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RESEARCH ARTICLE

Accelerators as Circular Ecosystem Facilitators: Heterogeneity and Resource-Based Value Drivers for Enterprises

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Abstract

Accelerators in the circular economy (CE) are more than matchmakers; they are resource orchestrators whose value depends on enterprise context. Drawing on the resource-based view (RBV), this paper analyzes intake and exit surveys from 37 startups and SMEs participating in a Southern Ontario agri-food CE accelerator in Canada, spanning four categories: Circular Agriculture, Consumer Goods from Upcycled Food, Circular Packaging Solutions, and Low Waste Food Retail. To capture differentiated value creation, we apply LDA topic modeling with TF-IDF validation and lexicon-based sentiment analysis to assess supports including training, mentorship, funding, and networking. Findings show clear category-specific heterogeneity. Circular Agriculture prioritizes training and funding; Consumer Goods from Upcycled Food emphasizes training; Low Waste Food Retail values funding most; and Circular Packaging emphasizes funding while training is largely absent. These distinct patterns align with each category's supply-loop position and baseline resource endowments, validating the RBV's central claim of heterogeneity in a CE setting. Robustness checks (TF-IDF overlap; document–topic probabilities) confirm results despite the modest sample size. The study's findings imply that one-size-fits-all accelerator design is inadequate. Tailored support bundles matched to enterprise category enhance efficiency and outcomes, positioning accelerators not only as ecosystem facilitators but also as value distributors, extending RBV from firm-level advantage to ecosystem-level resource orchestration.

Keywords Circular Ecosystem · Circular Entrepreneurship · Accelerator · Incubator · Training · Mentorship · Funding · Networks · Resource-Based View

1. Introduction

As global population and consumption continue to rise, the urgency of shifting towards more sustainable economic models has never been greater. The circular economy (CE) represents one such paradigm, offering an alternative to the prevailing "take–make–use–dispose" logic of industrial production. Instead, CE promotes closed-loop systems of "reduce, reuse, recycle, and recirculate" (Kirchherr et al., 2017). In principle, this entails minimizing waste by designing industrial systems that are restorative and regenerative by intention.

Yet despite its appeal, CE remains inconsistently defined and difficult to implement. Kirchherr et al. (2017) identify 114 different definitions of CE, most of which emphasize narrow activities such as recycling rather than systemic transformation. To avoid such ambiguity, this paper adopts the Ellen MacArthur Foundation's

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(2015) definition: "an industrial system that is restorative or regenerative by intention and design." This definition emphasizes CE not merely as waste reduction, but as a systemic reconfiguration of production and consumption patterns to ensure long-term resilience. Adopting this systemic framing is crucial for understanding the role of circular entrepreneurs, ecosystems, and accelerators in enabling a transition to circularity.

One key barrier to mainstream adoption of CE lies in the costs and risks of altering entrenched business models. Here, circular entrepreneurs—particularly startups and SMEs—serve as leverage points. With their flexibility, they can experiment with circular innovations that established firms often resist. At the same time, circular entrepreneurship faces amplified challenges: restricted supply chain options, resource constraints, and the need to align with closed-loop systems. Overcoming these challenges requires not just entrepreneurial drive but supportive circular ecosystems.

Circular ecosystems are networks of interconnected stakeholders that act in their respective roles along supply loops to both generate value and maintain circular resource flows (Pietrulla, 2022; Geissdoerfer et al., 2025). It is important to note that in their definition, Geissdoerfer et al. (2025) assert that circular ecosystems work to achieve the goal of making resource loops more circular. Circular accelerator and incubator programs connect entrepreneurs to ecosystem resources, provide training and mentorship, and strengthen circular entrepreneurship, thereby reinforcing CE systems (Bergmann & Utikal, 2021). However, existing programs often treat participants as homogeneous in terms of resource availability and requirements, overlooking the heterogeneity of firms' starting conditions and strategic needs within circular supply loops. Just as conventional businesses differ in their strategies and required inputs, so too do circular ventures. Failing to recognize these differences risks diluting the value that accelerators provide. Instead, accelerators must be seen not only as ecosystem facilitators—bridging entrepreneurs to relevant resources—but also as value distributors, tailoring support to ensure that diverse firms derive meaningful benefit.

Existing literature highlights the importance of training, mentorship, and funding in creating value for startups and SMEs (Brodie et al., 2017; Hermann & Bossle, 2020). Yet the circular ecosystem literature emphasizes that value also depends on how such supports are embedded within broader networks of interdependent actors (Geissdoerfer et al., 2017; Trevisan et al., 2022). In this sense, accelerators function as intermediaries, linking entrepreneurs with ecosystem actors (Sultana & Turkina, 2023). What remains underexplored, however, is how heterogeneity across circular enterprises shapes their valuation of different forms of support.

To advance this perspective, this paper applies the resource-based view (RBV) and dynamic capabilities (DC) framework to this empirical study of how accelerators create differentiated value for circular entrepreneurs. Using intake and exit survey data from 37 participants in a Southern Ontario agri-food circular entrepreneurship accelerator program, we analyze how firms in different enterprise categories leverage ecosystem support. A central tenet of the RBV is that firms are heterogeneous: they begin with different levels of resources, and they also require different bundles of resources to succeed (Wernerfelt, 1984). The DC framework takes this idea a step further and asserts that long-term success is also contingent on adaptability (Teece et al., 1997). Applying these perspectives to circular entrepreneurship suggests that challenges related to resources and resource use are largely structural. Circular firms face heterogeneous resource needs depending on their position in the supply loop, and their success depends on accessing different types of ecosystem connections. Conceptualizing challenges through the RBV thus provides sharper insights into how ecosystem actors, particularly accelerators and incubators, can best support entrepreneurs. By drawing on these concepts, we show that accelerators can play a pivotal role in tailoring resource provision, serving simultaneously as ecosystem facilitators and value distributors, thereby enhancing both entrepreneurial success and ecosystem resilience. Our findings demonstrate that firms are heterogeneous in the value they extract from accelerators, depending on their position in the circular supply loop.

Beyond these findings, the paper also highlights broader implications. Conceptualizing accelerator support through the RBV shows how incubators and accelerators can be more targeted and efficient in delivering resources to entrepreneurs, and why tailored approaches are critical for building resilient circular ecosystems. This insight extends the RBV from firm-level advantage to ecosystem-level resource orchestration, offering practical guidance for accelerator design and policy interventions that seek to strengthen circular economy transitions.

2. Related Works

2.1. The Role of Circular Entrepreneurship Accelerators and their Supports

Circular economy accelerator and incubator programs act as a bridge for small firms to become more circular and for circular startups to go to market. They do this, in part, by connecting firms to relevant actors within a circular ecosystem. These programs foster partnership and collaboration (e.g., Kohler, 2016). They also effectively address needs specific to CE entrepreneurs, such as opportunity recognition and pursuit, in ways traditional incubators cannot (Millette et al., 2020). Circular entrepreneurs can benefit from the concentrated resources provided by incubators and accelerators, which enhance their chances of success in the market (Lange, 2018). Our study is in no way the first to acknowledge heterogeneity across circular firms and the roles they play in broader circular ecosystems (Adner and Kapoor, 2010; Jacobides et al., 2018). While existing research has begun to explore the consequences of circular firm heterogeneity, the present study is the first to examine it in the context of accelerator programs. For example, de Vasconcelos Gomes et al. (2023) find heterogeneity in portfolio management of circular innovation projects across circular firms. They go on to suggest that firms differ in the resources they allocate across their portfolios. Based on this, we posit that this heterogeneity extends to the value heterogeneous firms derive from the various offerings of a given accelerator program. These needs are typically addressed through the different dimensions of support circular accelerators and incubators offer: training, mentorship, funding, and other supports such as access to relevant networks. Presently, research and practice treat the value circular entrepreneurs extract from these supports across all areas of the circular economy as homogenous.

