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RESEARCH ARTICLE

Consumer Behavior Analysis on Sales Process Model Using Process Discovery Algorithm for the Omnichannel Distribution System

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ABSTRACT Currently, Omnichannel distribution services are experiencing very rapid development around the world. In the Omnichannel distribution services, each existing sales channel will be connected to each other through integration capabilities so that no channels are left neglected. This is able to provide the best experience for consumers when shopping both online through mobile devices, laptops, and in physical stores. But on the other hand, this creates problems for business people who develop Omnichannel services. On the one hand, it facilitates the marketing process, but on the other hand, business people have difficulty reading the behavior of consumers who use Omnichannel distribution services. One way to analyze consumer behavior is to use the Process Discovery approach to obtain a process model. There are several Process Discovery Algorithms capable of describing and analyzing process models. In this paper, an experiment was carried out using the sales event log dataset generated from the Omnichannel distribution service system. Service channels used are Marketplace, Web Store, Social Media, Social Media Shop, and Media Messenger. Sales process modelling is generated using the Inductive Miner Algorithm, Heuristic Algorithm, Alpha Miner Algorithm and Fuzzy Miner Algorithm. Then the next step is to measure the process model obtained by Conformance Checking. The purpose of process modeling and measurement is to obtain a sales process model that can predict consumer behavior patterns well. The results of the analysis show that the process model generated by the Fuzzy Miner Algorithm is the best process model for describing consumer behavior in Omnichannel Distribution Services in this study. Based on the process model obtained with the Fuzzy Miner Algorithm, consumer behavior shows that the majority of consumers spend time on social media channels and then make purchases on the Marketplace channel. In addition, the results of the analysis show that consumers make more transactions on the Marketplace channel compared to the webstore channel or Social Media Shop channel.

INDEX TERMS Customer behavior, omnichannel distribution system, process mining, process discovery algorithm, sales process.

I. INTRODUCTION

The development of information technology is currently changing the pattern and way of life of humans in the world. One of the areas that has experienced a significant impact in the last 1 decade is the field of E-Commerce [1]. The process that runs in the field of e-Commerce has undergone significant changes. Activities that occur are constantly changing so that it affects the ongoing Supply Chain Management. One part that experiences fundamental changes in supply chain management is the downstream part, especially in the sales process [2]. The sales process in E-commerce has an

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important role for business people because this section is a meeting place for business people and consumers through digital media. In today's digital era, consumers are spoiled by the facilities and features available in E-commerce. The simple interface, features, and processes are attractive for consumers to make the purchase process [3]. This causes the pattern of consumers to change in determining their needs. Business actors are also developing in facing these conditions by providing, opening, and adding distribution channels to meet consumer satisfaction and desires [4]. This creates conditions that cause business owners to have more than one channel so that they start implementing multichannel services.

However, in the last 5 years, there has been a shift in the service model from multichannel to Omnichannel [5]. With omnichannel, the integrated system services provided allow consumers to use more than one channel, both offline and online. In the Omnichannel Distribution Services, every existing sales channel will be connected to each other through integration capabilities, so that no more channels will be neglected. This is able to provide the best experience for consumers when shopping both online via mobile devices, laptops, or in physical stores [6]. However, on the other hand, this creates problems for business people who develop Omni-Channel services. On the one hand, it facilitates the marketing process, but on the other hand, the pattern of consumers who switch channels makes it difficult for business people to read the behavior of consumers who use Omni-channel distribution services. Therefore, tools or methods are needed to read or predict consumer behavior in the Omnichannel business.

Most research on consumer behavior uses field observation approaches, survey research uses regression methods, factor analysis, and Structural Equation Modeling (SEM). The majority of these studies are highly dependent on questionnaires and opinions from users and business people. There is no research that analyzes consumer behavior on omnichannel distribution services with the Process Mining approach. With the process mining approach. The analysis is very real because it is based directly on the activity records or user track records in the Omnichannel service.

In principle, the pattern of consumer movement between one channel to another is a collection of activities carried out by consumers on Omni-channel services. There are two approaches in the process mining method used in this study, namely, process modelling with process discovery algorithms and measurement of conformance checking. This mechanism is able to describe the reality of changing activities and other related matters in describing changes in consumer behavior that are not based on mere opinions or have a rather static characterization. Therefore, this study proposes an alternative to analyzing consumer behavior of omnichannel service users using the Process Mining approach through Process Discovery and conformance checking. Through Process Discovery, obtained a model of the sales process carried out by consumers. The algorithms used in the Discovery process in this study are the Inductive Miner Algorithm, Heuristics Algorithm, Alpha Miner Algorithm and Fuzzy Miner Algorithm. Then the analysis is equipped with conformance checking measurements as the evaluation stage of the resulting process model.

The next sections of this paper are structured as follows: Section II contains an explanation of the previous research related to this paper. Section III describes the materials and methods including the experimental setup, data set, and proposed method. Section IV presents the experiments and discusses the analysis obtained from the four Process Discovery Algorithm approaches used. Then proceed with the analysis of consumer behavior based on the selected process model. and section V contains conclusions and opportunities for future research.

