# AN EMPIRICAL STUDY ON THE ROLE OF BIG DATA GOVERNANCE IN PERSONALIZING NEWSFEEDS AND ENHANCING CUSTOMER RELATIONSHIP MANAGEMENT IN THE DIGITAL ECONOMY

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## Abstract

The integration of big data into customer relationship management (CRM) has emerged as a critical strategy for businesses seeking competitive advantages in today's digital landscape. While organizations traditionally use big data to enhance customer service, it also serves to synthesize internal CRM data with external customer behavior and purchasing patterns (Taleb et al., 2020). This study investigates the factors through which big data enables newsfeed personalization, employing a quantitative research approach with data collected from 822 Thai respondents via convenience sampling. Using statistical analyses, including binary regression, the research identified multiple factors influencing newsfeed personalization: 1) knowledge scores, 2) demographic variables (gender, age, education, income, occupation), 3) user behavior (expenses, frequency), and 4) social media platform usage (Line, X, View). The findings revealed the intricate relationship between these variables in digital content personalization. These insights carry significant implications for various stakeholders: 1) businesses can enhance their targeted marketing strategies, 2) consumers can better understand their online experiences, 3) policymakers can develop more informed data usage regulations, and 4) researchers can further explore the ethical dimensions of big data applications. The study ultimately emphasizes the importance of responsible big data utilization in the evolving digital ecosystem.

**Keywords:** Big Data, Customer Relationship Management, Newsfeed's Personalization

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## 1. INTRODUCTION

The term "big data" along with other trending topics such as "data analytics" and "artificial intelligence (AI)" have become buzzwords in recent years (Bharadiya, 2023; Bose et al., 2023). In the past, businesses primarily collected data for routine recording purposes, such as sales tracking for accounting or monitoring advertisement views for revenue calculation. However, the perception of data has evolved significantly (Anshari et al., 2019). Nowadays, both private and public organizations recognize data as a valuable asset, transforming its use beyond its original intent. This shift has spurred the growth of the data analytics industry (Dash et al., 2019; Mikalef et al., 2019; Limna et al., 2021). A notable example is the strategic partnership between International Business Machines Corporation (IBM) and Twitter (now X), which combines IBM's analytical prowess with X's extensive data resources. This collaboration aims to sell analytical insights to corporate clients, enabling smarter, real-time business decisions. Such partnerships exemplify the leveraging of combined strengths and expertise (Clark, 2014; Anshari et al., 2019).

Big data has emerged as a key component in decision support and data management, profoundly influencing various business areas like customer relationship management (CRM), enterprise resource planning (ERP), and supply chain management (SCM). Managing strong customer relationships within an organization encompasses the principles, tools, and strategies of CRM. CRM, as a tool with web and app technologies, equips organizations with the capability to comprehend the behaviors and preferences of their customers or potential customers. Consequently, organizations can tailor their activities to persuade customers to engage in transactions and make informed decisions. An essential aspect to scrutinize is the role of big data in CRM strategies (Anshari et al., 2019). Big data plays a pivotal role in CRM by offering insights into customer behaviors, preferences, and purchasing patterns. It facilitates the customization of newsfeed, allowing businesses to tailor content and promotions to individual users based on their unique interests and past interactions. By analyzing vast datasets, companies can fine-tune their marketing strategies and enhance customer engagement, ensuring that the content delivered is both relevant and appealing to each recipient (Bleier et al., 2018; Damsten, 2023).

Given its critical importance, the role of big data in CRM is an essential area of research. Numerous studies have delved into this intersection. For instance, Jitsoonthronchaikul et al. (2019) investigated the application of big data in analyzing consumer behavior within two provinces in Thailand, Ratchaburi, and Phuket, while concentrating on the crucial local marketing strategies of modern trade businesses and stores, and examining how these strategies respond to customer needs and satisfaction. Taleb et al. (2020) conducted a series of survey interviews to assess how big-data technology enhances CRM. Their research focused on a thorough analysis of big data implementation in organizations, aiming to forge deeper connections with customers. However, there is a notable gap in the literature regarding the specific ways in which big data contributes to the personalization of newsfeeds. To address this gap, this study employs binary regression analysis to investigate the various factors through which big data enables the customization of newsfeeds. The implications and contributions of this study are significant. By identifying and analyzing these factors, the study not only fills a crucial gap in existing research but also provides actionable insights for businesses looking to leverage big data for more effective CRM strategies. The findings can guide organizations in optimizing their data analytics processes, leading to more personalized customer experiences and, ultimately, stronger customer relationships. This research contributes to a deeper understanding of the practical applications of big data in CRM, paving the way for future innovations in data-driven customer engagement strategies.