2.2. Circular ecosystems and Accelerators

In recent years, the circular economy literature has shifted its focus from circular business models to circular ecosystems (Kanda et al., 2021). However, little research exists on the role of accelerators as actors in circular ecosystems. To begin to understand the role of accelerators in circular ecosystems, we must develop a strong understanding of the concept of circular ecosystems. To do this, we must first look to the ecological definition of an ecosystem as a metaphor for circular ecosystems (Kanda et al., 2021). An ecosystem is generally understood by ecologists to be “all the organisms and the abiotic pools with which they interact [,]” and that “[ecosystem] processes are the transfers of energy and materials from one pool to another” (Chapin et al., 2011). This definition suggests an ecosystem is defined by its actors (living and non-living things) and the transfers of resources between them. In a similar vein, circular ecosystems are defined by the “living” stakeholders and the “non-living” (natural, economic, and political) landscapes they operate within, and the flow of relevant resources (financial or in-kind) between them.

For this paper, we adopt a modified version of Geissdoerfer et al. (2025)’s definition of circular ecosystems: networks of interconnected stakeholders and their environments who interact within their various roles in which many of the actors strive to improve the circularity of resource loops. It is important to note that our definition includes the “non-living” elements of the system and notes that not all actors within the ecosystem act to further the circular economy. Because of this, mutualistic relationships between actors should not be taken as given.

Using this foundation, we can apply frameworks for understanding the circular ecosystem concept such as that included in Pietrulla (2022). In this paper, Pietrulla argues that circular ecosystems can be classified on two axes based on their geographic reach (local versus global) and their scope (intra-industrial versus cross-industrial) (Pietrulla, 2022). We can also draw on the business ecosystem literature to better understand relationships between actors. For example, Yoon et al. (2022) compare inter-business relationships to different kinds of symbiotic relationships. They find that, though business relationships are inherently transactional, they can be categorized as either mutualistic, communalistic, or parasitic (Yoon et al., 2022). Under these two frameworks, accelerators exist in relatively local ecosystems and mutualistic relationships with the businesses they serve.

2.3. Sources of Value from Supports

2.3.1. Training Training is a key pillar of accelerator function, whether it is in the form of experiential learning or formal workshops (Seitz et al., 2025). Though the literature on the value of training at the intersection of circular business and entrepreneurship is sparse, studies on the role of training in improving either circularity or business aptitude point towards similar conclusions. Two recent studies on the role of training in promoting the circular economy find knowledge and skills gaps in fundamental business and sustainability topics such as life cycle assessment, digitalization, and sustainability management systems (Kargruber et al., 2025) as well as circular (re)manufacturing and product design (Trevisan et al., 2022). In their case study analysis, Rizos et al. (2016) identify barriers and enablers circular entrepreneurs face when implementing circular business models. Interestingly, their findings reveal that a lack of support for training is a major barrier. Conversely, in a survey of the barriers and enablers circular startups face, Van Opstal and Borms (2023) find that it is relatively less important than the other supports their study examines. This disagreement in the literature may be driven by firm- or sector-level heterogeneity in a firm's access to and capacity to use resources. These studies suggest that providing support for training in sustainability topics is one way in which accelerators can create value for their participants.

2.3.2. Mentorship Another way accelerators provide value to their participants is through mentorship (Seitz et al., 2025). In their 2025 meta-analysis of accelerator effectiveness, Seitz and coauthors find that mentorship is generally associated with positive outcomes for accelerator participants (Seitz et al., 2025). There is a rich literature examining the benefits of mentorship for entrepreneurs which can be extended to entrepreneurs in the circular economy. In their 2017 qualitative study of startup entrepreneurs, Brodie et al. examine the value mentorship has added for them. They find that the key avenues by which mentoring adds value for start-up entrepreneurs are through access to business knowledge, guidance and support in setting and prioritizing goals, increasing confidence, and accessing relevant networks (Brodie et al., 2017). As with the training literature, there are few studies on the value of mentorship for circular economy entrepreneurs. However, research suggests that mentorship fosters entrepreneurial skills (e.g., Virga et al., 2025). Interestingly, this stream of literature also suggests that mentorship needs are heterogeneous across entrepreneurial phases (Memon et al., 2018). This points toward the existence of heterogeneity in how entrepreneurs value different types of mentorship across startups and SMEs.

2.3.3. Funding The availability of seed funding is another fundamental component of business accelerators' offerings (Seitz et al., 2025). Obtaining the necessary funding to go to market, launching new products, or scaling is a major hurdle for circular businesses. For instance, circular entrepreneurs report financial support as an enabler of circular business practices, placing an emphasis on the benefits of bank guarantees for their investments (Van Opstal & Borms, 2023). Another study reports that public subsidies and available funds enable non-circular firms to implement circular practices (Aranda-Usón et al., 2019). Their key finding is that the extent to which a company becomes more circular is positively associated with their level of investments (Aranda-Usón et al., 2019). Interestingly, a 2022 qualitative study by Saarinen and Aarikka-Stenroos stresses the importance of diverse funding sources. They note that it is critical for funding to come from the private and public sectors to promote equal opportunities for CE entrepreneurs (Saarinen and Aarikka-Stenroos, 2022). Traditional bank lending is also a barrier (Saarinen & Aarikka-Stenroos, 2022). Because of this, it is not surprising that accelerator participants who receive additional funding benefit more from such programs than their base-funded counterparts (Cohen et al., 2019a, 2019b; Pauwels et al., 2016).

2.3.4. Networking Tailored networking is one of the distinguishing features of business accelerators (Seitz et al., 2025). Empirical evidence suggests that there is a positive relationship between network activities and startup success (e.g. Witt, 2004). While there are few studies supporting this claim among circular firms, existing literature suggests that networks are valuable to circular entrepreneurs. Van Opstal and Borms (2023) report that network building was among the most frequently mentioned enablers among the participants they

interviewed. Moreover, a 2024 study shows that network building capabilities have both an indirect and direct positive association with innovation function of circular startups (Narayana et al., 2024).

Overall, accelerators have been found to add value for their participants through the resources (training, mentorship, funding and networking) that they provide to their participants (Seitz et al., 2025). Despite this, it is crucial to consider that not all accelerator programs create the same value for participants. Rather, accelerator success depends on the design of the program and how it allocates resources to participants in addition to other factors (Seitz et al., 2025).

2.3.5. The Resource-Based View (RBV), Dynamic Capabilities and Circular Firm Heterogeneity

The relative value of an accelerator or incubator's supports can be conceptualized using the resource-based view (RBV). The crux of this paper is built on the argument that circular firms vary in their needs, goals, and characteristics. This is theoretically motivated by the *resource-based view* (Wernerfelt, 1984). The theory characterizes firms by their resources rather than their outputs (Wernerfelt, 1984). It defines resources as any tangible or intangible asset the firm possesses in the long run (Wernerfelt, 1984). Resources can be physical and human capital as well as networks, processes, and procedures (Wernerfelt, 1984). The theory has been developed since its conception to include more details about the resources firms possess, and their implications. Most notably, Barney (1991) asserts that one of the fundamental assumptions of the resource-based view is that firms are heterogeneous in their resources and capabilities. In essence, they differ in both their physical and human capital. In the context of this project, accelerators contribute to building these resources.