II. RELATED WORK

In the last 7 years, there have been many studies related to the analysis of reading patterns and consumer behavior. However, the analysis carried out by the majority is mostly done on a single-channel service model and is based on certain dimensions that are variables of consumer behavior. Research that uses a relatively simple method, namely, a descriptive approach is carried out by [7] and [8]. Both studies describe consumer behavior in certain cases based on descriptive data obtained through online surveys and field observations. Another study was carried out with a regression approach as carried out by [9] and [10], and a multiple regression approach conducted by [11], The research mechanism is to try to link the attraction of fear (health fear and economic fear) to changes in customer behavior and the impact of traditional and online shopping on COVID-19. The results showed significant differences and similarities in consumer behavior between generations. Factor analysis method is also used in describing the consumer behavior of E-Commerce. As research conducted by [12], this research begins by conducting a psychographic market segmentation analysis and finding four different online consumer segments. Then, the shopping behavior of each segment is determined and assessed using the developed behavior evaluation model. The findings of this study provide important information for e-retailers about the behavioral characteristics of each consumer segment. E-retailers can leverage the findings of this study to effectively allocate their marketing resources and design a more successful marketing mix in each of the consumer segments. Factor analysis is also used in the research conducted by [13], where the purpose of the research is to determine the factors that influence consumer desire to buy products from online stores. Research evaluates criteria based on how consumers make decisions when buying online. The study explores seven factors, where the most prominent factor is the price factor which explains the largest part of the variance in the data. Research from [14] also uses a factor analysis approach. The study examines the impact of financial risk, convenience risk, non-delivery risk; return policy risk, and product risk on Malaysian consumer online consumer behavior. The results show that product risk, convenience risk, and return policy risk have a significant and positive impact on online shopping behavior. Financial risk was found to have an insignificant and negative effect on consumer behavior. In addition, non-delivery risk was found to have a significant and negative impact on online shopping behavior. The research findings provide a useful model for measuring and managing the perceived risk in online shopping that may result in increased participation of Malaysian consumers. The same was also done by [15], where in his research proposes the segmentation of internet users by applying factor and cluster analysis to divide users into three groups, based on the main reported usage purposes of various internet applications and tools at a given time. The results of the analysis show that extracting the main factors that include different attitudes towards internet use as well as segment reflection has implications for the development of e-commerce management.

Another approach is also used in analyzing consumer behavior on multichannel with a path analysis approach, this approach is carried out by [16]. The results show that consumers with strong haptic traits prefer physical and cellular channels. The autotelic dimension is key in online channels. The findings in the study support the adoption of an effective multichannel strategy among retailers of high-haptic products and suggest that mobile media is a valuable alternative to in-store shopping. Several studies have developed using the Structure Equation Model (SEM-PLS) approach as the research conducted by [17] on single-channel model. The results showed that Hedonic Shopping Value (HSV) and positive emotions (PE) were significant and positive on impulse buying (IB), in contrast to Fashion Involvement (FI) and Sales Promotion (SP) which did not show a significant effect. In addition, PE is a significant mediator in relationship construction. Similar research was also conducted by [18], [19], and [20]. In the Omnichannel form, there is also research using the SEM-PLS method conducted by [21] which shows that consumer perceptions of channel integration, consumer empowerment, and trust have a significant effect on behavior in omnichannel retail. The research approach with the UTAUT2 method is also used to analyze consumer behavior as carried out by [22] on Omnichannel. The results show that consumers' intention to buy in an unusual store channel is influenced by personal innovation, expectations, and performance. In several studies, the method used in analyzing consumer behavior was developed using a data mining approach. Research by [23] performed K-Means Clustering analysis to find out and analyze EU consumer behavior in the online environment. The results of the study lead to the identification of five clusters in which EU countries are grouped according to the characteristics and behavior of consumers in the online environment. Clustering approach was also carried out by [24], which identifies consumer behavior on multichannel. This study explores how customers utilize multiple channels in a retail environment. This research provides a compatible framework for obtaining customer segmentation across all major products and product categories focusing online, reflecting dynamic purchasing needs across multiple channels, using latent class cluster analysis and focusing on demographic characteristics. Based on the literature that has been collected, what is most interesting is the research conducted by [25], which uses a process mining approach. The research was conducted on consumer behavior on the E-commerce Web. The research focused on recording consumer events in Web use. The results of the study show that the recording of the process carried out by consumers can be input for E-commerce Web owners to improve their features. Based on previous research, no one has ever used the process mining approach, especially process discovery, in analyzing E-commerce consumer behavior in an omnichannel distribution system.

III. MATERIALS AND METHOD

A. OMNICHANNEL IN E-COMMERCE

Omnichannel is a service using various channels that are used as company strategies to increase customer satisfaction, company sales, and other company needs [26]. Omnichannel is an integrative method between consumer and company relationships. Omnichannel e-commerce offers solutions for various marketplace platforms and e-commerce channels integrated with each other. Only through one platform, business can manage each online store in various marketplaces or other online sales channels that consumers like most [27]. This is as shown in Figure 1.

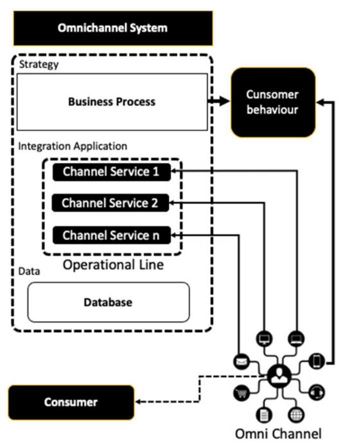

FIGURE 1. Omnichannel distribution system model.

