Received: 1 April 2022 | Revised: 18 October 2022 | Accepted: 24 October 2022

DOI: 10.1002/bse.3297

RESEARCH ARTICLE

Business Strategy and the Environment WILEY

Financing solutions for circular business models: Exploring the role of business ecosystems and artificial intelligence

Sara Fallahi | Ann-Charlotte Mellquist | Olof Mogren | Edvin Listo Zec | Peter Algurén | Lukas Hallquist

RISE Research Institutes of Sweden, Gothenburg, Sweden

Correspondence
Sara Fallahi, RISE Research Institutes of Sweden, Forskningsgången 2C, SE-417 56, Gothenburg, Sweden.
Email: sara.fallahi@ri.se

Funding information
Vinnova, Grant/Award Number: 2019-03166

Abstract

The circular economy promotes a transition away from linear modes of production and consumption to systems with circular material flows that can significantly improve resource productivity. However, transforming linear business models to circular business models posits a number of financial consequences for product companies as they need to secure more capital in a stock of products that will be rented out over time and therefore will encounter a slower, more volatile cash flow in the short term compared to linear direct sales of products. This paper discusses the role of financial actors in circular business ecosystems and alternative financing solutions when moving from product-dominant business models to Product-as-a-Service (PaaS) or function-based business models. Furthermore, the paper demonstrates a solution where state-of-the-art artificial intelligence (AI) modeling can be incorporated for financial risk assessment. We provide an open implementation and a thorough empirical evaluation of an AI-model, which learns to predict residual value of stocks of used items. Furthermore, the paper highlights solutions, managerial implications, and potentials for financing circular business models, argues the importance of different forms of data in future business ecosystems, and offers recommendations for how AI can help mitigate some of the challenges businesses face as they transition to circular business models.

KEYWORDS

artificial intelligence, circular business models, circular economy, digital technologies, finance, product-as-a-service

1 | INTRODUCTION

The circular economy promotes a transition away from wasteful, linear modes of production and consumption to systems with circular material flows that can significantly improve resource productivity (Ghisellini et al., 2016). A transition toward a circular economy requires engagement from manufacturing- and product-selling industries, which must introduce business models that facilitate high utilization, endurance, and recirculation of products and materials (Boyer et al., 2021). For many product companies, the transition to circular business models (CBMs) has involved introducing Product-as-a-Service (PaaS) business models that shift ownership of the product

Abbreviations: AI, artificial intelligence; B2B, business to business; B2C, business to consumer; CAC, Customer Acquisition Cost; CBMs, Circular Business Models; LTV, Lifetime Value; MLP, Multilayer Perceptron; OEM, Original Equipment Manufacturer; PaaS, Product-as-a-Service.

from the user to the producer (or seller) and enable higher utilization of products for the users.

Tukker (2004) argues that the economic potential of PaaS business models can be evaluated in terms of (i) tangible and intangible value for the user, (ii) tangible costs and risk premium for the provider, (iii) capital/investment needs, and (iv) issues such as the providers' position in the value chain and client relations. PaaS models therefore increase the incentive of the product company to capture value from product preservation (where the producer wants to keep the product attractive and in circulation for as long as possible) rather than product flow (where the aim is to sell as many products as fast as possible) (Stahel, 2010). However, selling functions rather than products can be perceived as a double-edged sword. On the one hand, it offers great potential for the product company to improve resource value preservation. On the other hand, it puts exhaustive demands on the balance sheet and cash-flows. Such challenges may inspire the perception that PaaS models are "just too difficult to implement" and therefore put a demand on more empirical evidence on PaaS as well as practical advice on how to make CBMs work (Kirchherr & van Santen, 2019).

As such, for businesses to transition from product-based to service-based CBMs, lack of access to financing and risk assessment tools to support change-in-ownership models is observed to be a key obstacle (Rizos et al., 2016). This highlights the importance of financial actors in facilitating such a transition by understanding and correctly assessing risks and potential of the new business models (ING bank, 2015; Toxopeus et al., 2021). However, *how* alternative risk assessment and financial solutions could look like to support CBMs remains unclear. Financial risk assessment models in CBMs would have to take into consideration a combination of factors regarding the long-term product value and market conditions and therefore should have the ability to collect large quantities of product and customer data. Digital technologies such as AI have the potential to make such models become feasible (Ellen McArthur Foundation, 2019), hence accelerate transition to CBMs.

The purpose of this paper is to explore financing solutions and innovations when moving from product-dominant business models to PaaS or function-based CBMs. In particular, two research questions that this paper addresses are as follows:

RQ1. What different financial actors and solutions could enable PaaS-based CBMs in circular business ecosystems?

RQ2. How can better predictions of residual values of products improve risk assessments for CBM?

We set out by describing our frame of reference in Section 2 and the method used in Section 3. We then present the results regarding financial solutions for circular business ecosystems in Section 4 and the results regarding financial risk assessments through AI-based predictions of asset residual value in Section 5. Section 6 offers a discussion followed by managerial implications in Section 7. Finally, Section 8 consists of some concluding remarks.

2 | THEORETICAL FRAMING

CBMs aim to improve resource efficiency—by extending the life spans of products and parts, by increasing the utilization of products, and by assuring recirculation of products and materials either through sourcing recycled material in production of a new item or by returning the product for recycling after its lifetime (Boyer et al., 2021). Previous literature often defines and categorizes CBMs in relation to how they improve resource efficiency by implementing the circular economy principles and strategies (Bocken et al., 2016; Linder & Williander, 2017; Nußholz, 2017). As such, Bocken et al. (2016, P.317) defines CBMs as "business model strategies suited for the move to a circular economy" based on the taxonomy of slowing, closing, and narrowing resource loops, or Lathi et al. (2018, P.3) propose a CBM definition "to explain how an established firm uses innovations to create, deliver, and capture value through the implementation of circular economy principles, whereby the business rational are realigned between the network of actors/stakeholders to meet environmental, social, and economic benefits."

For many major manufacturing and product selling companies, transition to a circular economy requires business model innovation as they need to rethink how they create, deliver, and capture value. CBM innovation therefore refers to the process of conceptualization, experimentation, and implementation of a new logic for creation, delivery, and capturing value (i.e., new CBM), which enables realizing environmental, social, and economic benefits (Chen et al., 2020; Frishammar & Parida, 2019; Lahti et al., 2018; Neligan et al., 2022).

Moving from the traditional, linear model of take-make-dispose to a circular model of make-use-reuse-remake-recycle, means that the firm creates value-in-use rather than in transaction and by bundling its products with advanced services to allow the products to be shared, repaired, upgraded, reused, refurbished, optimized, and eventually recycled (Frishammar & Parida, 2021). Kanda et al. (2021) discuss that business model as a firm-level unit of analysis has shortcomings in analyzing the industrial implementation of CBMs and argue for application of an ecosystem perspective as an appropriate concept to understand the high level of coordination required between different stakeholders necessary to implement circular systems. An ecosystem perspective can thus support innovation in the context of the circular economy where value is delivered through enhanced and new partnerships with ecosystem actors such as financial actors or service and technology providers. Moreover, this new logic increases the incentive for manufacturers to retain the ownership of their products and capture more long-term value from recurring revenues from leasing or rental fees combined with service contracts, instead of upfront payments.

Despite the sustainability and long-term economic benefits that the circular logic for value creation and capture (i.e., the CBM) posits, it poses challenges to standard financing solutions by (a) changing the nature of the cash flow of the firm in that the cash flow is delayed and more long-term cost-effective financing is required to achieve scalability and (b) increasing capital volume needs to prefinance the products that will have a long-term and hence riskier return-on-investment if they fail in retaining value over time (ING bank, 2015). Therefore, financial barriers are identified as an important category of barriers to circular economy transitions (Adams et al., 2017; Govindan & Hasanagic, 2018; Grafström & Aasma, 2021; Kirchherr et al., 2018; Rizos et al., 2016; Tura et al., 2019; Vermunt et al., 2019). Henry et al. (2020) recognize that start-ups are more flexible and less path-dependent than incumbents and thus are relatively well-positioned to adopt CBMs. They also find, however, that start-ups with service-based model constitute only a small fraction (9%) of their start-up sample and that one of the reasons for this is the asset-heavy innovation needed in combination with lack of financial resources. Linder et al. (2022) found that PaaS-based CBMs are at a disadvantage in terms of bank financing due to significant challenges related to both collateral-based and business case-based credit assessments.

While previous literature mostly discusses how manufacturing companies seek alliances with specialized service companies, digital actors, and sub-suppliers for value creating and delivery in CBMs (e.g., Frishammar & Parida, 2019; Lieder & Rashid, 2016; Reim et al., 2021; Urbinati et al., 2020), not much has been discussed in terms of the nature of relationships required between financial actors and product companies in future ecosystems that enhance financing CBMs. To overcome the financial barriers, both product companies and financial actors need to reconfigure their roles and strategies in future business ecosystem. Financial institutions can contribute to transition to CBMs in two ways; first by helping manufacturers to make the transition to a circular economy on a financial level by providing the appropriate financial structure and services; and second by embodying the principles of the circular economy in their own thinking and updating their way of doing business and assessing risks (Accenture, 2018).