Peteraf (1993) builds on this by stating that this heterogeneity is a necessary condition for sustained competitive advantage. If firms are not heterogeneous, they will fail to remain competitive in the long-run and eventually go out of business. Given this theory, it stands to reason that if firms differ in their levels of tangible and intangible assets, they will differ in their valuations of training, mentorship, funding, and other supports such as access to relevant networks. Another necessary condition in Peteraf's model is superior resources (1993). This suggests that circular accelerator and incubator programs help keep circular enterprises in business by offering supports that contribute to improving the quality of their participants' assets. Existing research finds that heterogeneity in firm capabilities leads to differences in networks across circular businesses and that these networks lead to improvements in the competence of circular firms (Lin & Chang, 2024). In essence, in the context of the circular economy, there are supports for firms that strengthen their capacity to succeed. In this case, networks can be described as a resource as well as a necessary building block for creating and maintaining existing resources. The findings of Lin and Chang (2024) suggest that we can conceptualize training, mentorship, funding, and networks as intermediates in production. In essence, program offerings are resources whose value depends on a firm's existing human and physical capital levels. We predict that this value will differ based on enterprise-level characteristics, specifically, where an enterprise is located within the circular supply loop.

The Dynamic Capabilities (DC) framework builds on the RBV. It conceptualizes the ways in which firms use the resources they have at their disposal as "ordinary capabilities" and introduces a way of thinking about how firms can adapt to innovate and adapt to change through their "dynamic capabilities" (Teece et al., 2007). In contrast with the RBV, the DC framework asserts that it is a firm's dynamic capabilities that ensure their competitiveness in the long run, rather than simply differing from other firms in their resources and ordinary capabilities (Teece et al., 2007). In a later paper, Teece (2007) builds on the original DC framework by introducing the key types of dynamic capabilities: sensing, seizing, and transforming.

3. Data and Methods

This paper follows the text analysis methods outlined in Buenaño-Fernandez et al., 2020. Our analysis is intended as an exploratory study to uncover trends that should be considered by practitioners and future researchers, rather than to make definitive claims. We constructed our text database by selecting and cleaning text data from intake and exit surveys from an incubator/accelerator program based in the province of Ontario, Canada. Our analyses focus on the information provided in the intended outcomes, achieved outcomes, unachieved outcomes, and testimonial sections of the surveys. Next, we performed text mining and topic modelling using the Latent Dirichlet Allocation (LDA) method and the term frequency-inverse document

frequency (TF-IDF) method as a robustness check. These methods assign importance scores to each word in a body of text and generate lists of top words that comprise the document's topics. We then selected the most relevant topics generated by the model and applied expert judgement and a large language model (LLM) to qualitatively explain the relevance of the topics our LDA model identifies in their respective documents.

3.1. Data

This study analyzes a dataset comprising 37 intake and exit surveys from the *COIL (Circular Opportunity Innovation Launchpad) Activate Accelerator* program, which offered training, mentorship, and funding to startups and SMEs in Southern Ontario's agri-food sector. Each of the intake/exit survey pairs represents a business that participated in *COIL Activate Accelerator.* Surveys were mandatory for all program participants. Out of a sample of 38 surveys, we omitted one due to blank responses in the exit survey. As strengthening the diversity of the circular economy was one of the objectives of *COIL Activate Accelerator*, our sample is inherently diverse.

The training took the form of 20 hours of curriculum on circular economy topics including waste and emissions calculation, ISO standards, circular business models and strategies, circular design principles, past client case study successes, doughnut economics, and cultural approaches to the circular economy. The mentorship component consisted of 24 hours with a mentor team to guide in the scaling of the business. Mentors were sourced primarily from Innovation Guelph, but support was also available from *10C*, *Anthesis Provision*, *Business Centre Guelph-Wellington*, and *LaunchIt Minto*. The mentors were assigned to clients based on a match between mentor expertise and entrepreneur need. The funding consisted of a grant of up to $20,000 (depending on level of revenue) to implement a circular project as well as optional financing in the form of access to a *Harvest Impact* loan of $2,500 to $10,000 offered at 0% interest for 24 months, with payments deferrable for up to 12 months from signing of loan agreement. The other supports the *COIL Activate Accelerator* program offered include multiple networking events offered through the *Coffee with COIL* networking series including national and international partners, engagement with the Trade Commissioners Office and partner consulates, and support from Guelph-Wellington's circular economy urban-rural testbed (a network of public, private, and not-for-profit organizations that enable businesses to prove and scale their circular approaches in real-world, but reduced risk, environments).

The dataset includes firm descriptions, circularity characteristics, intended, achieved, and unachieved outcomes, and testimonials. These data were collected through application and exit surveys. Our dataset is unique because it contains an array of enterprises from across the supply loop ranging in size and development stage. Though our dataset centers on a single industry, it encompasses firms with diverse interindustry operations. For example, one of the firms in our dataset uses technology to simplify recycling, employing sensors to optimize waste collection and food waste handling. We categorized firms into one of four enterprise types within the circular agri-food supply loop based on the firm descriptions reported in the intake survey. We determined these categories to align with the program's goals and administrative structure. Table 1 summarizes enterprise categories and descriptions.

The institutional context of this study can aid in understanding the values and norms related to CE and why CE entrepreneurial ecosystems emerged in certain regions. Ontario, has become the first jurisdiction in the Americas to enact a comprehensive circular economy law, the Resource Recovery and Circular Economy Act, 2016 ("RRCEA") (Cocker and Graham, 2019). Under this act, the producers will be the primary resource recovery party, solely responsible for complying with the Ministry's mandated obligations for resource recovery, with non-transferable liabilities. When the producer is assigned the responsibility for managing the product at its end-of-life, their decisions regarding the product's materials, composition, and dismantling features become crucial for effective waste management. This leads to the development of an integrated circular economy market (Cocker & Graham, 2019).

The Ontario government has also implemented various programs aimed at reducing landfill waste and promoting recycling and composting, such as the Blue Box Program- an integrated municipality recyclables collection program (Jacobs et al., 2022). Norms around sustainability are increasingly supported by collaboration among stakeholders, including municipalities, industries, and non-governmental organisations, fostering a culture of innovation and responsible resource use. Additionally, educational initiatives raise public awareness about circular economy principles, contributing to a societal shift toward more sustainable practices. This is also evident in the emergence of Circular Economy Labs and research groups in universities (Ivey

Business School, 2024). Ontario's enabling CE policies, strong sustainability mindset and solid supportive networks for innovation are precursors for the emergence of CE entrepreneurial ecosystems such as COIL. This policy context highlights Ontario's classification as an early-stage circular transition ecosystem. These results can be generalized to other early-stage circular transition jurisdictions. Moreover, the broad focus of this research is on everyday entrepreneurs, or entrepreneurs working in fields that are not defined by high growth or a focus on technology (Welter et al., 2017). Since everyday entrepreneurship is not tied to a specific location, Ontario can serve as a generalizable case.

Table 1. Descriptions of enterprise categories.