The paper is organized into six sections. Section 1 highlights the study's importance and objectives. Section 2 provides an extensive examination of existing research. Section 3 explains the methods used for data collection. Section 4 presents the outcomes of the study. Section 5 analyzes and interprets the results, and Section 6 summarizes the study, notes any limitations, and suggests areas for future research.

## 2. LITERATURE REVIEW

Data constitutes a fundamental component in the realm of personalization. An augmented repository of personal data facilitates a more refined customization of services, targeting individuals with heightened precision. This enhanced personalization serves multiple objectives: 1) it heightens the appeal and engagement quotient of the services offered, 2) ensures alignment with the distinct requirements of the recipients, and 3) exerts a persuasive influence on their purchasing choices. Consequently, the strategic harnessing of personal data stands as a pivotal element in tailoring services that resonate deeply with individual preferences and behaviors, thereby fostering a more impactful and meaningful user experience. Big data positively impacts the personalization of news feeds, as evidenced by the success of major online platforms. Amazon, for instance, has specialized in providing personalized news recommendations through Amazon Personalize, a platform powered by advanced machine learning algorithms. It tailors news recommendations to individual preferences, thereby improving user satisfaction and engagement. Similarly, platforms like Facebook and LinkedIn utilize user accounts and behavioral data to target products, ads, jobs, and services more effectively to specific users (Couldry & Turow, 2014; Joshi, 2023; Shahid & Sheikh, 2021; Cavlak & Cop, 2021; Maksimova et al., 2021).

Big data significantly enhances the personalization of newsfeeds, creating a tailored and engaging user experience on digital platforms. By meticulously analyzing user behaviors, preferences, and interactions, big data algorithms curate content that resonates with individual interests. This involves examining activities such as article choices, link clicks, and engagement duration. Thus, each user's newsfeed becomes uniquely customized, featuring content specifically aligned with their interests. Predictive analytics further refines this process, anticipating future content preferences based on past interactions. Sentiment analysis also helps in understanding user attitudes, allowing for more nuanced content recommendations. Importantly, these algorithms also introduce diversity, ensuring exposure to a range of topics and viewpoints.

The real-time adaptability of these systems ensures that as user preferences evolve, so does the content of their newsfeeds. Essentially, the application of big data in newsfeed personalization enhances user satisfaction and fosters increased engagement with the platform (Adisa, 2023; Bok, 2023; Dujeancourt & Garz, 2023; Eg et al., 2023; Rafieian & Yoganarasimhan, 2023; Rane et al., 2023).

Integrating big data into CRM systems revolutionizes how businesses understand and interact with their customers. Through the analysis of extensive customer data from various sources such as social media, transaction histories, and online behavior, companies gain a profound understanding of customer preferences and behaviors. This deep insight enables the creation of personalized customer experiences, enhances targeted marketing strategies, and improves customer service. Predictive analytics, a key feature of big data in CRM, allows businesses to anticipate future customer behaviors, aiding in customer retention and loyalty (Bradlow et al., 2017; Matilda,2017; Zerbino et al., 2018). Additionally, big data facilitates efficient customer segmentation, enabling more focused and effective marketing campaigns. Real-time data processing and analysis also enhance decision-making capabilities, ensuring businesses remain agile in responding to market trends and customer needs. Moreover, the integration of big data with social media platforms aids in monitoring customer sentiments and trends, further enriching customer engagement strategies. Hence, the application of big data in CRM is indispensable for businesses seeking to optimize customer interactions and maintain a competitive edge in today's digital landscape (Choi et al., 2020; Abu Ghazaleh & Zabadi, 2020; Gupta et al., 2021; Niu et al., 2021; Stylos et al., 2021).

