Using Big Data Analytics to Combat Retail Fraud

Danni Zhang[1], Steffen Bayer[1], Gary Willis[2], Gina Frei[1], Enrico Gerding[2] and PK Senyo[1]
[1]*Southampton Business School, University of Southampton, Southampton, U.K.*
[2]*Electronics & Computer Science, University of Southampton, Southampton, U.K.*

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Abstract: Fraudulent returns are seen as a misfortune for most retailers because it reduces sales and induce greater costs and challenges in returns management. While extant research suggests one of the causes is retailers' liberal return policies and that retailers should restrict their policies, there is no study systematically exploring the impacts of various return policies and fraud interventions on reducing different types of fraudulent behaviour and the costs and benefits of associated interventions. In this paper, we first undertook semi-structured interviews with retailers in the UK and North America to gain insights into their fraud intervention strategies, as well as conducted literature review on fraudulent returns to identify the influential factors that lead customers to return products fraudulently. On this basis, we developed a simulation model to help retailers forecast fraudulent returns and explore how different combinations of interventions might affect the cases of fraudulent returns and associated financial impacts on profitability. The background literature on fraudulent returns, the findings of interviews, and the demonstration and implications of the model on reducing fraudulent returns and related financial impacts are discussed. Our model allows retailers to make cost-effective evaluations and adopt their fraud prevention strategies effectively based on their business models.

1 INTRODUCTION

Retailers collect a vast amount of data on the channels shoppers use to buy their goods. This results in a 'lake' of big data leading to some powerful analysis on shopper behaviour. Retail businesses aim to give their customers a good experience when shopping. Part of this experience is to make it easy to return goods, referred to as frictionless returns and then increase sales. However, there are dishonest customers who will exploit lenient return policies to obtain money or use of goods illegally through fraudulent returns, at little or no cost to themselves (Harris, 2010; Speights & Hilinski, 2005; King, Dennis, & McHendry, 2007). Unfortunately, fraudulent returns could erase a retailer's 10%-20% profit margin (King, 2004). A survey conducted by the National Retail Federation in 2008 suggested that around 5.4% of merchandise loss is due to return abuse.

Many retailers have seen an extreme growth in their online business since the beginning of the pandemic. However, Covid-19 may aggravate the problem of high genuine and fraudulent returns, which have been increasing over the last few years (Jack, Frei, & Krzyzaniak, 2019; Smriti, 2018).

Specifically, many non-essential retailers have to change the way they manage their returns and refunds, which leads to less scrutiny and increases fraudulent returns over time. For example, most retailers extending their returns periods resulted in more dishonest customers returning a product long after extracting most of the product's market value. Retailers also try to reduce the time customers spend in-store by introducing drop-boxes and accepting returns at sister-brand stores, resulting in less inspection. Additionally, returned products need to be quarantined that retailers are unable to inspect the returns before refunding. Moreover, a surge of product returns arrived when non-essential retailers reopened; however, retailers lack the staff to thoroughly sort and check all returns. Therefore, problem behaviours that are costly in normal periods (e.g., fraudulent refunds, serial returners) have become worse in this pandemic period. The LexisNexis (2020) study confirms this and shows a considerable increase in fraudulent returns.

The effects of these changes on fraudulent rates are currently unknown and need investigation. To survive this crisis, besides needing to get a handle on returns rates, retailers must be robust when faced with non-genuine customers who want to abuse the system. In order to plan their returns strategies, it is

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important to be able to predict the fraudulent rates expected under varying conditions. Much research associated with fraudulent returns focuses on exploring fraudsters' motivations via surveys or interviews methods, or identifying fraudsters' returning patterns by analysing returns data (e.g., Urbanke, Kranz, & Kolbe, 2015; King & Dennis, 2006). Building a comprehensive customer profiling model for distinguishing and identifying abusive customers can be costly and time-consuming. Therefore, the aim of this research is to use the big data collected to develop a model that helps retailers understand the effects of their return policies and intervention in reducing fraudulent returns.

This position paper first presents the background literature on fraudulent returns and some of the measures that are taken to mitigate fraudulent returns. Then we present our model used to help merchants forecast the fraudulent returns and see how the measures might affect the cases of fraudulent returns.

