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Evaluation of precision marketing effectiveness of community e-commerce–An AISAS based model

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ABSTRACT

With the advent of the big data era, user needs have become more and more diversified and personalized. These new user characteristics are important for the sustainable marketing of enterprises. With intensified competition, how to attract clients at minimal cost has become the primary concern for community e-commerce platforms or other e-commerce platforms. One of the best solutions is precision marketing, which is an important part of sustainable marketing. In this paper, a modified AISAS model is proposed for evaluating precision marketing effectiveness using data from a real-world community e-commerce platform. Based on face-to-face expert interviews and questionnaire surveys, an analytic hierarchy process (AHP) method is used to determine weights of different indexes adopted in the evaluation model and then quantify the precision marketing effectiveness of the e-commerce platform. The marketing results are then verified. We found that community e-commerce platforms' marketing ought to be gentle and sustainable due to service area constraints or capacity limitations. The community e-commerce platform is more successful in attracting customers' attention and interest from the marketing effectiveness. However, it is inadequate to rely on customers' purchase and repeat purchase behaviors. Therefore, the precise selection of platforms is critical to the cultivation of customers' loyalty and the increases in their products' repurchase rate.

1. Introduction

As the world is increasingly shaped by mobile Internet and big data, community e-commerce platforms now play a crucial role in boosting residents' living and consumption standards by effectively integrating online and offline resources for communities and optimizing such resources as e-business promoters [1-2]. In the past few years, the growth of the community market has been accelerating. Emerging community e-commerce operators dealing with hypermarket distribution and fresh food sales continue to erode the market shares of traditional e-commerce players, and the competition between them is turning white-hot. In order to maintain sufficient competitiveness amid such fierce rivalry, community e-commerce platform operators have to accurately grasp users' consumption behaviors and preferences and create stronger purchase motivation among them using precision marketing. Furthermore, using precision marketing, enterprises can save resources and reduce waste to achieve sustainable marketing [3]. However, the implementation of precision marketing on community e-commerce platforms requires massive user data, while consumers' performance is diversified, dynamic, and unsustainable. Although the Internet provides a cheap and convenient platform for merchants to communicate with consumers, the consumers' behavior on the terminal is characterized by fragmentation and disorder. It is extremely difficult for merchants to find the products and services that consumers need from the vast and messy user data. Therefore, in order to effectively explore the real needs of consumers for merchants and recommend the right products to consumers at the appropriate time, the precision marketing effect evaluation can be introduced. Through effect evaluation, this paper identifies the precision marketing activities in consumer purchase and improves the precision marketing strategy, which improves the efficiency of precision marketing significantly.

Numerous studies have been conducted on marketing effectiveness evaluation models in the literature. Reyck et al. [4] developed a precision marketing decision model, which was used in advertisement and promotion, and helped improve marketing results and earnings; You et al. [5] proposed a marketing effectiveness evaluation model based on data mining technique to help managers identify potential features of

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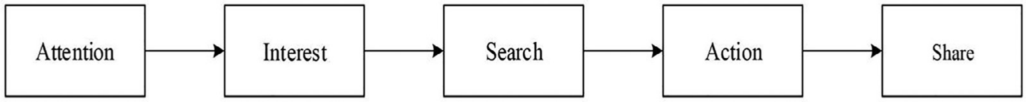

Fig. 1. The basic AISAS model.

Fig. 2. The modified model.

various customer groups. Zhu et al. [6] built a user interest chart model consisting of a three-level interest index system and 167 nodes. It provided important fundamental methods and valuable decision support for accurate and targeted evaluation of social marketing effectiveness. Gilmore et al. [7] used case study methodology to evaluate the contribution of Networking to marketing activities. Shuai et al. [8] evaluated the hotels' websites in Taiwan from an Internet marketing perspective. Karczmarczyk et al. [9] proposed the framework for a multi-objective evaluation of information spreading processes. This framework provided a method for evaluating the effectiveness of viral marketing in social networks. Csikòsová et al. [10] evaluated the banking sector's marketing efficiency based on the balanced scorecard. Gountas et al. [11] used neuroscience methods to evaluate the efficiency of advertising and marketing. Tsai et al. [12] proposed a model to evaluate the marketing effectiveness of five airline websites. The result of the model showed that Taiwan Airlines did not make full use of the marketing potential of the Internet. In order to achieve better Internet marketing effects, they suggested adding a price negotiation function to the website and adjusting the pricing strategy.