The recent advancements in big data and AI technologies in CRM prompted Ledro et al. (2022) to conduct a systematic exploration of this evolving field. The bibliometric analysis conducted in this study delineated three primary subfields within the AI literature in CRM: 1) the intersection of big data and CRM as a database, 2) the application of AI and machine learning techniques in CRM activities, and 3) the strategic management of AI-CRM integrations. Each of these subfields was examined for its prospective developmental trajectory. Moreover, a three-tier conceptual framework for the implementation of AI in CRM was proposed. This model is intended to aid academicians in furthering their understanding of the field and assist managers in formulating effective and coherent AI integration strategies within CRM. The model underscores the importance of a structured approach to AI adoption in CRM, balancing theoretical insights with practical applications, thereby contributing significantly to the knowledge base in this domain.

Zerbino et al. (2018) conducted a study to assess the impact of big data on critical success factors in CRM. This investigation unveiled the necessity of adapting CRM's critical success factors in response to the integration of big data. In addressing the prevailing "hype" around big data, the study's authors recommended an explorative methodology, underlining the significance of defining precise business goals, developing robust business cases, and implementing pilot tests. The research suggested viewing big data as an enabler within established frameworks like CRM initiatives, enabling organizations to incorporate new technological advances within known management structures, thus maximizing the advantages of big data. The findings of this study underline the transformative role of big data in reshaping CRM strategies, stressing the necessity for a systematic approach to incorporating big data into prevailing business models.

Wassouf et al. (2020) conducted a study on predictive analytics with big data to enhance customer loyalty, focusing on the Syriatel Telecom Company as a case study. Big data's impact on CRM is substantial, especially in deciphering customer behaviors, preferences, and buying tendencies. It has enabled more precise customer profiling in telecom through big data analysis, accurately predicting details like gender and age. Additionally, machine learning on big data platforms has made strides in customer churn prediction, with enhanced accuracy through social network data integration. Furthermore, studies using machine learning algorithms have successfully predicted customer loyalty, one showing an 81.02% accuracy with the C4.5 algorithm (Wassouf et al., 2020). Tools such as the Hortonworks Data Platform facilitate the handling of extensive datasets, vital for big data-driven CRM, allowing real-time data processing and flexible application deployment. This underlines big data's critical role in refining CRM strategies, leading to personalized, more effective marketing efforts by offering deeper insights into customer behaviors and preferences.

## 3. METHODOLOGY

The research adopted a quantitative approach, employing structured surveys for gathering data. These surveys were crafted from well-established and credible research sources. The research methodology employed an online questionnaire developed through a systematic three-stage process. The first stage involved a comprehensive literature review of academic publications, including peer-reviewed papers, scholarly articles, books, and credible online resources focused on big data governance's role in newsfeed personalization and CRM within the digital economy. In the second stage, survey questions were formulated based on the synthesized literature findings. The final stage incorporated expert validation, where three field specialists evaluated the questionnaire for contextual relevance, linguistic clarity, and structural appropriateness. These experts conducted an index of item-objective congruence (IOC) assessment, with values ranging from 0.80 to 1.00, well above the minimum acceptable threshold of 0.50 (Chutipat et al., 2023). This rigorous validation process ensured the instrument's reliability and content validity. As Kasemrat and Kraiwanit (2023) recommended, a preliminary test involving 30 people was conducted to refine the survey instrument.

The instruments' validity, reliability, and precision were thoroughly evaluated. Ethical guidelines were strictly followed, with the survey receiving approval from three business and social science specialists to ensure its suitability. Participants below 18 years were excluded from the study. All participants were fully informed about the study's aims and their right to withdraw at any moment. The requirement for participants to complete all survey questions led to the omission of partially filled questionnaires. The study targeted Thai residents aged 18 years old and above. Utilizing

Cochran's formula, with a 0.5 significance level, ±5% precision, and a 95% confidence level, a minimum sample size of 384 was determined (Uakarn et al., 2021). The initial participant pool comprised 822 individuals, selected via convenience sampling. The online survey was conducted over four months, from September to December 2023, to gather timely and relevant data. This period allowed for trend observation and variation, increasing the study's findings' accuracy and robustness. The data collection concluded when satisfactory results were achieved.

For data analysis, statistical software was used for both descriptive and inferential analysis, providing a comprehensive evaluation of the variables. The study primarily aimed to examine how big data influences the efficiency of newsfeed tools in CRM within Thailand, considering various independent variables. These variables included demographic, socioeconomic, and behavioral factors like score, gender, age, education status, marital status, income, occupation, expenditure, usage frequency, and social media platforms usage (Facebook, Instagram, Line, TikTok, X (formally Twitter), and view). Binary regression analysis was selected to explore the complex relationship between these variables and the effectiveness of big data in enhancing newsfeed tools for CRM in Thailand. This method enabled an in-depth analysis of how various factors might affect the success of big data in this context.

