two focus groups with staff from the MoH, health organizations, informal community health volunteers, and formal workers (health assistants and nurses), Karusala et al. found that participants experienced challenges setting up bank accounts due to varying degrees of financial literacy and remoteness from town center (i.e. adoption was slower in remote areas as opposed to urban areas). Many had to apply for a national ID card, which included paying extra transportation costs to submit paperwork. The paper also highlighted that those who had already done the process (assistants and nurses) acted as "*assets*" for others less familiar with the process (volunteers). Furthermore, while opening a bank account brought challenges, some participants showed resilience by approaching the process positively (gaining an understanding of what banks are for and how to access them). It is important to note that adapting digital payments in their daily lives was based on each worker's assets and constraints such as place of residence, status as informal or formal worker, and how well the tool aligned with their priorities. In many cases, cash was still preferred for receiving payment, and resilience through adaptation of digital payment was a conscious choice and based on individual needs (relative transportation costs, etc.).

Regarding delayed payments, people stopped "caring" and hoped payments would arrive later. Here, resilience was demonstrated as people continued working because they cared about their work and community. Still, money was a concern as food security and school fees presented challenges. A major obstacle was that community members would go to the volunteer health workers for emergencies, making it difficult to turn them away. Many participants also opted for side businesses to maintain financial stability, such as catering, selling food, selling clothes, etc. Furthermore, additional avenues for demanding income were shaped by the formality of their role (salaried workers could be in unions, could ask MoH staff about payments) but volunteers did not have many options, highlighting the role of intersectionality. Based on these experiences, the authors' design recommendations included: 1. encouraging system designers to investigate the assets that health workers rely on and explore whether more generative assets (or assets with more positive impact) might be available first, and 2. diving into the idea of *sharing assets* and mapping what it looks like (e.g. financial literacy at workplaces).

The last paper that was key to understanding resilience was Palacios Abad et al.'s work titled "*Alone and Together: Resilience in a Fluid Socio-Technical-Natural System.*" This paper studies disruption to everyday routines, in the context of everyday resilience and the role of technology, as well as non-technical practices centered around nature. It focuses on the experiences of long-distance hikers who sign up for a disrupted life and can be described as a "*purposefully marginal group*" that has the option to opt out of the prolonged disruption by ending their hike. The authors draw from the definition of resilience as "*the multilevel processes that systems engage in to obtain better-than-expected outcomes in the face or wake of adversity.*" To investigate the factors that contribute to resilience in a socio-technical-natural system, at both an individual and collective level, and how the setting of long-distance hiking can inform technology design for resilience in the everyday lives of the rest of us, the researchers conducted 16 semi-structured interviews to study hikers' interactions with technology and their environment. Before conducting the interviews, the researchers also studied user-generated content (social media posts and comments, trail website recordings, and comments in Guthook Guides application).

Findings were structured based on the encountered adversity and the resilient factor. While hikers relied on blogs and websites to prepare for hikes, and also prioritized purchasing appropriate tools such as GPS-enabled devices and tracking apps, the dependence on technology often came at a cost, given that technology can be fragile in natural environments. Here, the resilience factor was that hikers use technology to adapt to their environment, but these strategies can become useless in nature. Researchers also identified the adversity of hiking taking a toll on hikers' emotional well-being. In this case, hikers rely on technology use for "pleasure" such as music and audiobooks as opposed to "utility." The resilience factor here is that technology provides entertainment and pleasure, but the inability to communicate with others is a source of stress, as there is no guarantee that technology will always work. Other findings describe the limitations of technology. For instance, hikers have found ways to find connectivity on trails or places near the trails (considering elevation and terrain). The resilience factor is that hikers adapt to a lack of connectivity by carrying battery power, and using offline and non-digital technologies, learning to navigate in nature. Finally for the adversity of hikers' physical safety, hikers often rely on their intuition and personal resources to overcome dangerous situations in nature. Some prepare by having someone back home who knows of their whereabouts to mitigate danger and use personal locators. The resilience factor here is that while hikers leverage personal resources and communities to share information, they also heavily rely on technology for safety.

In line with the previous two papers, the authors discuss that while technology plays a part in building resilience during hikes, hikers also draw from nature, themselves, and *others* to build resilience [24, 10]. In other words, resilience can be highly present when it is part of a conversation larger than technology, such as communities, which is important for understanding how generative AI systems for necessity-based entrepreneurs can take resilience into account.

