International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Reinforcement Learning E-Commerce Cart Targeting to Reduce Cart Abandonment in E-Commerce Platforms

Praveen Kumar Padigela[1], Dr. R. Suguna[2]

Submitted: 29/08/2023 **Revised**: 24/10/2023 **Accepted**: 02/11/2023

Abstract— E-commerce has gained wide acceptance with rapid penetration of internet. Though E-commerce creates higher user visits and strong purchase intention among the consumers, only a fraction of product selected by user passes through sales tunnel and rest remain in cart. Recent studies have pointed 50% of total transactions are abandoned. There can be various reasons for cart abandonment like price, product specific features, and failures during purchase and lack of purchase options etc. This work proposes a reinforcement learning based solution which is able to predict the reasons for cart abandonment from click stream analysis and dynamically learn strategies to reduce cart abandonment rate. Different from existing method of frequent unsuccessful remainder, this work proposes personalized strategy with higher success rate. .

Keywords*-Reinforcement learning, e-commerce, E-commerce cart targeting, feature extraction, feature scoring, purchase response rate (PRR), footprint of cart abandonment (FCA), abandonment mitigation cost (AMC).*

I. Introduction

Internet availability and smartphone revolution have taken online shopping to an astonishing level. An estimated 2 billion people purchase goods online with a total revenue for online sale hitting a record high of 4.2 trillion US world according to a 2020 survey[1]. Recent forecast predicts a 17% of total sales made through e-commerce. With lockdown due to COVID-19, growth of e-commerce is even more accelerated [2]. Though online shopping through E-commerce is poised to grow many folds in coming years, the increasing trend of cart abandonment is worrisome of E-commerce service providers. According to recent estimates half of all online transactions are abandoned before completion [3]. Shopping cart abandonment is a behavioral outcome where users move the products to online shopping cart but does checkout without completing the purchase. E-commerce cart targeting (ECT) is being looked up as a solution to solve the cart abandonment problem. ECT leverages the digital trace data of consumers during browsing, searching and carting to gain more insights about cart abandonment. Online activities of consumer can be mined to gather information about consumer behavior. Past behavior of consumers spread through logs and the click stream data has wealth of information to predict consumer's future behavior. Many ECT based machine learning models using click stream data have been proposed in literature. These models predict cart abandonment. Industry accepted two practices to mitigate cart abandonment are incentives and scarcity messages. Each of these practices has various pros and cons. Price incentives are costly and can signal low quality [4-5]. Scarcity message is costless compared to incentive and can grab consumer attention. By creating a sense of urgency and fear of missing out, consumer can make the purchase [6-7]. Most of the existing ECT methods target users with a mix of both methods without gathering more insight into reason for abandonment. This can be counter-productive for E-commerce creative negative sentiments among the consumers. The way forward is to predict the reason for abandonment and propose a personalized strategy based on consumer interests to mitigate cart abandonment.

This work proposes a reinforcement learning based ECT to reduce cart abandonment. The proposed solution predicts the reason for abandonment using a fuzzy model. Fuzzy model is adopted as there could be multiple reasons with various importance for cart abandonment. Reinforcement learning is used to learn the best set of strategy based on consumer interest and past behaviors so that importance of various reasons for cart abandonment is minimized eventually leading to a sales success. Compared to using same strategy for all, the strategies are fined tuned and continuously learnt based on the success rate of the strategy for the specific consumer. Following are the contributions of the work

1. A fuzzy model to predict the reason for cart abandonment which provides importance scores for

1Research Scholar, Department of Computer Science, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, Tamil Nadu, India.

2Professor, Department of Computer Science, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, TN, India.
** Corresponding Author Email: praveen.padigela@gmail.com*

each reasons for cart abandonment

2. Reinforcement learning based personalized strategy selection based on the consumer interests and the success rate of past strategies.

The rest of the paper is organized as follows, in section 2, related works on ECT models and strategy selection for reducing cart abandonment are discussed. In section 3, the research gaps are identified. In section 4, the proposed reinforcement learning based ECT is detailed. In section 5, the performance results of proposed solution and comparison with state of works are presented. In section 6, the conclusion and future scope of work is presented.