Toxopeus et al. (2021) suggest three financing strategies for product companies seeking CBMs: (1) reducing the uncertainty around the CBM by signaling the future cash flow through customer contracts and pre-orders (Frishammar & Parida, 2019; Linder & Williander, 2017), (2) Building relationships with financial actors, suppliers and customers to co-create financeable value proposition and delivery (Brown et al., 2020; Veleva & Bodkin, 2018); and (3) overcoming the difficulty of lending based on firm-specific assets by enabling asset-based lending for the CBM through standardization and modularity (Kirchherr et al., 2018) and creating secondary markets to allow for better pricing of the residual value of circular assets for banks.

While Toxopeus et al. (2021) offers one of the most forward-looking contributions in terms of financing strategies, they do not provide guidance for how these strategies can be implemented in practice and what circular financial solutions could look like. This paper further investigates required financing solutions for CBMs by collecting both the perspectives of the product companies and financial actors. It further illustrates through an experimental model how residual value of circular products can be predicted in alternative ways, improving the collateral-based risk assessments and the pricing of circular assets in future financial ecosystems. More particularly, the paper illustrates a model enabled by AI, which draws on open data from second-hand markets and predicts the second-hand price of a product that can be one indicator for residual value.

3 | METHOD

The paper draws on results from an empirical research project conducted between 2019 and 2022, which aimed to reduce uncertainties regarding future value of products and thereby increase the willingness among financiers to be part of the development of new CBMs. The aim of the study was set based on knowledge from previous studies that identified financing as a barrier to CBMs due to risks associated with predicting the residual value of products in a circular economy (Linder et al., 2022).

We build on analytical frameworks from strategy and business model literature. Besides the business model as a construct for understanding the logic of a firm for creating and capturing value (Fallahi, 2017; Teece, 2010), we employ business ecosystem as a complementary construct to understand the relationship between product companies and financial actors, service providers or customers that build the foundation for successful CBMs. We draw on Adner's definition of a business ecosystem as configurations of strategies and activities across a multilateral set of partners that need to interact in order for a circular value proposition to materialize (Adner, 2012, 2017).

To tackle the first RQ on what financial actors and solutions can enable PaaS-based CBMs, a series of 25 interviews were conducted (during 2020, 2021 and beginning of 2022) with actors along the business ecosystem, including eight financial actors, two OEMs from clothing and white goods industries, and six "circularity-enablers" offering digital and platform-based services such as insurance, sharing or second-hand marketplaces, and subscription financing solution, see Table 1.

We first selected two OEMs from two separate sectors, one from clothing and one from home goods, which have already released a PaaS CBM to gain perspective on challenges, developments, and already existing solution they have for financing their CBMs. Moreover, we selected two banks, one insurance company and one public credit institute, interested in working with CBMs. The initial semi-structured interviews with these seven actors focused on financing problem description from their perspective, opportunities they perceived and wishes they had with alternative solutions, how they were influenced by other actors in the business ecosystem as well as data access and data needs they had for financial risk assessment in CBMs.

To assure triangulation (Jick, 1979) later we expanded on number and type of financial actors to include also retail financiers, financiers with more experience of assessing CBMs and even specialized CBM financing firms, and we included six circularity enablers covering different parts of the circular business ecosystem. The focus of the interviews was on understanding circularity visions and strategies,

TABLE 1 Overview of interviews

Focal company	Circular economy focus	Role of respondent	Nr of interviews
Financier A	Merchant bank wanting to explore circular financing opportunities	Sustainability expert	3
Financier B	Merchant bank wanting to explore circular financing opportunities	Product manager asset finance	3
Financier C	Merchant bank with interest in circular financing	Head of sustainable finance	1
Financier D	Retail bank providing financing for subscription models	Sales manager	1
Financier E	Product insurance company with interest in circular risk and financing	Business developer	1
Financier F	Public credit institute for growth companies interested in exploring circular financing	Credit counselor	2
Financier G	Financing company offering subscription financing	Sales manager partner financing B2B	1
Financier H	Start-up financing company specializing in circular financing	Co-founder and CEO	1
OEM A	Outdoor garment with leading sustainability profile	CFO	2
OEM B	White goods provider, testing PaaS models and acquiring PaaS company	Business developer	2
		Director environmental & EU affairs	1
Enabler A	Financing provider for hardware-as-a-service	Co-founder and CEO	1
Enabler B	Platform for sharing of garments	Founder	1
Enabler C	Platform for sharing of children's clothing	Founder	1
Enabler D	Circular insurance provider	Founder andbusiness developer	2
Enabler E	Second-hand marketplace for wedding dresses	Founder	1
Enabler F	"Future price provider" for financing of IT equipment	Innovation lead	1

valuation of products in CBMs, financial risk assessment, and relevant data needed in future business ecosystems. Interviews were conducted face-to-face or through online platforms and lasted between 30 and 60 min. After each interview, interview notes were provided by the researcher(s) present at the interview and reviewed by the rest of the research team.

A compilation of interview notes and summaries using open coding was made afterwards and preliminary results were complemented with group discussions at a workshop in the beginning of 2021, with three OEMs and three financial actors (two banks and one public credit institute). The workshop used the business model canvas (Osterwalder & Pigneur, 2010) as a framework to map new value creation and value capture logic for a hypothetical financial actor that will offer financing services to manufacturing companies that sell PaaS in B2B or B2C contexts (for a detailed agenda of the workshop, see Appendix A).

Afterwards, the results from the interviews and the workshop were expanded to involve a broader range of PaaS companies through a survey about financing PaaS models. The survey was launched in spring 2021 and investigated the product characteristics and company's type of PaaS offer (as subscription, function sales, short term/long term rentals, and/or performance-based), ownership setup, turnover, maturity of the PaaS business model, presence of the Paas model in different markets, as well as needs for financing and financing solutions available. Moreover, the survey included questions on the following:

- Company's role in the business ecosystem (supplier, manufacturer, retailer, platform owner, service provider, or other)
- Company's financing situation in general (e.g., "How have you financed your PaaS model so far?" and "On a scale of 0-5, how big a problem is financing for your PaaS business?"),
- What type of solutions they need and what type of actors they could imagine working with (e.g., "If you think you need external funding for the next two years, what type of external funding would you prefer to use?" and "How do you view sharing financing risk with other players in your value chain, downstream or upstream? (e.g., customers, subcontractors, platform players)")
- Their view on how data and digital solutions could help them (e.g., "What kind of information/data do you think could make it easier for you to get financing and is this data available (yes or no)?").

The survey was designed to take 10–15 min to fill in and it was sent out (via e-mail or via LinkedIn) to 39 companies that had a PaaS business model in at least one product or category of products. Companies were chosen to ensure high sample diversity by representing different (a) industries, (b) type of business (B2B or B2C), (c) company size, and (d) type of PaaS model. Out of the 39 companies, 24 responded to the survey, which provided a high internal validity of the results (see Table 2 for an overview of the survey respondents). Besides structured analysis of the responses to the close-ended questions, responses from the open-ended questions generated further

TABLE 2 Overview of survey respondents

Industry	Type of business	Company turnover (MSEK 2019)	Type of PaaS model	PaaS as % of total sales
Garden, DIY, and home appliances	B2C	0	Subscription	100
Bicycles	B2C	0	Subscription, long-term rentals	90
Lighting	B2B	0.32	Functional sales, long-term rentals	100
Furniture	B2B	50	Long-term rental	20
Sports gear	B2C	190	Subscription, functional sales, short-term rental	1
Clothes	B2C	1	Short-term rental	50
Entrance mats	B2B	51	Functional sales	100
Home appliances	B2C	120,038	Subscription, functional sales	<1
Clothes	B2C	0.033	Subscription	100
Measurement systems	B2B	85,000	Functional sales, performance sales	2
Handheld tools	B2B	1200	Subscription, functional sales	22
IT equipment	B2B	2500	Functional sales, short-term rental, long-term rental	65
Packaging	B2B	0	Subscription, performance sales	100
Furniture	B2B	4.7	Subscription	100
Software	B2B	2	Subscription	10
Aquaponic equipment	B2B	0.5	Subscription, long-term rental	100
Software	B2B	2.5	Subscription	100
Signs	B2B	28	Functional sales	<10
Furniture	B2B	113	Functional sales, short-term rental, long-term rental	20
Coffee machines and vending machines	B2B	900	Functional sales	100
Sports	B2C	0	Short-term rental	40
Batteries	B2B	40,000	Subscription, long-term rental	Confidential
Camera and video equipment	B2B	2.6[a]	Subscription, short-term rental, long-term rental, rent-to-own	10
Housing	B2C	0.33[a]	Long-term rental	100

[a]Converted to SEK from DKK at the exchange rate 1,3.

input for categorizing alternative financial solutions relative to the type of PaaS company and its sector. Our sample is not large enough for claiming high external validity of our findings. However, the diverse set of actors in our sample in relation to industry/sector, size, and maturity of the PaaS businesses and the triangulation method used gives cause to claim a high level of applicability of our results.