B. CONSUMER BEHAVIOR IN OMNI-CHANNEL DISTRIBUTION

Digital developments have changed the way and behavior of consumers shopping at online stores. Currently, consumers not only shop through desktops but also through various electronic devices. Consumers don't just access various devices, they even connect to brands through various channels ranging from the web, social media to physical stores [28]. It is easy for consumers to switch channels to fulfill their wants and needs for the desired goods due to technological advances, as shown in Figure 1. Consumers can view the online store website via a tablet, then view the brand page via Facebook, then register an email through a promo that is viewed on a search engine via a smartphone. The reach of consumers who use technology like this is very broad. Therefore, Omnichannel distribution services have an important role for brands and businesses to be able to provide consumers with a shopping experience. This is because the developed technology makes navigation easier for consumers to get an integrated shopping experience. Things that affect Omnichannel consumers, such as convenience, competitive prices, and the shopping experience that consumers get have made omnichannel distribution services very popular [29].

C. PROCESS MINING

Process Mining is an activity or mechanism used in exploring and analyzing event data to gain knowledge and insights generated during process execution [30]. The details of Process Discovery activities are discovery, modelling, monitoring, and optimization of the underlying process [31]. In general, this can be shown in Figure 2.

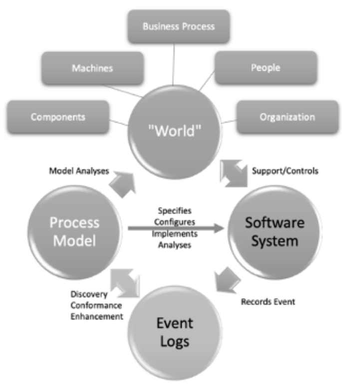

FIGURE 2. Process mining framework [32].

The following are the advantages that can be obtained when doing the mining process [33]:

1) Process discovery is the activity performed in converting event logs into process models for analysis.
2) Conformity checking is the activity of gathering information about the differences between the model and what happens in real life. With this step, the company will be able to find things that are needed to improve ongoing processes.
3) Throughput/bottleneck analysis is an activity to calculate the intensity of event implementation to determine potential bottlenecks in the process.

This kind of analysis can be used to improve Key Performance Indicators (KPIs) in time-related processes to minimize throughput/overhead time [34]. In principle, current process mining connects the gap between traditional model-based process analysis such as business process management simulation, and data-centric analysis techniques such as machine learning and data mining [35].

D. PROCESS DISCOVERY & CONFORMANCE CHECKING

Process Discovery is an automated data-driven mechanism for finding, mapping, and documenting existing business process activities. Then an analysis of the data obtained automatically is carried out so that it can be recommended automatically in the process modelling, or workflow [36]. A digital footprint is left in the system and a detailed representation of the business processes is generated automatically. The discovery and analysis of an organization's business processes can be used to identify key problem areas, not only at the start of a digital transformation initiative, but also when improving the performance of existing processes. Along with business process modelling, Process Discovery is an important part in improving the quality of business process management [37]. Figure 3 shows the process model in the form of a Petri net.

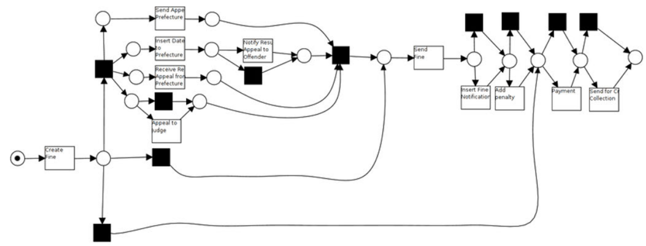

FIGURE 3. Example of petri net model [38].

Business process conformance checking is a family of process mining techniques for comparing process models with event logs from the same process. The technique used is to compare the actual event or process log with the existing reference model or target model for that process [39]. Based on research results [40] related to the performance of the process discovery algorithm. Measuring the performance of the process discovery algorithm is based on certain criteria. The criterion used on the selection was that the algorithm could discover a model in Petri net notation or another notation that could be translated to a Petri net. This requirement is related to available quality metrics, which could be applied only to Petri net models. The performance of discovery algorithms on real and artificial event logs is also considered. The results of the research show that several process discovery algorithms are recommended to be used because they have consistency in describing the process model. These algorithms are like the Inductive Miner and Fuzzy Miner Algorithms, while other algorithms are less stable in providing results. In this context, the algorithms can be grouped into two categories: the classic

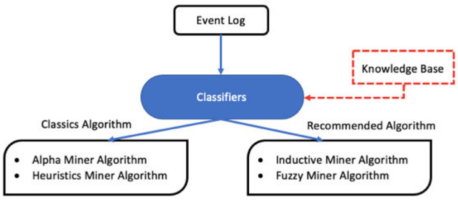

FIGURE 4. **Classics & recommended of process discovery algorithm.**

process discovery algorithm and the process discovery algorithm resulting from the recommendations, as shown in the Figure 4.

Based on Figure 4, this paper uses four process discovery algorithms namely Alpha Miner and Heuristics Miner in this case the classic Algorithm and Inductive Miner as well as Fuzzy Miner as a recommendation Algorithm representative to describe the Sales Process Model.