II. Related Work

Rausch et al [8] experimented with different machine learning approaches to predict card abandonment using clickstream data. Gradient boosting with regularization was found to perform better than other machine learning classifiers with an accuracy of 81%. The approach was able to classify the consumer tendency to abandon the cart or not based on his clickstream data, but could not classify the reason for abandonment. Bogina et al [9] proposed a method to determine shopping intent of anonymous visitors to E-commerce site. Session information, session temporal information and recent trend of the product are used to find purchase intention of the visitor. Recommendation is found only at end of session and it becomes fruitful only when the user visits again within some days. Huang et al [10] proposed a conceptual framework to explain the cart abandonment through mobile channels. Authors found that emotional ambivalence amplifies consumer’s hesitation during checkout stage and this leads to cart abandonment. The study recommended limiting the choices and recommending most appropriate item to solve cart abandonment through mobile channels. Kukar et al [11] attempted to identify the factors influencing online cart abandonment. Authors suggested cognitive and behavioral reasons for the abandonment. The study found many customers, use cart for shopping research and organization. They may decide to buy later or use another channel for buy. But nowadays there a product price comparison sites and consumer no longer use the cart for shopping research. Zheng et al [12] proposed a decision support system to classify online shopping visit to purchase oriented or a general session. Browsing content features are extracted from session and classified using extreme learning machine to purchase oriented session or general session. By this way efforts to promote items added in shopping cart during general session are abandoned. Tang et al [13] analyzed the influence of seller uncertainty, description uncertainty and performance uncertainty on shopping cart abandonment. The study found that seller uncertainty and performance uncertainty had strong influence on cart abandonment and proposed effective communication as a strategy to mitigate abandonment. Wu et al [14] analyzed the impact of value related and transaction cost related factors on repurchase intention from online shopper perspective. The cost is analyzed in three dimensions of information searching cost, moral hazard cost and specific asset investment. Among all the factors, information searchinga cost has more significant influence on repurchase intention. Providing sufficient cues to reduce information searching cost is recommended to motivate repurchase intention. Xu et al [15] analyzed the factors influencing cart abandonment through a survey study among 210 participants. The study inferred cart abandonment is dependent more on shopping process than cost. Organization and research of products within cart was found to be key variable influencing cart abandonment. Though the study was conducted with limited samples, organization of cart can be still considered as a strategy to mitigate abandonment. Jiang et al [16] proposed a intermediary of forgetfulness and choice overload to mitigate shopping cart abandonment. The solution is based on the theory that forgetting and shopping cart page rendering are the reason for cart abandonment. Authors tested three strategies of sorting the cart in chronological order, adjustment of cart opening frequency and remove choice overload and found that sorting of cart reduced the shopping cart abandonment. Albrecht et al [17] categorized the consumers to be of two types – task oriented and recreation oriented. Stress induced in shopping provokes task oriented consumer to exit the purchase, but recreation oriented consumers are less likely to exit. Thus the solution recommends customizing the shopping environment based on the category of consumers. Luo et al [18] proposed an optimized ECT using casual forest algorithm. The two strategies of scarcity and price incentives are fine-tuned based on individual consumer characteristics. Based on login frequency and number of page views as input the timing interval of scarcity and incentive percentage are decided using casual random forest created using honest tree algorithm. But the solution used only two strategies and adapted the strategies based on two parameters alone. Due to this, the model cannot sufficiently represent more categories of consumers. Hongwei et al [19] explored the impact of three consumer involvement strategies of time, attention and tag on shopping cart abandonment. Through clickstream analysis, authors inferred that more time involvement in reviews increases the likelihood of cart abandonment. Higher attention implies low probability of abandonment. Higher tag involvement involves chances of more negative reviews and increases the abandonment. Thus consumer involvement is found to increase the cart abandonment and it must be minimized to mitigate abandonment. Song et al [20] analyzed the influence of product factors on shopping cart abandonment. The study inferred that price, perceived importance, symbolic value, experience and purchase frequency have indirect significant effects on shopping cart abandonment and factors like motivation for shopping, physical inspection and hedonic shopping value have significant effect on cart abandonment. The approach analyzed the product factors impacting abandonment but it did not propose any mitigation strategies. Kim et al [21] categorized consumers to two categories of prevention focused and promotion focused. Prevention focused consumer use shopping carts more than promotion focused consumer. There is more chance for cart abandonment by prevention focused consumers as they focus more on negative results and losses. The study recommends customizing the remainder messages to prevention focused consumer in way to alleviate their fear and negative opinions to mitigate cart abandonment. Rubin et al [22] analyzed the role of consumer mindset in shopping cart abandonment. Two different mindsets of concrete and abstract are analyzed. The survey study found that consumers with abstract mindset are more likely to purchase products and through encouraging consumers to think abstractly, cart abandonment can be minimized. Wang et al [23] applied stimulus-organism-response model to analyze the factors impacting shopping cart abandonment. The survey study inferred that cart abandonment increases proportionately with increase in hesitation at checkout. The hesitation is overridden by strong fear factors COVID infection. Ishani Patharia et al [24] presented reasons for ESCA during different stages of Eshopping using PRISMA approach. The summary of survey in terms of factor for abandonment and strategy for mitigation is presented in Table 1. The most promising factors and strategies identified from survey is given in Table 2.

III.Research Gap

From the survey, it can be seen that most of the solutions identified reasons from perceptive of consumer , product , and shopping perspective , but none of work quantified the influence of each factors on cart abandonment. In short, the approaches could not classify the reason for abandonment even probabilistically. Many strategies were discussed to mitigate cart abandonment but there was no personalization in strategy selection.

Table 1 Survey summary

ID	Author	Factor considered	Mitigation strategy	Summary
[8]	Rausch et al (2020)	Click stream behavior like number of visits , product selection etc	None	The approach predict the cart abandonment in session , but it does not propose any mitigation plan
[9]	Bogina et al (2019)	Session information, session temporal information and recent trend of the product	Recommendation of product of interests	The approach is for anonymous visitor and there is no guarantee on recommendation being successful
[10]	Huang et al (2018)	consumer's hesitation during checkout stage	Limiting the choice	The strategies to identify the preference choices was not addressed
[12]	Zheng et al (2018)	Type of session: purchase oriented or a general session.	Targeting is done only for purchase oriented session	Enough factors for classifying purchase oriented session were not identified
[13]	Tang et al (2019)	seller uncertainty, description uncertainty and performance uncertainty	Effective communication strategy to tackle description uncertainty	Strategy to address seller uncertainty is not considered
[16]	Jiang et al (2021)	Forgetfulness and choice overload	Sorting the cart	Sorting was based only on chronological order and filtering to prevent choice overload was not considered
[17]	Albrecht et al (2017)	Consumer categorization: task oriented and recreation oriented.	Customizing the shopping environment for different users to reduce stress	The work identified the strategy but did not provide details on its realization
[18]	Luo et al (2019)	Login frequency , number of page views	Incentive and scarcity message	Consumer characteristics not