To tackle the second RQ on how better predictions of residual value or products can improve financial risk assessment, we draw on arguments provided by Toxopeus et al. (2021) that uncertainties around the CBM can be reduced by signaling the future cash flows and in presence of secondary markets to allow for better estimation of residual values of circular assets. To better understand how residual value of products can be estimated in CBMs, we first (in the beginning of 2020) held a workshop with two OEMs, four financial actors (two banks, a public credit institute and an insurance company), and three technology enablers where the "Six thinking hats" method (de Bono, 1985) was applied. The focus of the workshop was on developing a vision for future circular and digital business ecosystems by asking the following questions:

Financier point of view:

- What type of information is critical for banks to be willing to take risks in new CBMs with new collateral?
- What are the most important aspects that digital technologies such as machine learning can add to risk assessment of collateral in CBMs, when historical data is missing?

OEM point of view:

- What type of product information could/should product companies share to support banks' risk assessments of the CBMs?
- How do the OEMs assess risk and opportunities in their own business?

- How would OEMs like the financiers to think and act to be able to expand their CBMs?

Enabling companies' point of view:

- What technologies are critical to enable financing of a transition to CBMs?
- How can "intermediary technology-based companies"/"innovation enablers" support this process?
- How could future business ecosystems look like?
- What other technology or enabling roles are there to fill?

A more detailed workshop agenda can be found in Appendix A.

Finally, to approach the question of estimating residual value of circular assets to reduce the risk in PaaS financing, experiments were set up to model residual value in used items. For this, data was collected regarding second-hand sales of used items in online auctions. The dataset contained 88,511 ads for items in the clothing categories of an online auction site in Sweden. The dataset was split into training, validation, and testing sets, and a number of machine learning models were trained and evaluated on the data. The ending price of auctions were used as the target predictive value. The aim was to obtain a trained model that could take information about used items (such as images, text descriptions and seasonal trends) and give accurate estimates for unseen items, to help estimating the value and risk of the PaaS business. As targets were rather sparse, and presumably containing substantial amounts of noise, the target values were discretised into different bins. These bins can be interpreted as price categories of the investigated products, ranging from low price items to high price items. See Appendix B for further description of the AI model and Table 6 for a summary of the price classes.

4 | FINANCIAL SOLUTIONS FOR CIRCULAR BUSINESS ECOSYSTEMS

Our results confirm the challenges and highlight opportunities and potential solutions for financing CBMs and the effect on roles and actors in the business ecosystem. The results from the survey show that the companies that struggle the most with financing (responding 4 or 5 on a scale from 0 to 5 representing difficulty with financing) are companies that want to scale relatively low-valued product, such as clothes and sports articles, and/or products that are new in the PaaS space and that do not have established second-hand markets, such as cameras, lighting, and aquaponics equipment.

The survey results also show that the majority of the respondents look for traditional financial actors to collaborate with, when scaling PaaS business models. The smaller start-ups often look for venture capital and other types of owner investments, and companies that sell (access to) relatively high-value products, such as coffee machines, IT equipment or office furniture, often see leasing companies as a natural partner. Several of the respondents also wish that their bank could offer a flexible solution for "PaaS scale up credit." A few of the respondents already use less traditional financing solutions involving actors in different part of the value chain (mainly suppliers, but also customers and retailers), and a clear majority of the respondents are positive to these kinds of collaborations.

Based on the lending technologies employed by banks to assess credit risk (Berger & Black, 2011; Berger & Udell, 2006) and earlier studies in the PaaS financing space (Linder et al., 2022; Toxopeus et al., 2021), we identify and categorize our results on financial solutions and opportunities for PaaS-based CBMs into three groups:

1. asset-/collateral-based, where the asset (product or contract) used as collateral can be liquidated by the financier in case of default of the product company, and the residual value thus realized.
2. business-case-based, where the loan repayment capacity of the product company is assessed through future business projections.
3. relationship-based, where the trustworthiness of the team behind the business is assessed, together with its collaboration partners.

Asset-based solutions can be enabled through standardized, modular, and adaptive product designs (Kirchherr et al., 2018), which keep the product attractive and retain its value over a longer period, hence allowing for better estimation of the residual value of circular assets for banks (Toxopeus et al., 2021). For products to be continuously attractive and thus attract customers with a sufficient willingness to pay, it is required that over time they are not only technically sustainable (do not break down) but also functionally (can be upgraded to new needs), esthetically (can withstand fashion fluctuations), and socially (what is acceptable and what works with current policies) sustainable (Nyström, 2019). This facilitates the dialogue with investors, where maintaining value over time for the products is important with regard to stable financial security.

Moreover, PaaS companies should preferably not grow faster than a second-hand market with residual value statistics would have time to be built up. Financiers find it easier both to assess the value of and—in case of default of the product company—to liquidate the products when an aftermarket exists. This indicates that there is a need to build an aftermarket, and that this might be easier in the presence of other industrial players offering similar products and services.

> "A large secondary market increases the opportunities for borrowing, even if the values are relatively low individually. But everything that can be sold on a secondary market is good and can in principle be mortgaged. Here, the residual values can be very important. It is important to understand these residual values over time."— Financier B

Contract lending based on large contracts and long contract periods can be an alternative to object financing. Short notice periods, on the other hand, are critical for customers in some service models, and would deteriorate the loan case. In those cases, the mass of customers, for example in a subscription model, could, however, constitute a redundant inertia and thus a sufficiently secure mass of contracts for the financier. If the dropouts begin to exceed the number of customers, or the consumer behavior declines among existing customers, the company has time to gradually sell a corresponding proportion of the capital-binding objects. Contract lending is particularly suitable when the service is based on low-value products or where the services themselves are what create value rather than the hardware. Also, this scenario is simplified if there exist (several) other industrial players that could potentially take over the contracts of the product company, in case of default.

Leaseback is a solution where the product company sells the product to a finance company and then leases them back with interest and with a repurchase clause. The customer relationship stays with the product company, and the balance sheet value and the risk are then moved to the leaseback financier. A financier specializing in such credit solutions could be considered a more secure and less risky debtor than each product company by itself.

Lease-on-lease. Transfer the PaaS model in the value chain—either to suppliers or customers. Creating "leasing chains" is a way of transferring the risk along the value chain to where it could most easily be incorporated into (the balance sheet of) a running business, or to the final user (in B2C cases).

Stepwise loans within a larger loan frame, can be an alternative solution where a successive scale-up of credit is needed. A gradual upscaling of the business can allow a stepwise increase of the credit based on, for example, the total amount of subscriptions from subscribers, without needing to perform a full-scale credit check each time.

Business-case-based solutions are enabled by the product company showcasing the profitability and growth potential of the CBM (Frishammar & Parida, 2019; Toxopeus et al., 2021). The business model should preferably show greater potential than the linear model if the latter is still in operation. The depreciation rate and the time period for comparison should be picked in order to secure this. It is also good to present the risks associated with the linear business model, such as increasing concern for supply of raw material and inputs, changing customer preferences and more focus on sustainability and business solutions that tackle climate change. New ventures are always considered more risky than existing ones, but in a changing environment the risk of inertia is often underestimated.

The product company can signal high-quality forecasted revenue streams as they can estimate the year's sales figures in advance (existing monthly revenue from existing customer base plus new customers minus dropouts, so-called churn). This is an important aspect in dialogue with financiers so that a positive inertia in revenue streams or early warning signals such as a downward trend can be detected. The product company can also choose more in advance to use the future margin to increase growth (e.g., by investing more in communication) or to consolidate and reduce the growth ceiling (increase profit). A large number of customers (as in B2C) also creates redundancy and thus financial stability, which can be a considerable advantage, especially for business models with low-value products.

> "Some customers say that they wish these models with stable revenue streams were already in place. 'Too bad they were not in place before covid-19', they say."— Financier B

Moreover, it is important to reduce financial risks with controlled growth. Excessive exponential growth of business models that have their best profitability in the latter part of the product life cycle (when the product cost has been fully depreciated but the product is still attractive) leads to the potentially negative margins of new, yet unprofitable units overshadowing those that have become profitable. This is a risk particularly when a fast depreciation rate of the assets is applied, and where it could be mitigated with a balanced growth rate.