E. ALPHA MINER ALGORITHM

Alpha miner algorithm is an algorithm used in the mining process, which aims to reconstruct the causality of a series of sequences of events. Alpha miner is the first process discovery algorithm ever proposed, and it provides a good overview of the purpose of process discovery and how the various activities in the process are executed [41]. The goal of Alpha miner is to turn the event log into a workflow net based on the relationships between the various activities in the event log [42]. The event log is a multiset trace, and the trace is a sequence of activity names.

F. INDUCTIVE MINER ALGORITHM

The Heuristic Miner algorithm is a process model discovery algorithm that handles spaghetti process problems by focusing on the number of occurrences of relations between activities with each other in the event log in forming the process model [43]. Sometimes the resulting process model is an event log that has too many relationships and is complicated and difficult to read, so we need a process model that is able to simplify complex forms into simple ones. The basic principle is that the relationship between activities with a small amount will not appear in the process model formed by the Heuristic Miner algorithm [44].

G. INDUCTIVE MINER ALGORITHM

The basic concept of the Inductive Miner algorithm is to find the type separation that occur in the event log, such as sequential, parallel, concurrent, and loop. After finding the split, the algorithm is repeated on the sub-logs (found by applying the split) until the fundamental model is found in the investigated case. The use of inductive mining algorithms is also considered an important factor capable of analyzing the overall activity [45].

H. FUZZY MINER ALGORITHM

The fuzzy miner algorithm was developed by [46]. The fuzzy miner algorithm is included as one of the youngest algorithms in process discovery compared to alpha miner and heuristics miner algorithms. The main advantage of this algorithm is that it can directly solve the problem of a large number of activities and highly unstructured behavior. This method is used when the organization has complex and unstructured event logs.

I. INSTRUMENT

The instrument used in this study is the event log and activity standards as a reference for pre-processing event log datasets. The dataset used in this study is a sales dataset generated from an omnichannel distribution service system in Jakarta, Indonesia. The data withdrawal period is 1.5 weeks involving 1981 channel feature transactions by consumers. Table 1 shows the Event Log obtained and used in this study.

TABLE 1. **Event log sales transaction activity on omnichannel distribution.**

Case_ID	Activity	TimeStamp
190810123661B9A	See_posts_homepage_explore Social Media	07/09/19 11.36
190810123661B9A	Leave_Comment Social Media	07/09/19 12.06
190810123661B9A	Leave_Like Social Media	07/09/19 12.14
190810123661B9A	Follow_account Social Media	07/09/19 13.20
190810123661B9A	View_Stories Social Media	07/09/19 13.40
190810123661B9A	Click_Link_in_Bio Social Media	07/09/19 13.43
190810123661B9A	View_product_details Marketplace	07/09/19 13.49
190810123661B9A	View_Reviews_&_Testimonials Marketplace	07/10/19 14.10
190810123661B9A	Add_Product_to_Cart Marketplace	07/10/19 14.36
190810123661B9A	View_Cart_contents Marketplace	07/10/19 22.24
190810123661B9A	Add_Product_to_Cart Marketplace	07/10/19 22.34
190810123661B9A	Chat_Seller Marketplace	07/12/19 18.28
190810123661B9A	Make_an_offer_Price Marketplace	7/13/19 6.29
190810123661B9A	Selecting_the_type_of_payment Marketplace	7/14/19 6.54
190810123661B9A	Making_payment Marketplace	7/15/19 7.04
190810123661B9A	Save_Post Social Media	7/15/19 12.30
190810123661B9A	Share_Post Social Media	7/15/19 12.40
190820055566B6G	See_posts_homepage explore Social Media	07/09/19 04.55
190820055566B6G	Leave_Like Social Media	07/09/19 04.58
190820055566B6G	Follow_account Social Media	07/09/19 22.17
190820055566B6G	View_Stories Social Media	07/09/19 10.39
190820055566B6G	Click_Link_in_Bio Social Media	07/09/19 13.39
…	…	…

The activity standards used in pre-processing are as shown in Table 2.

Table 2 shows the activities recorded on the system carried out by potential consumers of Omnichannel distribution service users.

J. METHOD

The proposed method is shown in Figure 5 and more detailed description be explained as follows:

1) PROCESS BY SYSTEM

The distribution service system records all sales activities carried out by customers and business managers. All activities

TABLE 2. Activity standards that are used as a reference in pre-processing.

Marketplace	Webstore
View_seller_profile	View_product_details
View_product_details	View_Reviews_Testimonials
View_Reviews_&_Testimonials	Add_Product_to_Cart
Add_Product_to_Cart	Account_registration
View_Cart_contents	Account_login
Chat_Seller	Admin_Chat
Make_an_offer_Price	Read_Articles
Buying_product	View_Gallery
Selecting_the_type_of_payment	View_the_contents of the cart
Making_payment	Purchase_product
Transaction_canceled_the system	Choose_type_of_payment
Transaction_canceled_buyer	Make_payment
Confirmation_arrived	Transaction_canceled_by_the_system
Assessing_store_goods_and_services	Transaction_canceled_by_the_cust
Buying_goods_Already_purchased	Confirmation_arrived
	Appraise_product_services
	Purchase_previously_items
Social Media Shop	**Messenger Media**
View_product_details	Chat_ask_product_availability
View_Reviews_Testimonials	Chat_asking_for_product
Add_Product_to_Cart	Prov_personal_data
View_Cart_contents	Ordering_products
Chat_Seller	Get_order_recap
Buying_products	Making_payments
Selecting_type_of_payment	
Making_payment	
Transaction_canceled_by_the_system	
Transaction_canceled_by_the_cust	
Assess store goods and services	
Purchase_previously_items	
Social Media	
See_posts_homepage_explore	
Leave_Comment	
Leave_Like	
Save_Post	
Share_Post	
Follow_account	
View_Stories	
Interact_on_stories	
Click_backlink	
View_profile	
View_last_post	
Click_Link_in_Bio	
Watch_Live	
Interaction_on_Live	
Chat_Direct_Message	
Chat_buyer_details	
Chat_Direct_Message_order	
Chat_Direct_Message_closing	