2 RELATED WORK

Modelling has been at the centre of forecasting returns (Drechsler and Lasch 2016; Potdar and Rogers 2012). Machine learning (Smriti 2018; Cui, Rajagopalan, & Ward, 2020) and AI (Urbanke, Kranz, & Kolbe, 2015) has been used to forecast returns volumes from fashion online sales in order to develop returns strategies, identifying consumption patterns associated with a high return rate. Zhu et al (2018) used historical data to address the much-criticised 'one size fits all' approach to differentiate the service approach, predict returns and derive strategical implications for retailers. Ketzenberg et al (2020) utilised an extensive data set with over 75 million transactions from a US retailer and identified the characteristics of abusive returners.

However, this body of work is based on relatively stable behaviour patterns to predict aggregate return volumes or individual level return probabilities. In the current, rapidly changing situation due to the pandemic, the usefulness of such approaches is limited: understanding patterns in past purchase data is not enough to create robust strategies to deal with the very significant uncertainty of the present and the future. There are limited studies that have explored the types of interventions that retailers can take to reduce fraudulent return rates. The effects of interventions remain under-researched in simulation and modelling based analysis.

2.1 Fraud Triangle

The fraud triangle framework developed by Donald Cressey and W. Steve Albrecht has been widely used to explain why people violate trust and commit fraud (Homer, 2020). The triangle suggests three elements, namely pressure, opportunity, and rationalisation, that are the motivations for fraudsters to commit the crime (Cressey, 1973).

The reason for committing fraud varies, but it often comes from financial pressure. Specific to fraudulent returns, Wachter et al (2012) suggested that a combination of product's high prices and fraudsters' low income resulted in them utilising the lenient returns policy to gain benefits (e.g., returning used products). Additionally, the financial shortage caused by the pandemic crisis may lead more dishonest customers to consider generating financial benefits by making a fraudulent refund, for example, returning an empty box for a full refund.

Organisations with inadequate internal controls, procedures and processes, or physical safeguards can create an opportunity for fraud to be committed and concealed (Counter Fraud Services, 2016; DeltaNet, 2021). Some employees do the return transaction for their family members illegitimately or even do a refund to their personal account without any purchases. A recent review paper suggests that opportunity is the most important factor for explaining fraudulent behaviour in contrast to other elements (Homer, 2020). People with antisocial tendencies tend to believe, if someone is scammed it is their own fault (Sarah, 2019). Piron and Young (2000) found that recidivists blame the loss caused by wardrobing (represents the situation that customer legitimately buying an item for a specific occasion with the intention of returning it after use) is retailers' fault, and some of them manifested their surprise at how easy it to return the used products.

2.2 Theory of Planned Behaviour

The Theory of Planned Behaviour (TPB; Ajzen, 1991) was developed from the Theory of Reasoned Action (Ajzen & Fishbein, 1973) is also implemented on examining the fraudulent behaviour (non-financial generate purpose). In the TPB framework, there are three psychological variables, namely attitudes, subjective norms, and perceived behavioural control, that all together lead to the formation of a 'behavioural intention' which in turn influence the behaviour (Ajzen, 2002).

King et al. (2008) is the first study that applied the TPB to analyse consumers' dishonest returning behaviour via a self-administered questionnaire with 535 female consumers. Their results justified that if a person believes that dishonest returning will be an easy or pleasant experience, they are more likely to do it. King and Dennis (2006) is a follow-up study that conducted in-depth interviews with dishonest returners. Their results suggest that returners' prior returning experience is linked to their proclivity of fraudulent returning in the future. According to Johnson and Rhee (2008), if the return procedure is complicated or there is a cost attached to returning or getting a refund may be difficult, it reduces opportunistic return behaviour, and the customer may decide against return. In the retails, there are a number of techniques fraudsters use to commit theft through product returns (Speights and Hilinski, 2005). Some of the most common types are:

