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The role of generative design and additive manufacturing capabilities in developing human–AI symbiosis: Evidence from multiple case studies

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Abstract

The benefits of additive manufacturing (AM) extend beyond the attributes of physical products and production processes they enable. Experience with AM can augment the way design is approached and can increase opportunities to pivot toward less familiar design tasks. We begin this qualitative study with a natural experiment made possible by an exogenous shock: the COVID-19 pandemic. Through a three-stage case study approach using a grounded theory-building method, we contrast AM usage among a set of firms, half of which pivoted their resources away from their traditional production and toward a response to this shock. We engage in an abductive reasoning approach to consider common threads in AM capabilities that facilitated this pivoting. Our analyses suggest that the advanced use of generative design (GD), a category of computational technologies enabling novel and optimized design, is a critical attribute of these firms that ended up pivoting to make COVID-related products. Specifically, firms with experience applying this capability demonstrated a unique ability to pivot during this shock and emphasized their valuation of AM-enabled agility. We revisited these firms 2 years after initial contact and found that GD was associated with higher levels of innovation and was largely viewed by designers as a mechanism driving double-loop learning. Overall, our study provides insights into the symbiosis between human and artificially intelligent GD, and the role of such symbiosis in advancing AM capabilities.

KEYWORDS
additive manufacturing, case study, generative design, theory building

1 | INTRODUCTION

Additive manufacturing (AM) is a class of production process technologies that produce objects by applying layered materials based on three-dimensional design models. This is in distinct contrast to more traditional subtractive and formative production techniques and translates into several unique opportunities for operations. Inventory and waste reduction, light-weighting, prototyping, enhanced part complexity, surface optimization, conformal cooling, multi-material, and nondestructive encapsulation represent just some of the advantages often touted in descriptions of AM (Khajavi et al., 2014; Mithas et al., 2022). AM has been criticized for its inherent challenges relative to traditional manufacturing, including speed for mass production, limits on material options, and energy costs (Baumers & Holweg, 2019). However, these drawbacks are being overcome as advancements in AM technology progress. With these advancements in speed and cost, novel end-user production activities with AM are proving increasingly viable, under the broader umbrella of direct digital manufacturing (cf. Gibson et al., 2021; Holmström et al., 2016).

Beyond direct manufacturing, there are some instances, such as tooling production, that AM options (e.g., using silica and binder inputs) present more cost-effective and energy efficient approaches than more traditional metal extractive approaches (Gilmer et al., 2021). Because of these factors, and given established expertise, equipment, and personnel trained in non-AM techniques, many firms have been leveraging AM in a hybrid sense (e.g., prototyping ahead of subtractive builds, mold creation, printing wax products for investment casting, and printing metal items for preform forging) (Badanova et al., 2022). Such approaches have enabled novel and critically important capabilities in the production of competitive goods for their core business lines (e.g., GE's fuel injector for LEAP jet engine). In some cases, AM has also offered opportunities to extend or create new business lines previously not viable. It is in this area that our study delves deeper to offer a unique explanation.

Certain broad questions require a closer consideration of these technology experiences. Specifically, our research investigates the following: *How does experience with AM help firms to innovate into different markets? Are certain AM capabilities particularly helpful in this regard?* If the latter is the case, management may need to rethink the role of AM as not just a passive means-to-an-end enabler of new product opportunities, but as a more pervasive catalyst of innovation. To investigate this possibility, research must delve into the details of recent use cases across industries. Ideally, this examination would involve both dynamic scenarios, including those in which firms are stressed by exogenous shocks to change how they leverage AM in production, as well as conditions under which AM experience can be leveraged in a steady-state innovation capacity. In this manuscript, we explore this challenge by conducting a three-stage, multi-firm case study, spanning 3 years (2020–2022), to investigate the role of AM in enabling production pivoting in the face of exogenous shocks. We also adopt a grounded theory-building approach (Strauss & Corbin, 1994) to collect and analyze data from these firms simultaneously and refine our understanding using an abductive reasoning method (Suddaby, 2006).

The exogenous shock in our study relates to the normative pressure to design and develop healthcare-related components during the COVID-19 pandemic. Our research design seeks to understand the broader innovation-capability implications of experiences with AM, specifically the use of generative design (GD), a category of computational technologies that can offer novel design options and optimize preexisting designs to accommodate customized criteria (Wu et al., 2019). Although AM technologies existed even prior to the pandemic, firms having certain aspects of AM capabilities, such as GD, were able to effectively use them to pivot to new markets. By definition, GD is a process in which design engineers provide an artificial intelligence application, often embedded with some form of machine learning, with a baseline digital design. The features, materials, costs, and spatial dimensional constraints can vary (aka rules), as can the objectives regarding mechanical performance (e.g., weight and resilience to strain). The algorithm goes through a series of iterations in adjustments to design within the decision space, making use of a wide variety of structural options, simulating the mechanical performance of the digital forms. Output designs are then scrutinized by design engineers, often via physical prototyping and testing, resulting either in the selection of a workable model, partial adoption of a design, or additional feedback into, and iteration with, the GD tool.

In the first stage of our work, we leverage a natural experiment involving an exogenous shock (COVID-19 pandemic) to examine the conditions leading to production-pivoting responses of 34 AM-equipped manufacturing firms in a range of industries, predominantly in the United States and Europe. Half of these firms were selected for consideration given their choice to pivot AM resources toward the production of COVID-19-related items (face masks, swabs, ventilator components, etc.), whereas the other half did not. We use established case study methods to identify these firms for examination (Eisenhardt, 1989; Lee & Klassen, 2008; Yin, 2014), ensuring representativeness and contrast, supplemented by archival data collected through publicly available sources. Through recommended grounded theory development tactics (Corley & Gioia, 2011; Gioia et al., 2012; Glaser & Strauss, 2009), we carried out structured interviews with multiple managers and engineers at each firm (May 2020–July 2020) to understand the decision-making toward COVID-19-related item production. These interviews were coded and analyzed to derive initial insights regarding the decision-making triggers within these firms.

This was followed by a second stage approximately half a year later (November 2020–January 2021), prompted by initial responses, to assess the performance of production efforts (e.g., quality, profitability, etc., of production of pivoted or otherwise) and to consider changing conditions as the impact of the exogenous shock evolved. A third stage of case inquiry was conducted 18 months later (July 2022–November 2022), allowing retrospection and a deeper dive into the nature of design and innovation processes. This approach of collecting data from three different time intervals allowed a thorough examination of factors, capabilities, dynamics, and associated outcomes. It also helped to refine our understanding of these concepts using the principles of abductive inquiry (i.e., iterating between inductive data collection and deductive reasoning).

Our cross-case analyses revealed several common drivers of AM-production shifts, and the performance outcomes of such pivots, in the face of an exogenous shock. The presence of an unambiguous source of demand, well-matched to idle capacity at the focal firms, was a catalyst for change, as would be expected based on existing theories (Cachon & Terwiesch, 2012). Make-to-order (MTO) and design-to-order (DTO) orientations, similarities between the design and manufacturing of core emergent production needs, and familiarity with associated regulations proved to also be relevant enabling drivers. Yet most interestingly, our within-case analyses suggested a new feature that has been notably absent from existing literature on the use of AM. We found that the impact of each of these drivers was augmented, by a deep knowledge of design for additive manufacturing (DfAM) core capabilities, and most notably, the extent to which the focal firms made considerable use of GD software. GD proved to be a major factor that helped explain the effectiveness of responses to the exogenous shock, for firms within the same industry having similar capabilities. Our analyses of our cases led us to highlight the role of GD in enabling responsive capabilities in the presence and application of AM.

To develop further insights into the role of GD, we conducted additional interviews and analyses to understand the theoretical underpinnings behind its application. This approach of iteration among existing literature, case analyses, and new data allowed us to develop a better understanding of the role of GD in AM contexts. Interestingly, although GD was typically not used directly in facing the exogenous shock (i.e., COVID-19 designs were largely traditional and standardized because of regulation), we found that firms with a deep knowledge of this design technique tended to enjoy a particularly broad understanding of opportunities in AM design, a substantial awareness of design challenges and solutions, and a rational view of their own in-house design strength. This understanding enabled the firm's ability to dynamically adapt and pivot to new manufacturing efforts. In our third-stage interviews, 2 years after our initial contacts, we also discovered that interactions with GD rendered a kind of reinforced double-loop learning mechanism that advances the way designers think about design more broadly, thus potentially extending the design agility of organizations beyond AM-specific production considerations. Specifically, the presence of a GD capability within firms allowed them to overcome some of the resistance among engineers toward design support provided by artificial intelligence, or AI (e.g., perceptions of unnecessarily changing processes, threatening IP, and undermining job security), and instead complement them using human intelligence.

Overall, our findings yield critical insight for innovation and product development research and practice, about the emergence of human–AI symbiosis facilitated in AM production settings. The specific human–GD–AM triad that we examine holds the potential for both highly effective production flexibility and substantial augmentation of ongoing innovation capabilities. This informs discussions such as those around digitalization, and specifically the prospective uses of digital twins, by demonstrating a hybrid engagement with physical testing and human decision processes. The findings have particular relevance to the fuzzy front-end of new product development, occasionally stressed by market innovation pressures (cf. Bendoly & Chao, 2016).

The rest of the article is organized as follows. In the next section, we review the existing literature on AM, success factors, and decision-making. We identify capabilities in AM production settings that have the potential to augment flexibility and design, which the extant literature has only begun to consider. We then discuss our three-stage case study approach and the natural experiment that allowed us to study some of these factors during a recent exogenous shock. The methods discussion is followed by our cross-case analyses that delve into the impact of factors and AM experience on production pivoting and success in the face of this shock. We then evaluate these capabilities to develop a higher level understanding of how they advance broader advantages in product design and innovation. Specifically, we highlight the symbiosis between human and artificially intelligent GD in AM production settings (human–GD–AM triad), as an extension to theory on human–AI interaction and double-loop learning. We conclude with a discussion of implications, caveats, and future work.