in distribution channels in the form of *Marketplace, Web Store, social media, and messenger tools have activity and time records (Timestamp).*

2) GENERATED SYSTEM BECOMES EVENT LOG

Traces of activities and transactions that exist in the system are then generated becomes a Sales Log Event Dataset. The recorded Event log dataset must have at least a Case ID, Activities, Timestamp and other capture able resource data.

3) DATA PRE-PROCESSING

The resulting Event log dataset then performs pre-processing to suit the needs of the process modelling that will be carried out. Pre-processing activities carried out include checking data records and converting attributes that are not in accordance with process modelling standards in process mining.

4) PROCESS DISCOVERY ALGORITHM

The sales process model is generated using a process discovery algorithm, namely the Inductive Miner Algorithm, Heuristics Algorithm, Alpha Miner Algorithm, and Fuzzy Miner Algorithm.

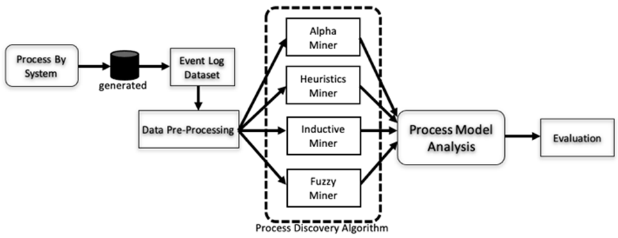

FIGURE 5. Proposed method.

5) PROCESS MODEL ANALYSIS

The process model generated by each Process Discovery algorithm is then analyzed by conformance checking approach. Conformance checking is used to analyze the precision, fitness, simplicity, and generalization of the resulting model process, while in this study two techniques are used, namely, fitness and precision.

6) EVALUATION

Existing process discovery algorithms usually consider, at most, two of the four main quality dimensions namely fitness and precision. This is because these four forces of quality pull in different directions and whenever one is optimized, quality is usually lost in the measure of the other. Fitness is a value that indicates the number of cases found in the process model [47], [48]. The value ranges from 0 to 1, where 0 means that no cases are found at all in the business process, while 1 means that all cases can be found by the algorithm and displayed in the business process model. The fitness value (FV) can be measured by Eq. (1).

$$FV = \frac{Case\ Captured}{Caseson\ Actual\ event\ Logs} \tag{1}$$

While Precision is a value that indicates the accuracy of the trace captured by the business process model [49]. The precision value ranges from 0 to 1, where 0 means that no cases are captured from the event log by the algorithm, while 1 means that all cases can be captured in the process model.

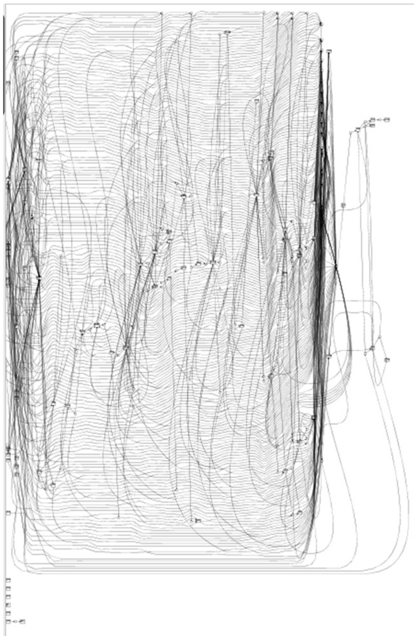

FIGURE 6. Process model of 'spaghetti' from omnichannel sales.

The precision value (PV) is calculated by Eq. (2).

$$PV = 1 - \frac{sum\ of\ bias\ traces}{traces\ from\ logs} \tag{2}$$

The selected Process Model based on conformance checking becomes a reference in analyzing consumer behavior in Omnichannel distribution services.

IV. EXPERIMENT RESULT, AND DISCUSSION

A. EXPERIMENT RESULT

Descriptive calculation results of the Event log used in this study are as shown in Table 3.

Table 3 shows that the total activity recorded on the system is 78 of 77 potential omnichannel consumers who carried out 1981 events in a one-week period. The average Omnichannel consumer spends time using the Omnichannel service is 24.5 minutes and the longest is 221 minutes. An overview of how consumer activities run in a period of 1 week can be seen through the process model. The next step is to conduct a model search experiment using the process discovery algorithm in the event log obtained from the results of the omnichannel sales system generated. The process discovery algorithm used is the Alpha Miner Algorithm, Heuristics Miner, Inductive Miner, and Fuzzy Miner.