## 4. RESULTS

The majority of these respondents were female (67.9%) and fell within the 20 years old to 29 years old age bracket (42.8%). Furthermore, 49.2% of them held a bachelor's degree, and a significant portion were single (82.6%). About 32.6% reported having a monthly income exceeding 40,000 baht. In terms of online behavior, the majority of respondents (78.7%) used online platforms daily.

**Table 1.** Crosstabulation showing the newsfeed experience and newsfeed view

| | | | *Newsfeed view* | | *Total* |
|---|---|---|---|---|---|
| | | | *No* | *Yes* | |
| Newsfeed experience | No | Count | 22 | 0 | 22 |
| | | % within newsfeed | 100.0 | 0.0 | 100.0 |
| | Yes | Count | 92 | 768 | 860 |
| | | % within newsfeed | 10.7 | 89.3 | 100.0 |
| Total | | Count | 114 | 768 | 882 |
| | | % within newsfeed | 12.9 | 87.1 | 100.0 |

Table 1 cross-references the newsfeed experience (whether users had it or not) against the newsfeed view (whether they viewed content or not). Individuals (22) did not have a newsfeed experience and did not view the newsfeed. This group represents 100% of those without newsfeed experience and 12.9% of the total participants. Individuals (92) had a newsfeed experience but did not view the newsfeed, while 768 did view it. Of the individuals with a newsfeed experience, 10.7% did not view the newsfeed and 89.3% did. This indicates that having a newsfeed experience highly correlates with viewing the newsfeed. Out of the total 882 participants, 114 did not view the newsfeed while 768 did. Overall, 12.9% did not view the newsfeed, while a significant majority of 87.1% did.

**Table 2.** Crosstabulation showing the newsfeed view and purchase

| | | | *Purchase* | | *Total* |
|---|---|---|---|---|---|
| | | | *No* | *Yes* | |
| View newsfeed | No | Count | 76 | 38 | 114 |
| | | % within view | 66.7 | 33.3 | 100.0 |
| | Yes | Count | 66 | 702 | 768 |
| | | % within view | 8.6 | 91.4 | 100.0 |
| Total | | Count | 142 | 740 | 882 |
| | | % within view | 16.1 | 83.9 | 100.0 |

Table 2 cross-references whether individuals viewed the newsfeed against whether they made a purchase. Individuals (76) who did not view the newsfeed did not make a purchase, but 38 did make a purchase. Of those who did not view the newsfeed, a majority of 66.7% did not make a purchase, while 33.3% did. Of the 768 individuals who viewed the newsfeed, 66 did not make a purchase, while a significant 702 did. This shows that only 8.6% of the viewers did not purchase, whereas a vast majority of 91.4% did. This suggests a strong relationship between viewing the newsfeed and making a purchase. Out of 882 participants in total, 142 did not make a purchase, and 740 did. Overall, 16.1% of the total participants did not make a purchase, while 83.9% did, indicating that most participants made a purchase, likely influenced by viewing the newsfeed.

**Table 3.** Omnibus test of the model's performance (all independent variables)

| | | *Chi-square* | *df* | *Sig.* |
|---|---|---|---|---|
| Step 1 | Step | 238.184 | 15 | 0.000 |
| | Block | 238.184 | 15 | 0.000 |
| | Model | 238.184 | 15 | 0.000 |

The chi-square statistic tests the association between categorical variables, with degrees of freedom linked to the number of variable categories. A result is statistically significant if the p-value is $\leq 0.05$, as seen in Table 3 with a chi-square statistic of 238.184 for 15 degrees of freedom, indicating a significant relationship between the variables.

**Table 4.** The model summary (all independent variables)

| *Step* | *-2 log-likelihood* | *Cox & Snell R-square* | *Nagelkerke R-square* |
|---|---|---|---|
| 1 | 456.900[a] | 0.242 | 0.436 |

*Note: [a] Estimation terminated at iteration number 8 because parameter estimates changed by less than 0.001.*

Cox & Snell and Nagelkerke R-square are pseudo-$R^2$ statistics in logistic regression, measuring model fit by estimating variance explained by independent variables. Cox & Snell may underestimate this value, whereas Nagelkerke provides a more accurate approximation, ranging from 0 to 1. Both are crucial for evaluating logistic models. In Table 4, an R-squared of 0.436 indicates the model explains 43.6% of the variance, with a significance level of 0.05 confirming the relationships are statistically significant at the 5% level.