Enterprise Category	Description
Circular Agriculture (*n = 12)*	Enterprises operating in primary production with a focus on reducing waste and closing the agricultural supply loop
Consumer Goods from Upcycled Food (*n = 10)*	Enterprises striving to upcycle food into consumer goods
Circular Packaging Solutions (*n = 7)*	Enterprises aiming to make food and agricultural product packaging more sustainable
Low Waste Food Retail (*n = 8)*	Food retail enterprises with a waste reduction focus

3.1.1. Text Preprocessing The first step in our data preprocessing was to remove surveys containing blank responses to one or more questions. We then separated responses to questions regarding intended outcomes, achieved outcomes, unachieved outcomes, and testimonials into their own documents. After loading the responses from the four selected survey questions into R, we preprocessed the data. First, we removed stop words using a standard dictionary in R as well as a list of stop words specific to our dataset which included company and product names, dates, and other numbers. Next, we performed tokenization using the *unnest_tokens()* function within the *tidytext* package in R. After removing intake-exit survey pairs containing blank responses, we were left with a dataset of 37 intake-exit survey pairs.

3.2. Methods

3.2.1. Latent Dirichlet Allocation (LDA) In their 2019 paper, Kirchherr and van Santen criticize the lack of medium-N and large-N empirical studies in CE research. In this paper, we aim to fill this gap by developing a framework and investigating whether we can generate meaningful insights using quantitative methods in this domain. We elected to use LDA topic modelling because it is a good fit for both our data and key research question. Our ability to answer this research question hinges on whether we can identify themes in survey responses and map those themes onto the documents they emerged from. Since LDA is designed to extract patterns from textual data, it proves to be a good fit for this research. LDA also offers benefits over other methods of text analysis as it is an unsupervised learning method and reduces the need for researcher-imposed coding structures.

We used a standard LDA approach which is summarized in Figure B1 in Appendix B. We selected the four topics (*k = 4)* to identify whether each circular enterprise category is associated with a distinct thematic focus within the survey responses.

Figure 1 provides diagnostic results on potential values of *k.* The value of *k*, or number of topics, should balance exclusivity and coherence. Coherence is a commonly used proxy for semantic interpretability, with higher scores indicating more well-defined topics (Newman et al., 2010). Exclusivity refers to the degree to which top words are unique to each topic (Ulstein, 2024). Smaller values of *k* increase topic breadth, which can reduce interpretability (Barnett et al., 2023). Conversely, as *k* increases, topics generally become more distinct. However, if *k* becomes too large, topics can become redundant (Barnett et al., 2023). We aim to choose a value of *k* that balances between having topics that are excessively broad (*k* is too small), and topics that are excessively narrow (*k* is too large) (Barnett et al., 2023). For our dataset, models with three and four topics generate similar values of exclusivity and coherence, indicating similar model quality. While exclusivity continues to rise as *k* increases, coherence, or interpretability, sharply drops for models with more than four

topics. We ultimately used $k = 4$ as this allows us to assess whether topics map onto one of the four enterprise categories in our dataset.

We fit the model with Gibbs sampling over 1000 iterations, and a seed of 123 to strengthen replicability. To ensure the robustness of our LDA model and identify trends in focus by enterprise category, we performed gamma testing with a threshold of 0.2 to identify which enterprise categories are associated with each topic.

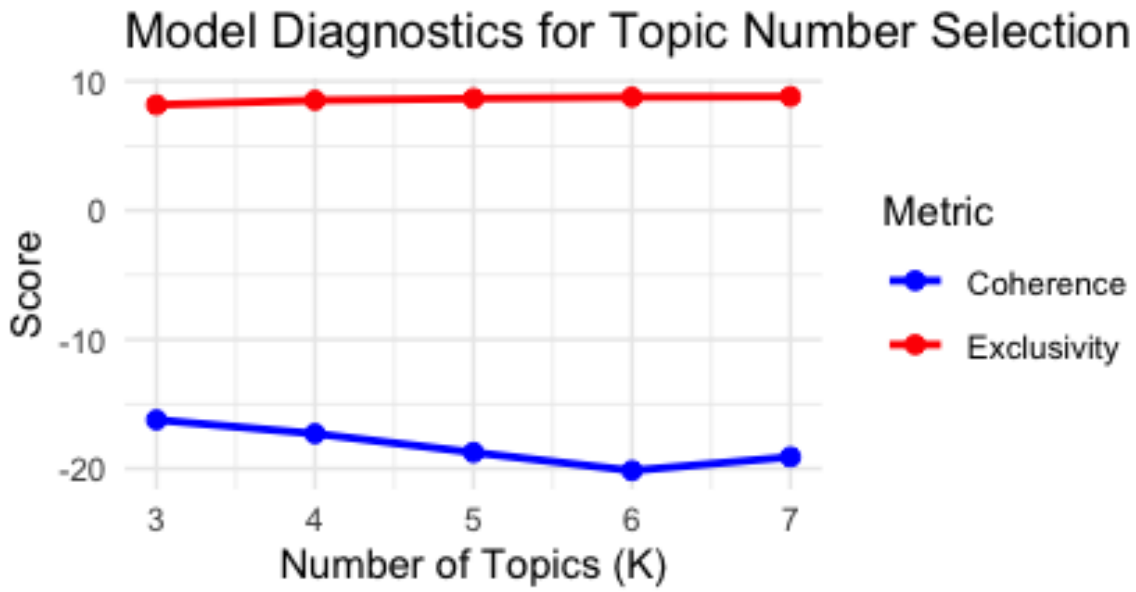

Figure 1. Exclusivity and Coherence of models with three to seven topics (k).

While classical power analyses are not used for unsupervised learning methods such as LDA, we use other approaches to ensure the robustness of our results. Power analyses estimate the probability of a particular test rejecting the null hypothesis if the alternative is true (Dalmaijer et al., 2022). However, statistical power does not directly apply when working with unsupervised models as they do not test hypotheses (Dalmaijer et al., 2022). For this reason, a priori power analyses are not conducted for unsupervised models. Instead, researchers generally rely on the application of commonly used algorithm selection guidelines (Dalmaijer et al., 2022). Because of this, we rely on robustness checks to ensure the reliability of our model. To ensure our model is stable and interpretable, we used TF-IDF and a modified LDA model as robustness checks to determine whether the topics generated by our original model produced interpretable and consistent topic structures.

3.2.2. Sentiment Analysis Sentiment analysis, a subfield of natural language processing (NLP), is a method of extracting sentiments expressed in a specified body of text (Wankhade et al., 2022). We applied lexicon-based sentiment analysis, as it is suitable for structured text such as surveys (Wankhade et al., 2022). Lexicon-based sentiment analysis takes a document, breaks it down into individual words, referred to as tokens, scores them, and aggregates the scores across the document (Wankhade et al., 2022). This method can be extended to the application of sentiment scores in addition to positive, neutral, or negative scores. To do so, we used R to obtain the National Research Council (NRC) dictionary through the function *get_nrc_sentiment* found in the *syuzhet* package.

4. Results

In the following subsections, we discuss the technical details of our findings. First, we explore the central finding of this research: that our model extracted key words that map onto distinct themes from survey responses across categories. We ensured these results were robust by confirming that each topic mapped onto a single category. This means accelerator participants were more similar to other firms within their category than across categories. The results also held when we used an LLM to name the key themes from the top words

identified by our model. This suggests goals, achievements, and next steps are distinct across enterprise categories. The full details of this analysis can be found in section 4.1.

Our secondary finding looks at how entrepreneurs in different enterprise categories felt about each of the dimensions of support offered by their accelerator program. Like our first finding, sentiments about training, mentorship, funding, and other supports including networking opportunities differed across enterprise categories. Interestingly, our sentiment analysis reveals only positive and neutral sentiments about the program. While the lack of negative sentiments in our analysis may raise suspicions of bias, our context points toward another explanation. Since *COIL Activate Accelerator* is not the only *program Innovation Guelph* offers, it is in participants' best interest to provide honest feedback as it may be incorporated into future programs they apply to. The full details of this analysis can be found in section 4.2.