				considered for strategy selection
[19]	Hongwei et al (2021)	Review time, attention and tag	Limit the reviews	Strategy for review selection was not considered
[20]	Song et al (2019)	Product features: price, perceived importance, symbolic value, experience and purchase frequency	No	The study identified the product features which have influence on cart abandonment. But it did not propose any mitigation strategy
[21]	.Kim et al (2018)	Consumer characteristics: prevention focused and promotion focused	customizing the remainder messages to prevention focused consumer in way to alleviate their fear and negative opinions	Feedback was not measured
[22]	Rubin et al (2020)	Consumer mindset : abstract and concrete	Encourage consumer to think abstract	The action plan enabling abstract thinking was not discussed
[23]	Wang et al (2021)	Hesitation in checkout	Fear factor	Creating fear factor many degrade consumer experience

Table 2 Promising factors and strategies

Factors	Consumer hesitation Cost value Description uncertainty Forgetfulness Choice overload Consumer categorization – task or recreation orientation Review – time, attention and tagging Consumer characteristics – prevention or promotion focused Consumer mindset – abstract and concrete
Strategies	Incentives Scarcity message Limiting choice Customize shopping environment Limit the reviews Sorting cart Customizing reminder messages Cart organization

Work by Luo et al [18] was an attempt in this direction by opting between strategies of incentive and scarcity messaging based on login frequency and number of page visits. Research along the direction of this work with consideration of more factors and selection among a pool of strategies based on consumer characteristics like mindset (abstract or concrete), orientation (task or research) are still lacking. Even in [18] , there are no scope for self-learning. Due to consumer evolution over the period of time, the same set of strategies which worked at a time may not work at a later point of time. Thus strategies must be adapted. There were no existing works with this scope of adaption in learning. The proposed solution in this work is designed based on these gaps.

IV. Reinforcemeny Learning ECT

The proposed reinforcement learning ECT(RL-ECT) has following stages

1. Feature extraction
2. Factor scoring
3. Strategy plan generation

The R-ECT uses three information of click stream in a session and past transaction of consumer in logs. Features extraction from this data is used to construct the fuzzy model, which provides the scoring for each of the factors influencing the cart abandonment for a consumer. A strategy plan is dynamically created for the consumer based on the factors score. This strategy plan is revised continuously through modifying the strategy parameters or removing the strategy from the plan. This revision is facilitated through evaluating the cart dynamics against the strategy plan implementation through reinforcement learning. Each of the stages in the proposed R-ECT is detailed in below subsections.

Feature extraction

The proposed R-ECT system extracts features from the clickstream data of sessions and the past transaction histories. The features extracted from these click stream are given in Table 3.

A. *Factor scoring*

The card abandonment can be due to various reasons. This work models the cart abandonment in terms of following factors: consumer hesitations (F1), Description uncertainties (F2), Choice overload (F3), Cost value (F4). The cart abandonment can be due to influence of these four variables in different scale. Since there is no linear or nonlinear relationship, this work models the influence of each factor on cart abandonment as a fuzzy function. The fuzzy function takes the features extracted (Table 3) as input and provides a score of 1 to 5 for each factor. Fuzzy modeling is done for each factor.

A dataset is created with features. This dataset is clustered using Fuzzy C means clustering with number of clusters (P) as 5. (Each factor is scored from 1 to 5). The cluster center after the fuzzy C means clustering is defined as

$$D = \{ D_{e,q} , e = 1,2 \ldots P \ and \ q = 1,2,3\}$$

Where $D_{e,q}$ is the qth coordinating of the eth cluster. The closeness of the qth feature of the rth data f r,q with qth coordinate of eth cluster is defined using Gaussian function as[20]

$$G(f_{r,q}, D_{e,q}, \sigma_{e,q}) = e^{\frac{(f_{r,q}-D_{e,q})^2}{\sigma_{e,p}^2}} \quad (1)$$

Where

$$\sigma_{e,q} = \frac{1}{N_e}\sum_{r=1}^{N_e} (f_{r,q} - D_{e,q})^2$$

The closeness of features of rth data to the eth cluster is given as

$$\Psi_{r,e} = \prod_{q=1}^{P} G(f_{r,q}, D_{e,q}, \sigma_{e,q}) \quad (2)$$

The output label for eth cluster is found from the linear regression of input features $f_{r,q}$ as

$$\Phi_{r,e} = W_{e,0} + \sum_{q=1}^{P} W_{e,q,f_{r,q}} \quad (3)$$

Where W is the regression coefficient of the eth cluster. Since each of the rth data has membership value to all P clusters, final label of that particular link is given by weighting the label of the link with its membership value as

$$\underline{N}(r) = \sum_{e=1}^{P} \Psi_{r,e}\Phi_{r,e} \quad (4)$$

The value of $\underline{N}(r)$ calculated above may have an error with respect to $N(r)$ from training. The total error is calculated as

$$E = \sum_{r=1}^{N} ||\underline{N}(r) - N(r)||^2 \quad (5)$$

The Gaussian parameters $D_{e,q}, \sigma_{e,q}$ and the regression coefficients $W_{e,p}$ are tuned to reduce the error defined above using gradient decent method.

$$D_{e,q}(t+1) = D_{e,q}(t) + \eta_C \frac{\partial E}{\partial D_{e,q}} \quad (6)$$

$$\sigma_{e,q}(t+1) = \sigma_{e,q}(t) + \eta_\sigma \frac{\partial E}{\partial \sigma_{e,q}} \quad (7)$$

$$W_{e,q}(t+1) = W_{e,q}(t) + \eta_W \frac{\partial E}{\partial W_{e,q}} \quad (8)$$

Where t is the iteration number and $\eta_C, \eta_\sigma, \eta_W$ are the learning parameters. The iteration is stopped when error threshold is reached. From training the Fuzzy Gaussian membership functions are obtained for each of five cluster in terms of the features.