2 | LITERATURE REVIEW AND THEORY

Although AM concepts can be traced back to the late 1980s, it is only in recent years that we have observed the widespread application of AM capabilities in various stages of operations, including design, prototyping, tooling, and manufacturing (cf. D'Aveni, 2018; Friesike et al., 2019). AM's diffusion can be attributed to advances in materials, printing machinery, and design software, as well as to the multitude of advantages that firms can obtain from using AM in their manufacturing and production operations (Boehme et al., 2021; Dinar & Rosen, 2017). AM allows, ostensibly, for more distributed manufacturing tactics, faster times to design for increasingly complex and customized parts and tooling, greater availability of prototype testing and, in some cases, higher flexibility in production batches (Heinen & Hoberg, 2019). Although firms differ in their leveraging of these features, it is thought that each can present unique opportunities for adding value to the end customer and expanding their market reach (Baumers & Holweg, 2019; Olsen & Tomlin, 2020). However, the dedicated integration of AM in many firms is relatively nascent and leaves open the question of which features are most aligned to specific operational objectives. For example, it is unclear which aspects of AM, and which operational orientations around its application, prove particularly valuable when facilitating rapid production pivoting in response to exogenous shocks. This also raises the question of whether these same attributes facilitate subsequent new product innovation efforts.

Questions like this, regarding design and production agility, are critical for at least two reasons. From a broad operations management perspective, the world is becoming more variable in its demands and opportunities, and the ability to rely on stable supply chain (SC) processes is not a foregone conclusion. Exogenous shocks are becoming a common attribute of many operating environments, meaning that the ability to pivot can help firms to better confront volatility in customer requirements and supply challenges and, ultimately, serve as a competitive advantage (Bag et al., 2018). One of the core attributes of AM technologies has long been the ability to rapidly take a conceptual design form and make it physically tangible (Rindfleisch et al., 2017). Yet new product design involves far more than the physical manifestation of ideas. It requires the formation of the concept prior to manifestation (de Brentani & Reid, 2012). The role that AM plays in this fuzzy front end has been less evident up until recent years. Understanding what that role looks like, and the conditions in which it can be effective, can offer paradigm shifts for firms particularly interested in agility. We review what is known about these topics as well as identify the gaps that need to be addressed.

2.1 | The role of fit

The degree of "fit" between opportunities to redeploy production resources and the fundamental strategic and operational conditions of firms faced by exogenous shocks is a common element in motivating pivoting actions and associated performance outcomes (Henderson & Clark, 1990; Leonard-Barton, 1990). This basic notion is supported by theories such as strategic contingency theory (Das & Narasimhan, 2001; Zajac et al., 2000). Operations management scholars have also long argued that organizations should be careful to ensure a fit between SC and production systems, manufacturing strategies, and the competitive priorities of the firm as opportunities and challenges present themselves (Boyer & Lewis, 2002; Hayes & Wheelwright, 1984; Hill, 1993; Skinner, 1969, 1974).

Similarities between production expertise and capabilities in the face of an exogenous shock and the production requirements of demand emerging from that shock can differ. Traditional subtractive and forming manufacturing techniques often capitalize on dedicated machine and tooling configurations, with the deliberate intention to produce quantities of products in a cost-effective way. However, there are fundamental limits to the speed at which these kinds of capital resources can be reconfigured in a limited timeframe. Depending on the complexity of the product, certain reconfigurations are simply not possible with extractive approaches. AM, in contrast, presents opportunities for far more rapid reconfigurations (D'Aveni, 2018; Holmström et al., 2019) and can accommodate product designs of a greater variety (with clear caveats regarding material limitations for certain AM technologies). As a result, firms with more substantial AM capabilities may possess a higher potential level of fit to new demands emerging from exogenous shocks (Khajavi et al., 2015).

The human side of fit must also be considered in such cases. Designers and production engineers require sufficient expertise to take what may be a technically feasible design, assuming appropriate equipment is on hand, and transform that into a production reality. In the case of AM, individuals also need to be sufficiently experienced with variations in how AM equipment can be applied (Stanko & Rindfleisch, 2023). Designers' mental models of how to deploy a potentially very different production run must be proximal enough to that which is required for the emergent demand (Ketokivi & Schroeder, 2004; Sousa & Voss, 2008). An investigation into the drivers and success of pivoting production capabilities must therefore consider the fit between human and technical elements. We know very little from the existing literature on the type of fit between these two entities and how it can help make better decisions.

2.2 | The role of flexible orientations

Even when organizations have appropriate equipment and expertise to allow for rapid and effective redeployment of production resources, they may not have processes in place or established operational cultures that easily accommodate such change. On the other hand, some organizations deliberately embed flexibility into their operational cultures in order to accommodate strategic interests in flexibility and customization (e.g., dynamic capabilities; Narasimhan et al., 2004). MTO and DTO settings are not only built around sufficiently flexible manufacturing resources but also foster a sense of "yes we can do that" in designers and production engineers (Basak et al., 2022). Doing so allows for opportunities for pivoting in response to exogenous shocks to appear more as "challenges" and less as "burdens."

DfAM takes advantage of free form fabrication and geometrical complexity enabled by AM, offers another level at which MTO and DTO can operate, and has the potential to greatly augment the reactions that designers and engineers possess to the prospect of major redeployments in production (Dinar & Rosen, 2017; Friesike et al., 2019). The adaptability offered by AM, and associated DfAM, complements the ethos of MTO and DTO, removing barriers to change and customization (Haruna & Jiang, 2022). Indeed, Roscoe et al. (2019) noted that AM capabilities are typically underpinned not only by flexible processes but also by consensus-based hierarchical structures (i.e., microfoundations). These structures and processes encourage individuals to interact and share knowledge. In the case of MTO and DTO, this can include increased dialog between those offering AM production solutions and the ordering clients. Therefore, the strength of MTO and DTO operational cultures in firms equipped with AM technologies presents another potentially critical driver of action and consequence in the face of exogenous shocks, not yet studied regarding AM.

2.3 | The role of decision support

In AM settings, the freedom to learn through failure and to develop flexible and ad hoc problem-solving processes can be significant (Roscoe et al., 2019). Exploration is facilitated by design options that are otherwise unconstrained by the fixed molds and machine constraints of conventional subtractive or formative methods (Baumers & Holweg, 2019). However, humans are often not simply interacting with passive or pure "agent" technologies in AM settings. Rather, modern AM software can incorporate advanced, artificially intelligent, and computer-aided design applications such as

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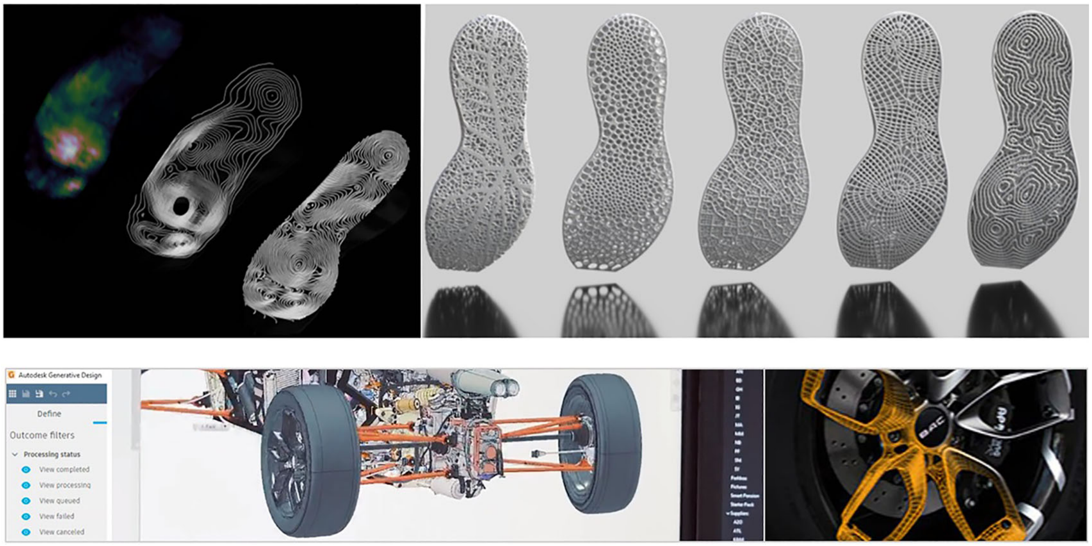


FIGURE 1 Performance-optimizing product designs emerging from generative design (GD). Top panel: New Balance's Midsoles effort, custom to user weight distribution, with options provided via GD. Bottom panel: Briggs Automotive Company's use of Fusion 360's GD application to cut 35% of tire weight.

those allowing for GD, including, but not limited to, topology optimization (Briard et al., 2020; Grover et al., 2022).

Broadly speaking, GD involves a group of technologies that enable the user to arrive at novel design options or to optimize an existing design to meet the criteria of the end user (Wu et al., 2019). The use of GD software proposes optimized part designs based on starting CAD geometries (often), use and nonuse area specifications, material options, and a host of physical performance requirements examined through associated simulation (Schnitger, 2020; Wu et al., 2019). Design options that emerge from the GD process can often have an organic aspect, frequently appearing alien to traditional designs, being of variable thickness, and often being asymmetrical. One result is that these components are almost impossible to manufacture using subtractive or formative methods, thus lending GD to AM approaches in particular (Briard et al., 2020), as illustrated in the top panel of Figure 1, depicting midsole designs of highly complex geometry.