The aforementioned research has provided the support for the evaluation of precision marketing effectiveness for community e-commerce platforms from both theoretical and strategic perspectives. As the mobile Internet continues to evolve, consumer behaviors and habits change dynamically. Marketing effectiveness evaluation from the perspective of consumer behaviors is gaining increasing attention in academics. AISAS, a consumer behavior model, has been used more frequently in such evaluation. As a new model based on consumer behavior analysis in the Internet age, AISAS was developed by Japan-based Dentsu Group [13]. AISAS model adopts the perception that consumers tend to share commodity and service information after making purchases and consequently shape the shopping behaviors of others, in this age of rapid exchange of information. This process consists of five stages, namely Attention, Interest, Search, Action, and Share. Fumito [14] was the first to strategically use the AISAS model to support corporate precision marketing activities. Ritsuya [15] made recommendations based on the AISAS model that advertising companies adopted new media marketing policies to attract consumers. Chang et al. [16] used the AISAS model to explore accurate and effective advertising in games and concluded that boosting consumer interest plays a key role in precision marketing. Pelawi et al. [17] referred to the AISAS model when evaluating the effect of video podcasts on improving marketing effectiveness. DU [18] analyzed the impact of WeChat marketing on college students based on the AISAS model. The results showed that brand influence, information quality, interactivity, opinions of opinion-leaders, promotion, and personal interests have apparently positive effects on WeChat marketing.

In summary, with the development of the Internet, consumers have become "new consumers" with new behavioral characteristics of "independence, distinctive personality, paying attention to participation and well-informed consumption," and with more right of speech. Their behavior and attitude have experienced fundamental and structural changes as well. The traditional AIDMA model of consumer behavior is suitable for the traditional marketing era, and it can primarily explain the behavior model of consumers in the economy. However, as a new consumer behavior model in the current network era, AISAS model replaces the Desire and Memory stages of the traditional AIDMA model with Search and Share Stages. It can adapt to the behavioral characteristics of new consumers better, and it has good prospects when precision marketing evaluation is applied to community e-commerce platforms. In this paper, using a real-world case study, we develop a modified AISAS model, construct a precision marketing effectiveness evaluation index system, and verify the model with data collected from the corresponding enterprise. Our research findings offer theoretical support for the formulation of corporate precision marketing strategies in the future.

2. Model and index system

2.1. A precision marketing effectiveness evaluation model

T-APP is an integrated intelligent community service platform. It has integrated three major functions of administrative logistics, resource sharing, and e-commerce to enable both online and offline public services. In this paper, with the AISAS model taken as a theoretical basis, a modified precision marketing evaluation model is developed. It is based on both the actual conditions of the e-commerce platform shown and the previously mentioned five stages of consumer behaviors in Fig. 1.

In March 2019, through interviews, questionnaire surveys, and consideration of the community e-commerce nature of T-APP, it was discovered that the Share stage in the AISAS model is not noticeable in the case of T-APP. At this platform, more users prefer offline information sharing rather than online sharing. In addition, the platform operator attached great importance to customer loyalty and constantly tracks active participation behaviors (views, clicks, and purchases by customers via the APP) and repeated purchases. Hence, we redefined the five stages of the AISAS model as Attention, Interest, Active Participation, Action, and Repeated Purchase, as shown in Fig. 2.

2.2. Construction of a precision marketing effectiveness evaluation index system

To ensure the scientificity and validity, we made theoretical analysis, questionnaires and face-to-face interviews to set up an evaluation index system. In October 2019, we designed and distributed a questionnaire after initially establishing a modified model. Based on the results of the questionnaire, the specific indexes in the model were further refined. And we finally determined consumer's purchase frequencies, shop reputation, brand awareness and other indicators as important indicators of marketing evaluation through related literature [19-21]. In June 2020, we conducted a second interview with the community e-commerce platform operation team. Combined some of their revision opinions, we finally determined the precision marketing effectiveness evaluation index system, as shown in Fig. 3. This system is organized hierarchically into three levels. The top-level index refers to T-APP big data precision marketing effectiveness and reflects evaluation target and purpose. The middle-level comprises five Tier 1 indexes and corresponds to the five