Lastly, the authors suggest continuing conversations for designing for infrastructure resilience, in particular with cellular network access, which also requires understanding the possibilities and limitations of policies and laws.

4.3 Design Considerations for Generative AI: A Resilience- and Agency-Centered Approach

Finally, I selected a few papers that offer common design guidelines, principles, and considerations for creating generative AI systems, intending to build on these from the lenses of agency and resilience.

Guidelines by Amershi et al. (2019) [1] and Weisz et al. (2024) [25] provide actionable principles for designing generative AI systems, such as supporting user override, surfacing uncertainty, and aligning AI behavior with user intent. Amershi et al.'s 18 design guidelines, derived from 150 AI-related design recommendations and validated with a user study of 49 design practitioners, against 20 AI-infused products, were framed based on when the interaction occurs (initially, during interaction, when output is wrong, and over time). For instance, they suggest that over time, generative AI systems should maintain short-term memory and allow users to make efficient references to that memory, provide global controls (location history), and notify users about any changes to the system. Additionally, Weisz et al.'s design principles for generative AI applications include: design responsibly, design for mental models, design for appropriate trust and reliance, design for generative variability, design for co-creation, and design for imperfection. While this work highlights robust and actionable guidelines for generative AI design, these frameworks are primarily oriented towards usability and user experience and often overlook the structural inequities, contextual adversities, hidden labors, and survival motivations that are pertinent to specific populations, such as necessity-driven entrepreneurs. For example, Heldreth et al. [7] demonstrate that smallholder farmers distrust AI tools that replace traditional practices, especially when outputs are opaque, culturally misaligned, or hard to interpret. For necessity-driven entrepreneurs, similar dynamics may apply within high-risk and resource-constrained environments.

Viewing the design of generative AI through the lens of resilience can challenge conventional usability success metrics. As Vyas and Dillahunt [24]and Karusala et al. [10] argue, resilience is not just a simple adaptation, but a continuous and often invisible effort to navigate life and situations, whether it is for seeking financial stability by necessity [20, 10, 24] or being in a constrained and high-risk environment by choice [19]. Designing for resilience, therefore, requires centering individuals' situated experiences, communal and social care networks, and an effort to account for long-term adaptability grounded in an individuals goals and needs.

Together, the works on agency and resilience in the previous sections underscore that designing generative AI systems for impact and equity can require a deep understanding of contextual factors beyond those suggested by [1, 25, **?**]. For instance, for necessity-driven entrepreneurs encountering uncertainty-aware outputs, there should be visible indicators and markers that either flag low credibility, offer clear explanations, and ultimately offer transparency that can empower them to use their agency in assessing whether to use the output or not. Similarly, necessity-driven entrepreneurs may benefit from resilience-oriented designs that specifically plan for the possibility of adverse situations (lack of cellular access, internet, capital, and access to training and information). Inspired by Vyas and Dillahunt's work, this would center resilience as a pillar for designing with infrastructural gaps in mind, not against them. Additionally, interfaces could offer a "*low-resource mode*" for users in constrained settings, with offline-compatible options, simplified interfaces, or even pre-generated templates, but ultimately aligning with the individual's business goals.

In sum, designing generative AI systems with **agency and resilience in mind** is not simply about making them more "usable," "productive," or "effective." It requires asking difficult questions about the lived experiences of those who choose to use or not use these tools, especially those with fewer resources. It also calls for the initiative to look for the additional labors involved in using generative AI, as well as a critical eye to how current design guidelines and principles are presented in the literature.

5 Patterns in the Literature

Beyond the themes identified in this review (necessity-driven entrepreneurship, the additional labors of using generative AI, and the need for adopting resilience and agency in the design of generative AI tools), additional patterns emerged across the papers situated within the HCI, CSCW, and entrepreneurship fields. This section identifies and reflects on two patterns: (1) the need to understand the capabilities of generative AI within regulatory or governance frameworks; and (2) the focus on trust and ethics.