Apart from enabling out-of-the-box design concepts, GD can also resolve design dilemmas that can stymie formulaic design tactics. As a result, design options presented by GD can use less material (less cost and weight), deliver complex geometries in parts and tooling (e.g., for conformal cooling), reduce the need for post-processing, and augment multidimensional strength, while also reducing design-to-manufacture lead times (Sossou et al., 2018). The lower panel of Figure 1 provides an example of such boons realized through applied GD. Benefits such as these naturally translate into further advocacy of DfAM at organizations that strongly leverage GD in particular (Briard et al., 2020; Dinar & Rosen, 2017).

Although MTO and DTO, facilitated through AM, can encourage dialog among designers, engineers, and external clients, GD can inspire the same outcomes while facilitating a very different kind of communication. Specifically, the iterative use of GD to extract designs, validate their effectiveness, and modify system specifications for next-generation GD efforts, presumes the ability of designers and engineers to communicate effectively with the software. It may require rationalization, akin to reverse engineering, which can entail novel discussions between designers and engineers. The dynamics implied can further ready organizations for other kinds of novel design challenges that exogenous shocks entail.

As a caveat, it is worth noting that conflicts may arise between experienced engineers and advocates for the use of GD, often due to a sense that the value added by engineers might be squeezed out of design processes (cf. Bucchiarone et al., 2020; BuHamdan et al., 2021; Gonzalez, 2016). In particular, it may be suggested that exchanging traditional design "formulations" based on theoretical physics with alternate evolutionary approaches leveraged by GD may introduce unacceptable risk. However, GD still relies heavily on engineering knowledge and physical laws. As with the majority of engineering evaluation, GD is highly data driven (data evolves the design), and its rapid turnaround further encourages prototyping and testing along standard engineering protocols. As a result, these "perceived" risks appear to be largely unfounded, and ignoring the overall prospective benefits of GD is becoming increasingly challenging (Gibson et al., 2021). This is captured in the growing uptake of GD solutions in major industries, such as the automotive and aerospace industries, for the AM of metallic parts (Briard et al., 2020; Roscoe et al., 2023). The question is whether GD, as well as other drivers such as flexible orientations and fit, can be observed as influential in facilitating operational pivots, during exogenous shocks as well as in efforts that follow.

3 | METHODOLOGY

To evaluate the roles of the AM-related factors described in Section 2, we utilized a research design to build new theory using multiple case studies (Corley & Gioia, 2011; Eisenhardt, 1989; Eisenhardt & Graebner, 2007). Such an approach has proven effective in several operations management contexts where industry experience and/or research knowledge is relatively nascent (Fisher & Aguinis, 2017; Lee & Klassen, 2008; Pagell & LePine, 2002; Yin, 2014). While guided by some a priori theoretical considerations (e.g., strategic contingency theory), we remained open to unanticipated findings and the possibility that the general theory required reformulation based on the evidences from the field (Merton, 1968). To meet the duality criterion of rigorous case research (Ketokivi & Choi, 2014), we grounded the study within the context of firms who sought to pivot an AM capability in response to an exogenous shock, namely, the COVID-19 pandemic. The timeliness of this shock provided something of a natural experiment, because it was a shock that all firms in our sample experienced. However, we did not limit ourselves to a single period. Instead, we designed the study to gather information for our cases at three distinct time points (at the onset of the shock, 6 months afterward, and a further 18 months later to reflect on the decisions). This research design allowed us to reflect on and develop insights into the longer term implications of the AM-related pivot enablers of interest (fit, flexible orientation, and decision support).

The approach to collecting and categorizing data over multiple time intervals often creates conditions for improved theory building (Grodal et al., 2021). It also allowed us to practice abductive reasoning wherein an observation is made, which is then compared with existing theories to identify the anomalies that are further explained through additional data collection and analyses (Saetre & Van de Ven, 2021). At each stage, we conducted in-depth evaluations of the factors detailed in the semi-structured interviews. This also resulted in making refinements to our interview protocols which is fairly common during grounded theory building (Suddaby, 2006). Throughout the study, we attempted to reconcile the idiosyncrasies of the cases, and when unanticipated findings emerged, we were able to elaborate upon strategic contingency theory. In the following subsections, we outline the specific methods applied in each stage, along with critical details regarding our sample. We will dive further into the insights gained at each stage in Section 4.

3.1 | Stage 1—a natural experiment

The economic shutdown in response to the COVID-19 pandemic resulted in both downstream demand- and upstream capacity-depression effects, forcing several manufacturing industries to change their operations. As was anticipated by researchers and practitioners, it resulted in a large number (over 36%) of manufacturing firms reporting some form of manufacturing and SC disruptions (Haren & Simch-Levi, 2020; NAM, 2020). The Alliance for Automotive Innovation reported that 41 out of the 44 auto-assembly plants in the United States were closed in March 2020, stopping all manufacturing, design, and SC activities in the automotive industry (Linton & Vakil, 2020). Idle resources are difficult to justify at any time, and a number of firms invested in AM capabilities were able to pivot these resources toward emergent demands that the epidemic created. That is, the nature of the COVID-19 pandemic, as a natural exogenous shock, involved both losses in demand for many conventional products of many firms and opportunities to pivot production toward efforts that were somewhat unfamiliar to these same firms (e.g., face masks, nasal swabs, and ventilator parts).

With this setting as a general backdrop, our targeted sample consisted of small, medium, and large manufacturing firms that had AM capabilities, predominantly headquartered in the United States and Europe. We were specifically interested in understanding how the natural shock of COVID-19 impacted the firm's use of AM capabilities and its effect on the firm's operations. To obtain the list of firms, we worked with several manufacturing and research consortiums, including America Makes, the Center for Design and Manufacturing Excellence, the Manufacturing Advocacy and Growth Network, and the State-based Business Incubator, as well as through key AM-related discussion forums on LinkedIn. This resulted in a set of over 100 candidate firms that met our theoretical sampling criteria, 48 of which provided suitable primary contacts. For the purpose of this study, we focused our sample on the United States and Europe, because recent studies have shown that a vast majority (around 70%) of AM system installations reside in these areas (Wohlers et al., 2020). The primary contacts in these firms had various titles, including design and production engineers, an R&D director, a director of operations, vice presidents, and CEOs. This formed the overall sample for our case studies.

Our next step involved contacting informants from the 48 firms to ask them about the AM capabilities of their company. Firms that were found to be machine or material providers or that lacked experience with conventional manufacturing approaches (i.e., were new to manufacturing and only used AM) were excluded from our sample. For the remaining firms, we formally requested their participation in our research approach. Because our intention was to compare the AM-related factors for firms that chose to pivot, against those which did not, our intent was to pursue as even a split as possible, which also achieved repeated representation of multiple industries, similar to the strategy of Pagell and LePine (2002). Following the sample reduction, 34 manufacturing firms remained in our sample—26 in the United States and 8 in Europe or the Pacific (Australia/New Zealand). Half of these (17 firms) reported involvement in pivoting manufacturing resources (people and equipment) to product lines they had previously not been producing, whereas the other 17 firms did not. Pseudonyms for firms in our sample are broken into participating and nonparticipating groups in Table 1. The largest industry representations were firms in the healthcare (mainly prosthetics, implants, and den-

TABLE 1 Industry pseudonyms used to reference firms in our sample of cases.

Pivoted production		Did not pivot	
Automotive1p	Aerospace1p	Automotive1n	Aerospace1n
Automotive2p	Aerospace2p	Automotive2n	Aerospace2n
Automotive3p	Medical1p	Automotive3n	*Aerospace3n*
ConsGoods1p	Medical2p	ConsGoods1n	Medical1n
ConsGoods2p	Medical3p	ConsGoods2n	Medical2n
ConsGoods3p	Medical4p	ConsGoods3n	Medical3n
ConsGoods4p	Industrial1p	Military1n	Medical4n
Military1p	Industrial2p	Military2n	Industrial1n
	Industrial3p		Industrial2n

Note: Aerospace3n did not participate in the second stage of case interviews.

tal; 23.5%), consumer goods (20.6%), automotive (both large commercial and boutique; 17.6%), and aerospace (14.7%) industries.

Formal discussions with these firms were carried out between May and July 2020, with a focus on firms' decision to pivot AM production resources toward participation in the COVID-19 response. We conducted 60-min semi-structured interviews with the designers, engineers, and senior leaders from these firms. Our interview protocol was based on existing AM literature and was informed by the events that occurred during the COVID-19 pandemic as reported in the business press and found using media searches in Factiva. We carried out all interviews via Zoom, due to pandemic restrictions. Multiple researchers participated in each interview and took notes that were then used in the data analyses. Researchers also met immediately after these interviews to share their perspectives, which were documented for coding purposes. Across the 34 firms, we conducted over 47 interviews in our first stage of inquiry (several involved immediate follow-ups with additional contacts). Apart from topics relating to fit, flexible orientations, and decision support, discussions delved into the specific nature of in-house AM machinery, and the extent to which AM efforts at the firms relied significantly, albeit not necessarily predominantly, on third parties for AM service work (aka AM service bureaus). Appendix A gives a subset of questions asked during these interviews.

Following Miles and Huberman (1994), these interviews were recorded and coded for analysis purposes. We followed the well-established grounded theory method of open, axial, and selective coding during the qualitative analyses process (Strauss & Corbin, 1994). In the open coding stage, we used the vocabulary from the interviews in response to questions outlined in our protocol. For example, we found that some of our interview respondents cited "lack of business," "stopping of customer orders," and "doing good to the society" as some of the reasons for participating, or not participating, in the COVID-19 response. Then, in the axial coding stage, we grouped some of these reasons into themes, such as "local demand needs" and "internal enablers," that reflected higher order concepts. Finally, in the selective coding stage, these themes were compared between firms to understand the inherent relationships among them. In all cases, at least two researchers manually iterated between data and the coding template to obtain reliability in our coding process. Similar to the process used by Pagell and LePine (2002), we controlled for a priori beliefs by relying on two engineers at separate institutions to provide verification in coding. In the following section, we offer details on our cross-case analyses, used to develop propositions that directly address the two research questions posed.