**Table 5.** Classification table for back-testing (all independent variables)

| *Observed* | | | *Predicted* | | |
|---|---|---|---|---|---|
| | | | *Purchases* | | *Percentage correct* |
| | | | *No* | *Yes* | |
| Step 1 | Purchases | No | 63 | 57 | 52.5 |
| | | Yes | 20 | 720 | 97.3 |
| Overall percentage | | | | | 91.0 |

*Note: The cut-off value is 0.500.*

A classification table is used to evaluate classification models like logistic regression, showing prediction accuracy. Back-testing assesses a model's predictive ability using historical data. In Table 5, a model predicting the effect of big data on newsfeed personalization achieved a 91.0% accuracy rate with a 50% cut-off, indicating effective prediction in 91.0% of cases in the dataset, demonstrating strong predictive performance.

**Table 6.** Variables in the model (all independent variables)

| *Variables* | | *B* | *Std. error* | *Wald* | *df* | *Sig.* | *Exp(B)* |
|---|---|---|---|---|---|---|---|
| Step 1 | *Score* | 0.349 | 0.168 | 4.327 | 1 | 0.038 | 1.418 |
| | *Gender* | 1.753 | 0.434 | 16.273 | 1 | 0.000 | 5.770 |
| | *Age* | -0.505 | 0.223 | 5.124 | 1 | 0.024 | 0.604 |
| | *Education* | 1.897 | 0.440 | 18.571 | 1 | 0.000 | 6.667 |
| | *Single* | -0.079 | 0.460 | 0.030 | 1 | 0.863 | 0.924 |
| | *Income* | 1.505 | 0.376 | 16.056 | 1 | 0.000 | 4.503 |
| | *Occupation* | 0.609 | 0.162 | 14.227 | 1 | 0.000 | 1.839 |
| | *Expense* | 0.576 | 0.293 | 3.861 | 1 | 0.049 | 1.780 |
| | *Frequency* | 0.424 | 0.176 | 5.812 | 1 | 0.016 | 1.528 |
| | *Facebook* | -0.784 | 1.790 | 0.192 | 1 | 0.661 | 0.457 |
| | *Instagram* | 0.740 | 0.552 | 1.796 | 1 | 0.180 | 2.095 |
| | *Line* | 3.511 | 1.439 | 5.953 | 1 | 0.015 | 33.472 |
| | *TikTok* | 0.651 | 0.434 | 2.243 | 1 | 0.134 | 1.917 |
| | *X* | 2.067 | 0.395 | 27.423 | 1 | 0.000 | 7.899 |
| | *View* | 3.524 | 0.355 | 98.365 | 1 | 0.000 | 33.908 |
| | Constant | -18.264 | 3.813 | 22.947 | 1 | 0.000 | 0.000 |

The predictive regression equation of Model 1 using the coefficients from Table 6 can be described by the following equation:

*Model 1*

$$P = \frac{1}{1 + e^{-z}} \quad (1)$$

where, $P$ is the influence of big data.

$$Z = -18.264 + 0.349(score) + 1.753(gender) -0.505(age) + 1.897(education) + 1.505(income) + 0.609(occupation) + 0.576(expense) + 0.424(frequency) + 3.511(Line) + 2.067(X) + 3.524(View) \quad (2)$$

Table 6 provides a detailed statistical analysis showing the impact of various independent variables on the dependent variable, which in this case is the influence of big data on newsfeed personalization. The table identifies significant predictors including *score*, *gender*, *age*, *education*, *income*, *occupation*, *expense*, *frequency*, and the use of *Line*, *X*, and overall viewing. Specifically, an increase in *score* by one unit correlates with a 1.418 rise in the influence of big data. Being female is associated with an increase of 5.770 in big data's influence, whereas aging reduces the influence by 0.396 for each year, altering the coefficient from 1 to 0.604. Educational advancement leads to a 6.667 increase in influence. Similarly, increments in *income*, *occupation*, and *expense* contribute increases of 4.503, 1.839, and 1.780 respectively. *Frequency* of engagement results in a 1.528 rise in influence, and using the *Line* app significantly boosts the influence by 33.472. Engagement with platform *X* correlates with a 7.899 increase, and heightened viewing habits lead to a 33.908 rise in influence. Conversely, being single and using social media platforms like Facebook, Instagram, and TikTok were not found to be significant predictors. This comprehensive analysis underscores the multifaceted impact of various demographic and behavioral factors on the effectiveness of big data-driven personalization in digital environments.