- **Wardrobing or Renting**: Here the shoppers buy an item (e.g., clothing or a digital camera) with the intention of using it for an event then returning it after the event.
- **Price Arbitrage** (online frauds): Here the shoppers (1) replace the cheaper item/counterfeit in the expensive item's packaging and return it for a full refund, or (2) purchase a new item, then return an older or non-working version of the same item, using the packaging from the newer merchandise for a refund.
- **Payment Fraud**: offenders purchase items with an illegitimate credit/debit card or with one backed by insufficient funds and then return the merchandise before the card clears by the bank.
- **Insider Fraud**: Offenders receive assistance from employees to return stolen goods, or employees return the stolen goods for their own benefits.
- **Returning Stolen Merchandise** (in-store frauds):
  - *Returning shoplifted items*: individuals or gangs shoplift goods in-store and then "return" the item without a receipt for a refund or store credit.
  - *Receipt Switching*: offender makes a genuine purchase, leaves the store with the item and receipt, then re-enters later (or goes to another store but the same company), and picks up an identical item. Then using the receipt, the individual claim a refund on the item they have just picked. The fraudster has in effect received the first item for free.
  - *Receipt Fraud*: offender with a receipt obtained from somebody else (or the sites selling fake receipts either digital or physical) goes to shop to return the stolen item for a refund.

The above findings and discussions indicate that it is important to reduce the opportunity to initiate a fraudulent or abusive return at the first purchase stage and explore how different return policies and interventions will affect the fraudulent rates.

3 INTERVENTION TO LIMIT FRAUDULENT BEHAVIOUR

In this section, we discuss the interventions to reduce fraudulent behaviour, which is based on our interviews with retailers. The interventions aim to remove the fraudulent opportunities at customers' purchase and returns stages.

The interviewed retailers were drawn from the Efficient Consumer Response (ECR) Retail Loss Group. This is a community in which retailers discuss issues they are facing. The interviewed organisations were selected purposively that retail a wide range of products, including groceries, clothing and general merchandise products such as home entertainment and small electrical goods. We asked the interviewees to answer our questions regarding non-food products. They are major players in the market, with the number of stores ranging from 150 to 750 in the year 2021. Therefore, they all have significant impacts on society and the economy. Having conversations with these organisations' loss prevention managers allows us to develop various practical interventions in the fraudulent prediction model (Section 4). The interview duration was between 90 and 120 minutes. As with security generally, retailers are willing to discuss with researchers on fraud prevention methods but not will have their name associated with a particular method.

First, having a generous returns policy not only make it easy for fraudsters to return but also to obtain a refund illegally. A 'no quibble' policy gives the feeling of trying it out first, but it can make it easy for the fraudsters to steal items and money unless there are some checks being done by the retailer. Common generous policies include giving customers a refund in cash or a gift card even if they do not have a receipt, extending the returns period, no return costs (e.g., free to return to stores or provide a pre-paid return label). Much of the work has highlighted that generous return policy is the critical driver of fraudulent returns (e.g., Harris, 2010; Speights & Hilinski, 2005; Tyagi & Dhingra, 2021). For example, in one organisation, we were told:

'*We have a quibble policy up to £40 pounds. If anyone comes to our store wanna a refund of the £40, we don't ask them why. If something that a shoplifter brings for a return and refund, we wouldn't have questioned it. However, we should*' (Loss prevention manager A, Company A)

'*While our customers come in and will not have a receipt and we will still refund it, we shouldn't, but that still happens, unfortunately.*' (In-store Loss prevention manager, Company B)

The type of intervention that retailers suggested have been shown to make it more difficult for fraudsters include:

- Setting a shorter return period.
- Increasing the deployment of CCTVs & guards in-stores.
- Online, customers need to contact Customer Services to arrange a return and fill out forms before sending them back, as opposed to where a return label is already included.
- Providing clear communication of return policies: no receipt, no refund (exchange possible), if the serial number did not match, no refund (if appliable) and no swing tag, no return (exchange possible).
- Returning funds to the same payment method only.

One manager commented that:

'*We spend now roughly £40 million a year on guarding [in-store] when it was £20 million pre-pandemic, which obviously reduces the likelihood of having a theft, but also significantly reduces the likelihood of fraudulent returns. I suppose there's theoretically more visibility over shoplifters and fraudsters…the feedback is the visual deterrent. We have workshops with ex-offenders, so, we have a team that asking them[offender], how would you steal and fraud, and what would put you off? And they [offenders] all said that having a visible and clearly looking guard is the biggest deterrent.'* (Loss prevention manager B, Company A)

Second, other organisational processes aid the fraudsters. These are poor returns management, poor cyber security, a universal product code for the same category's products, weak supervision in the workplace regarding returns and refund processes, and lack of sufficient training to spot fraudulent returns. Based on the discussion with retailers, a number of interventions have been shown to improve organismal procedures**.**

- In-store, all returns have to be handled by the Customer services (well-trained staff and supervision).
- Employees cannot refund their own purchased products without the presence of a manager.
- Managers should take turns to supervise refunds.
- Using Address Verification Service to ensure the cardholder has provided the correct billing address associated with the account.
- Using 3-D Secure service, Payment services (PSD 2).
- Using new technology: Radio frequency identification (FRID).
- Reporting fraudulent retunes behaviour (e.g., using fake products/cards) to the police for investigation.