5.1 Situating Generative AI Tools Within Policymaking

Many studies across this review, especially those in AI ethics and sociotechnical systems research, emphasize that generative AI tools do not operate in a silo [13, 5, 22, 6, 23]. Kudina and van de Poel [13] argue that AI, its capabilities, behaviors, and risks must be understood within broader social, cultural, legal, political, and economic infrastructures. They remind us that concepts like fairness, explainability, and responsibility are not solely technicalities, but value-laden and context-dependent. Consequently, these values are negotiated and often put at risk at multiple levels, including policy and organizational levels. Zhang's ethnography of AI data trainers in China [26] also reveals how AI "capabilities" are dependent on invisible labor, often performed by underpaid workers in the Global South. This calls into question the *illusion of intelligence* and highlights the need for policy interventions that enable transparency and ethical labor practices.

Similarly, Heldreth et al. [7] show how unregulated or poorly contextualized AI systems can generate untrustworthy recommendations for smallholder farmers. This again reinforces that generative AI must be regulated not only in terms of performance or success benchmarks but also through its alignment with the situated experiences of its users. This is echoed by studies on specific groups including necessity-driven entrepreneurs and hikers [6, 17, **?**]. Mueller and Pieperhoff's integrative review of necessity entrepreneurship outlines how those who engage in informal entrepreneurship, that is, businesses that are not registered and operate on the edge of the law, do so out of economic necessity and survival. They suggest that for these individuals and necessity-driven entrepreneurs in general, policymaking should not assume a uniform entrepreneurial baseline as it risks overlooking the heightened risks and additional labors carried by necessity entrepreneurs. Instead, governance efforts should "*stimulate entrepreneurship as an instrument for alleviating poverty and generating employment*" and offer programs to specifically support these groups [17].

5.2 Trust as a Pillar of Generative AI Design and Deployment

Another dominant trend in these papers is the role of trust and ethics in the development and adoption of generative AI. One study cautions against the oversimplified narratives of "AI as a collaborator" [21] and instead calls for a critical interrogation of how *trus*t is built and distributed. Additionally, Weisz et al. [25] and Amershi et al. [1] propose design strategies that clarify AI capabilities, provide room for user override, and build trust incrementally. However, it is important to note that trust with generative AI cannot be designed or achieved solely through effective interfaces. Instead, it must be earned through access, communal support, supportive regulatory infrastructures, among other sociotechnical considerations. This insight is echoed by Gray [5] who argues for a human rights framework that supports public trust and data stewardship. She claims that "*only when the effects of AI models reflect the interests of the communities on which they are based will we know that research is truly in line with the obligation to respect human rights,*" supporting the idea that centering the lived experiences of specific groups, including necessity-driven entrepreneurs, may lead to the creation of more holistic generative AI design considerations. Trust also intersects with issues of marginalization. Studies like Hui et al. [8] and Avle et al, [2] show that necessity-driven entrepreneurs often adopt a cautious and strategic stance toward technologies—balancing their utility with concerns about legitimacy, safety, and control. These studies show that trust is not just about whether the tool works but whether it can be trusted not to betray, exploit, or disempower.

Moreover, trustworthy and ethical generative AI design also requires policies for oversight, as any sociotechnical system does, which may call for the creation of institutions, user manuals, policies, and instructions [13]. From the perspective of necessity-driven entrepreneurship, these concerns become heightened. As generative AI tools are deployed without regulation, marginalized users are often left vulnerable to misinformation or predatory practices. This calls designers to think about how they can have a positive role in either informing communities about regulatory efforts or perhaps creating application-specific policies for their users.

6 Gaps and Potential Future Research Directions

Despite the richness and growing breadth of research on generative AI, entrepreneurship, and sociotechnical considerations such as resilience, agency, and policymaking, several critical gaps remain. In particular, these gaps limit our understanding of how generative AI systems can be designed to empower necessity-driven entrepreneurs and other groups living in resource-constrained environments. This section outlines three gaps where future research is needed: 1. limited knowledge on the impact of community-driven approaches with necessity-driven entrepreneurs, 2. lack of frameworks for designing generative AI systems with resilience and agency in mind, and 3. lack of human-first approaches in generative AI literature.