> "The problem with start-ups that want to grow fast: If they accumulate capital faster than they will earn the profit of older depreciated garments, then they will never reach profitability."— Financier F

A solution that is fundamentally different from the two solutions above, is to use the so-called LTV/CAC ratio (Lifetime Value/Customer Acquisition Cost) to convince the financier of coming profitability. Instead of relying on trustworthy forecasts based on the existing customer base, this solution speculates on the profitability of future customers. This could be particularly useful for small companies in the early stages, with highly attractive service offerings. The total future value from a new customer (LTV) can be, for example, three times greater than the cost of bringing in that customer (CAC) and then the customer is considered profitable even if the revenue comes later. If the ratio is positive, the company theoretically becomes richer the more it grows. For the financier, the risk should be reasonable if the ratio is positive, and even smaller if the company can ongoingly repay the capital plus interest, based on future income.

Relationship-based solutions include opportunities for collaboration and defining new roles in the business ecosystem, where credit services are developed together with and for new actors and for solutions combining several actors. Access to finance can be facilitated directly through relationship building with customers and banks (Toxopeus et al., 2021). Financing from customers can be in the form of crowdfunding or pre-payments, especially in the case of having an engaged and loyal customer base. In part, customer financing provides capital, but it also gives a signal of stability to future financiers if the company has a broad customer base with many owners crowdfunding the business.

> "Rental customers could be co-owners/micro-investors with kickbacks, mouth-to-mouth-method, references etc. (like when Uber started out in Sweden). This could also be a good basis for a bank loan 'on top'."— Financier A

Besides customers, building a close collaboration with the financier can also facilitate relationship-based financial solutions. In addition to better understanding the business, revenue streams, and the value of the products over time, this provides opportunities for the financiers to explore and understand the roles they can play in the new circular business ecosystem, such as taking a position as a strategic advisor and to develop new credit products and services based on deep industry expertise. Involving the customer of the PaaS company in these dialogues could strengthen the case further. Closer collaboration between the PaaS company and the bank could allow for small-scale "in blanco loans", where the financier takes a deliberate risk with the purpose of developing the business and learning. A potential solution that has been identified in our study—and that could be seen as a next step after building competence and collaborating closely with customers—is to start industry-specific financing vehicles. As financiers gain a deeper understanding of an industry with its customers, products, and trends, specializing in financing solutions for that industry is a risk minimizing strategy.

> "There is a possibility that the development will be more towards niche financiers, who know their industry and/or their objects. It has always been like that, but it could develop even more. It could even develop towards a role that is not only a financier, but also part of the value chain."— Financier B

Customer relationships as well as specialized partner relationships can make the entire business case stronger and more stable. Today, there are companies that specialize in special insurance, recycling, repair as well as in providing (or realizing) the residual value of the product. A lot can be achieved in the short term in collaboration with them instead of trying to do everything in-house, which often requires a lot of time, focus, and resources and which may still not become equally good in the end. Table 3 summarizes the 15 different financial solutions presented in this paper.

5 | FINANCIAL RISK ASSESSMENT THROUGH AI-BASED PREDICTIONS OF ASSET RESIDUAL VALUE

Our workshop findings suggest that data on asset residual value are, together with data on the customer's customers (payment statistics, churn, lifetime value), the most important type of data needed to assess the risk of the credit case. The financial actors identify that both customer and contract data, which reflect the state of the business rather than the value of an asset, will become increasingly important as PaaS-based businesses become more common. There is still, however, a strong focus on asset value, which points at the importance of the AI-based predictions also carried out in the project. A thorough technical description of the AI-based modeling work can be found in Listo Zec et al. (2022). Our data-based research shows that with the help of AI it is possible to predict residual value data (e.g. price levels and how quickly the products can be sold) but that it takes time to train the intelligence for each product and industry and that the open source range of information is often limited to open second-hand market platforms, such as on-line auction sites.

> "Resale value of equipment can change over the term of the contract. Here, AI can help to continuously assess resale value."— Financier B

Results from the data-driven experiments carried out in this project to model residual value in used items showed that the online auction ads contained sufficient signal in user uploaded images and text descriptions to make coarse-grained predictions of the residual value of used items based on the existing data. We trained a multilayer perceptron (MLP) and a logistic regression and compared them using different data as input (text and/or images). The results are summarized in Tables 4 and 5. See Appendix B for more details of the modelling.

TABLE 3 Overview of financing solutions per category

Solutions/categories	Asset-/collateral-based	Business case-based	Relationship-based
Adaptive product design	X		
Build an aftermarket	X		
Contract-based lending	X		
Leaseback	X		
Leasing chains	X		
Stepwise loans	X		
Compare with and outperform the linear model		X	
Consider the linear risk		X	
Show high-quality revenue streams		X	
Controlled growth		X	
Show LTV/CAC ratio		X	
Customer financing			X
Closer collaboration with financier			X
Industry-specific financial actors			X
Specialized partner relationships			X

TABLE 4 Test accuracies for different machine learning models and representations of the four price classifications task

Model	Accuracy (%)
MLP (clip image)	49.32
MLP (clip text)	53.18
MLP (clip text + clip image)	54.37
Logistic reg (unigram)	54.12
Logistic reg (bigram)	56.11
MLP (bigram)	57.03
MLP (bigram + clip image)	57.40

TABLE 5 Test accuracies for different machine learning models and representations of the nine price classifications task

Model	Accuracy (%)
MLP (clip text + clip image)	33.86
Logistic reg (unigram)	34.33
Logistic reg (bigram)	36.08
MLP (bigram)	36.96
MLP (bigram + clip image)	37.2

Further, our analysis shows that in the rare event of a failure of price predictions, the model will still be close to the correct price range and does not over- or underestimate to a large extent. This can be seen in Figure 1, which shows a confusion matrix of the best performing model's predictions, and it is further emphasized in Figure 2, which shows the difference between true classes and predicted classes (see Table 6 for description of classes and price ranges). Each row in the confusion matrix represents the true class, while each column represents the predicted class by the model. It shows how often the model predicts the correct label (the diagonal) and how often it performs a classification error. A perfect model would have a score of 1.0 in the diagonal.

We also wanted to evaluate if the model could estimate the value of a stock of items. To do that, we ran the best performing model (i.e., the MLP) (bigram + image) through the 17,704 items in the test set and calculated the sum of the predicted price ranges. We discarded all 1773 items in class 8 (401+ SEK) since they did not have an upper range. The resulting estimate of the stock was 1,263,419–1,928,556 and the true value of these items is 1,711,444 SEK, which lies in the predicted price range. Our results thus show that the model is able to estimate also the value of a stock of items.

The results from the AI-based modeling experiments thus suggest that there is sufficient signal in the collected data to make coarse-grained predictions about price categories. While the data may have significant differences compared to data that can be envisioned being used in PaaS companies' stock inventories, the results indicate that given the correct data as input, it is possible to predict price ranges of used clothing items, both at individual and aggregated level. These results are particularly relevant to strengthen the asset-/collateral-based financial solutions (as per the categories in Section 4).

An evaluation comparing the AI model's performance to humans was also carried out. A questionnaire was created and answered by 37 humans, where 10 random images from the test set were chosen, and the question posed was "What do you think the end price of this auction was?" The alternatives were the nine different price categories. The results can be seen in Figure 3. The AI model accuracy, shown in orange, achieved a score of 40%. This can be compared to the mean human accuracy of 18.75% (green bar). Only two humans were equally good as the AI, and only one beat it. Seven humans got a score of 0%. Moreover, a majority human vote (red bar) only achieved 10%, not performing better than random chance (11.11%). These results indicate how hard it is for humans to estimate price ranges of used clothing items, and that an AI model is able to better asses this value.

6 | DISCUSSION

There is an array of different PaaS scenarios, including both subscription models, long- and short-term rentals and functional and performance sales. The types of companies that operate (and want to operate) PaaS business models are diverse and different from each other (for example in terms of size and planned speed of scaling), as are the products and services involved, implying that there is a need for a varied set of financing solutions. Earlier studies have listed the challenges of financing such PaaS-based CBMs (Linder et al., 2022) as well as the solution strategies (Toxopeus et al., 2021) along the lines of the lending technologies used by financiers, grouping them in asset-/collateral-based, business case-based, and relationship-based.

We position our findings in line with these three categories and further both confirm earlier research on challenges (Adams et al., 2017; Govindan & Hasanagic, 2018; Grafström & Aasma, 2021; Henry et al., 2020; Kirchherr et al., 2018; Tura et al., 2019; Vermunt et al., 2019) and add more concrete solution suggestions:

The ***asset-based solutions*** we propose include product design for value retention, actively building an aftermarket for products and services, using contracts as collateral and using credit products, such as leaseback, lease-on-lease, and stepwise loans. The ***business case-based solutions*** proposed include making direct comparisons with the linear model over a relevant period of time to show the advantage of the circular business case, stressing the linear risk and the high-quality revenue projections of the circular case. In addition to this, the growth rate might need to be controlled so that profitability can be made visible, and a more opportunistic approach is to convince the financier of future profitability through the so-called CAC-LTV ratio. We also suggest ***relationship-based solutions***, emphasizing the relationship between the PaaS-company and the financier, but also pointing at risk sharing with customers through prepayments and crowdfunding, as well as with actors in the supply chain. A truly deep understanding of a customer segment might develop into industry-specific financial actors. Involving other actors that can provide repair and refurbishing services as well as the realization of the residual value of the product, will also help providing trustworthiness in your case toward the financier.