Each of the cluster is given scores in range of 1 to 5 by the domain expert in scoring table (ST) below

Factors	**Clusters**				
	C1	C2	C3	C4	C4
F1	1	3	5	4	2
F2	4	2	1	3	5
F3	5	1	2	3	4
F4	2	1	3	5	4

The score of factor (F_x) is calculated by finding the cluster index with maximum fuzzy function value and looking up in the ST for the score in that index corresponding to factor. It is given as

$$F_x = ST[x][\prod_{r-1}^{5} max(\Phi_{r,e})] \quad (9)$$

Strategy plan generation

Consumer behavior is dynamic and based on the dynamics the strategy must also adapt itself. This adaption is possible through learning. Reinforcement learning is used in this work to adapt the composition of the strategies with goal of minimizing the cart abandonment footprint. Reinforcement learning (RL) is built on three core concepts of: state, action and reward. The behavior of RL model is illustrated in Figure x.

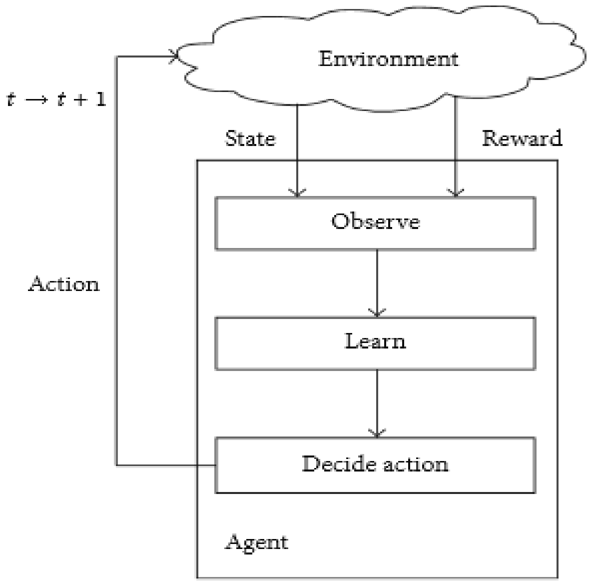


Fig 1 RL Model

Agent is the controller which controls the three core concepts of state, action and reward. A decision is made by the agent. The output is observed over the time by the agent and it fine tunes the decision to arrive at desired output. State is the variables on which the decision is made. Actions by agent create a change in the state. The actions are scored with a reward which can be positive or negative. Agent makes a actions and when the action brings the