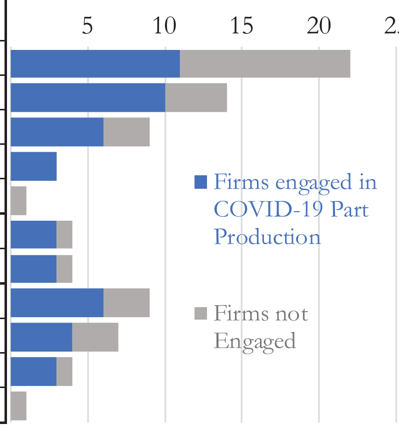
The interviews revealed that half of the firms (17) described themselves as strongly oriented toward standardized production, whereas the other half described themselves as having a notable orientation toward customization (MTO and/or DTO). This distinction was roughly split between firms that chose to pivot and those which did not (9 of the 17 COVID-19 response firms were customization shops, whereas 10 of the 17 firms not participating in the response were customization shops). Although almost all firms made use of AM for some prototyping efforts, only about two thirds regularly engaged in significant new product design efforts using AM, with a similar number engaged in AM for final part production. Fifteen of the firms described a significant reliance on third-party service bureau engagement for AM work ($\geq$10% of all such work), whereas the remaining 19 either had much more incidental engagements or had taken positions that retained all AM work in-house. Moreover, half made use of AM to create tooling (e.g., molds for conventional manufacturing work). Table 2 presents an overview of AM technologies used by 34 firms in our initial sample.

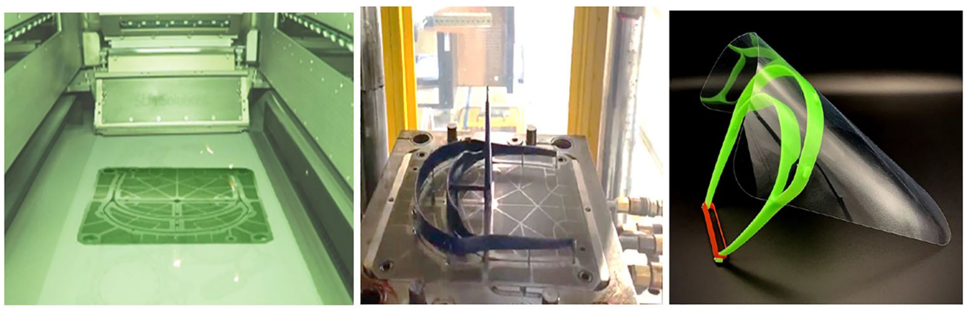
Although COVID-19-related parts predominantly rely on plastic manufacturing capabilities (e.g., FDM), the availability of metal printing capabilities also played a crucial role, as several firms contributed through hybrid approaches. Specifically, certain firms developed AM designs and printed metal molds (e.g., SLM), or silica binder molds in some cases, allowing them to use more conventional means (e.g., injection molding) to then support pivoted production needs. Figure 2 displays an approach used by one of the firms in our sample. We reference their name directly in this case with their permission; however, to attribute these images going forward, we will refer to them (and others in our sample) using a pseudonym.

Our first-stage semi-structured interviews also permitted the gathering of information regarding the strengths, weaknesses, opportunities, and threats identified by firms in their use of AM, as these relate to their core business efforts. We also learned more about the challenges faced by firms involved in the COVID-19 response. Analyzing this data allowed us to better understand the use of AM technologies in helping firms to adapt. However, the focus of our first round of interviews was primarily on the role of external and internal factors that triggered such as response. To understand more on the use of AM technologies and the surrounding capabilities, we conducted additional rounds of interviews.

TABLE 2 Overview of additive manufacturing technologies used by firms in the case sample.

3D Print Technology		Common materials	% of Sample with
FDM/FFF	Fused Deposition	Plastic	65%
SLA	Stereolithography	Plastic	41%
SLS	Selective Laser Sintering	Plastic	26%
MJ	Material Jetting	Plastic	9%
MJF	Multi-Jet Fusion	Plastic	3%
DLP	Digital Light Projection	Plastic/Metal	12%
BJ	Binder Jetting	Plastic/Metal	6%
SLM	Selective Laser Melting	Metal	24%
EBM	Electron Beam Melting	Metal	21%
WAAM	Wire and Arc	Metal	15%
ADAM	Atomic Diffusion	Metal	3%





SLM printing (e.g., face shield molds) | *Injection molding of face shields* | *Final product assembled*

FIGURE 2 Hybrid approach to COVID-19-related part production at Catalysis3D. Selective laser melting (SLM) printing (e.g., face shield molds), injection molding of face shields, final product assembled.

Appendix A contains a subset of questions used in these interviews.

In addition to these interviews, and to help ensure the validity of interpretation through a "chain of evidence" (Yin, 2014), we further collected archival reports and news information on topics related to the firms' AM capabilities, COVID-19 efforts in the regions proximal to AM manufacturing facilities, and the location of the firms' headquarters. Most of this supplemental information was collected through various sources, such as the coronavirus tracker, Google News, and regional news websites.

3.2 | Stage 2—pivot performance

With an interest in understanding the success of production pivoting, as well as the performance of firms that chose not to pivot, our second stage of interviews took place between November 2020 and January 2021. Observations that emerged from Stage 1 insights provided considerable guidance in designing our interview protocol in Stage 2, in line with recommendations for updates and improvements in case study protocols (Eisenhardt, 1989; Glaser & Strauss, 2009; Pagell & LePine, 2002). Specifically, our initial interviews inevitably left us curious about the evolution of AM use at these firms as a result of the exogenous shock, as well as despite it. Findings from the first round also inspired us to dive deeper into the specific nature of GD use as an approach to product development.

To help us make comparisons in the second stage, we asked firms to rate their use of GD on a Likert-type scale (five representing regular use in all design efforts, and one representing the absence of GD as an approach at their firm). The 6-month time interval also allowed time for our contacts to view their pivot decision (go or no-go) from a retrospective vantage point. By drawing on their experience over the prior 6 months, informants were encouraged to describe or speculate on future plans for maintaining the pivot, reverting entirely to pre-shock activities, or following a dual path (e.g., maintaining a new business line). From a theoretical and methodological standpoint, the 6-month time gap allowed us to iterate back and forth between the Stage 1 analyses and the evidence from the literature. This resulted in the generation of newer anomalies (e.g., why did GD help in pivoting? What was GD's role beyond augmenting AM capabilities) that were explored in Stage 2. This approach is in line with Saetre and Van de Ven (2021), who set out how to develop theory from abduction. Appendix A also contains questionnaires used during Stage 2 of the study.

Apart from inquiring into the use of GD, we also used this stage to drill further into the rationale for pivoting and how much it was related to losses in core product line demand, resource availability, or upstream SC support. Of the 34 first-stage participants, 33 continued to participate in this stage (a total of 45 interviews and short post hoc discussions to provide clarity). The one firm that did not participate in this round was contacted by multiple means and ultimately cited timing or personnel changes for discontinuing participation. We followed a similar approach of conducting Zoom interviews with the participants to obtain feedback on the performance implications emerging from their responses to the exogenous shock. We use the same best practices for coding as applied in Stage 1.

3.3 | Stage 3—AM facilitated learning

A final follow-up with firms in our sample was carried out 2 years from the original point of contact, between July 2022 and November 2022. Apart from allowing further time for firms to assess performance and rationalize plans for ongoing AM production capacity, this third interview stage gave us the opportunities to dive into one question, based on observations in our first two stages (Glaser & Strauss, 2009). For example, respondents were asked: "given the apparent association of advanced decision support applications like GD with pivot success, by what means does that benefit emerge?" We were curious as to whether experiences with GD were viewed as spilling into broader impacts on design ethos and approaches, and whether it distinguished firms in other dimensions of AM use and success.

Although specific questions relating to GD clearly would only be relevant to those employing this approach in AM, we nevertheless also reached out to firms in our sample that did not previously describe such use, in the event that adoption may have occurred in the last 18 months. We were also interested in seeing whether any broad markers of success related to production agility and innovation could further distinguish GD and non-GD use cases. In total, we were able to receive responses from 15 of the original firms in our sample, 8 of which had discussed considerable use of GD in Stage 2. These final interviews are supplemented with a keyword search of firm names in combination with a range of common terms that came up repeatedly in prior interview stages ("new process," "new product," "innovate," "failure," etc.). Such an effort, again, reflects modern case research best practice, recommending the use of such alternative sources of information for validation purposes (Lee & Klassen, 2008; Pagell & LePine, 2002; Yin, 2014). Ultimately, our intention in the present inquiry is to draw attention to shared experiences and to provide synthesis to help advance discussions to a stage at which objective assessments can be targeted through theory testing. As with all abductive studies, we allow the evidence to lead our inquiry rather than adhere to a deterministic journey.

4 | ANALYSIS AND INTERPRETATION

4.1 | The pivot decision: insights from Stage 1

Cross-case analyses of all firms revealed that several factors drove production pivoting. These included proximal demand for pandemic-related support/innovation and organizational orientations toward flexible production deployment (MTO and DTO orientations). As discussed, folded into our interpretation of proximal demand is that of similarity/familiarity with emergent production specifications (e.g., requirements "proximal" to extant core production capabilities). Products made by the firms that chose to participate in this effort ranged from nasal swabs to headgear for facemasks, goggles, and ventilator parts. In some instances, the parts were printed directly using AM equipment. For example, *Medical2p*, a dental implants firm, produced thousands of nasal swabs using its own in-house material jetting and DLP machines. In other instances, such as *ConsGoods2p* (a firm focused on making consumer electronics), tooling (e.g., metal molds) was printed additively, whereas parts were produced using conventional techniques (e.g., injection molding).