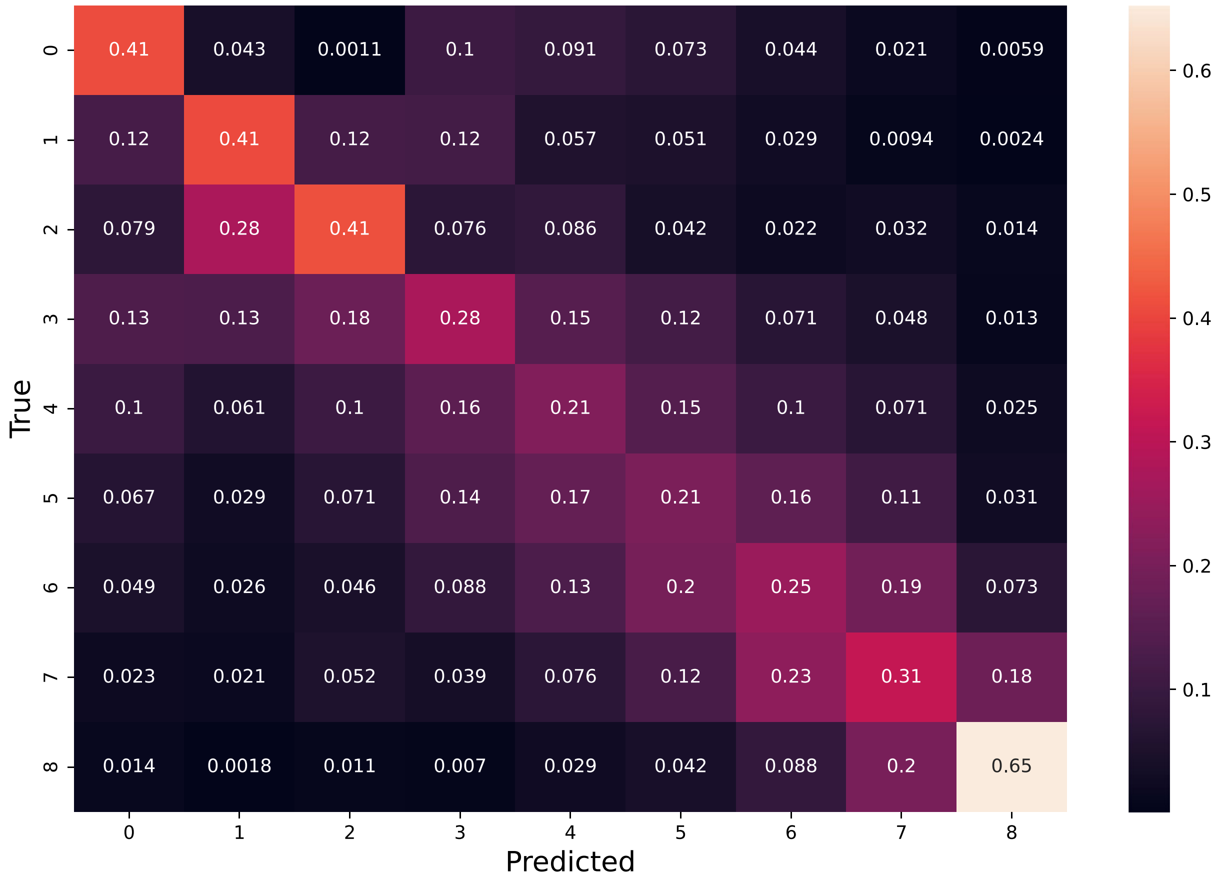

FIGURE 1 Confusion matrix normalized over the predictions for the nine-class task for the best performing classification model, that is, the MLP (bigram + clip image) model

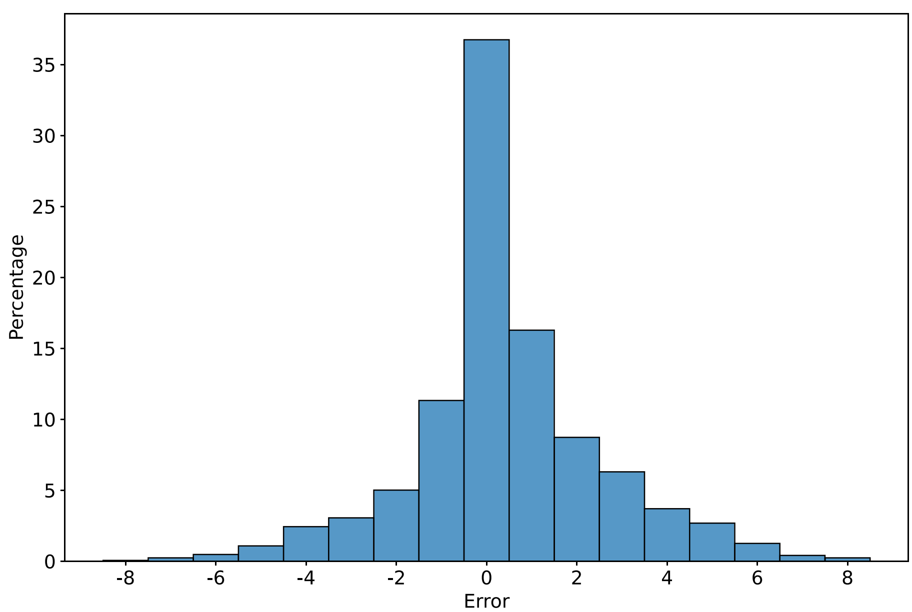

FIGURE 2 Test errors (true-predicted) for the nine-class task of the best performing classification model, that is, the MLP (bigram + clip image) model

Furthermore, we have shown that it is possible to some extent to predict auction end prices for categories clothing. Our results show that image representations of auction items can be used to train a small neural network to model the residual value. Together with text representations from CLIP, the performance can be boosted. However, in the end the simplicity of only using unigram and bigram representations gave the best results, combined with the image representations. This is a promising result, indicating that AI-predictions could be used to better assess risk in asset- or collateral-based risk assessment scenarios. An objective value calculated by an AI-model could be used to strengthen the arguments for both asset-based and business case-based assessments, since they would potentially be more trustworthy than manually estimated values.

TABLE 6 Description of classes and price ranges (for four and nine classes, respectively)

Class	Price range (SEK)
0	1–50
1	51–75
2	76–150
3	151+
Class	**Price range (SEK)**
0	1–34
1	35–49
2	50
3	51–79
4	80–103
5	104–154
6	155–249
7	250–400
8	401+

These suggested solutions for financing of CBMs sometimes overlap, and they can be combined with each other. The solutions are focused on how to solve the need for bank credit when scaling PaaS models. Depending on the situation and development phase of the PaaS firm, financing solutions could of course also include equity investments and different forms of venture capital, especially in earlier phases. It is also possible to solve some of the challenges of transitioning an existing linear company to a PaaS-based business through placing the circular business in a separate business unit or even company. This could enable the use of more precise and suitable key figures and financial ratios for the benchmark of business cases. Our conclusion is, however, that at some point in the scaling of the PaaS business, whether a start-up or an existing company, bank credit will be a necessary prerequisite for most companies.

While residual value and the possibility to realize collateral through the liquidation of the asset used as security is one of the key aspects of credit assessment frameworks today, it should be noted that in a future more circular world, where the value of products is retained for as long as possible, it is possible—even likely—that there will be no aftermarket for products in PaaS-based CBMs. The products will be kept by the PaaS provider and deliver value for a very long time, until they can no longer be used for their purpose, and need to move into a less value-preserving circular loop such as recycling. This means that residual value as a concept will become less important. This will also possibly blur the lines between the two credit