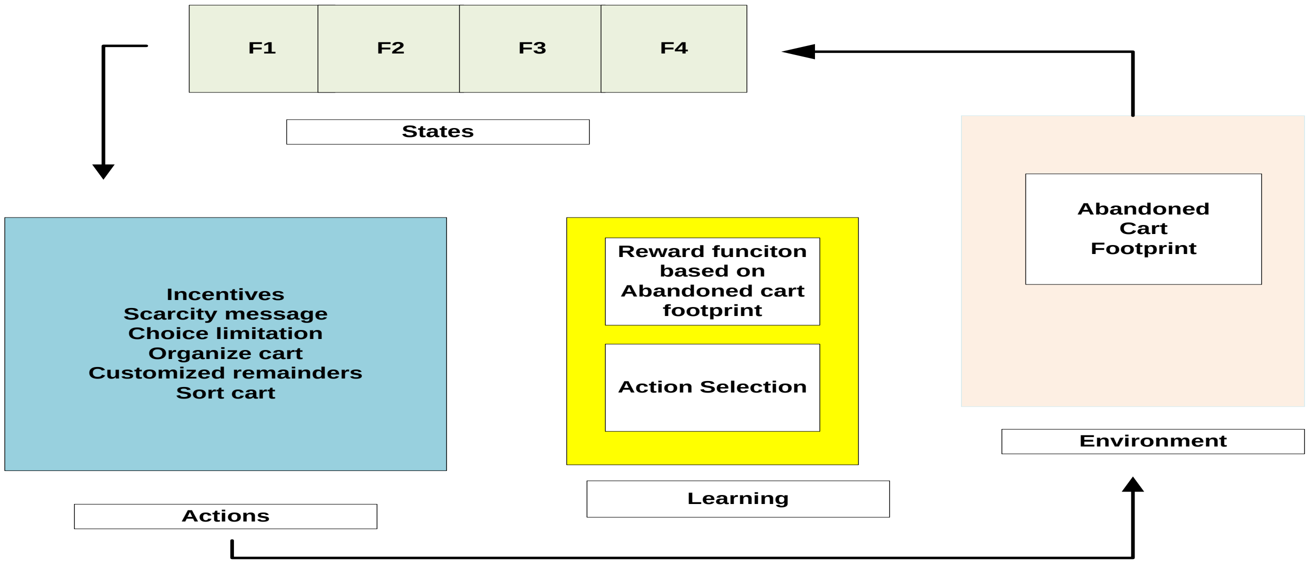


Fig 2 RL in proposed system

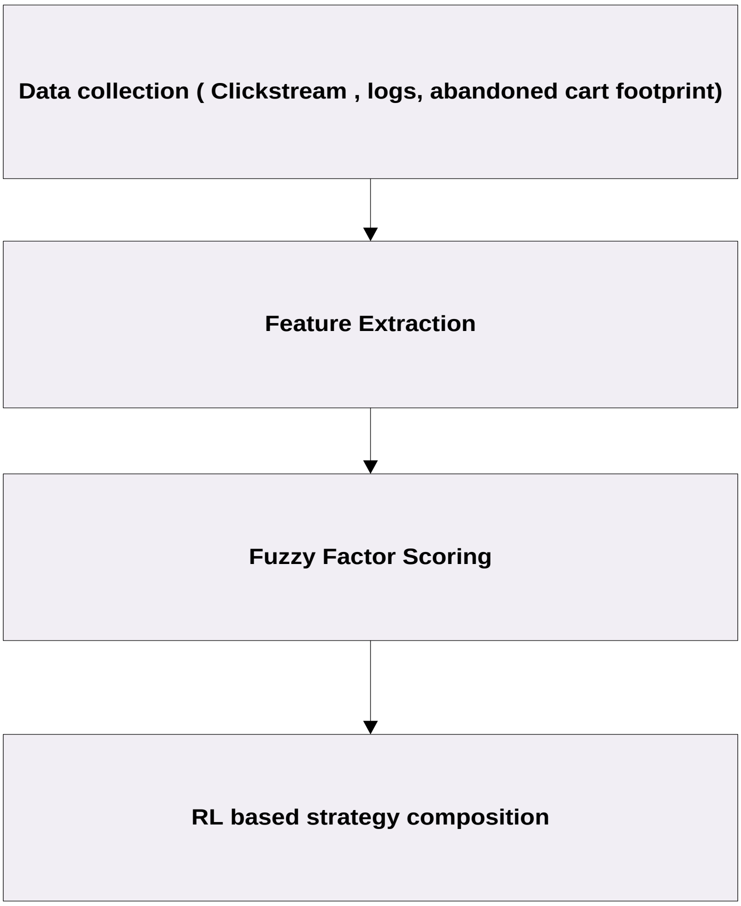


Fig 3 Architecture of RL-ECT

Table 3 Features extracted

ID	Feature Name	Description
Clickstream features		
1	Session activity count	Number of times a customer is going to the different pages
2	No Items Added In Cart:	Number of items in cart
3	Is_Product_Details_viewed	Whether the customer is viewing the product details or not
4	No_Items_Removed_FromCart	Number of items removed from the cart
5	No_Cart_Viewed	Number of times, customer visited cart page
6	No_Cart_Items_Viewed	Number of times consumer is viewing the product from cart.
7	No_Page_Viewed	Number of pages viewed by the customer
8	No_search_viewings	Number of search result page viewings
9	Access_Desktop	Is customer accessing site via desktop
10	Access_Mobile	Is customer accessing site via mobile
Log and past transaction features		
11	No_of_productype	Number of product types in cart
12	Value	Value of items in cart
13	Days in cart	Number of days items staying in cart
14	No of revisit to product page	Number of revists made to product page for products in cart
15	Average successful cart item purchase	Average number of days customer taken time to purchase cart time in past

decision to expected result, positive rewards are given for action else actions are given negative reward. The rewards for the actions are the knowledge learnt by RL and it learns to make best set of actions based on the reward at each state. The proposed RL-ECT algorithm is the agent.

The reinforcement model architecture for strategy selection in this work is given in Figure 2.

The values of F1,F2,F3,F4 factors estimated by fuzzy function using the features (detailed in Section B) is the state. The footprint of the abandoned cart is the environment. Selection of one or more strategies is the action. By taking the action, the effect of action on foot print of abandoned cart is observed to provide the reward. Based on the reward, the best action with a optimized composition of strategies maximizing the reward is found through reinforcement learning.

The learning starts at state S0 which is the feature values for F1-F4 on observation of first cart abandonment. An action is taken in form of selection of one or more strategies and its influence on environment is used to calculate the reward r_1. We use Boltzmann distribution function for action selection. In this the probability of selecting action a_i in the state s_k is given by

$$p(s_k, a_k = i) = \frac{e^{Q(s_k, a_k = i)/t_n}}{\sum_{j=1}^{N_a} e^{Q(k, a_j)/t_n}} \quad i = 1, \dots N_a \qquad (12)$$

Where $Q(s_k, a_k = i)/t_n$ is the state-action value function that evaluates the quality of choosing action $a_k = i$ at state s_k.

N_a is the number of actions.

t_n is the time varying parameter controlling the degree of exploration versus exploitation. All the actions are equally probable for larger values of t_n. Agent explores the opportunities to achieve potentially higher lower abandonment footprint in the future in this case. In case of smaller value of t_n the action with maximum $Q(S, a)$ is favored. Agent exploits the current knowledge of best selections of agent to achieve the potentially lower footprint in this case. As more episodes are devoted to testing that changes the strategy from exploration toward exploitation, the value changes from large to small to assure that the convergence is achieved. The value of t_n is decremented using a linear function over the episode as follows

$$t_n = -(t_0 - t_n).\frac{n}{N} + t_0$$

Where N is the total episodes.