Overall, the cross-case analyses from the first round of interviews suggested that familiarities in terms of design, production, and regulatory knowledge were some of the factors that stood out as important difference between the firms that pivoted to those that did not. Previous studies have discussed the importance of these factors when making decisions regarding entry into new markets and services (Kunovjanek & Wankmüller, 2021). In addition to these factors, the cross-case comparisons further suggested another important but less understood factor that differed between the two groups. Specifically, we found that the firms that pivoted stood out with respect to their technical AM attributes in terms of the design and deployment of these capabilities. When asked about the potential use of technologies such as 3D Printing/AM when making decisions to pivot, respondents brought out the importance of GD and the associated software (e.g., Fusion 360) and its use in adapting to new conditions. What was particularly striking were two points in this regard: (1) GD was mentioned only by pivoting firms, and (2) firms did not describe the use of GD in this pivoting effort, but rather as a matter of course in their main business lines. That is, even though GD was not relied on for the design of goods meeting the need of the exogenous shock, it appeared that firms with GD nevertheless were more likely to engage in pivoting. A couple of statements from follow-up calls at this stage were suggestive of these observations.

> More and more we are designing aided by our work in Generative. We hope to push further

into design-to-order, less make-to-order [as in the COVID-19 pivot]. (Medical3p)

We use GD in AM all the time, well not here in [COVID-19 part production]. But, yah, we generally rely on it for a lot. Gets us places we couldn't, and confidence on new things. (Automotive2p)

The popular media, at the time, presented GD as a problem-solving resource, but not something that had added value outside of a specific application (cf. Business Wire, 2019; Hexagon, 2019). Most of the existing knowledge around GD relates to its ability to improve performance in terms of design features and cost efficiencies. The general tenor of pivoting firms in this regard, however, leads us to suspect that GD's impact was far more formative with regard to individual designer and production engineer skillsets (and mindsets) than its depiction in research and popular technical media currently suggested. We state the following propositions on the importance of GD in terms of a firm's ability to pivot its design and production efforts.

P_1: The deeper and broader a firm's leveraging of GD in additive manufacturing efforts, the greater the capacity to successfully pivot to AM design and production resources.

To understand the additional benefits from GD, we relied on our second round of interviews that dealt more with the internal capabilities of GD that gave firms the ability to develop flexibility.

4.2 | GD differences and pivot performance: insights from Stage 2

Our second-stage interviews allowed us to inquire into the post-pivot performance of firms as well as delve into some of the minutia of GD use. We approached the latter aspect with the knowledge that computationally derived designs, as per GD, are often notably distinct from designs that would typically emerge from a traditional engineering design process (Plocher & Panesar, 2019). Traditional design approaches often begin with preexisting designs and strive to adjust such designs to meet current needs. When weaknesses are identified, supplemental adjustments are further conducted. In contrast, GD-developed designs can begin with very limited preexisting foundations, if desired, and permit complete restructuring, or ground up builds based on what is needed, where material can exist or not exist, and overall physical properties. Designs emerge and are vetted through simulation and machine learning (or similar tactics) that are applied to create superior next-generation options.

As is often the case with new technology, lessons from GD usage are not confined to the use of software but rather can have a fundamental impact on the through processes and workflow of engineers and the organizations for which they work (cf. Nandhakumar et al., 2005). We begin our discussion of this stage of interviews by focusing first on how GD may have come into play in rationalizing pivoting behaviors among firms in our sample.

4.2.1 | Removing barriers

Because aspects of design quality (e.g., strength and durability) are not compromised through GD optimization processes, the more engineers and their managers are exposed to design concepts emerging from the use of GD, the more they are open to new designs that they might not otherwise have come up with themselves. That is, these engineers and managers we met with were not looking at GD as a capability that would eliminate human design but rather as the one that augments human capabilities. For example, firms such as *ConsGoods1p* (for wearables) and *Automotive1p* (for racing vehicles) were both reliant on decision support in AM designs for customization and rapid/novel design iteration. For these firms, the prospect of pivoting a portion of production resources in the face of the exogenous shock was a natural one. Both were quick to accept external design guidance regarding these parts and rapidly integrate those "foreign" designs (i.e., those not created largely by in-house engineers) into production processes.

Responses to our questions in the second stage of interviews ultimately ranged widely with regard to the integration of GD and are shown below (see Figure 3).

Overall, there was a slightly greater tendency for participating firms to cite higher levels of regular use of GD in their core business products. Ten of the pivoting firms (out of 17) suggested at least broad occasional use, whereas 8 of the non-pivoting firms suggested that they lacked experience with GD entirely. These differences, in a limited sample, are certainly not sufficient to qualify generalizable claims regarding the direct effect of GD on pivot-readiness. However, additional case-specific details combining these GD levels with other contextual factors do provide some interesting enrichments.

For example, among all firms that described a level of fit, those with a higher level of GD experience appeared still more likely to participate in the COVID-19 response. As an example, *Industrial2n*, a maker of industrial filtration solutions, which had in fact identified a potential client and had some idle capacity, ultimately described the prospect as "low interest" and not worth the time that would need to be invested in design and development. Although a large organization, with ample AM capabilities and broad traditional in-house design experience, it described its use of GD as all but nonexistent (only having "explored" related software). As a result, the prospect of organizing resources around a "foreign" design was not something in the comfort zone of the organization.

When more specifically assessing part design similarities, and associated supply-chain similarities, as well as levels of

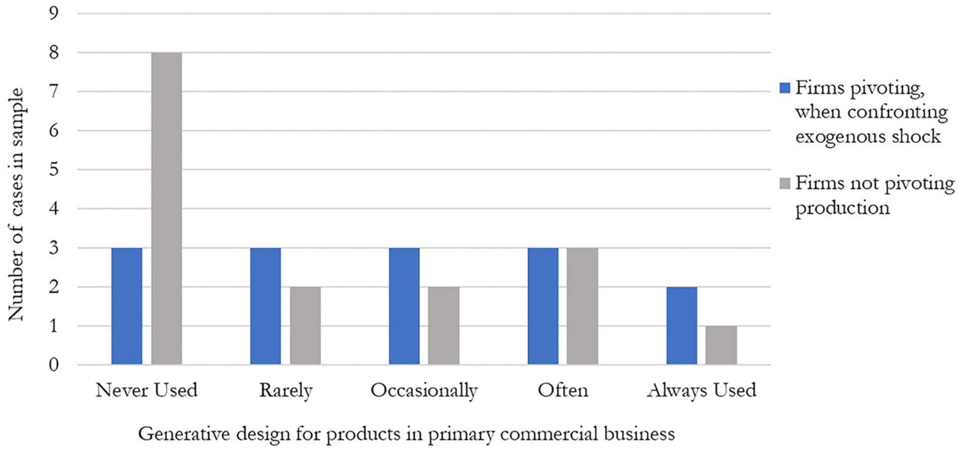


FIGURE 3 Variation in generative design (GD) use among firms, split by pivots in response to exogenous shock.

regulatory familiarity, we found that GD strengthened the positive role these factors played in decisions to participate in the COVID-19 effort. Firms possessing both (1) high levels of product similarity and/or familiarity with COVID-19 regulatory requirements and (2) high levels of GD expertise were most likely to participate in the effort. *Medical2p*, for example, possessed high levels of these factors across the board and was considerably proactive in seeking out opportunities for participation. As described by *Medical2p*,

> We learn (from GD) as well about how typical things can be improved, so it assists us in both what we do day in and out and new work… (plus) we were already registered with the FDA, same class-2 medical device, and it was a natural transition to making swabs.

In contrast, other firms with low levels of both regulatory knowledge and product similarity, as well as lacking in GD experience (e.g., *Medical1n* and *Military1n*), broadly disregarded the potential for involvement early on. This once again suggests that although GD was not sufficient to determine involvement during this pandemic, it does play a role in combination with other factors.

Our second-stage interviews also yielded evidence of GD expertise affecting the relationship between firms' demand-driven customization, measured using MTO and DTO orientations, and their decision to participate. As with GD, part of our discussion with organizations involved asking these firms to position themselves on a scale from noninvolvement in MTO (or DTO) to such orientations being core to the strategy and regular operations of the organization. Here, the impact of GD at high or low levels of MTO and DTO was distinct from that encountered with regard to market demand. Although higher levels of MTO and DTO tended to be associated with higher participation in the COVID-19 part production response, we found that GD tended to substitute or "compensate" for lower MTO and DTO orientations.

For example, *Automotive2p*, while not typically interested in either MTO or DTO activity, nevertheless possessed a moderate level of flexible design acumen through growing GD investments and expertise and was willing to participate in the COVID-19 production efforts. In the words of our main contact at *Automotive2p*,

> We have been learning to use AM to design things in a pinch, even though we really aren't a make-to-order shop; still, sometimes we have major design changes we need to make… Weight is obviously important, so (GD) design software has been making more of a difference, and we are starting to appreciate it more because of agility… (for COVID-19); we were trying to act the role of a responsible firm, and that flexibility helped.

In contrast, *Automotive2n*, despite slightly higher self-assessments of MTO/DTO, had no experience with GD and did not participate in COVID-19 part production, citing (similarly to *Industrial2n*) a lack of sufficient return for the amount of effort required. This in turn formed two key implied propositions regarding the role of GD in pivoting to different product streams as well as the substitutionary effects of GD in compensating for the firm's lack of customization capabilities.

As with the compensatory role of GD regarding lower MTO and DTO orientations, GD seems to make up considerably for deficits in pandemic-specific capabilities. For example, although *Medical1p* had some familiarity with related regulatory standards, the organization suggested that the design and required supply of materials for contributing to the pivoted production effort was not similar to what it had previously dealt with for its core business. However, it did possess considerable expertise in GD and the accommodation of new designs in a production setting. According to *Medical1p*,

> (GD) really made a difference in our understanding of smart designs. It allows us to focus on other things that are important, while cutting out some time and cost.