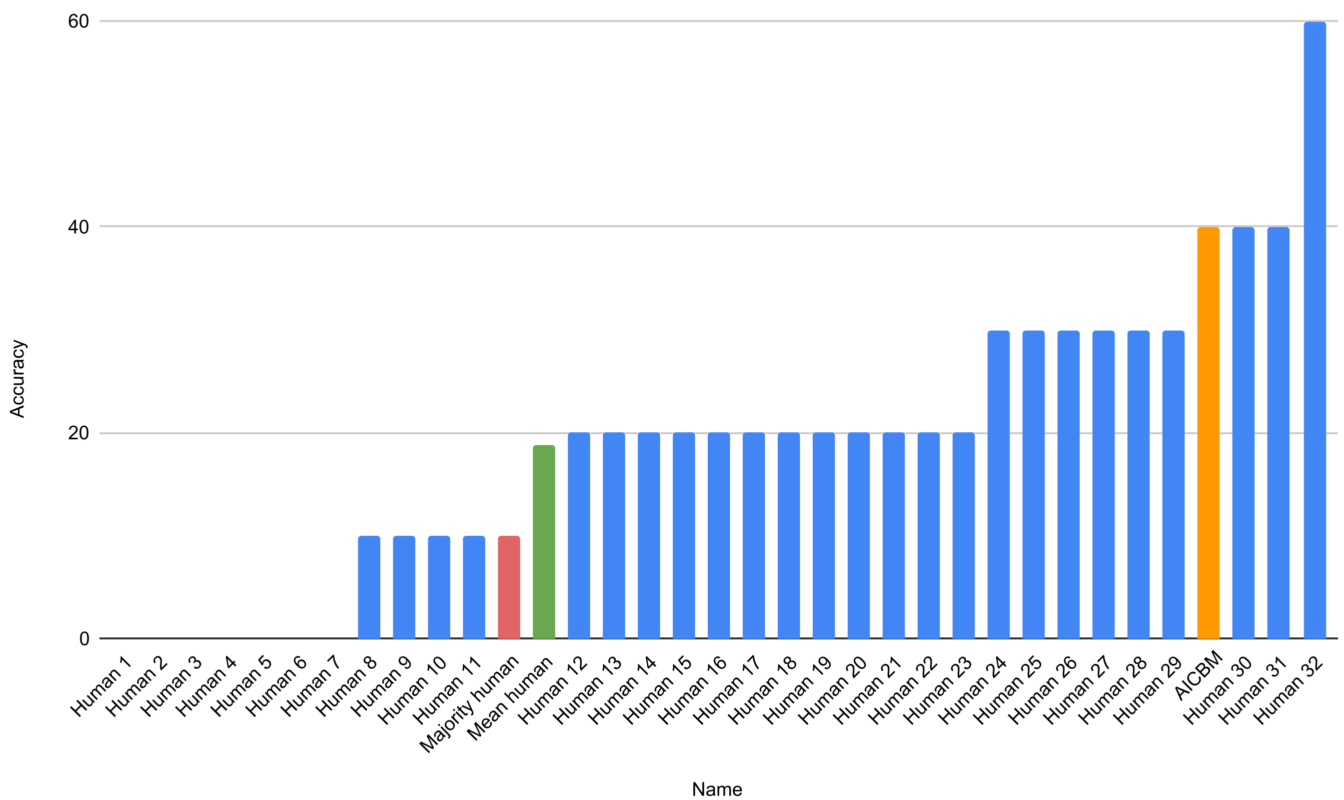

FIGURE 3 Results from the human evaluation. Accuracies for 32 humans (blue) and the proposed vision model (AICBM; orange) on 10 random images from the test set. We also report the achieved accuracy of the mean human (green) and majority human voting (red).

assessment categories, asset-based and business-case based. For the time being, however, it seems likely that solutions trying to predict residual value in an objective way, such as the AI-model in our study—and asset-based credit assessment in general—are important enablers for the circular transition through PaaS CBMs.

7 | MANAGERIAL IMPLICATIONS

For the PaaS-companies, our research results have some important practical implications. Firstly, the business case-based financial solutions indicated above, are all directed toward the PaaS-company, giving them hands-on tips on how to present and package the circular business case in the dialogue with potential financial partners. The asset-based solution on future and modular product design also indicates the importance of combining product and business model design both for optimal circular results and for addressing the risk averse financier. Solutions pointing at the need for new types of relationships also give an indication to the PaaS-company of the importance of establishing and developing networks and relationships beyond the traditional ones, for example, to help establishing value retention through repair and refurbishment partners and to establish residual value points and aftermarkets, through more collaborations with—potentially competitive—actors in the same sector.

Our AI results indicate that there are potential AI-based solutions to tackle financing based on "hard-to-value" assets. And if residual value predictions are combined with monitoring and predicting customer, contract, and payment data, there is an opportunity for a "risk monitor" that could potentially strengthen both the internal management decisions and the dialogue with the financier. Moreover, AI modeling of residual value can be used for other purposes than financial assessment. The quality of production and materials used in the product (offered for sale or as a service) is of crucial value also for strategic decision making in terms of product and business model design decisions, for example, identifying frequent points of failures of a product may give invaluable signals to improve the value retention of products.

For the banks and financial actors, this study points at several concrete solutions to be able to take on the financing challenge of CBMs. The suggested list of credit instruments (leaseback, lease-on-lease and stepwise loans) in the asset-based solutions, points at opportunities that might not be new, but still seem under-explored and under-used in relation to CBMs. Moreover, the suggested relationships-based solutions have strong implications for banks and other financiers, since they go beyond the normal bank–company relationships of today, involving both closer collaboration and deeper business understanding, but also involving other partners that have the potential to share the risk burden. This is a huge opportunity for learning and business development for the bank and might even develop into realization of new financing instruments and vehicles to better serve the financing market for PaaS CBMs.

Further our results indicate that a machine learning model is a much better predictor of residual values of used clothing than humans. This is an important result, since collateral-based risk assessment based on residual values is still important for banks, and if those residual values were assessed by a machine instead of a human being, they could be considered more neutral, trustworthy, and valid. Moreover, the possibility for an AI model to also assess "time before sell" could further decrease the risks associated with taking over inventory/assets in case of default.

8 | CONCLUSIONS

This study extends the short body of empirical literature on managing transition to CBMs by paying particular attention to innovations needed in financial risk assessment and financial instruments for CBMs. The current study is the first to concurrently examine the cross-section of CBMs, business ecosystems, finance, and artificial intelligence by discussing the future of circular business ecosystems and the nature of collaborations required between incumbents and financial actors when moving from mainly linear to innovative CBMs.

This paper provides Circular Economy practitioners with recommendations and insights related to potentials and challenges for financing CBMs. Furthermore, it demonstrates how AI modeling can be incorporated in financial risk assessment, presenting a novel AI solution, which will be made openly available, and a thorough experimental evaluation of its properties. This suggests that AI-based solutions are applicable in the setting of CBMs and motivates further work in this direction. Understanding what alternative financial solutions in new circular business ecosystems could look like will in turn decrease the perceived uncertainties and risks associated with practice of circular economy and can accelerate the transition toward CBMs.

8.1 | Theoretical contributions

This article makes theoretical contributions to the literature on CBMs, sustainable finance and servitization in the following ways:

First, our results contribute to CBM literature by particularly responding to previous literature highlighting financial barriers to CBM when firms transition from product-based to service-based business models. We provide empirical solutions for sustainable financing of CBMs from multiple stakeholders' viewpoint by focusing on both product companies and financial actors needs and uncertainties. The 15 financial solutions provide concrete examples for how the circular financing strategies suggested by Toxopeus et al. (2021) can be implemented by product companies and financial actors.

Second, we show how application of cutting-edge digital technologies such as AI can facilitate modeling the residual value of products and thereby calculating financial risks in circular economy. Awan et al. (2021) found that among empirical studies of digital technologies in the context of circular economy, artificial intelligence was discussed only in a few works, while IoT was more prevalent. Rusch et al. (2022) even revealed that the frequent occurrence of AI as a keyword in this setting did not reflect the prevalence of an AI-related research. Instead, the keyword AI was in most cases assigned wrongly to papers that did not even mention AI technology but only use references that have the word “Artificial Intelligence” in the title. The experimental model developed in the current article therefore fills this existing gap and makes a novel and hand-on contribution to our understanding of the importance of cross-section of digital technologies and circular economy previously highlighted in the CBM literature (Chauhan et al., 2022; Ellen McArthur Foundation, 2019).

8.2 | Limitations and suggestions for future research

Our study has certain limitations that should be acknowledged when interpreting the results and findings:

First, our study focused on financing solutions from the viewpoint of large international banks and product companies that already have developed PaaS-offerings and have a CBM in operation. This was to be able to gain insights on financing solutions already in place and possible learnings from previous experiences. These insights, however, are limited to specific products in the Swedish market and adopting a broader case selection to test viability and feasibility of the different financing solutions in different industries and markets would provide more generalizable results. We recommend that future research explores how market characteristics and customers' willingness to pay can affect financing solutions available in different markets. From the financial point-of-view other types of risks than residual value of assets are also interesting to explore, for example risks related to different lengths and terms of contracts and risks related to customer behavior and payment history.

Second, the AI-model and experimentation presented in this paper was developed based on data from one of the largest second-hand auction markets available in Sweden. The model was developed based on one product category, which had the largest number of transactions at the time data was exported. By extending the model to other product categories, more insights can be generated for better cross-case analysis. An interesting question for future research is to investigate whether predictions of residual value is more critical and generates more effect in risk assessment for specific product and price classes. The proposed AI approach can be adapted to new settings and other data sources, to enable such investigations.