4.1. LDA Topic Modelling

Given our choice of k (k = 4), our LDA topic model generated four topics for each question (*Unachieved Outcomes, Planned Outcomes, Achieved Outcomes, Intended Outcomes, Testimonials*). An LDA *topic* is a collection of a specified number of words that have scored the highest in relevance for each topic. Our gamma tests (document-topic probabilities) highlight which categories each topic is based on.

Table 2 summarizes the results of our LDA on responses to the "Achieved Outcomes" survey question. Each category is associated with a distinct topic. Figure 2a presents the gamma distributions associated with our LDA model, demonstrating that each topic aligns with a single category. Table 2 shows the highest scoring words from the LDA model for each topic, the topic name defined by the research team, the topic name defined by a large language model (LLM), and the category most strongly associated with the topic. Figure 2b displays the top word probabilities by topic. We find that across survey responses topics are distinct across categories. This means that the intended, achieved, and unachieved outcomes of the enterprises in our dataset differ by enterprise category. The full list of top words, topic names, and associated categories can be found in Table 2 in Appendix B.

(a) Document distribution by topic and category *(b) Top word probabilities in each topic*

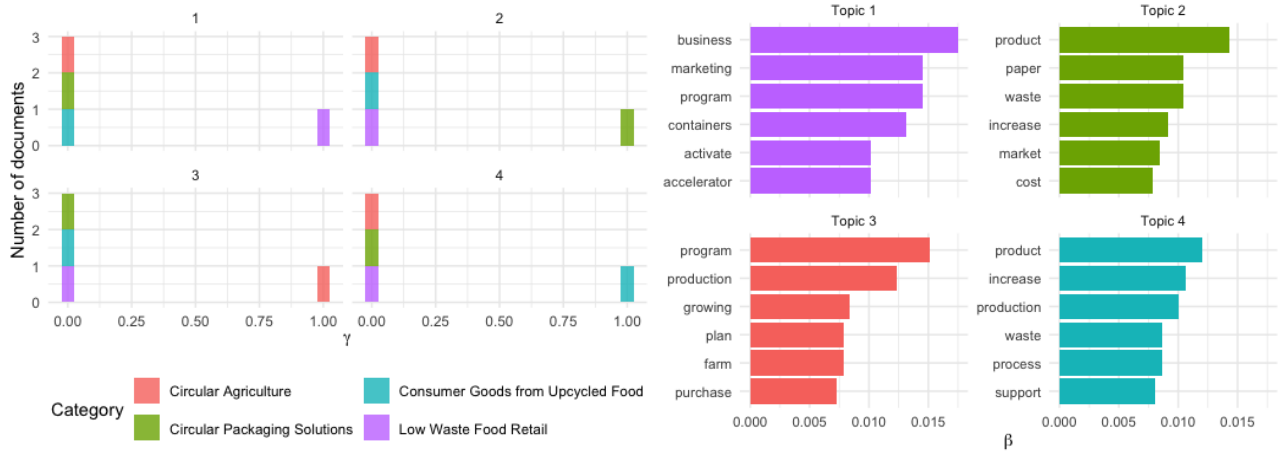

Figure 2. LDA topic modelling results. (a) Document distribution by topic and category. (b) Top word probabilities by topic.

Table 2 also details the topics that emerged from responses to the "Overview of Achievements" survey questions. The topics are, for the most part, distinct from one another, and have a coherent focus. For example, *farm production and local waste stream integration* differs greatly from *material innovation in packaging design.* To check the robustness of the LDA model, we asked an LLM to name each topic based on their sets of top words. The LLM was not only able to create coherent topic names, but those names also overlapped with the names we created. Similar results can be seen for the responses to the survey questions included in the appendix. This means there exist coherent themes in the outcomes participating enterprises achieved.

We checked the gamma distribution, or measure of document-topic probabilities (Figure 2a), to identify whether the topics that emerged from the survey responses could each be attributed to a single category. As

predicted, each topic is based on the survey responses from a single category. This distinct topic-document mapping is also evident in the survey responses included in the appendix. In context, this means the outcomes an enterprise achieved over the course of the program were specific to their position on the circular supply loop. Moreover, Table 3 shows the results of our LDA model using all survey responses combined. Its key advantage is its larger sample size, and its results are comparable to the results of our original model.

Table 2. Top LDA words, topic names, and document-topic probabilities for responses to the "Overview of Achievements" survey question.

Overview of Achievements			
Top Words (Highest Probability)	**Researcher-Defined Topic Name**	**LLM-Defined Name**	**Dominant Category**
packaging, waste, process, customers, marketing, online, sales	Customer acquisition and packaging waste	Customer-focused sales and sustainable packaging improvements	Low Waste Food Retail
paper, product, polymer, waste, market, provide, time	Packaging development	Material innovation in packaging design	Circular Packaging Solutions
product, increase, waste, protein, revenue, production, ingredients	Product development and increasing revenue	Revenue growth through protein-based product development	Consumer Goods from Upcycled Food
production, farm, local, purchase, floor, waste, growing	Improvements to circularity of agricultural production	Farm production and local waste stream integration	Circular Agriculture

Table 3. Top LDA words, topic names, and document-topic probabilities for responses to all of the survey questions in our dataset.

Entire Dataset			
Top Words (Highest Probability)	**Researcher-Defined Topic Name**	**LLM-Defined Name**	**Dominant Category**
business, marketing, program, containers, activate, accelerator, process	Marketing circular packaging solutions	Business Development & Program Participation	Low Waste Food Retail
product, paper, waste, increase, market, cost, reduction	Reducing Packaging Waste Cost Effectively	Sustainable Product & Waste Management	Circular Packaging Solutions
program, production, growing, plan, farm, purchase, season	Planning Agricultural Production	Farm Production Planning	Circular Agriculture
product, increase, production, waste, process, support, products	Reducing Waste and Improving Production Processes	Production Optimization & Support	Consumer Goods form Upcycled Food

To assess the robustness of our LDA model, we compared its words to a TF-IDF-generated top words. The TF-IDF model generated comparable lists of top words, indicating that the topics generated by both models are similar. This match in top words suggests that the topics our LDA model identifies reflect genuine patterns in participants' responses rather than model artifacts or noise. We report full results from the TF-IDF models in Appendix B.

4.2. Sentiment Analysis

The results of our sentiment analysis reveal heterogeneity in the valuation of supports by enterprise category. Focusing on positive sentiments, Figure 3 shows that in the *Circular Agriculture* enterprise category, training and funding tie for the most positive sentiments, mentorship and other supports. Across all categories, sentiments were either neutral or positive implying participants in general gained from participation. In the

Consumer Goods from Upcycled Food enterprise category, training leads, followed mentorship, other supports, and funding, respectively. This ranking flips for *Low Waste Food Retail* firms, with funding leading, followed by mentorship, training, and other supports, respectively. Finally, responses from *Circular Packaging Solutions* firms do not feature training across any sentiments and rank funding first and other supports last.

While the neutral and positive results of the sentiment analysis may raise suspicions of social desirability bias in survey responses, we argue that this is not necessarily the case in this context. A unique feature of programs offered by *Innovation Guelph* is that participation does not make a business ineligible to participate in future programs. Because of this, it is in each firm's best interest to answer honestly to increase the probability of future programs they participate in them better meeting their needs.