The reward function is given as (11)

$$r_{k+1}(s_k, a_k) = ACF_{t+1} - ACF_t$$

Where ACF is the abandoned cart footprint (ie the number of products in abandoned cart)

The cumulative reward over the entire episode n is calculated as

$$R_n = \sum_{i=1}^{K} r_i$$

Learning is repeated till its stabilized and at the end of learning, the best action with a optimized set of strategy composition is available which can reduced the abandoned cart footprint.

The architecture of proposed RL-ECT is given in Figure 3. Clickstream data, transaction logs and abandoned cart footprint are collected frequently. Features are extracted from the cart. Using the fuzzy scoring function, the feature values are mapped to factor scores. Based on the factor score, RL identifies the suitable composition of strategies to minimize the cart abandonment footprint. The actions to be realized in the E-commerce portal for each strategy is given below.

Table 4 Realization of strategies

Strategies	**Realization**
Incentives	Offer the discount and highlight discount in cart and also in remainder message
Scarcity message	Send scarcity message in the configured intervals
Choice limitation	Display the product in cart which are also found by recommendation systems
Organize cart	Provide carts with sufficient information of incentives and present the link in notifications
Customized remainders	Remainders with more details on product and purchase offers to be mailed
Sort cart	Sort cart in chronological order

V. Results

The performance of the proposed RL-ECT is tested against YooChoose dataset [25]. The dataset has 6 month session logs of a e-commerce company YooChoose which operates in the area of personalized shopping experience. The dataset has wide product categories. The dataset has two files – one is clickstream data and another is event logs. This dataset is preferred for testing in this work due to its wide use for purchase intention prediction and behavior modeling. The performance of the proposed solution is evaluated using following metrics: purchase response rate (PRR), footprint of cart abandonment (FCA), abandonment mitigation cost (AMC). PRR is measured as the rate of products converted to sales from abandoned cart. FCA is measured as the number of products in the abandoned cart. AMC is the amount of cost spent of incentives for mitigating cart abandonment divided by original cost of items in cart. There are not many machine learning models on cart abandonment for comparison. The most recent and relevant work is Casual forest algorithm proposed by Lu et al [18].This work is used for comparison against proposed solution.

PRR is measured and the result is given in Figure 4.

The proposed solution has 4% higher PRR compared to [18]. It is due to adaptive composition of multiple strategies in the proposed solution while [18] applied only two strategies of incentives and scarcity message. FCA is measured and the result is given in Figure 5. The proposed solution has 42.85% lower FCA compared to [18]. FCA has reduced in proposed solution due to adaptation of strategies based on foot print of abandoned cart. The AMC is measured and the result is given in Figure 6. The AMC has reduced by 15% in proposed solution. This has reduced due to less involvement of incentives in proposed solution.

PRR, AMC and FCA are measured in solution over a period of time and the result is given in Figure 7. The PRR has increased over the period of the. FCA and AMC has reduced over the period of time. This is due to the learning ability in proposed solution.

The performance of proposed fuzzy model for factor scoring is compared in terms of RMSE between the actual and predicted fuzzy scores.