Third, results from the AI model are based on predictions of residual values drawn from existing peer-to-peer transactions in an auction-based second-hand market, which might not reflect the long-term future residual values of products in a circular economy where items are maintained, repaired, and reconditioned to retain value over a longer period. The model can therefore be further trained with other types of data provided by product companies that retain ownership of the products to prepare them better for circulation between multiple users. Moreover, it is important to remember that the existing peer-to-peer transactions are still bound by the limits of a linear economy that is dominating on the markets. These values are not equally representative in reflecting the residual value of products in a future scenario where circular business models are up and running. We therefore propose that the technology should be continuously updated and retrained to mirror the changes through the transition from linear to circular business models. This will decrease the potential error from transferring the model from the linear domain to the circular domain.

Fourth, as more businesses embrace circular business models, an AI model trained on residual values in a linear economy will no longer be valid and may not reflect the dynamics present in the new setting. We need more investigation into this and hope to be able to return to it in future work. In this setting, other properties of items may be of more interest. How much remaining life does an item have? What are the detailed properties of an item at this point in time? What uses are suitable for an item with a specific remaining life and specific properties? All these questions should be possible to model using AI techniques, and as we further transform into circular economy, we will get the data needed to start tackling them.

Finally, the collected data contains used items put online for sale by individuals. The advertisements contain misspellings, varying formatting, and photographs produced by amateurs without editing. This puts a cap on the accuracy achievable by a predictive model trained on the data. Further investigation should be put into working with data that was more curated, or more uniformly produced. Such data may be available from online retailers, who run second-hand stores for different brands, or from the brand owners themselves. For other future work, it would be interesting to collect and use larger data sets in the modeling. If data is collected over several months, or even years, seasonality and trends could be used to further optimize when the best time to sell an item is, and to estimate the profit. More frequent collection and analysis of data, for example, on a daily basis, could also potentially add value to risk assessments based on residual value, especially for products in fast changing markets.

ACKNOWLEDGMENTS

We are grateful to Vinnova (Sweden's Innovation Agency) for financial support (grant number 2019-03166) through the research project AID-CBM: AI Driven financial risk assessment for Circular Business Models.

CONFLICT OF INTEREST

The authors declare no conflict of interest in this work.

ORCID

Sara Fallahi https://orcid.org/0000-0003-4820-5104
Ann-Charlotte Mellquist https://orcid.org/0000-0002-3462-5987
Olof Mogren https://orcid.org/0000-0002-9567-2218
Lukas Hallquist https://orcid.org/0000-0001-9037-1486

REFERENCES

Accenture. (2018). *Sustainable banking: Finance in the circular economy*. Technical Report. Accenture. Retrieved from: https://www.accenture.com/ma-en/case-studies/banking/sustainable-banking-circular-economy

Adams, K., Osmani, M., Thorpe, A., & Thornback, J. (2017). Circular economy in construction: Current awareness, challenges and enablers. *Waste and Resource Management*, *170*(1), 1–11. https://doi.org/10.1680/jwarm.16.00011

Adner, R. (2012). *The wide lens: A new strategy for innovation*. Penguin Books.

Adner, R. (2017). Ecosystem as structure: An actionable construct for strategy. *Journal of Management*, *43*(1), 39–58. https://doi.org/10.1177/0149206316678451

Awan, U., Sroufe, R., & Shahbaz, M. (2021). Industry 4.0 and the circular economy: A literature review and recommendations for future research. *Business Strategy and the Environment*, *30*(4), 2038–2060. https://doi.org/10.1002/bse.2731

Berger, A. N., & Black, L. K. (2011). Bank size, lending technologies, and small business finance. *Journal of Banking & Finance*, *35*(3), 724–735. https://doi.org/10.1016/j.jbankfin.2010.09.004

Berger, A. N., & Udell, G. F. (2006). A more complete conceptual framework for SME finance. *Journal of Banking & Finance*, *30*(11), 2945–2966. https://doi.org/10.1016/j.jbankfin.2006.05.008

Bocken, N. M., De Pauw, I., Bakker, C., & Van Der Grinten, B. (2016). Product design and business model strategies for a circular economy. *Journal of Industrial and Production Engineering*, *33*(5), 308–320. https://doi.org/10.1080/21681015.2016.1172124

Boyer, R. H. W., Mellquist, A., Williander, M., Fallahi, S., Nyström, T., Linder, M., Algurén, P., Vanacore, E., Hunka, A. D., Rex, E., & Whalen, K. A. (2021). Three-dimensional product circularity. *Journal of Industrial Ecology*, *25*(4), 824–833. https://doi.org/10.1111/jiec.13109

Brown, P., Bocken, N. M. P., & Balkenende, R. (2020). How do companies collaborate for circular oriented innovation? *Sustainability*, *12*(4), 1648. https://doi.org/10.3390/su12041648

Chauhan, C., Parida, V., & Dhir, A. (2022). Linking circular economy and digitalisation technologies: A systematic literature review of past achievements and future promises. *Technological Forecasting and Social Change*, *177*, 121508. https://doi.org/10.1016/j.techfore.2022.121508

Chen, L. H., Hung, P., & Ma, H. W. (2020). Integrating circular business models and development tools in the circular economy transition process: A firm-level framework. *Business Strategy and the Environment*, *29*(5), 1887–1898. https://doi.org/10.1002/bse.2477

De Bono, E. (1985). *Six thinking hats*. Penguin Books.

Ellen McArthur Foundation. (2019). *Artificial intelligence and the circular economy AI as a tool to accelerate the transition*. Cowes, UK. Retrieved from https://emf.thirdlight.com/link/dl06eujbcbet-wx40o7/@/preview/1?o

Fallahi, S. (2017). *A process view of business model innovation*. (Doctoral dissertation). Chalmers University of Technology.

Frishammar, J., & Parida, V. (2019). Circular business model transformation: A roadmap for incumbent firms. *California Management Review*, *61*(2), 5–29. https://doi.org/10.1177/0008125618811926

Frishammar, J., & Parida, V. (2021). The four fatal mistakes holding back circular business models. *MIT Sloan Management Review*, *62*(3), 68–72.

Ghisellini, P., Cialani, C., & Ulgiati, S. (2016). A review on circular economy: The expected transition to a balanced interplay of environmental and economic systems. *Journal of Cleaner Production*, *114*, 11–32. https://doi.org/10.1016/j.jclepro.2015.09.007

Govindan, K., & Hasanagic, M. (2018). A systematic review on drivers, barriers, and practices towards circular economy: A supply chain perspective. *International Journal of Production Research*, *56*(2), 1–34. https://doi.org/10.1080/00207543.2017.1402141

Grafström, J., & Aasma, S. (2021). Breaking circular economy barriers. *Journal of Cleaner Production*, *292*(2021), 126002, ISSN 0959-6526. https://doi.org/10.1016/j.jclepro.2021.126002

Henry, M., Bauwens, T., Hekkert, M., & Kirchherr, J. (2020). A typology of circular start-ups: An analysis of 128 circular business models. *Journal of Cleaner Production*, *245*, 118528. https://doi.org/10.1016/j.jclepro.2019.118528

ING bank. (2015). *Rethinking finance in a circular economy—Financial implications of circular business models*. ING Bank Report. Retrieved from: https://www.ing.nl/media/ING_EZB_Financing-the-Circular-Economy_tcm162-84762.pdf

Jick, T. D. (1979). Mixing qualitative and quantitative methods: Triangulation in action. *Administrative Science Quarterly*, *24*(4), 602–611. https://doi.org/10.2307/2392366

Kanda, W., Geissdoerfer, M., & Hjelm, O. (2021). From circular business models to circular business ecosystems. *Business Strategy and the Environment*, *30*(6), 2814–2829. https://doi.org/10.1002/bse.2895

Kirchherr, J., Piscicelli, L., Bour, R., Kostense-Smit, E., Muller, J., Huibrechtse-Truijens, A., & Hekkert, M. (2018). Barriers to the circular economy: Evidence from the European Union (EU). *Ecological Economics*, *150*(2018), 264–272, ISSN 0921–8009. https://doi.org/10.1016/j.ecolecon.2018.04.028

Kirchherr, J. W., & van Santen, R. (2019). Research on the circular economy: A critique of the field. *Resources, Conservation and Recycling*, *151*, 104480. https://doi.org/10.1016/j.resconrec.2019.104480

Lahti, T., Wincent, J., & Parida, V. (2018). A definition and theoretical review of the circular economy, value creation, and sustainable business models: Where are we now and where should research move in the future? *Sustainability*, *10*(8), 2799. https://doi.org/10.3390/su10082799

Lieder, M., & Rashid, A. (2016). Towards circular economy implementation: A comprehensive review in context of manufacturing industry. *Journal of Cleaner Production*, *115*, 36–51. https://doi.org/10.1016/j.jclepro.2015.12.042

Linder, M., Mellquist, A., Vanacore, E., Hallquist, L. & Whalen, K. (2022). *Financing circular business models: The case of product-as-a-service. Submitted for publication.*

Linder, M., & Williander, M. (2017). Circular business model innovation: Inherent uncertainties. *Business Strategy and the Environment*, *26*, 182–196. https://doi.org/10.1002/bse.1906

Listo Zec, E., Mogren, O., Mellquist, A., Fallahi, S., & Algurén, P. (2022). *Residual value prediction using deep learning for circular economy*. 2nd International Workshop on Big Data Analytics for Sustainability (BDA4S 2022). Osaka, Japan.