B. PROCESS MODEL OF ALPHA MINER ALGORITHM

In this section, process discovery is carried out to obtain the process model generated from the Alpha Miner Algorithm. The resulting process model looks very complicated to analyze. This is because the Alpha Miner algorithm has a tendency to record all sequences of activities that occur in the event log dataset. this has resulted in the resulting process model being referred to in some references as Spaghetti. Figure 6 shows the Spaghetti process model generated from this algorithm on the Omnichannel distribution sales transaction dataset.

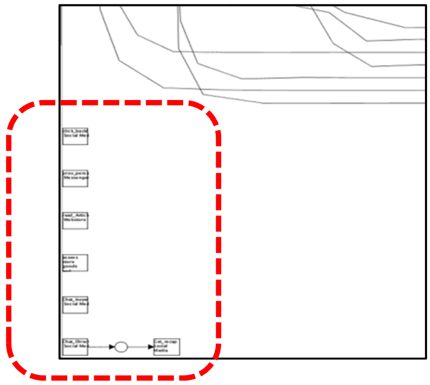

FIGURE 7. Separate activities of the omnichannel 'spaghetti' process model.

There are separate activities from the set of activity relations as shown in Figure 7.

Activities that are separated from the model (as shown in the red line boundary) will make the analysis biased and invalid. The Alpha miner algorithm is more suitable for event log datasets that have less traces and activities.

C. PROCESS MODEL OF HEURISTICS MINER ALGORITHM

The process model generated from the Heuristics Miner Algorithm approach in principle improves the Process Spaghetti model. The number of recurring activities can be well described in the form of a Petri net, but the number of relations between activities that have a small occurrence in the event log can be considered a disturbance so that the relationship will not be displayed in the process model. The process model of the omnichannel Distribution sales transaction dataset generated using this algorithm is shown in Figure 8.

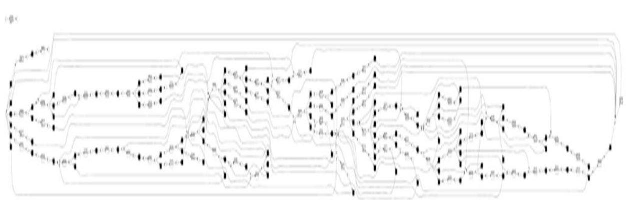

FIGURE 8. Process models generated from the miner's heuristics algorithm.

There are separate activities from the set of activity relations as shown in Figure 9. A separate activity (as in the red line) of course as well as the Process Spaghetti model will make the analysis biased and invalid.

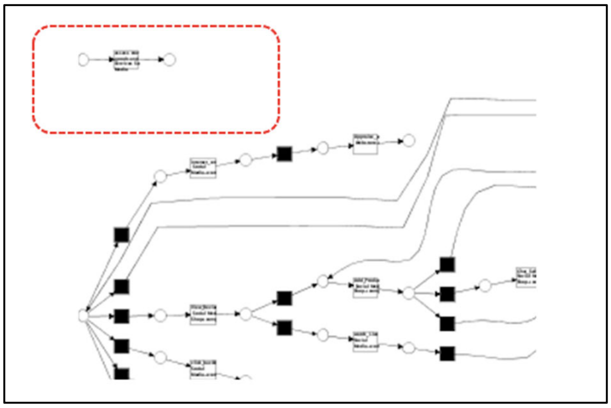

FIGURE 9. Separates activities from the Omnichannel Heuristics process model.

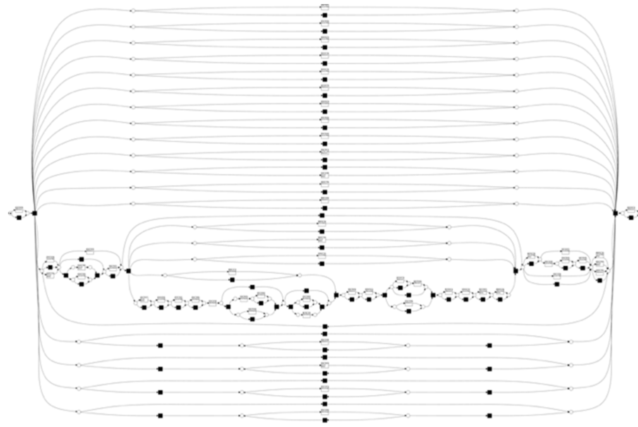

FIGURE 10. Process model generated from inductive miner algorithm.

FIGURE 11. Process model generated from inductive miner algorithm.

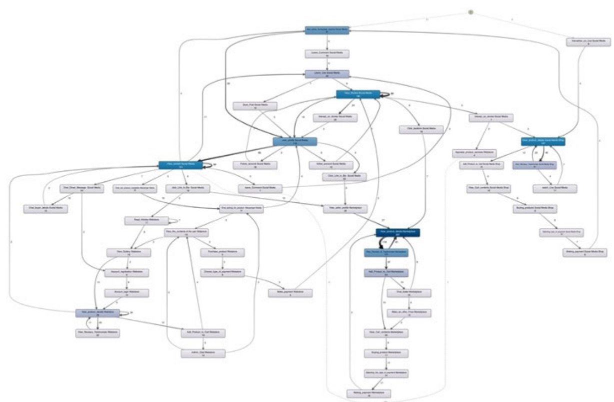

FIGURE 12. The process model generated from the fuzzy miner algorithm.