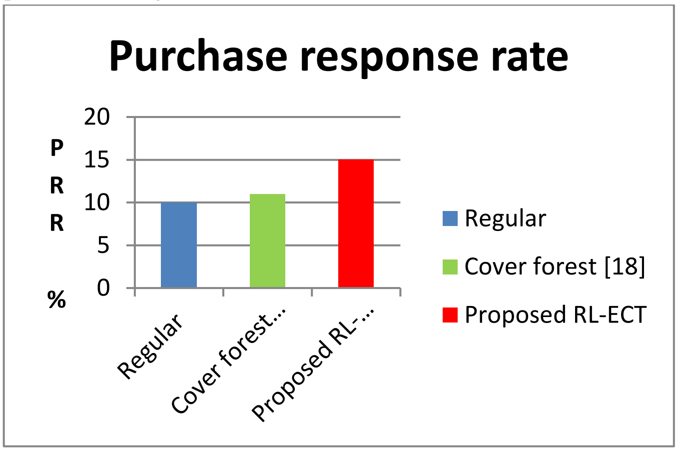


Fig 4 Comparison of PRR

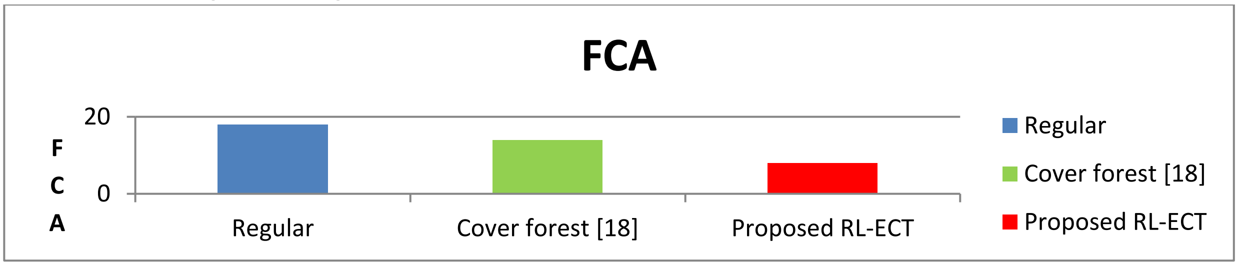


Fig 5 Comparison of FCA

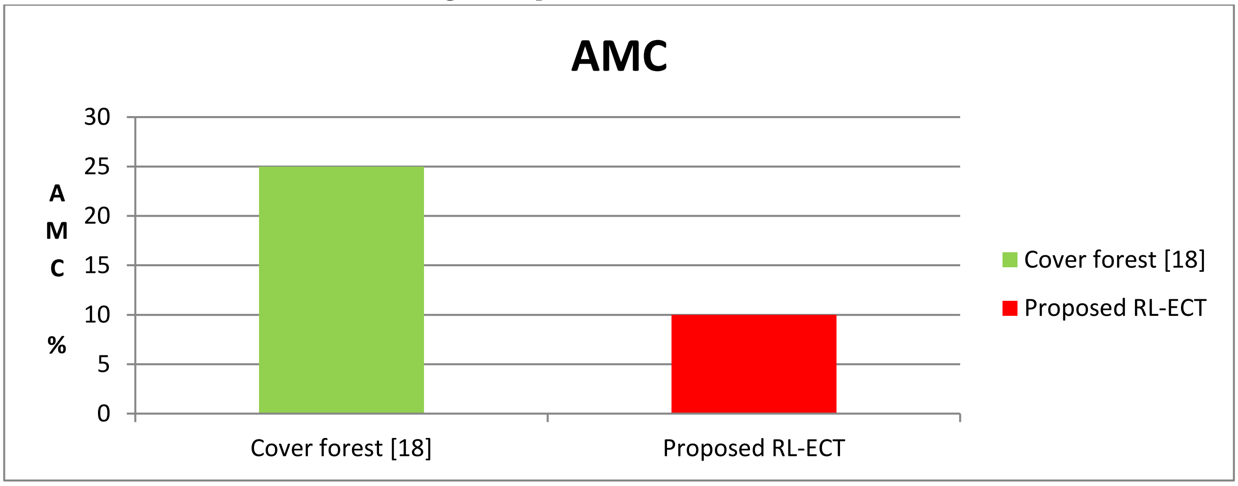


Fig 6 Comparison of AMC

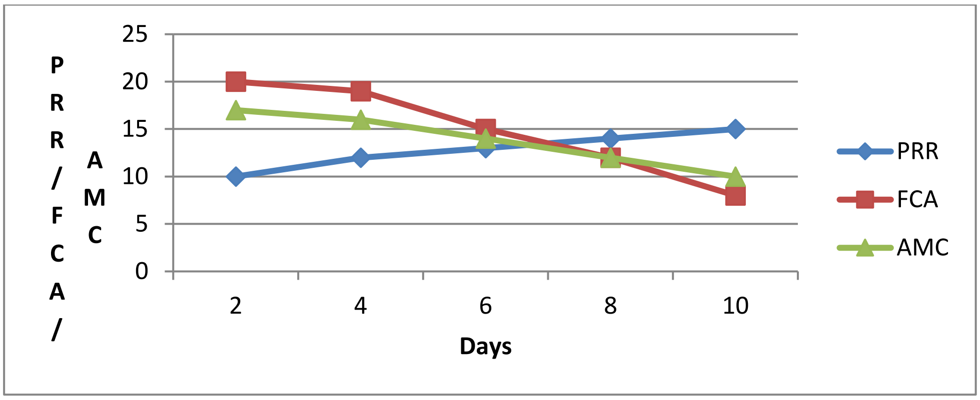
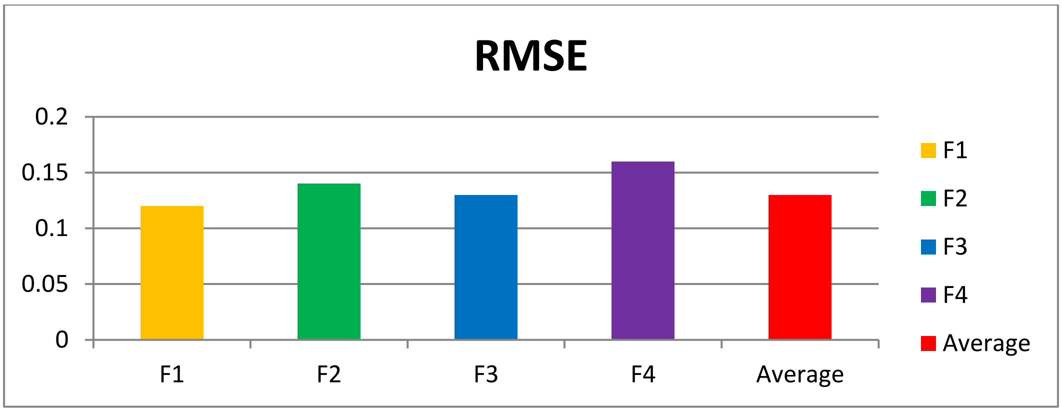


Fig 7 Performance over days



Average RMSE value is 0.13 indicating a good accuracy of factor scoring

.

VI. Conclusion

This work proposed a reinforcement learning based ECT with the goal of mitigating cart abandonment. Through survey, the study identified the factors impacting abandonment and the strategies used for mitigation. Considering the consumer characteristics, this work proposed an adaptive strategy selection to reduce the footprint of shopping cart abandonment. The performance results proved the effectiveness of proposed solution in reducing the abandonment footprint. Extending the work for more consumer characteristics is in scope of future work.

References

[1] https://www.statista.com/topics/871/online-shopping/.

[2] Worldpay (2016). Worldpay Consumer Behavior and Payments Report 2016. London: Worldpay.

[3] WARC (2020). Online Shopping IPSOS Report

[4] Jedidi K, Mela CF, Gupta S (1999) Managing advertising and promotion for long-run profitability. Marketing Sci. 18(1):1–22.