For example,

'*We also go down the civil recovery route in terms of bricks and mortar fraud, even going to bailiffs. So, we're really aggressive with that, so we give ourselves a reputation with the bad people, not to bother with us because we will hunt you down. We do see the immediate effect of reducing the fraud returns.*' (Fraud prevention manager A, Company C)

'*…now, we've got a policy in place where all refund of £9 and above needs to be signed for by a senior manager. So, they need to basically see the product, see the receipts to make sure it's been refunded appropriately. So, we don't get colleges refunding themselves for products fraudulently, which we had been in the past…We have got that policy that reduces the probability of inside fraud.'* (Loss prevention manager B, Company A)

Third, good use and analysis of the retail data generated can reduce fraud. Data analysis can flag serial/repeat offenders, leaving the customer service team free to deal with cases without suspicion.

Data analytics can be used to:

- Identifying serial offenders and blocking them.
- Reporting on the categorisation of frauds that result in financial and non-financial loss.

One manager highlighted that:

'… now we're doing everything with machine learning and getting all this fraud data into an online screening tool. We're actually seeing that we're not getting attacked as much now, because we're identifying these people every week and putting new data in. So, our database of customers that have committed fraud with us is really big. We've got about 4,000 customers out of 20 million. And as we go, we'll build that up. So even though they're not unique customers, we're able to look at people that are linked to them by a delivery address, an email etc. Something like that, we can start really analysing who's targeting us and manage that risk.' (Profit Erosion and Data Mining Manager, Company D)

4 MODELLING

The aim of our modelling was to create a tool for retailers to evaluate the impact of different policies on fraud. A retailer could use this model to choose cost-effective strategies and explore complementarities between measures targeted to reduce genuine returns and fraudulent returns. In our approach, we summarise different fraud types and then apply which policies would impact fraudulent returns over time.

First, we consider six stringencies of fraud controls that are only targeted at reducing fraud. These targeted controls include:

1. Unique barcode for each product.
2. Radio frequency identification (RFID).
3. Limited payment methods & Stronger security of online payment.
4. Sending warning messages.
5. Increased inspection at stores (e.g., increasing the deployment of CCTVs & guards).
6. Stricter supervision on the returns process. Second, we consider seven return policies that impact return volumes as well as fraud attempts.
7. Setting a shorter the return period.
8. Requiring original receipts.
9. Requiring more return efforts for online returns (e.g., account registration, contact customer services for online returns).
10. Items can only be returned with tags still attached.
11. No Pre-paid return label for online returns (i.e., customers either pay the shipping fee or contact the retailers first).
12. All returns have to be handled by the Customer services.
13. Returning funds to the same payment method only.

These policies and controls are drawn from interviews and literature review, which have been implemented or are considered by retailers. The model allows employing these policies alone or in combination with others. In this way, we can assess any complementarity between measures.

The model (see Figure 1 for the relationship on which the calculations are based) then predicts the number of fraud attempts and successful frauds as well as the number of returns under different