4.2.2 | Promoting success

As noted, another key intention of our second-stage interviews was to get a sense of how successful the act of pivoting was for those who opted to do so. We specifically asked this subset of firms to rate the performance of production effort they pivoted to, along dimensions such as product quality, cost, and speed of development, relative to other firms they believe are producing such items (1–5; 5 = “Performance was far above the norm,” 3 = “On par,” etc.). On the average, customization drivers (MTO and DTO) were associated with very little variation when looking at performance outcomes. In contrast, as would be expected, the degree of similarity between the core products and pivoted production does appear to trend with performance. Further, firms possessing high levels of COVID-19-related regulatory familiarity attested to somewhat higher levels of speed and cost performance, compared to those with less familiarity. Such associations align well with operational fit arguments. The greater these factors are present, the more easily knowledge can be transferred between the two production contexts, with associated benefits in response to performance.

Examples of firms for which this association was observed include *ConsGoods2p*, *ConsGoods3p*, and *Industrial2p*, each of which attested to high degrees of similarity in the materials and processes required for pivoted production. These firms also expressed familiarity with any associated federal regulatory standards as well as cited high levels of performance across the board in relation to the dimensions of quality, cost, and speed of development for parts made. In the case of *ConsGoods2p*, using 3D-printed molds, the organization recorded a particularly rapid and high-yield ramp in their production efforts and went from making 1000 parts to eventually 50,000 parts in a few weeks. Further related claims came from the respondent from *ConsGoods3p*:

> We have built our system in mind to be able to introduce new products quickly, although in 10 days quickly was never the plan, but we have built the system in order to facilitate quick design, development, and introduction of new products. [We] not only showed that it can be done, but it actually exceeded our expectations of what we can do about it.

When comparing firms with higher levels of GD experience, we observed superior levels of cost, quality, and speed of development across our sample of participating firms. On average, GD shaved approximately 4.5 days from the overall design and development time for these products (from an average of about 10.5 days to roughly 6 days of total design time prior to production).

4.2.3 | Fostering insight

Beyond pivot-specific performance, the second-stage interview also provided an opportunity to examine whether broader benefits had evolved through the usage of AM over the last half-year, regardless of shock-related pivoting actions. Interview responses were coded, by the same research team and external engineering professionals, into distinct categories. These included design-related lessons (e.g., relating to design agility and processes), market lessons (e.g., relating to revealed market opportunities or the fragility of an existing AM customer base), and lessons regarding their manufacturing and SC system (e.g., the capabilities of AM partners, logistical lessons in shipping new AM-produced products, or weaknesses in material availability).

Albeit isolated, striking examples of lessons learned include that of two pivoting firms, in particular. The first firm, *ConsGoods3p*, rapidly and successfully developed a novel design for protective eyewear, which resulted in an entirely new product line that prospered after the pandemic due to its potential for generalized use. A second firm, *Industrial2p*, retrofitted an otherwise largely idle warehouse to start up an entirely new division with a long-term dedication to PPE production. In almost all other cases, there was little intention to continue to produce PPE or other COVID-19-related parts beyond the pandemic period. The hope, in general, was to return to “business as usual” with their core business lines in AM. More subtle gains in knowledge were nevertheless prevalent, with some notable distinctions between pivoting and non-pivoting firms.

Pivoting firms cited proof of design agility far more frequently than those that did not participate (65% vs. 13%). They also commonly referred to the strength of partner relationships and lessons learned in the logistical management emerging from their experience (53% in both cases). In contrast, those not participating made no mention of the value of partner relationships and were far more inclined to mention concerns regarding narrow client portfolios (31% of nonparticipants vs. 12% of those participating) and concerns over insufficiently robust stocks of materials for production (31% of nonparticipants vs. 6% of those participating). Take, for example, the following statements from pivoting firms:

> I do think it was beneficial … that people got to see that there was a technology (AM) that could respond very quickly; that was very adaptive; that, if you didn’t need some quantity of products while you were building injection molds so you can make millions and millions more, you could still efficiently and effectively 3D-print components. (Medical4p)

> We took a giant leap from a design standpoint. That was a big learning experience … and this is very much applicable to other applications outside the face-shield one. (ConsGoods2p)

> In general, the main learning was that we kind of proved that we can quickly introduce new products, as we had hoped and designed our business for. The need allowed us to push ourselves and show how agile we could be. (ConsGoods3p)

In contrast, consider the following statements typical of those not involved in pivoting of AM resources in response to the exogenous shock:

> We need to try to find ways for others (e.g., customers) to adopt the technology and accept AM … Really tough to convince customers when we can't show physically. (Industrial2n)

> We had a customer who we felt we were being good-faith with, and they took advantage of it. We invested, and they dropped the ball. So, we have learned to be a little more cautious with larger customers in the auto-industry. (Automotive2n)

The difference in both the tone and the content of these retrospectives among pivoting and non-pivoting firms is somewhat striking. However, the act of pivoting was likely not the only factor at play. Given our interest in the impact of GD, we also considered the potential for differences in the occurrence of these lessons among high- and low-level use cases of GD. Of those with levels of GD above the sample mean, many attested to positive lessons learned regarding their own design agility (44%), relating to the capability of such firms to strategically pivot production resources when market and other forces apply pressure, logistical processes (38%) associated with new product launches, and the value of partners (44%). This can be compared to the 35%, 18%, and 12% rates for those with GD levels below the sample mean. Of those with higher GD usage levels, only 13% attested to revealed risks in client diversity (vs. 29% of those with low GD), and only 6% cited revealed risks regarding stock availability (vs. 29% of those with low GD). Still more striking, among firms pivoting production, 70% of those with high levels of GD experience attested to SC-related gains, and none made mention of stock availability or client diversity risks.

Consider the following two statements by high-GD pivoting firms:

> We are very focused on managing unknown risks in the supply chain [SC] using AM. We've been doing AM for a long time, so not too many surprises. Obviously proven that we can extend into other industries quickly. AM is very well positioned for managing problems in SC in a crunch. (ConsGoods1p)

> (We realized) how partners with different capabilities can come together for a common good. The responsiveness and capabilities. (Medical3p)

In contrast, consider the following statement from a low-GD pivoting firm:

> I think (we) were a little hemmed in and couldn't shift around as much as we would have liked. That made us much dependent on things like wobbles in supply and demand. (Industrial1p)

4.2.4 | GD as a symbiotic learning mechanism

Taken as a set, these assorted observations regarding the role of GD, both in encouraging pivoting and subsequent support of quality and cost-effectiveness in accommodating emergent demand, and extended insights relevant beyond the exogenous-shock context, further lines up with proposition P1. Lacking, at this point, was a richer understanding of "how"; that is, the mechanism by which experience with GD might be translated into such broad outcomes. To attempt to answer this question, we returned to the literature. We were inspired by the following recent statement by Na and Kim (2021):

> Generative design can be used as one of the methodologies that can be explored in the ideation stage in that it produces modeling that exceeds the creative capacity of human beings …. [GD] not only provides designers' creative modeling inspiration and solutions for design, but also reduces friction between designers, developers, and clients. It is expected that it will be able to help establish a new convergence and complex process as an alternative to minimizing and developing competitive products. (pg. 96)

The authors suggest that GD not only reaches beyond the creative bounds of designers but also expands those bounds, with associated benefits for multiple stakeholders. In other words, the authors are describing the existence of a learning dialog existing between the designer and the software. Our third wave of data collection would focus on whether this was evident in our sample of firms. As we have noted, GD involves the process of human designers providing specific design parameters to an artificial intelligence-driven mechanism (i.e., teaching the tool), receiving design outputs, and then selecting and rationalizing choice (validated through simulation and physical testing). These latter steps have the potential to expand mental models of what is possible in design, what works and why.

This dynamic, involving the rationalization of feedback and the evolution of mental models, is referred to as double-loop learning and has long been studied (Argyris, 1977; Sterman, 1994; Weick, 1988). Similarly, the notions of human–AI interactions (including symbiosis) are not entirely new (HBRAS, 2018; Jarrahi, 2018; Wilson & Daugherty, 2019). More precisely, the human–AI dyad has been discussed variously, including more recent discussions of interactions with generative AI writ-large. Yet definitions of generative AI (cf. Stanford University, 2023) are still decidedly oriented toward textually prompted artifacts, rather than the generation of technical design specifications core to the functionality and role of GD (as a subset of generative AI). Two excellent contemporary reviews of human–AI interactions and generative AI are provided by Bankins et al. (2023) and by Nah et al. (2023). The first of these provides a distinctly organizational perspective and extensive consideration of human perception and angst with regard to AI. The latter provides greater emphasis on social ethical perspectives. Both, however, largely consider non-symbiotic human–AI interactions, with greater attention to largely agent–principal interaction rather than interactive co-development with shared principal and agent roles (cf. an associated discussion of such roles in Angelopoulos et al., 2023).

Based on our experience with the firms in the study, we believe that the use of GD during AM presents a unique set of conditions that is not present in all settings, and certainly one that is underrepresented in the extant literature. A triad setting, involving humans interacting with the artificial intelligence of GD, and with the near-immediate ability to not only verify simulated design performance with finite element analysis but also print a tangible prototype for physical testing, means that lags in double-loop learning are greatly mitigated (cycle times for mental model revision greatly enhanced). This is depicted conceptually as Loop 2b in Figure 4, with Loop 1 and Loop 2a, adopted from Sterman (1994).

Systems perspectives such as this, with outputs subsequently impacting the manner in which inputs and resources are utilized, in turn yielding fundamental changes in processes and networks, are seeing increased real-world applications (see, e.g., the work of Anderson et al. (2022) regarding the electronic vehicle markets providing a cyclically reinforcing platform for innovation).