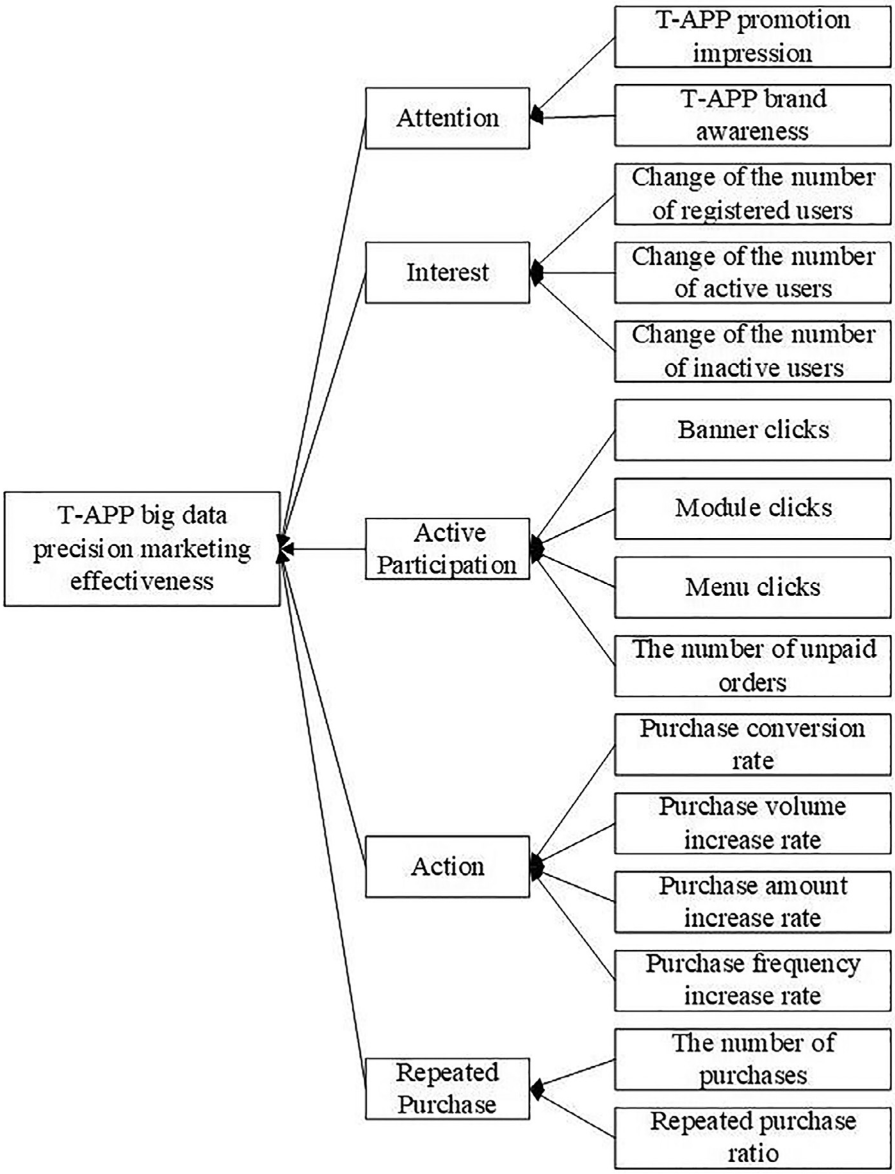

Fig. 3. Structure of the T-APP precision marketing effectiveness evaluation index system.

stages (Attention, Interest, Active Participation, Action, and Repeated Purchase) of user behaviors in the modified AISAS model. The Tier 2 indexes at the bottom level are the breakdown of different stages, which can be directly obtained and mined in the operation of the T-APP data.

2.2.1. Attention stage

In the Attention stage, the background of T-APP analyzes customer data in order to deliver accurate information to existing customers and attract more new customers' attention. For the platform operator, gaining the attention of new users with T-APP is the key to the success of precision marketing. This stage is evaluated with the aid of two indexes – product promotion impression and brand awareness. Product promotion impression is used to estimate promotion coverage and frequency, while brand awareness serves to measure the acceptance level of T-APP among users.