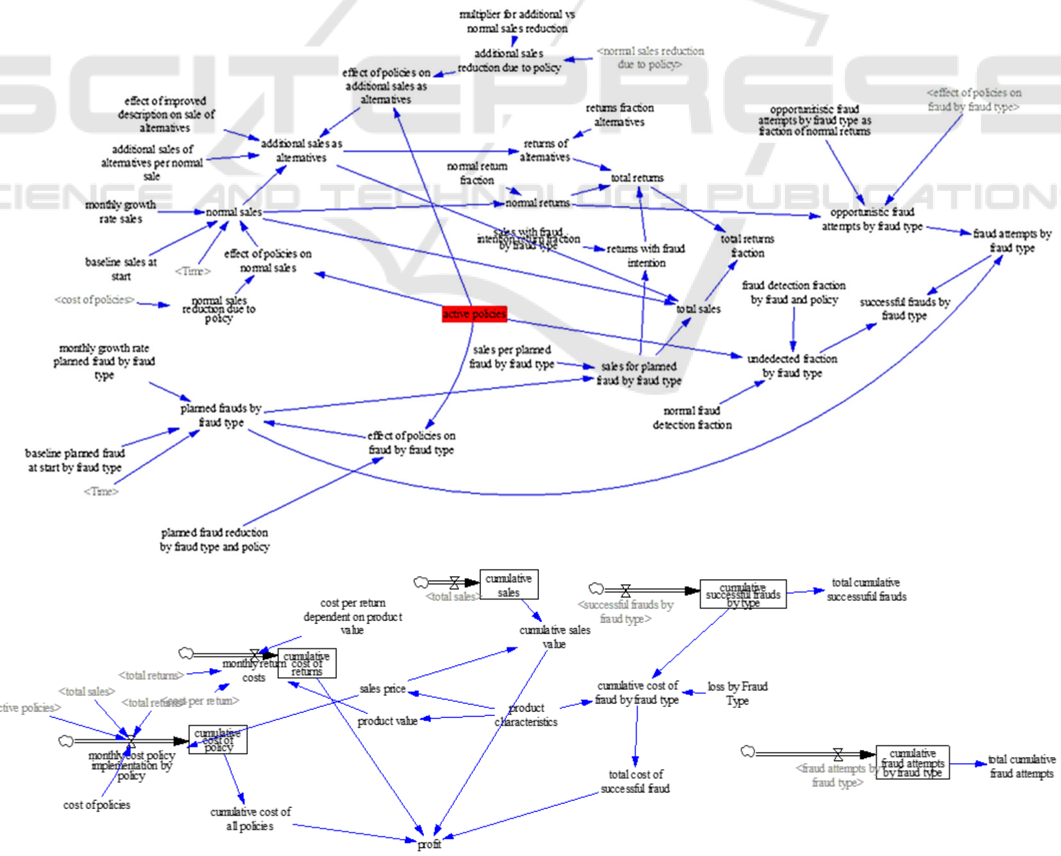

Figure 1: The demonstration of the model for the relationship on which the calculations are based.

Table 1a: Fraud attempts over two 24 months depending on policies adopted.

Cumulative fraud attempts by type	**Ward-robing**	**Price Arbitrage**	**Payment Fraud**	**Returning shoplifted items**	**Receipt Switching**	**Receipt Fraud**	**Insider fraud**
Baseline	1243	1243	1243	1243	1243	1243	1243
Stricter Fraud Controls	343	244	301	283	356	844	419
Stringent Return Policies	63	80	238	281	447	854	894
All Interventions	18	16	58	64	128	580	301

Table 1b: Successful fraud over two 24 months depending on policies adopted.

Cumulative successful frauds by type	**Ward-robing**	**Price Arbitrage**	**Payment Fraud**	**Returning shoplifted items**	**Receipt Switching**	**Receipt Fraud**	**Insider fraud**
Baseline	621	621	621	621	621	621	621
Stricter Fraud Controls	127	8	103	106	141	418	61
Stringent Return Policies	23	29	65	131	204	415	264
All Interventions	5	0	11	22	46	279	26

combinations of these 13 interventions over a two-year time horizon distinguishing seven different types of fraud. The fraud types are: wardrobing, price arbitrage, returning shoplifted items, receipt switching, receipt fraud, payment fraud, insider fraud.

In addition, the model allows users to assess the financial impact of fraud as well as other key performance indicators.

Table 2: Financial outcomes over two 24 months depending on policies adopted.

Cumulative cost of all policies (£)	
Baseline	0
Stricter Fraud Controls	86896
Stringent Return Policies	28171
All Interventions	110901
Cumulative cost of returns (£)	
Baseline	319632
Stricter Fraud Controls	197063
Stringent Return Policies	174781
All Interventions	139616
Cumulative sales value (£)	
Baseline	3863440
Stricter Fraud Controls	3278380
Stringent Return Policies	3011640
All Interventions	2843790
Total cost of successful fraud (£)	
Baseline	328896
Stricter Fraud Controls	80720
Stringent Return Policies	93559
All Interventions	36720

As we have not yet have been able to apply our model to retailers' data, our results are illustrative and indicative, we based this information on our interviews with retailers. Tables 1a and 1b show the impact of different combinations of policies on fraud attempts and successful frauds over two years. For illustration purposes, we assumed fraud attempts are equally divided between fraud types, and all fraud types have the same success rate. Table 2 shows financial outcomes over two years depending on the combination of policies adopted.