If this additional learning mechanism is prevalent in settings where GD usage is high, it is possible that GD applications (in AM settings) are having profound impacts on the innovative capabilities of designers, engineers, and the firms that employ them. Such innovation should be observable, such that firms with a high level of GD demonstrate greater levels of openness to resource pivoting during exogenous shocks, as well as demonstrating general innovation advantages relative to firms with lower levels of GD use. We would also anticipate that designers and engineers are cognizant of the learning they experience with these tools. Accordingly, we suggest the following proposition:

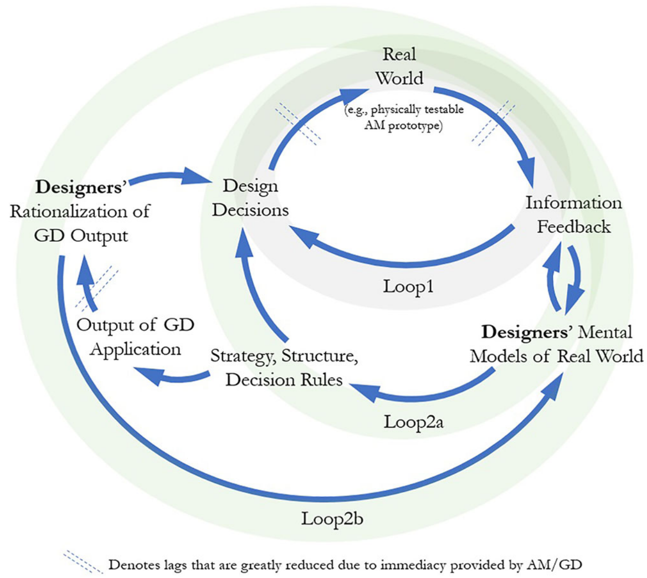


FIGURE 4 Double-loop learning facilitated in a human–generative design (GD)–additive manufacturing (AM) production setting.

P_2: The double-loop learning benefits associated with GD in additive-equipped settings will be directly observable by AM designers interacting with the technology (i.e., human–AI symbiosis).

4.3 | Learning dynamics and advantages in design agility: insights from Stage 3

The primary intention of our third and final stage of interviews was to see if evidence could be uncovered in support of broad innovative benefits and recognizable learning in GD additive settings. Prior to conducting Stage 3 interviews, broad distinctions between firms with high- and low-levels of GD usage were reconsidered. An equal number of firms in each industry was selected for use in an, albeit highly cursory, online media search of key terms ($N = 10$). This was accomplished to understand how the firms were performing in general over the last 2 years amidst the pandemic. For this process, we identified key terms such as "new product," "new technology," "new market," "innovate," and "patent" that were described as critical factors for performance in the second-stage interviews. The total number of occurrences of articles including each term and a given firm's name was divided by the total number of articles for the firm as a whole. The percentages of mentions including each term were then averaged for the high GD and low GD subsets. Figure 5 depicts these simplistic hit rates in summary.

With the caveat that this kind of an examination is highly exploratory, and that it is impractical to attempt to speculate on endogeneity at this level, some of the differences in keyword hit rates nevertheless stand out. High GD firms, for example, are far more likely to be mentioned in conjunction

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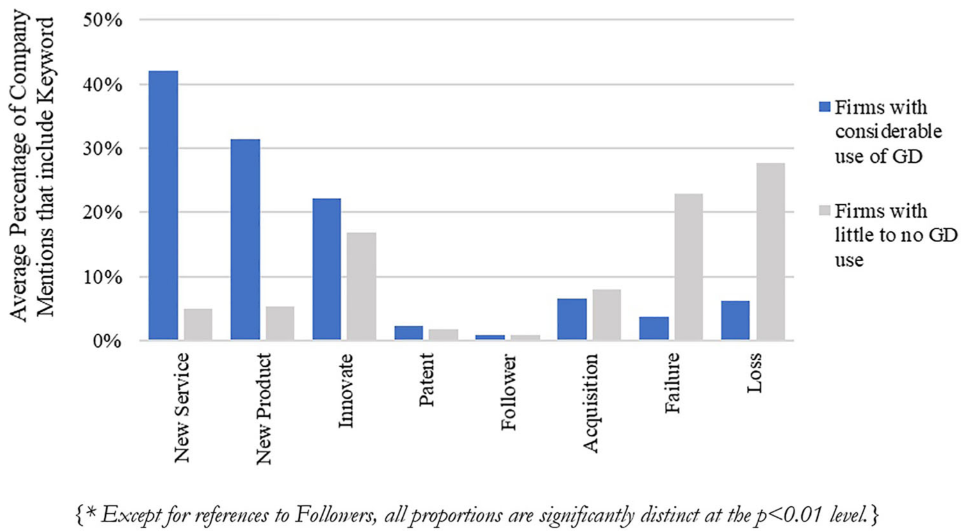

FIGURE 5 Keyword-firm matches among firm mentions online. (*Note*: Except for references to followers, all proportions are significantly distinct at the $p < 0.01$ level.)

with "new product" and "new service" entries. Examples include the development of novel techniques and products in dentistry, and new business lines in consumer products and aerospace components. Although patents represent a small fraction of all mentions, these mentions are also 25% greater than for firms with low GD use. In contrast, low GD firms are mentioned more so with the acquisition of other firms and the capabilities of those firms acquired. Although acquisition can serve many purposes, it is often a sign that organizations are not organically developing new solutions themselves (Cartwright & Schoenberg, 2006). They are also far more likely to be mentioned with regard to design failures and losses. However, like all other aspects of this inquiry, this is only one kind of signal, and a clearly imperfect one at a very high level of consideration.

To obtain greater fidelity, we relied once again on the case interview process (see Appendix A). We began by returning to the firms that voiced some notable use of GD in the second round. We asked individuals to voice their general views of openness to GD as a tactic, inputs provided to GD and a general sense of whether individual engineers have experienced learning can be applied to future GD–AM efforts, as well efforts that do not utilize GD or AM. At this stage, we also obtained supplemental details regarding goals generally associated with DfAM as well as general signs of innovativeness. Specifically, we explored whether firms saw growth in such dimensions over the last 2 years. These latter questions were asked of both firms with high GD usage, as well as those suggesting minimal use in the second stage. Responses to these are summarized in Figure 6.

Although most firms that described themselves as nonusers of GD remarked that little has changed along these points over the last 2 years, firms with higher GD tended to report relatively higher levels of customization, ability to utilize hybrid applications of AM, and principal DfAM targets such as light-weighting and part reduction. Take for instance the following comment made by one of our interviewees at this stage:

> [We] were able to take that generative design output, see where we could reduce material, and then produce a similar product to what they took a year to redesign and I think it was three percent is what it said on that other page, a three percent less material which they make ($100K annual in two weeks time). (Industrial1n)

Unfortunately, in this small sample, most GD-users suggested little change in such matters as new business line development. Granted, we appreciate that a limited sample and still more limited time frame (2 years) set up certain challenges for such observation. Nevertheless, the following comment provides a striking demonstration of the belief that longer term impacts are down the road:

> Now we can both manufacture and design high efficiency parts because of generated [GD]. Big freaking deal. I mean, it's a game changer in, uh, a lot of industries. In the last 3000 years we make a design, we test it, make changes, etc. Always the designer conceives the design. NOW, the rules are provided and the design comes. GD spawns a lot of designs. We still test them. We still learn what works and doesn't work, but we also gain an understanding of why is the design is what it is. (Aerospace1p)

The words of the interviewees also spoke volumes regarding the potential long-term benefits of GD. Take for example the following quotes from this stage:

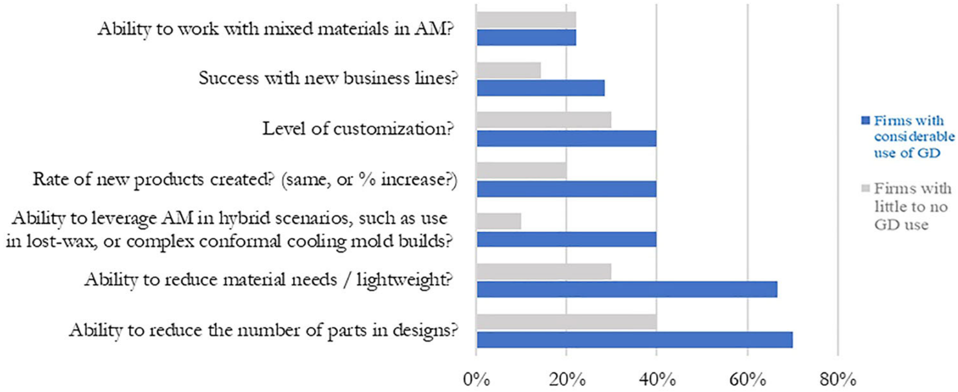

FIGURE 6 Firms reporting gains in dimensions of success and design for additive manufacturing (DfAM).

> Now [there is] a kind of a cycle of learning between designers and the AM technologies that they're using, that allows a kind of a dialogue that maybe we haven't had before. (Automotive1n)

> Everything is an experiment. I personally document all of the things I learn from the use of GD and associated validation tests. There can be 20% of proposed GD designs that fail in FEA or physical testing (lie a unanticipated temperature drop in manufacturing or use), so we need to learn from those and make future specifications so that the AI doesn't consider those in future builds. Proper documentation is key here, beyond the CAD models that is stored in the cloud, for example. (ConsGoods4p)

> [With GD outputs in hand] the designer … can go to a classical FEA code, like, and rerun this cases and validate that the stuff you gave me is good … and that helps sensemaking, relies on it, and can make for further advancement of design. (Automotive1p)

Each of these touches on the presence of a presumptive double-loop learning process. A process made possible through the combination of an artificially intelligent design mechanism (GD), a means by which to immediately substantiate outputs of GD for physical testing (AM), and the evolving expertise and mental models of individuals willing to scrutinize, deconstruct and ultimately appreciate the practical benefits those outputs (designer/engineers). As in Figure 4, we see the confirmation of lag minimization between outputs created and passed between each role in this triad. In sum, these points also suggest the following proposition regarding the performance outcomes from GD.