D. PROCESS MODEL OF INDUCTIVE MINER ALGORITHM

The Process Model generated from the Inductive Miner Algorithm is shown in Figure 10. Figure 10 shows that the resulting process model is quite good because it can record all activities that occur in the Omnichannel distribution sales transaction dataset. However, the model seems to have flaws in the relationship. The drawback of the process model generated from the inductive miner algorithm is the generalization of the model. The resulting model is so simple that it ignores the important events that occur in the event log. This is shown in Figure 11.

There are process activities that are described as consisting of only 3 activities in the process model. In Figure 10, there is an activity flow for *Read_Article Web Store→Make_Payment_Web_Store → Appraise_product_services Web Store*. Process activities consisting of 3 activities like this are not just one but quite a lot. This shows that the resulting process model is quite biased because according to Table 3, the description of the Event Log shows that the minimum process in the recorded dataset is 6 activities.

E. PROCESS MODEL OF FUZZY MINER ALGORITHM

The last part of the experiment is the process model that is generated from the Fuzzy Miner Algorithm approach. The resulting Process Model is very good and is able to describe the general process that occurs. 78 Activities in the dataset read well from the resulting model. There are no separate activities. This is as shown in Figure 12.

TABLE 3. Descriptive data from event log of omnichannel sales activity.

No	Indicators	Score
1	Number of Event	1981
2	Number of users	77
3	Number of activities recorded	78
4	Maximum number of activities per case	51
5	Minimum number of activities	6
6	Frequency Average user activity	25.4 minutes
7	User's maximum activity frequency	221 minutes

F. EVALUATION

After modelling the process using the four Process Discovery Algorithms, the next step is an evaluation mechanism using the Conformance Checking approach to see the Fitness & Precision values of the four process models produced.

Table 4 shows that the value of fitness and precision of the process model for the Omnichannel sales dataset is the highest process model generated by the Fuzzy miner algorithm of 1. Based on this, the process model resulting from the fuzzy miner algorithm is valid as the basis for analyzing consumer behavior in the case of Omnichannel sales in this study.

G. DISCUSSION

Based on the process model generated from the Fuzzy Miner Algorithm as shown in Figure 12, the proportion of distribution channels involving many consumers is shown in Table 5.

TABLE 4. Evaluation of the process discovery algorithm.

Algorithm Process Discovery	Fitness	Precision
Alpha Miner	0.40	0.24
Heuristics Miner	0.26	0.00
Inductive Miner	0.60	0.28
Fuzzy Miner	1.00	1.00

TABLE 5. Proportion of the number of frequencies on the omnichannel distribution channel.

Distribution Channel	Frequency	Relative Frequency
Marketplace	579	29.23%
Social Media	813	41.04%
Social Media Shop	284	14.31%
Webstore	230	11.60%
Messenger Media	75	3.77%
Totally	1981	100.0%

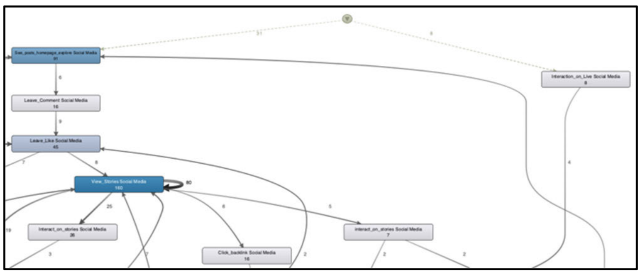

FIGURE 13. Initial activities of consumer behavior on social media channels on omnichannel.

Table 5 shows that Social Media distribution channels are the most visited channels by consumers at 41.04% followed by Marketplace distribution channels at 29.23%, and then the rest followed by social media Shop, Webstore, and Messenger Media respectively 14.31%, 11.60%, and 3.77%.

The majority of consumer activity in Omnichannel distribution starts from social media channels through *see_posts_homepage social media*and *Interaction on live on Social Media* activities. However, consumers more often start activities on the *see_posts_homepage activity* of social media. Then consumers continue to activities that are still on Social Media distribution channels such as *Leave_Comment Media Social→ Leave_Like social media→ Interact_on_Stories Media Social*.

Figure 13 shows that Social Media Distribution Channels have a very important role in the Omnichannel business model. Social media is a strategic medium for meeting potential consumers and omnichannel service providers as shown in Table 5 and Figure 13. Omnichannel service providers can make social media the leading channel in attracting prospective consumers. The frequency of Consumers doing the most activities on Social media on the *View Stories Social Media* feature is 160 as shown in Figure 14.

How is consumer behavior after social media distribution channels? Figure 15 shows Consumer behavior after spending time on social media channels switching to Media Messenger, Webstore, and Marketplace channels.

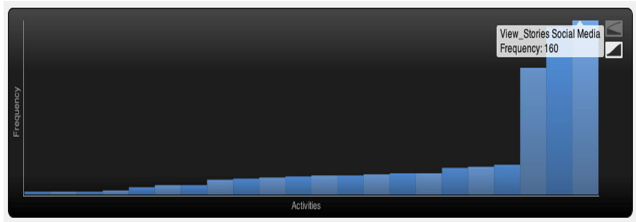

FIGURE 14. Graph of the frequency of consumers doing activities on social media.