Figure 2 shows the number of successful frauds under different scenarios, and Figure 3 demonstrates the profit comparison under different scenarios. By comparing scenarios, we can see how the introduction of more stringent return policies will reduce sales, partly by discouraging honest shoppers. Additionally, we assume a reduction on stricter fraud detection in fraud attempts as awareness of our policies will spread.

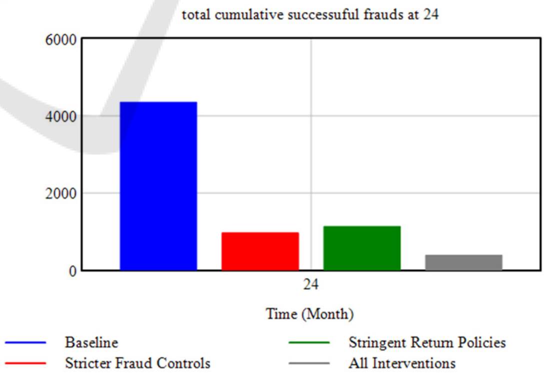

Figure 2: Successful frauds under different scenarios.

The combined impact of policies can be surprising: in our illustrative example (see Figure 2 and Figure 3), we see that while the introduction of all policies combined reduces fraud the most, it is not the most profitable. Under the current assumptions of cost and impact of the interventions, just focusing on stringent return policies is more profitable than a combination of all policies with a focus on fraud detection alone being the second-best choice. These results could be the starting point to discussion among stakeholders across different departments in an organisation tasked with meeting sometimes competing objectives such as increasing sales or reducing fraud. The model and the simulation results could guide further data gathering and the development of strategies based on a more holistic understanding.

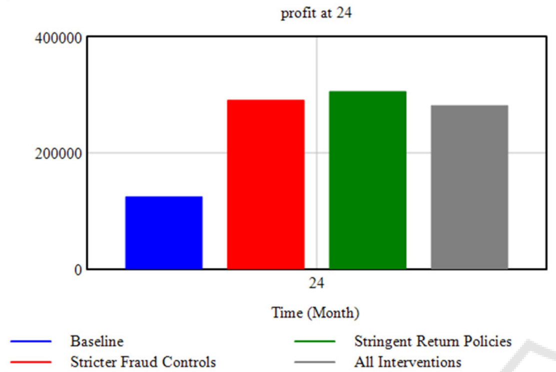

Figure 3: Profit comparison under different scenarios.

5 CONCLUSION

Evidence shows that fraudulent returns cause great losses for retailers. Retailers try to be robust by implementing or planning various strategies to enhance customer experience and mitigate the probability of fraudulent returns. However, extant returns and fraudulent research tend to focus on the prediction of returns rates but not the rates after changing certain policies and/or implementing new interventions. Furthermore, managers need to know the financial impacts of their strategies for reducing fraudulent returns. In response, the model we proposed in this paper demonstrates the impacts of interventions on fraudulent rates and associated costs, as well as other financial indicators (e.g., the potential negative impact on sales value). The model takes costs and profitability into account as they are key factors for retailers when making strategic decisions.

This model has significant implications. First, it promotes conversation between the loss-prevention department and other stakeholders within the company so that strategic approaches are aligned (e.g., not incentivising fraudulent sales). Second, it assists retailers to make effective judgements regarding the dilemma of balancing amongst return policies, costs and profits in retail businesses. Third, the model offers insights for other research domains, such as marketing management, and strategic management, as well as practitioners. As the model indicated, implementing stringent return policies is likely to reduce sales values; therefore it is crucial to balance sales and reduce fraudulent returns. Retailers can use the model as a scenario-based analysis tool that evaluates the impacts of different scenarios (i.e., different combinations of interventions). Our next stage is to establish a greater degree of accuracy by offering our model to retailers and applying real-world data. We believe that this model provides a solid foundation for further research and development.

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