[5] Kopalle PK, Mela CF, Marsh L (1999) The dynamic effect of discounting on sales: Empirical analysis and normative pricing implications. Marketing Sci. 18(3):317–332

[6] Balachander S, Liu Y, Stock A (2009) An empirical analysis of scarcity strategies in the automobile industry. Management Sci. 55(10):1623–1637.

[7] Stock A, Balachander S (2005) The making of a "hot product": A signaling explanation of marketers' scarcity strategy. Management Sci. 51(8):1181–1192

[8] Rausch, Theresa & Derra, Nicholas & Wolf, Lukas. (2020). Predicting online shopping cart abandonment with machine learning approaches. International Journal of Market Research. 10.1177/1470785320972526.

[9] Bogina V, Mokryn O and Kuflik T (2019) Will this session end with a purchase? Inferring current purchase intent of anonymous visitors. Electronic Commerce Research and Applications 34: 100836.

[10] Huang G-H, Korfiatis N and Chang C-T (2018) Mobile shopping cart abandonment: The roles of conflicts, ambivalence, and hesitation. Journal of Business Research 85: 165–174.

[11] Kukar-Kinney M and Close AG (2010) The determinants of consumers' online shopping cart abandonment. Journal of the Academy of Marketing Science 38(2): 240–250.

[12] Zheng B and Liu B (2018) A scalable purchase intention prediction system using extreme gradient boosting

machines with browsing content entropy. In: 2018 IEEE International Conference on Consumer Electronics (ICCE): Piscataway, NJ: IEEE.
[13] Tang H., Lin X. (2019). Curbing shopping cart abandonment in C2C markets—An uncertainty reduction approach. Electron. Markets 29 533–552. 10.1007/s12525-018-0313-6.
[14] Ravindra Changala "A Survey on Development of Pattern Evolving Model for Discovery of Patterns in Text Mining Using Data Mining Techniques" in Journal of Theoretical and Applied Information Technology, August 2017. Vol.95. No.16, ISSN: 1817-3195, pp.3974-3987.
[15] Ravindra Changala, Framework for Virtualized Network Functions (VNFs) in Cloud of Things Based on Network Traffic Services, International Journal on Recent and Innovation Trends in Computing and Communication, ISSN: 2321-8169 Volume 11, Issue 11s, August 2023.
[16] Wu L. Y., Chen K. Y., Chen P. Y., Cheng S. L. (2014). Perceived value, transaction cost, and repurchase-intention in online shopping: a relational exchange perspective. J. Bus. Res. 67 2768–2776.
[17] Xu Y., Huang J. S. (2015). Factors influencing cart abandonment in the online shopping process. Soc. Behav. Pers. 43 1617–1627. 10.2224/sbp.2015.43.10.1617
[18] Jiang, Dan & Zhang, Guangling & Wang, Lu. (2021). Empty the Shopping Cart? The Effect of Shopping Cart Item Sorting on Online Shopping Cart Abandonment Behavior. Journal of Theoretical and Applied Electronic
[25] Rubin, D.; Martins, C.; Ilyuk, V.; Hildebrand, D. Online shopping cart abandonment: A consumer mindset perspective. J. Consum. Mark. 2020, 37, 13
[26] Wang, Siqi & Hwa, Cheah & Jean, Lim & Leong, Yee & Choo, Wei. (2021). Thanks COVID-19, I'll Reconsider My Purchase: Can Fear Appeal Reduce Online Shopping Cart Abandonment?. Journal of Retailing and Consumer Services. 64. 10.1016/j.jretconser.2021.102843.
[27] [24] Patharia, I., & Jain, T. (2023). Antecedents of Electronic Shopping Cart Abandonment during Online Purchase Process. Business Perspectives and Research, https://doi.org/10.1177/22785337221148810
[28] [25] https://www.yoochoose.com/f a figure.
Commerce Research. 16. 1973-1996. 10.3390/jtaer16060111.
[19] Albrecht, C.-M.; Hattula, S.; Lehmann, D.R. The relationship between consumer shopping stress and purchase abandonment in task-oriented and recreation-oriented consumers. J. Acad. Mark. Sci. 2017, 45, 720–740
[20] Luo, X.; Lu, X.; Li, J. When and How to Leverage E-commerce Cart Targeting: The Relative and Moderated Effects of Scarcity and Price Incentives with a Two-Stage Field Experiment and Causal Forest Optimization. Inform. Syst. Res. 2019, 30, 1203–1227
[21] Hongwei, L.; Mingjun, Z.; Mengting, F.; Zhouyang, L. Research on the Impact of Online Reviews and Product Involvement on Virtual Shopping Cart Decision-making Based on Consumer Involvement. Chin. J. Manag. Sci. 2021, 29, 6
[22] Song, J.D. A Study on Online Shopping Cart Abandonment: A Product Category Perspective. J. Internet Commer. 2019, 18, 337–368.
[23] Kim, N.; Chun, S. Add to Cart or Buy It Now? Factors Influencing the Usage Intention of Online Shopping Cart. J. Inf. Technol. Appl. Manag. 2018, 25, 117–132.
[24] [22] Ravindra Changala, "Evaluation and Analysis of Discovered Patterns Using Pattern Classification Methods in Text Mining" in ARPN Journal of Engineering and Applied Sciences, Volume 13, Issue 11, Pages 3706-3717 with ISSN:1819-6608 in June 2018.