Neligan, A., Baumgartner, R. J., Geissdoerfer, M., & Schöggl, J. P. (2022). Circular disruption: Digitalisation as a driver of circular economy business models. *Business Strategy and the Environment*, 1–14. https://doi.org/10.1002/bse.3100

Nußholz, J. (2017). Circular business models: Defining a concept and framing an emerging research field. *Sustainability*, *9*(10), 1810. https://doi.org/10.3390/su9101810

Nyström, T. (2019). *Adapative Design for Circular Business Models in the automotive manufacturing industry*. [Licenciate]. University of Gothenburg.

Osterwalder, A., & Pigneur, Y. (2010). *Business model generation: A handbook for visionaries, game changers, and challengers*. John Wiley & Sons.

Reim, W., Sjödin, D., & Parida, V. (2021). Circular business model implementation: A capability development case study from the manufacturing industry. *Business Strategy and the Environment*, *30*(6), 2745–2757. https://doi.org/10.1002/bse.2891

Rizos, V., Behrens, A., Van der Gaast, W., Hofman, E., Loannou, A., Kafyeke, T., Flamos, A., Rinaldi, R., Papadelis, S., Hirschnitz-Garbers, M., & Topi, C. (2016). Implementation of circular economy business models by small and medium-sized enterprises (SMEs): Barriers and enablers. *Sustainability*, *8*(11), 1212. https://doi.org/10.3390/su8111212

Rusch, M., Schöggl, J. P., & Baumgartner, R. J. (2022). Application of digital technologies for sustainable product management in a circular economy: A review. *Business Strategy and the Environment*, 1–16. https://doi.org/10.1002/bse.3099

Stahel, W. (2010). *The performance economy*. Palgrave Macmillan Hampshire.

Teece, D. J. (2010). Business models, business strategy and innovation. *Long Range Planning*, *43*(2–3), 172–194. https://doi.org/10.1016/j.lrp.2009.07.003

Toxopeus, H., Achterberg, E., & Polzin, F. (2021). How can firms access bank finance for circular business model innovation? *Business Strategy and the Environment*, *30*(6), 2773–2795. https://doi.org/10.1002/bse.2893

Tukker, A. (2004). Eight types of product–service system: Eight ways to sustainability? Experiences from SusProNet. *Business Strategy and the Environment*, *13*(4), 246–260. https://doi.org/10.1002/bse.414

Tura, N., Hanski, J., Ahola, T., Ståhle, M., Piiparinen, S., & Valkokari, P. (2019). Unlocking circular business: A framework of barriers and drivers. *Journal of Cleaner Production*, *212*(2019), 90–98. https://doi.org/10.1016/j.jclepro.2018.11.202

Urbinati, A., Rosa, P., Sassanelli, C., Chiaroni, D., & Terzi, S. (2020). Circular business models in the european manufacturing industry: A multiple case study analysis. *Journal of Cleaner Production*, *274*, 122964. https://doi.org/10.1016/j.jclepro.2020.122964

Veleva, V., & Bodkin, G. (2018). Corporate-entrepreneur collaborations to advance a circular economy. *Journal of Cleaner Production*, *188*, 20–37. https://doi.org/10.1016/j.jclepro.2018.03.196

Vermunt, D. A., Negro, S. O., Verweij, P. A., Kuppens, D. V., & Hekkert, M. P. (2019). Exploring barriers to implementing different circular business models. *Journal of Cleaner Production*, *222*(2019), 891–902, ISSN 0959-6526. https://doi.org/10.1016/j.jclepro.2019.03.052

How to cite this article: Fallahi, S., Mellquist, A.-C., Mogren, O., Listo Zec, E., Algurén, P., & Hallquist, L. (2022). Financing solutions for circular business models: Exploring the role of business ecosystems and artificial intelligence. *Business Strategy and the Environment*, 1–16. https://doi.org/10.1002/bse.3297

APPENDIX A

Workshop 1 World Café/Six Thinking Hats (Stockholm, Sweden, January 30, 2020)

World café instructions:

- Three groups/tables, split based on role (see next slide)
  - Banks and financiers
  - Product companies
  - Innovation Enablers
- Discussion 2–3 questions per table/topic.
- One host per table, taking notes. Everyone else moves (after the first round) to a table of choice. 20 + 10 + 10 min/table.
- Each discussion starts with the host doing a short "recap" of previous discussion(s)
- Summary and presentation 3 * 5 min by the hosts.

Groups and questions:

Banks and financiers (Financier A, Financier B, Financier E, Financier F)

What type of information is critical for banks to be willing to take risk in new circular business models and new types of collateral? (How important are residual value and existing second-hand markets compared to other aspects—persons, business case, cash flow?)

What are the most important aspects that AI and Machine learning can add to risk assessment of collateral, where historical data is needed/lacking?

Product companies (OEM A, OEM B)

What type of product information can/should product companies share to support the banks' risk assessments of CBMs? How do product companies value risk and opportunities of CBM in their business?

How should banks and financiers preferably think and act to enable the expansion of CBMs by product companies?

Innovation enablers (Enabler G, Enabler H, Enabler I)

What technologies are critical to enable financing of a transition to CBM?

How can "intermediary technology-based companies"/"innovation enablers" support this process?

What does the future business ecosystem (where banks and producers work in closer collaboration to scale up CBM) look like? What tech- or other supporting roles are there to fill?

Workshop 2 (On-line format facilitated by a Mural canvas, 28th January 2021)

Purpose:

Identify and sharpen the understanding of how the business model of the bank could support financing of PaaS models.

Workshop scenario:

Industry will go through an extensive transition to circular business models and will—for example—transition from linear product sales to keeping ownership of the products and selling their function. We have resigned from earlier positions to start a new company—The Function Bank AB—which will offer financial services to circular companies offering function (or product-as-a-service). In the same way that Omocom realized the lack of a specific service offer for functional sales companies in the insurance industry, we see the potential of competing with existing financiers with a service offer for functional sales-based circular businesses. Today we will meet some potential customers, both start-ups and established larger companies, to discuss and collaborate on how to find a win-win solution.

Instructions—Part 1:

Describe the business model for Function Bank AB in the BMC canvases—for the case of your group (B2C or B2B). Focus on the value proposition (why would the customer buy your service) and your key resources and key activities. Please also note which actor will be the owner of the product, that is, have the booked value on its balance sheet.

The 30-min discussion in breakout-rooms. After that, each group presents its business model, and we will comment and discuss each other's results.

Instructions—Part 2:

Reflect on and answer the following questions. Work with your case, or with both—free of choice.

a. What other actors (outside the product company and the bank) could enable the cases, and what roles could they take?
b. How would the business model/value proposition of Function Bank AB be affected if their customers sell functions/pay-per-use instead of subscriptions?
c. How can data and AI support your model?

The 15-min individual brainstorming. Note the answers on sticky notes in the canvases.

The 45-min presentation and joint discussion.

APPENDIX B

In this work we are training two different models: a logistic regression model and a neural network. Logistic regression is a simple algorithm that can be trained to learn a linear mapping $\mathbf{y} = \mathbf{W}\mathbf{x} + \mathbf{b}$ from some input data $\mathbf{x}$ to classes $\mathbf{y}$. $\mathbf{W}$ is called a weight matrix and b a bias term, both learned from the training data. A neural network (or multi-layer perceptron, MLP) can be viewed as an extension of this where we add layers of more weight matrices $\mathbf{y} = \mathbf{W_2}\ (\sigma\ (\mathbf{W_1 x} + \mathbf{b}))$. This gives the model more capacity to learn more complex patterns in the data. σ is called an activation function, and is a non-linear function added to make it possible to learn non-linear patterns in the data.

In order to solve the auction end price classification task, we have used the title and the description of each item as well as an image of the item to make the prediction. For the text descriptions, we have experimented with three different types of representations: unigrams, bigrams, and Swedish CLIP embeddings. A *n*-gram representation is a simple way of representing text and consists of a sequence of n items (in our case words). For unigrams ($n = 1$), this means that we for each sentence (or description of an item) count which unique words are present. For a bigram ($n = 2$), we instead count unique pairs of words, which gives us spatial information of the sentence.

CLIP is a large deep learning model that is trained to predict which images were paired with which texts in a dataset. We use the Swedish language model in CLIP to create text representations of item descriptions, and we use the vision model (a ResNet RN50x4) to create image representations.