P_3: The deeper and broader a firm's leveraging of GD in AM efforts, the greater the innovative advantage and potential for innovative outcomes.

5 | DISCUSSION AND CONCLUSIONS

5.1 | Contributions to theory

In recent years, the use of AM capabilities has advanced beyond the prototyping needs of firms to encompass both tooling and even direct manufacturing activities. In this research, we focused on understanding why certain firms chose to pivot their AM capabilities in response to exogenous shocks, to support nonconventional emergent demand, whereas others did not. We investigated the success of, and broader performance benefits emerging from, such participation using a three-stage qualitative case study design following firms over 2 years. The first year of the COVID-19 pandemic, 2020, presented a convenient natural experiment context for our study. To this point, America Makes, which we worked with during this study, is now moving to promote "pandemic drills" to better prepare for future shocks. Our own cross-case comparison of these decisions, along with a range of associated outcomes, offers insights into such industry efforts, as well as the product development, operations strategy, and AM literature.

First, our case examination revealed pivoting firms capitalizing on their own unique knowledge and experiences to meet pressing, and in some cases highly unfamiliar, demand in unique ways. While fit played a role, so too did flexible operational orientations toward customization (MTO, DTO). The existence of AM capabilities, from simply having rapid prototyping polymer printers in place, to the hybrid integration of AM with conventional manufacturing techniques (e.g., use in investment casting or conformal cooling tool designs), to the extensive application of GD, surely complemented the latter efforts (DfAM). In that sense, our work contributes to the emerging body of management research in AM (Holmström et al., 2019; Roscoe et al., 2019) by viewing the pivotal role of AM as an enabling infrastructure.

Perhaps more intriguing and novel insight from our study, however, are the findings regarding specific experience with GD software. When looking at the specific AM capabilities held by firms, our analyses found the role of GD to be a particularly important factor that facilitates resource pivoting in response to the exogenous shock of the pandemic. GD is a category of technologies that enable firms to arrive at novel design options or to optimize an existing design to meet the criteria of the end user (Wu et al., 2019). Although this class of technologies can exist outside of specific AM capabilities, we did find that having GD in conjunction with AM offers synergies that advance the agility of firms as they make changes to their design and manufacturing functions. Our case analyses and cross-case comparisons suggest that firms that participated in pandemic-related production had somewhat higher levels of GD usage compared to those that did not. The regular use of GD highlights an organizational openness to a broader range of designs. However, it also mandates a broader comprehension of design dynamics, made apparent specifically through prototyping and testing experiences with GD.

High levels of GD experience can compensate for shortfalls in factors such as fit and flexible production orientations (MTO, DTO). Overall, our study demonstrates the importance of this GD technique in terms of its ability to heighten agility in firms' operations during a shock. Despite this point, our case interviews did suggest that an inherent tension might nevertheless exist between the use of GD and creative human elements of design, which may explain why some firms have not yet invested largely in this technology. The trust that workers place in AI, in many forms and contexts, is certainly at the center of numerous contemporary management discussions, with sentiment ranging from outright avoidance and circumvention to overreliance and scapegoating (cf. Bedué & Fritzsche, 2022; Glikson & Woolley, 2020; Omrani et al., 2022). Acceptability of the role of, and associated affinity toward, GD is also likely to change as additional evidence of successful integration of GD and its benefits to designers and engineers emerge. Our research therefore also contributes to a discussion about both the resource agility and design-process complementarity that this computational approach to design can offer to manufacturers, as they assess its costs and benefits.

Our analyses further suggest that using GD enables designers and engineers to think and interact differently with the AM creating a double-loop learning cycle. That is, in the presence of GD, designers can offer specific design inputs based on real world needs to an AI-driven mechanism and are able to receive design outputs that can help in refining and selecting their ideas. This dynamic involving the rationalization of feedback and the evolution of new mental models creates a unique human–AI symbiosis in the presence of GD. Although previous research has discussed the role of double-loop learning in creating better outcomes (Argyris, 1977; Sterman, 1994), our study offers insights on how GD creates this possibility for firms, augments critical resilience to shocks, and in turn offers them competitive edge. We believe the appreciation of the human–GD–AM triad is an important contribution to the emerging literature on human–AI interactions and the possibilities enabled from this combination.

These insights have several important implications for the management and workforce development in this newer operating world of AI and human decision-making. First and foremost, the implication is that these skillsets are subject to continuous and potentially rapid co-development with technology, particularly as experiences with GD–AM grow. Precursors to such development are likely to include a joint facility with both product design and a foundation in the use of computational modeling, though these are surely not new to hiring and training at most modern firms. However, we do see that generating the benefits of human–AI decision-making may require organizations to be open to engineers thinking outside the box, and promoting a culture that values frequent experimentation and develop a perspective that failure is just another opportunity for learning. These are not necessarily "traditional traits" sought in the hiring of design engineers (one of our authors, speaking from experience), as much as they have been viewed as "plusses." The same virtues, nonetheless, should be demonstrated by managers if they hope to inspire gains through the symbiosis of this triad.

5.2 | Limitations and future research directions

Our research has several limitations that can serve as opportunities for future research. First, our research design, using a three-stage qualitative case method, is exploratory. Although we took care in terms of our research design by having multiple informants, investigators, triangulating with other sources of data, we acknowledge that insights developed through our study are limited to the 34 firms identified in our study. Further work would be required to validate the propositions that are developed in our work. Case study research inherently has strong internal validity but is limited in external validity (Eisenhardt, 1989). We thus urge OM scholars to conduct additional work in this area to validate the importance of GD capabilities beyond our study context. This could occur through a large-scale empirical study that measures the firms' GD capabilities and correlates them with performance outcomes in terms of agility and adaptability. Second, our inferences are based on information from a limited number of firms that were theoretically sampled and hence may have good internal validity but fall short in external validity. We recommended that scholars continue this line of inquiry with other firms to improve the generalizability from our study.

Third, our analyses show that firms learned valuable lessons through pivoting production resources in the presence of an exogenous shock. Indeed, two of the firms ended up generating new business lines because of participation. However, in most cases, firms returned to business as usual. Although we discuss a range of lessons learned, we focus largely on those relating to design and manufacturing. Other lessons may also emerge from experience with AM resource pivoting and the use of GD applications. There are hence future research opportunities to learn about the indirect impact of exogenous shocks on capacity expansion decisions as well as SC design decisions. For instance, in one case, we observed that a firm's overreliance on SCs that were globally distributed created problems in local relief participation. Although effective local AM relationships can ameliorate this risk, the flexibility of AM and the presumption of rich digital product details can nevertheless inspire new global design collaborations, while keeping production proximal. We urge OM scholars to conduct further research on the relationship between AM capabilities and SC design decisions.

Notwithstanding these limitations, our study offers preliminary insights into how AM capabilities influence strategic decisions regarding the way in which firms adapt and evolve during times of uncertainty. We hope that our exploratory work will help to propel more discussion about the usefulness of AM capabilities as well as their benefits to traditional operational and product development decisions.

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APPENDIX A

SUBSET OF QUESTIONS FROM FIRST STAGE INTERVIEWS

How does your organization traditionally use AM capabilities? (Design, Prototyping, Tooling, Production)

If you are printing prototypes, production or tooling, what materials are you printing these in? (All materials that apply, specific to use of each)

What type(s) of 3D printing do you perform? (Printer technology use)

Does your company source components from outside United States?

Are you involved in efforts to support community health, related to the COVID-19 crisis?

If yes, what kinds of parts (note all that apply)? How is AM applied in that work?

Does your company traditionally make these products?

What do you view to be the greatest strength of your current use of AM? Shortcoming or limitation?

If applicable, how long did the last development of printed tooling take you? Can you elaborate on what you believe added the most time to this effort? How did this compare to non-AM tooling lead-times?

SUBSET OF QUESTIONS FROM SECOND STAGE INTERVIEWS

Thinking back to November 2019, and into the start of the COVID epidemic, how would you characterize what was happening with your core production lines/core business? Has this shifted over the last 12 months? Discuss the volume and business over the last few months? Machine and worker capacity shortfalls or idleness? Has any COVID-related disruption to core business line now been resolved?

Regarding the use of software-assisted generative design techniques, to what extent did your AM activity leverage such software-assisted designs. In November of 2019? In April of 2020? Today?

Thinking back, were there any specific reasons that we missed during the last round of conversations that triggered your (non-) participation? Specifically, were you (not) motivated due to technical capabilities, was it altruism, or was it due to requests from local institutions (Give examples)?

(For those participating) Do you still plan on continue making the products for COVID-19? If you do, will you continue to use AM, or shift predominantly to other manufacturing methods? Explain.

SUBSET OF QUESTIONS FROM THIRD STAGE INTERVIEWS

How would you rate the openness of your engineers to generative design outputs (i.e., informed/rule-constrained topology optimization): Now versus prior to 2020? Versus other firms in your industry?

How do your engineers rationalize/evaluate for practical purposes the designs that come out of GD?

Does that feedback into new specifications for future GD processes? If so, how?

Do you feel your engineers are learning about new design options via GD that can be applied to:

- Future GD efforts
- Non-GD efforts in AM
- Designs that don't involve AM

Can you describe any advancements experienced over the last 2 years with AM-use? (New product creation rate, level of customization, reduction in material needs or number of parts, combined AM/non-AM tactics)

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