2.2.2. Interest stage

In the Interest stage, after knowing T-APP, customers may be interested and want to further understand the information of relevant products on T-APP. At this time, we can measure the change of customer interest by three indexes: change of the number of registered users, change of the number of active users, and change of the number of inactive users. When the users register or browse the product at this stage, it means that the users are likely to be truly interested. Here, the registered users refer to the users who have officially registered identity information in the application. The active users refer to those who have placed an order in the past seven days, and the inactive users refer to those who visited the APP in the past seven days with placing no order.

2.2.3. Active participation stage

In the Active Participation stage, interested users may actively engage in a series of activities in the APP, including browsing and clicking. At this stage, the indexes that reflect the T-APP precision marketing effectiveness are banner clicks, module clicks, menu clicks, and the number of unpaid orders. Since all banners, modules, and menus at T-APP contain certain commodity information, these indexes can measure the actual results of precision marketing.

2.2.4. Action stage

In the Action stage, customers actively purchase products in the T-App. The precision marketing effectiveness in this stage may be measured with purchase conversion rate, purchase volume increase rate, purchase amount increase rate, and purchase frequency increase rate. Purchase conversion rate refers to the ratio of the number of users with a purchasing history at the platform during the precision marketing period to the total number of platform users. Purchase volume increase rate refers to the ratio of the purchase volume of this year to that of the year before the implementation of precision marketing. Purchase amount increase rate refers to the ratio of the purchase amount of this year to that of the year before the implementation of precision marketing. Purchase frequency increase rate refers to the ratio of the purchase frequency of this year to that of the year before the implementation of precision marketing.

2.2.5. Repeated purchase stage

In the Repeated Purchase stage, users may purchase again after they are satisfied with the purchase of goods in the community e-commerce platform. In this paper, the number of purchases and repeated purchase ratio are taken as evaluation indexes for this stage. The number of purchases refers to total purchases of a certain product by a single user, while repeated purchase ratio refers to the probability of a user repurchasing a certain product on the 1st, 3rd, 7th, or 11th day after the initial purchase. A higher number of purchases or repeated purchase ratio indicates more interest in the T-APP product in question and a stronger attachment between the buyer and the product, in which case precision marketing will be more effective.

2.3. Determination of index weights

An analytic hierarchy process method is used in our study to determine the weights of different indexes for precision marketing effectiveness evaluation. As the perception of the significance of indexes varies greatly among people, the weight assigned to the same index may differ among individuals. To adequately address such difference, we communicated with the operation and development teams of T-APP a couple of times and designed index significance comparison questionnaires together with them. Based on the data collected with the questionnaires, the relative importance of different indexes was then quantified.

After constructing the judgment matrix, we derived the relative weights of indexes with the power method. The results are shown in Tables 1, 2, and 3. The importance of different Tier 2 indexes relative to the decision targets is listed in descending order by weight in Table 1, and that of Tier 1 indexes relative to the decision targets is listed in Table 2. It can be seen that among the Tier 1 indexes, Active Participation, Action, and Attention are in the top three places. Among the Tier 2 indexes, module clicks, purchase conversion rate, and T-APP promotion impression have the largest weights.

The final weights of different indexes are then derived, as shown in Table 3.

Table 1
Importance of Tier 2 indexes relative to decision targets in descending order.

Bottom-level index	Weight
Module clicks	0.1299
Purchase conversion rate	0.1155
T-APP promotion impression	0.1106
Banner clicks	0.1002
T-APP brand awareness	0.0922
The number of purchases	0.0791
Purchase frequency increase rate	0.0582
Menu clicks	0.0559
Purchase volume increase rate	0.0470
Repeated purchase ratio	0.0458
Change of the number of active users	0.0432
Purchase amount increase rate	0.0425
The number of unpaid orders	0.0309
Change of the number of registered users	0.0282
Change of the number of inactive users	0.0208

Table 2
Importance of Tier 1 indexes relative to decision targets in descending order.