6.1 A Need for More Community-Driven Approaches with Necessity-Driven Entrepreneurs

Mueller and Pieperhoff's systematic review revealed that of the 95.7% empirical studies on necessity-driven entrepreneurship, 74.6% employed quantitative research methods, 18.1% qualitative studies, 1.5% mixed methods, and 1.5% fuzzy qualitative comparative analysis [17]. Furthermore, previous work on how entrepreneurs adapt generative AI tools has also been grounded in quantitative methods [6]. While insights from these papers are significant, it is important to consider how findings on the experiences of necessity-driven entrepreneurs and their adoption of generative AI tools would differ when centering community-driven approaches. Studies like Hui et al.'s [8] and Lin et al.'s [15] demonstrate that community organizations often act as intermediaries providing trust, support, and infrastructure for marginalized entrepreneurs. Lin et al. specifically propose that community members and stakeholders be viewed as co-leaders in the design of generative AI systems [15]. In addition, by taking a co-design approach to onboard local entrepreneurs to generative AI, Kotturi et al. revealed a list of operational skills required beyond prompt engineering for successful use of the tool. Still, there is limited research on how necessity-driven entrepreneurs adopt generative AI in coordination with community groups, or how participatory partnerships could support the successful and meaningful use of generative AI. This is a significant oversight, as Avle et al. [2] and Kotturi et al. [12] show that entrepreneurs already engage in informal learning, peer-to-peer support, and collective experimentation. Future research should investigate community-driven generative AI adoption pathways, exploring how local organizations and networks can help navigate barriers related to digital literacy, trust, or infrastructure.

6.2 Lack of Frameworks for Designing Generative AI Systems with Resilience and Agency in Mind}

While there is substantial literature on making generative AI systems usable, explainable, responsible, and trustworthy [25, 1, 9, 4], far fewer frameworks explicitly center resilience and agency as primary design goals. As Vyas and Dillahunt [24], Karusala et al. [10], and Palacios Abad et al. [19] argue resilience is not a fixed trait but an adaptive, daily, and often infrastructural process. Similarly, Fanni et al. [4] propose active human agency, claiming that technological systems such as generative AI may challenge how people perceive their own agency "*not only as a human but also as a citizen being part of a society in which mediation plays a central role.*" Still, many existing design models emphasize automation, productivity, and speed over supporting a user's resilient adaptation, negotiation, and control. Without robust frameworks that treat resilience and agency as foundational principles rather than secondary concerns, generative AI systems risk masking the complexity of the larger systems they are embedded in. This may leave users with little power to shape outcomes or recover from failure. Future research should develop new and clear design methodologies that explicitly prioritize agency and resilience, particularly among users with constrained resources and high-stakes contexts.

6.3 Human-First Designs are Still Rare in Generative AI Literature

Across the selected papers, a notable pattern is that research often begins with the capabilities or limitations of generative AI tools and only considers the human perspective later [25, 1, 13]. Sarkar [21] critiques this framing, arguing that even the "human-AI collaboration" narrative often positions AI as the primary actor, with humans adjusting around its behaviors. This narrative also challenges the orientation advocated by Gray's human rights framework [5] which asserts that public trust in AI begins with centering human needs.

A more human-first research agenda would start not with what generative AI can do, but with what people need. This includes the identification of a group's goals and constraints, and whether they are supported by what the generative AI field promises. As the literature on necessity entrepreneurship shows [17, 6], users often adopt technologies not for novelty or opportunity, but for survival and economic stability. Future research should prioritize human-first rather than tool-first questions, drawing on participatory methods, co-design, and critical HCI to develop generative AI systems that are not just inclusive, but relevant, empowering, and grounded in lived experience.

7 Conclusion

This literature review examined the motivating factors for necessity- and opportunity-driven entrepreneurs, the additional and often invisible labors involved in engaging with generative AI tools, and the sociotechnical design considerations needed to foster resilience and agency. Synthesizing insights from 26 interdisciplinary sources, the review found that necessity-driven entrepreneurs face distinct challenges shaped by structural inequalities, contextual constraints, and survival-driven motivations. While generative AI holds promise for lowering barriers to entrepreneurship, it often introduces new complexities that can be categorized as additional labors — requiring the acquisition of multiple digital skills, interpretive questions about generative AI, and iterative experimentation. Current design frameworks and policy discourses tend to center tool capabilities over user needs, missing opportunities to meaningfully support those most in need of inclusive innovation. To move forward, researchers and designers must prioritize community-driven approaches, adopt frameworks that foreground human agency and contextual resilience, and shift toward human-first paradigms that begin with the everyday realities of users. Doing so will not only produce more equitable and empowering generative AI systems but will also broaden our understanding of entrepreneurship and technological participation in a rapidly evolving digital age.

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