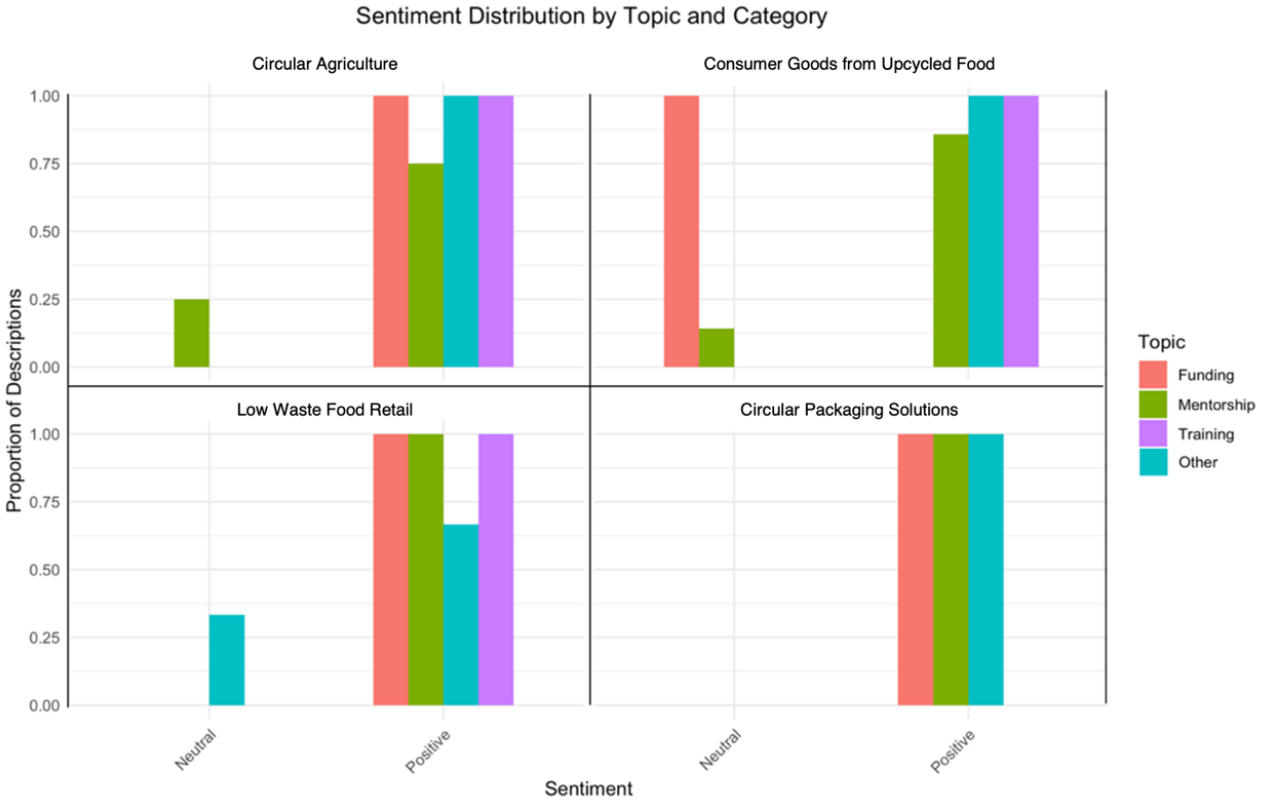

Figure 3. Distribution of sentiments by support type across enterprise categories for responses to the "Testimonials" survey question.

5. Discussion

5.1. Heterogeneity of Firms Within Circular Ecosystems

The core finding of this research is that the firms included in the dataset focused on distinct circularity goals across enterprise categories. Taking a circular ecosystem approach, the key finding is that accelerators play a key role in strengthening the circular economy by directing resource flows. This study contributes to the circular firm heterogeneity literature (e.g., Adner and Kapoor, 2010; Jacobides et al., 2018; de Vasconcelos Gomes et al., 2023) by extending their findings to the context of accelerator programs. Specifically, these findings indicate that heterogeneity in circular firms exists even at the earliest stages of firm development. It also speaks to the consequences of these differences. As enterprises differ in their goals, they will also differ in their outcomes. This suggests that evaluations of success in accelerators and incubators (both professional and academic) should acknowledge the breadth of what it means to become "more circular."

This difference in goals drives what entrepreneurs in different categories consider a valuable support. The RBV provides a framework for this phenomenon: if firms differ in their resources, they will differ in their

outputs. As firms in different enterprise categories within the agri-food sector have vastly different resources, it is not surprising that they use them to accomplish different goals. Building on the idea that entrepreneurial supports can be viewed as intermediates in production, it is also important to note that enterprises used the same levels of training, mentorship, funding, and access to relevant networks to accomplish vastly different goals. Once again, this is likely driven by different initial levels of tangible and intangible assets. This connects the literature on circular enterprise heterogeneity, RBV, and circular ecosystems by highlighting how early-stage circular enterprises differ in their use of the resources available to them in their ecosystem. This research also contributes to general knowledge on accelerators by identifying differences in value of program characteristics across enterprise categories. This suggests that in the circular economy as well as the traditional economy, businesses in different enterprise categories are likely to respond heterogeneously to accelerator offerings.

5.2. The Definition of Circular Ecosystem

Our key finding also relates to the concept of circular ecosystems, as circularity looks different at each stage of supply loop, from primary production to waste reclamation. In fact, these differences contribute to a circular ecosystem's capacity for cooperation. This suggests Geissdoerfer et al. (2025)'s definition of circular ecosystems can be expanded to include the notion of firm diversity, similar to the ecological concept of biodiversity. More broadly, this research reinforces the idea that circular ecosystems are much more than a business model or value proposition; they represent a meaningful systemic change (Geissdoerfer et al., 2017). This change looks different at each part of the circular supply loop, reinforcing the need for a tailored approach when working with entrepreneurs and upholding the notion of interconnectedness across ecosystem stakeholders (e.g., Trevisan et al., 2022; Geissdoerfer et al., 2025).

5.3. Sources of Value from Support and the Resource-Based View

In line with the RBV and DC framework, the firms in our dataset differ by enterprise category in the value they place on the various dimensions of support they received. This finding reinforces the idea seen across the circular ecosystem literature that the role of accelerator and incubator programs goes being simply connecting actors. Rather, a tailored approach involves maximizing the synergies between participants and the broader circular ecosystem to advance systemic change. Using the language of industrial ecology, accelerators should facilitate the flow of resources between stakeholders in circular ecosystems for their mutual benefit. As one can assume that levels of tangible and intangible assets vary by enterprise category, such differences in value support the RBV. Theoretically, this paper extends Lin and Chang (2024)'s work on the RBV in two main ways. First, we find evidence to suggest that other supports along with networking can act as resource intermediaries. Second, we uncover patterns in heterogeneity of value for supports between firms operating in different points along the circular supply loop. This links Lin and Chang (2024)'s finding that network building improves firm competence to the RBV's core idea that firms possess different resources. This finding points toward an important practical implication: tailored supports for entrepreneurs. As accelerators and incubators are cost-constrained, they should provide different supports based on firm characteristics to optimize their impact. While we offer suggestions for practitioners (Table 4), we acknowledge that our analyses cannot be used to make causal claims. However, the well-defined trends in value derived from different aspects of the COIL program suggest that accelerator and incubator program organizers should consider ways to gauge participant interest in various program elements (e.g. through a survey) rather than offering a one-size-fits-all program. From a theoretical standpoint, this paper adds to the RBV by viewing differences in resources as the driving force not only for differences in output and performance, but also for differences in value for supports and ecosystem connections. In essence, this study suggests that the RBV can be used to explain the relative impacts of input-level supports.