Middle-level index	Weight
Active Participation	0.3169
Action	0.2631
Attention	0.2028
Repeated Purchase	0.1249
Interest	0.0923

3. Calculation of precision marketing effectiveness

3.1. Data preparation

Following frequent communication with T-APP personnel, we sorted various users, commodity, and order data, eliminated outliers, and selected adequate information for different indexes in the system. Simple calculations were made for certain data. After implementing precision marketing, the platform operator brought online a WeChat public account for T-APP, aiming to expand sales channels, get access to more users, and improve marketing effectiveness. In response, we added some new data selection criteria. For instance, pertinent WeChat data was used when the calculation of the index of menu clicks.

Since the data concerning Action and Repeated Purchase stages involved large quantities of commodities, we selected the top five products in terms of sales volume and sales amount for easy calculation. The final results are given in Table 4.

Table 3
Final weights of different indexes.

General index	Tier 1 index		Tier 2 index	
	Index	Weight (W)	Index	Weight (W)
T-APP precision marketing effectiveness (A)	Attention (B_1)	0.2028	T-APP promotion impression (C_1)	0.5454
			T-APP brand awareness (C_2)	0.4546
	Interest (B_2)	0.0923	Change of the number of registered users (C_3)	0.3055
			Change of the number of active users (C_4)	0.4680
			Change of the number of inactive users (C_5)	0.2265
	Active Participation (B_3)	0.3169	Banner clicks (C_6)	0.3162
			Module clicks (C_7)	0.4099
			Menu clicks (C_8)	0.1764
			The number of unpaid orders (C_9)	0.0975
	Action (B_4)	0.2631	Purchase conversion rate (C_{10})	0.4390
			Purchase volume increase rate (C_{11})	0.1786
			Purchase amount increase rate (C_{12})	0.1615
			Purchase frequency increase rate (C_{13})	0.2209
	Repeated Purchase (B_5)	0.1249	The number of purchases (C_{14})	0.6333
			Repeated purchase ratio (C_{15})	0.3667

Table 4
Final results of different indexes.

General index	Tier 1 index	Tier 2 index	Final value
T-APP precision marketing effectiveness	Attention	T-APP promotion impression	2336
		T-APP brand awareness	0.842
	Interest	Change of the number of registered users	1579
		Change of the number of active users	528.712
		Change of the number of inactive users	394.568
	Active Participation	Banner clicks	6.85909
		Module clicks	440.8954
		Menu clicks	1.73827
		The number of unpaid orders	578
	Action	Purchase conversion rate	0.842
		Purchase volume increase rate	2.79
		Purchase amount increase rate	1.0197
		Purchase frequency increase rate	3.07
	Repeated Purchase	The number of purchases	236.1667
		Repeated purchase ratio	0.3235

3.2. Standardization of index data

Standardization of index data refers to converse index data of various types into the same unit and order of magnitude in some way to facilitate comparison and calculation. The original indexes for T-APP precision marketing evaluation are also different in unit and order of magnitude. For example, the "purchase amount increase rate" is a percentage, while the "change of the number of registered users" is an integer number. In order to address such major differences and enable a more logical assessment, the data used in our research received standardization before formal calculation.

Data standardization methods vary with specific applications. In this paper, such standardization is based on an existing approach: All indexes are mapped to the interval of (0,1), thus to create forward relative values [22].

3.3. Calculation results

After the evaluation system index weights are determined and the data are standardized, the comprehensive index method is used to measure the target level T-APP precision marketing effect value and the B_1-B_5 criterion level effect value. In this paper, Yi represents the value of each index of the scheme layer after standardization. W represents the corresponding weights of different indexes. Xi represents the measured data value of the marketing effect at each stage of the criterion level. M represents the calculated target-level precision marketing effect value. The calculation results are given in Table 5:

Table 6
Ranges of the marketing effectiveness value.

Range	0-0.4	0.4-0.6	0.6-0.8	0.8-1.0
Rating	Poor	Average	Good	Excellent

4. Precision marketing effectiveness verification

In order to verify the effectiveness of T-APP precision marketing and discover existing issues in precision marketing, we define the following ranges for effectiveness value as shown in Table 6 and analyze the quantified evaluation results accordingly [23].