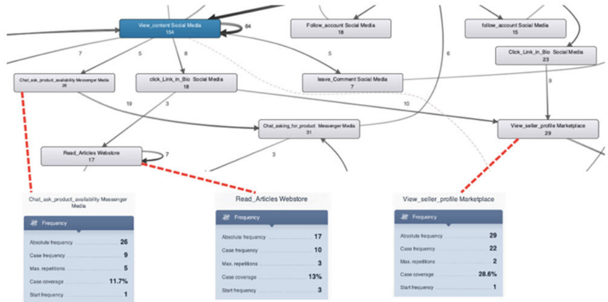

FIGURE 15. Consumer Behavior tendency to switch channels after from social media channels.

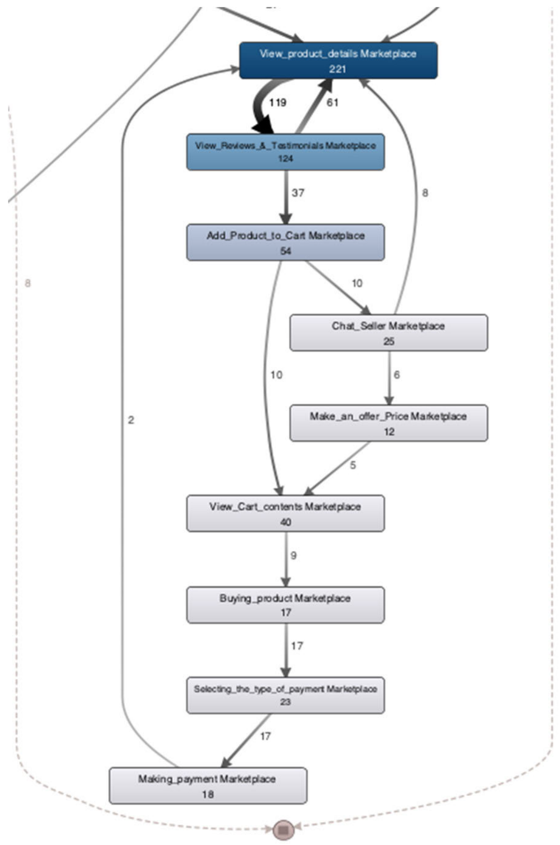

FIGURE 16. Consumer activity on marketplace channels.

After social media channels, consumers tend to move more to the Marketplace channel by 28% compared to other

TABLE 6. Omnichannel transaction proportion.

No	Activity	Frequency	%
1	Making Payment Webstore	8	23.53
2	Making Payment Marketplace	18	52.94
3	Making Payment Social Media Shop	8	23.53

channels. Consumer Behavior on the Marketplace channel as shown in Figure 16.

based on the results of analysis and recording of sales datasets on the process model in the marketplace channel section. there are 221 frequencies of consumers who enter the Marketplace channel, and 18 of them make payments. if the transaction is converted in percentage, 52.94% is obtained compared to the Webstore or Social Media Shop channels. The proportion of consumers who buy products can be seen in Table 6.

The results of the analysis are highly dependent on the condition of the event log obtained from the Omnichannel distribution system. In this case, the results of the analysis as a whole can recommend that business owners who manage the Omnichannel distribution system pay attention to social media channels as the entry point for consumers to obtain product information and make product payment transactions on the Marketplace channel. The drawback of this research is that the physical store distribution channel cannot be shown in the process model. In some references, the Physical Store also has a fairly large role in Omnichannel distribution. This happens because there is no omnichannel system that records consumer behavior activities in stores. The only activity recorded in the system is payment activity. therefore, we did not include physical store activities in this study.

V. CONCLUSION & FUTURE WORKS

The results showed that the process model generated from the Fuzzy Miner Algorithm had the best fitness and precision values compared to the Alpha, Heuristics and Inductive Miner Algorithms. The Process Model generated by Fuzzy Miner is able to read all activities recorded in the Omnichannel Sales Dataset properly. This process model is the reference in reading the behavior of consumers who carry out activities on Omnichannel distribution services.

In the process model, it can be seen that the majority of consumers use Omnichannel services starting from the Social Media Distribution channel. Consumer behavior also shows a tendency after the majority of social media channels switch to the Marketplace channel compared to other channels. Marketplace channels have an essential role in the sales process. Consumers make purchase transactions of 52.94% on this channel. This is also reinforced by the total frequency of activity, which shows that the channels that have the most role in omnichannel distribution services are social media, marketplaces, followed by social media shop, webstore, and messenger media channels. This result can be a reference for the owner of the omnichannel distribution service business model in developing, repairing, and closing their distribution channel.

Research on consumer behavior with the Process Mining approach is minimal or even non-existent. Therefore, it is very open once the concept of process mining is used to examine user behavior or activities in processes running on Supply Chain management.

CONFLICT OF INTEREST

The authors state that they have no known conflict of interest that could affect the work reported in this paper.

DATA AVAILABILITY

The Event Log data used to support the findings of this study have been deposited in the Mendeley Data repository https://data.mendeley.com/datasets/tdz6rp2gmg (DOI: 10.17632/tdz6rp2gmg.2)

AUTHORS' CONTRIBUTIONS

All authors have read and agreed to the published version of the manuscript. All the material presented in this manuscript has been used through the study and discussion of all authors. All authors have read and approved the published version of the manuscript.

CREDIT AUTHOR STATEMENT

Ferra Arik Tridalestari: conceptualization, methodology, data curation, writing–original draft preparation. Mustafid: supervision and validation. Ferry Jie: writing-reviewing and supervision.

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