Table 4. Summary of Policy Recommendations for Practitioners.

Policy Recommendation	Key Finding
Design programs with diverse goals in mind.	We find that across survey responses topics are distinct across enterprise categories. This implies the goals and achievements are more similar within categories than between categories.
Match participants to resources based on enterprise category.	Sentiment analysis indicates valuation of program supports differs by enterprise category.
Evaluate program participants based on the unique attributes of their respective enterprise categories.	The topics that emerged from responses to the "Overview of Achievements" survey questions are generally across enterprise categories and have a coherent focus within.
Collect feedback from program participants.	Our results show that collecting feedback from participants can be a fruitful endeavor that reveals meaningful patterns in preferences.

5.4. A Note on Sample Size

Though 37 documents is a small sample size, the LDA literature and our sensitivity analyses suggest our results are robust. First, the suitability of LDA depends on the richness of the corpus and structure of the words within it (Blei, 2012). In our case, we have relatively few documents, but a relatively rich corpus of 10,421 words, and on average nearly 70 words per document. Moreover, prior work has demonstrated interpretability for smaller corpora when documents contain sufficient content (e.g., Chang et al., 2009).

While a larger sample is always preferable, our main model suggests that what our dataset lacks in size, it makes up for in textual richness. To check this, we performed two sensitivity analyses. In the first, we combined all survey questions (our four *sub corpora*) for each firm and re-ran the topic model. In this specification, each document in the dataset contained on average about 280 words. Since topic models identify themes based on patterns observed in text (Blei, 2012), increasing document size increases the amount of information available for identifying those patterns. Second, we used a TF-IDF model and compared the results. In both alternative models, the resulting topics were substantively consistent with our primary specification.

On a more practical note, our sample represents all the participants from their cohort, less one participant whose response contained null entries. It is also important to note that it is rare for an accelerator cohort to be as large as 37 participants. Moreover, this number represents the number of SMESs the Government of Canada decided was necessary to support the initial stages of a circular transition in Ontario. Because of this, the results are a valuable resource for researchers, accelerators, entrepreneurs, and policymakers. Using the proposed framework, we hope there will be opportunities to explore the questions raised in this paper with larger datasets.

6. Conclusion

This study identifies two key trends in added value from accelerators and incubators to entrepreneurs. First, entrepreneurs from different enterprise categories are heterogeneous in how they value supports from accelerator and incubator programs. Second, it demonstrates that goals and success for circular startups and SMEs looks different across enterprise categories. It builds upon the RBV by suggesting that different resource compositions not only drive differences in firm performance but also differences in response to supports. It suggests that accelerators and incubators should offer a tailored approach, with program supports differing by enterprise category. This also suggests that firm success should be evaluated with enterprise category-level heterogeneity in mind. Circular startup and accelerator programs should adjust their offerings based on the enterprise category of each of their applicants. For example, firms with a focus on low waste food retail could receive training specific to refining supply chains and customer acquisition and retention, while ecosystems built for firms doing work related to producing consumer goods from upcycled food could receive relatively more mentorship. Looking to the future, policies that govern government-funded accelerator and incubator programs should consider enterprise category-level differences in goals and projects when evaluating applications to such programs as well as program success.

While this study's context is Ontario's agri-food sector, the analyses do not hinge on each firm's connection to agri-food, but rather the differences in firms across enterprise categories. Where this study is unique from other research on accelerator and incubator programs is its focus on circular enterprises. Circular enterprises are unique in their business models, products and services, and strategies as well as their barriers and inhibitors, making these findings unique to circular firms. Specifically, circular firms must be intentionally regenerative or fit into the take-make-use-reuse paradigm. This puts significant constraints on which business models and resources may be used, and what kinds of business ecosystems a circular enterprise can inhabit. The most obvious limitation of this research is its relatively small sample size. However, the TF-IDF and undivided corpus LDA robustness checks support the robustness of our original topic model. A less obvious limitation is the lack of triangulation with objective metrics. Though our dataset did not permit such analyses, this represents a promising direction for future research. Future studies could also explore the impacts of different dimensions of support on business and circularity outcomes across a panel dataset.

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Data Availability Data are not publicly available due to confidentiality restrictions. The data were collected through a circular economy accelerator program for which participants did not agree to the dissemination of their survey responses. Aggregated results and analysis are available from the authors upon reasonable request, subject to approval by the data-providing organization.

Declarations

Competing Interests The authors declare no competing interests.

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Appendix A

Intake Survey

Investee Name:

Project Name:

1. Overview:

Please edit any previously provided responses, as required.

A. Company Description:

B. Product/Service Offering:

C. Problem Solved:

D. Product/Service Innovation:

E. Public Facing Project Description (Please note this will be shared widely by the COIL delivery team.)

2. Circularity Characteristics

A. Responses Selected:

Participate in any form of regenerative agriculture
Use of waste as an ingredient/input (e.g. food waste)
Affordability of products/services
Proactively reduce the amount of waste going to landfill (e.g. food packaging and other non-food waste)
Emissions reducing activities
Products/services that are locally sourced
Products/services that support good nutrition
Employees paid a living wage
The use Data and/or Technology in their business

Project Plan - Funding Stage 1

3. Planned Activities

List at least five specific activities that will be undertaken to achieve the project goals. Organize activities in sequence with expected timing, as progress toward these will trigger release of the 2nd tranche of project funding.

Activities	Description	Expected Date

4. Intended Outcomes

Outcome	Key Performance Indicator	Detail

Exit Survey

COIL Activate Accelerator - Final Project Report

In this Project Report, investees should provide a summary of how they have achieved the program activities and outcomes outlined in their initial Project Plan.

Project Name:

Investee Name:

1. Narrative

Provide an overview of your achievements towards the intended outcomes outlined in your Project Plan. ***(Word Limit: 300)***

2. Activities

Describe up to 10 activities that were undertaken during the COIL Activate Accelerator Program.

Activity	Description of activity and how it contributed to your project goal(s)

3. Project Outcomes

List project outcomes (up to 5) achieved through this project.

Completed Project Outcomes	Key Performance Indicator (KPI) Measurement of Outcome

4. Project Reflections

What were the key lessons that you learned over the course of this program? ***(Short answer)***

Are there any project activities or outcomes that you were unable to achieve? Please explain. ***(Short answer)***

Please provide a brief testimonial (1-2 sentences) to describe your experience in Activate Accelerator.

Appendix B

We used a standard LDA approach which is summarized in Figure B1 in Appendix B. We selected the number of topics, $k = 4$, to match the number of categories in our dataset to aid in interpretability. We fit the final model four-topic model using Gibbs sampling with a burn-in of 1000 and 5000 iterations, and a seed of 123 to strengthen replicability. To ensure the robustness of our LDA model, we performed gamma testing to identify which subgroups (enterprise categories) are associated with each topic.