(1) Attention stage: The calculated marketing effectiveness is 0.9279, which is higher than 0.8, indicating excellent precision marketing in this stage. Hence the company should maintain the current level of marketing in the future.
(2) Interest stage: The calculated marketing effectiveness is 0.9983, a level much higher than 0.8, showing that precision marketing is quite fruitful. The company therefore only needs to continue the existing marketing operations in the future.
(3) Active Participation stage: The calculated marketing effectiveness is 0.8513, which is also higher than 0.8, indicating excellent precision marketing in this stage. Hence the company should maintain the current level of marketing in the future.
(4) Action stage: The calculated marketing effectiveness is 0.6363, lying between 0.6 and 0.8. It suggests good marketing results. In the future, the company should focus more on using the personalized recommendation system so that users can get better access to desired commodities and make more purchases.
(5) Repeated Purchase stage: The calculated marketing effectiveness is 0.7493, lying between 0.6 and 0.8. It suggests good marketing results and repeated purchases are often appearing on the community e-commerce platform. Looking into the future, the company should make more recommendations on extremely popular commodities to further promote repeated purchases.

The above analysis gives an overall T-APP precision marketing effectiveness score of 0.8111. As the score is higher than 0.8, the T-APP precision marketing operations are excellent.

Table 5
Calculation results of precision marketing effectiveness.

Target level (M)	Tier 1 index (B)			Tier 2 index (C)		
	Index	Weight (W)	Value (Xi)	Index	Weight (W)	Value (Yi)
0.8111	Attention (B_1)	0.2028	0.9279	T-APP promotion impression (C_1)	0.5454	0.999571
				T-APP brand awareness (C_2)	0.4546	0.842
	Interest (B_2)	0.0923	0.9983	Change of the number of registered users (C_3)	0.3055	0.99936
				Change of the number of active users (C_4)	0.4680	0.99810
				Change of the number of inactive users (C_5)	0.2265	0.99746
	Active participation (B_3)	0.3169	0.8513	Banner clicks (C_6)	0.3162	0.854208
				Module clicks (C_7)	0.4099	0.997731
				Menu clicks (C_8)	0.1764	0.424715
				The number of unpaid orders (C_9)	0.0975	0.998269
	Action (B_4)	0.2631	0.6363	Purchase conversion rate (C_{10})	0.4390	0.842
				Purchase volume increase rate (C_{11})	0.1786	0.641577
				Purchase amount increase rate (C_{12})	0.1615	0.019319
				Purchase frequency increase rate (C_{13})	0.2209	0.674267
	Repeated purchase (B_5)	0.1249	0.7493	The number of purchases (C_{14})	0.6333	0.995765
				Repeated purchase ratio (C_{15})	0.3667	0.3235

5. Conclusions

In this paper, we study the evaluation of T-APP precision marketing effectiveness with the real-world data from a firm located in Beijing City. Based on the actual usage and experience of an e-commerce platform, a modified AISAS model is proposed and an analytic hierarchy process method is adopted for calculation and analysis. The results confirmed the effectiveness of the precision marketing activities. There are some important findings as follows.

(1) Among the five Tier 1 indexes, Active Participation has the largest weight, which underlies the importance of user clicking operations at the platform. Hence, we advise that the operator of the community e-commerce platform design operation pages more suitable for the taste of users in order to facilitate their commodity searches.
(2) The marketing results in the first three user behavior stages, namely Attention, Interest, and Active Participation, are more encouraging compared to those in the last two stages. Therefore, the platform operator should allocate more resources and devote more effort to improving the marketing effectiveness in the last two stages. In particular, developing brand loyalty among customers and increasing repeated purchase ratios would be the key for boosting marketing effectiveness.
(3) For community e-commerce platforms, marketing programs have to be carried out gently and continuously due to limitations in service coverage and capabilities. It is possible that their marketing activities fail to produce significantly higher conversion rates in the near term. However, the platform operators should focus more on customer loyalty for the sustainable long-term development.

Precision marketing effectiveness evaluation for community e-commerce platforms is a promising research topic. Despite research that have been carried out so far, there is still no census on the optimal evaluation system in the literature. In this paper, a precision marketing effectiveness evaluation system is constructed, and real-world data from an enterprise is used to verify it. Due to limited data available, our study has been conducted with only one community e-commerce platform. In the future, When more data are made available and collected, we intend to evaluate the precision marketing effectiveness of more community e-commerce platforms during the same period, and thus explore further the potential value of precision marketing effectiveness evaluation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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