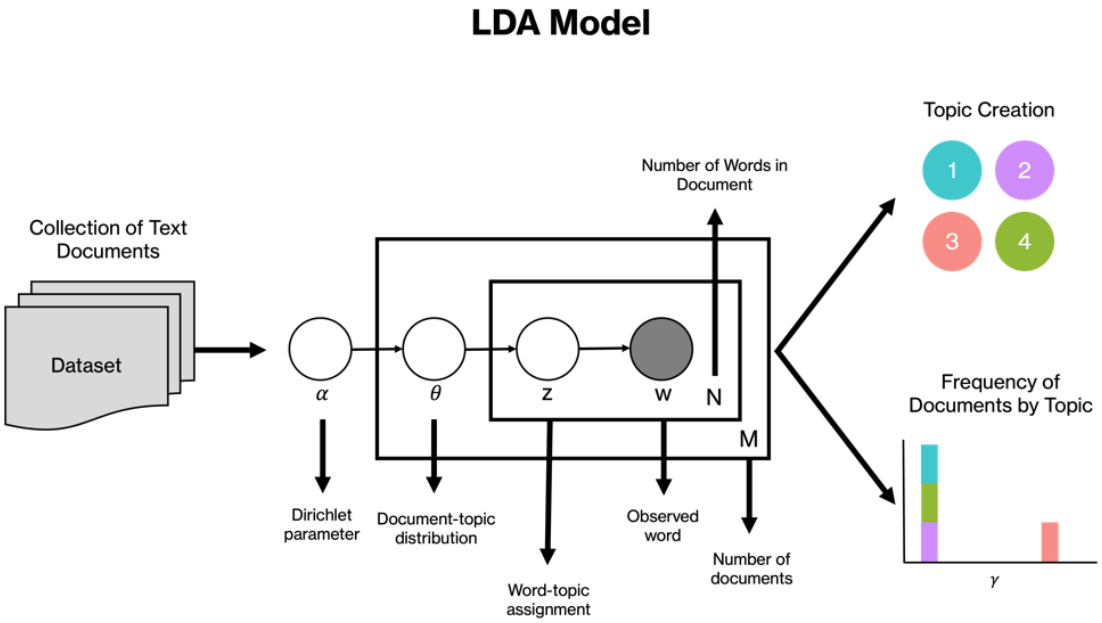

Figure B1. LDA Workflow. Adapted from Buenaño-Fernandez et al. (2020)

Term Frequency-Inverse Document Frequency (TF-IDF)

Term frequency-inverse document frequency (TF-IDF) is a text analysis technique that measures keyword relevance within a specified set of documents (Qaiser and Ali, 2018). Like LDA topic modelling, it begins with data collection and preprocessing. It differs from LDA topic modelling in that it is a bag-of words model, making it more appropriate for small datasets.

Term frequency (*TF*) is defined as the number of times a term appears in a document divided by the number of terms in the document (Qaiser & Ali, 2018). Dividing by the number of terms in the document is a standardization method that accounts for differences in document length (Qaiser & Ali, 2018). *Inverse document frequency* (*IDF*) is a measure of keyword rarity, assigning a higher importance to words that appear in fewer documents (Qaiser & Ali, 2018). TF-IDF is simply the product of term frequency and inverse document frequency (Qaiser & Ali, 2018).

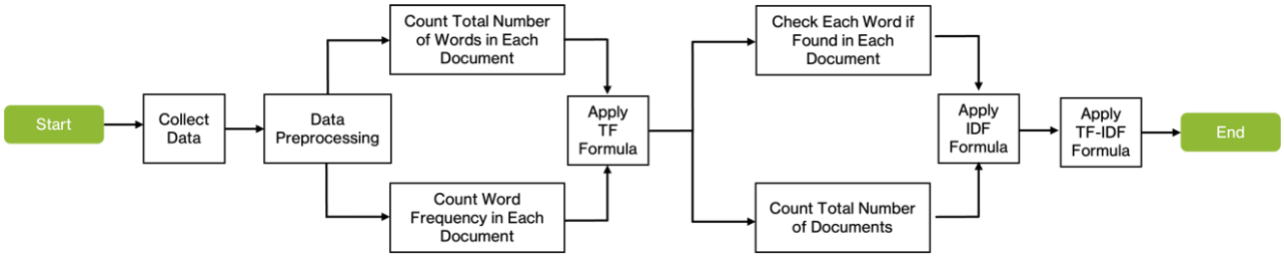

Figure B2. TF-IDF Workflow. Adapted from Qaiser and Ali (2018).

We use TF-IDF as a robustness check to determine whether the topics generated by our model are comprised of keywords that are relevant to their respective categories.

Table B1. Top LDA words, topic names, and document-topic probabilities for responses to the "Unachieved Outcomes" survey question.

Unachieved Outcomes			
Top Words (Highest Prob)	**Researcher-Defined Topic Name**	**LLM-Defined Topic Name**	**Dominant Category**
month, achieve, pilot, followers, increases, instagram, jars	Social media marketing and R&D in packaging and accessories	Product marketing trials and social engagement challenges	Circular Packaging Solutions
containers, build, marketing, business, inventory, create, set	Building business through marketing and inventory	Business infrastructure and inventory planning	Low Waste Food Retail
products, production, increasing, shelf, process, related, labour	Increasing shelf life through new product development	Product scaling and shelf-life extension challenges	Consumer Goods from Upcycled Food
season, plan, equipment, production, growing, due, meant	Planning agricultural production	Seasonal planning and equipment-related production delays	Circular Agriculture

Table B2. Top LDA words, topic names, and document-topic probabilities for responses to the "Testimonials" survey question.

Testimonials			
Top Words (Highest Prob)	**Researcher-Defined Topic Name**	**LLM-Defined Name**	**Dominant Category**
business, future, provided, focus, success, knowledge, mentors	Building business knowledge with mentors	Mentorship impact on business focus and knowledge	Circular Packaging Solutions
business, growth, circular, allowed, concepts, economy, mentorship	Mentors teaching about business growth in the CE	Mentorship on circular economy and business growth	Low Waste Food Retail
experience, opportunity, ideas, business, positive, perspective, future	New opportunities and perspectives from education	Educational experiences fostering new perspectives	Consumer Goods from Upcycled Food
business, mentorship, experience, funding, impact, product, access	Program supports were impactful	Program resources and mentorship enabling growth	Circular Agriculture

Table B3. Top LDA words, topic names, and document-topic probabilities for responses to the "Overview of Achievements" survey question

Overview of Achievements			
Top Words (Highest Prob)	**Researcher-Defined Topic Name**	**LLM-Defined Name**	**Dominant Category**
packaging, waste, process, customers, marketing, online, sales	Customer acquisition and packaging waste	Customer-focused sales and sustainable packaging improvements	Low Waste Food Retail
paper, product, polymer, waste, market, provide, time	Packaging development	Material innovation in packaging design	Circular Packaging Solutions
product, increase, waste, protein, revenue, production, ingredients	Product development and increasing revenue	Revenue growth through protein-based product development	Consumer Goods form Upcycled Food
production, farm, local, purchase, floor, waste, growing	Improvements to circularity of agricultural production	Farm production and local waste stream integration	Circular Agriculture

Table B4. Top LDA words, topic names, and document-topic probabilities for responses to the "Intended Outcomes" survey question.

Intended Outcomes			
Top Words (Highest Prob)	**Researcher-Defined Topic Name**	**LLM-Defined Name**	**Dominant Category**
packaging, waste, process, customers, marketing, online, sales	Customer acquisition and packaging waste	Customer-focused sales and sustainable packaging improvements	Circular Packaging Solutions
paper, product, polymer, waste, market, provide, time	Packaging development	Material innovation in packaging design	Consumer Goods form Upcycled Food
product, increase, waste, protein, revenue, production, ingredients	Product development and increasing revenue	Revenue growth through protein-based product development	Circular Agriculture
production, farm, local, purchase, floor, waste, growing	Improvements to circularity of agricultural production	Farm production and local waste stream integration	Low Waste Food Retail