**Table 7.** Omnibus test of the model's performance (only significant independent variables)

| | | Chi-square | df | Sig. |
|---|---|---|---|---|
| Step 1 | Step | 232.363 | 11 | 0.000 |
| | Block | 232.363 | 11 | 0.000 |
| | Model | 232.363 | 11 | 0.000 |

Table 7 shows a chi-square test with 11 degrees of freedom, resulting in a statistic of 232.363, significant at the 0.05 level. This indicates a statistically significant relationship between the dependent variable and several independent variables.

**Table 8.** The model summary (only significant independent variables)

| Step | -2 log-likelihood | Cox & Snell R-square | Nagelkerke R-square |
|---|---|---|---|
| 1 | 462.720[a] | 0.237 | 0.427 |

*Note: [a] Estimation terminated at iteration number 8 because parameter estimates changed by less than 0.001.*

Table 8 reveals that the model possesses an R-squared value of 0.427, suggesting that it accounts for approximately 42.7% of the variance in the dependent variable. Furthermore, a significance value of 0.05 indicates that the relationships between the independent variables and the dependent variable are statistically significant at the 5% level.

**Table 9.** Classification table for back-testing (only significant independent variables)

| Observed | | | Predicted | | |
|---|---|---|---|---|---|
| | | | Purchases | | Percentage correct |
| | | | No | Yes | |
| Step 1 | Purchases | No | 52 | 68 | 43.3 |
| | | Yes | 17 | 723 | 97.7 |
| Overall percentage | | | | | 90.1 |

*Note: The cut-off value is 0.500.*

Table 9 evaluates a predictive model through a classification table, assessing its performance in predicting how big data influences the personalization of newsfeeds. Using only significant independent variables, the model reached an accuracy rate of 90.1% with a 50% cut-off value, correctly predicting the outcome in approximately 90.1% of the cases in the back-testing dataset. This high accuracy rate demonstrates the model's effective predictive capability for this specific task.

**Table 10.** Variables in the model (only significant independent variables)

| Variables | | B | Std. error | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|---|
| Step 1 | *Score* | 0.334 | 0.127 | 6.904 | 1 | 0.009 | 1.397 |
| | *Gender* | 1.839 | 0.383 | 23.014 | 1 | 0.000 | 6.290 |
| | *Age* | -0.757 | 0.179 | 17.831 | 1 | 0.000 | 0.469 |
| | *Education* | 1.764 | 0.397 | 19.754 | 1 | 0.000 | 5.836 |
| | *Income* | 1.588 | 0.313 | 25.800 | 1 | 0.000 | 4.896 |
| | *Occupation* | 0.661 | 0.147 | 20.338 | 1 | 0.000 | 1.937 |
| | *Expense* | 0.565 | 0.241 | 5.474 | 1 | 0.019 | 1.759 |
| | *Frequency* | 0.447 | 0.164 | 7.448 | 1 | 0.006 | 1.564 |
| | *Line* | 3.166 | 1.535 | 4.258 | 1 | 0.039 | 23.722 |
| | *X* | 2.180 | 0.348 | 39.188 | 1 | 0.000 | 8.849 |
| | *View* | 3.513 | 0.348 | 101.605 | 1 | 0.000 | 33.543 |
| | Constant | -17.564 | 3.133 | 31.419 | 1 | 0.000 | 0.000 |

The predictive regression equation of Model 2 using the coefficients from Table 10 can be described by Eq. (1).

$$Z = -17.564 + 0.334(score) + 1.839(gender) - 0.757(age) + 1.764(education) + 1.588(income) + 0.661(occupation) + 0.565(expense) + 0.447(frequency) + 3.166(Line) + 2.180(X) + 3.513(View) \tag{4}$$

Table 10 elucidates the significance levels of several independent variables in modeling the influence of big data on the personalization of newsfeeds. The dependent variable in this study is significantly affected by a variety of predictors including *score*, *gender*, *age*, *education*, *income*, *occupation*, *expense*, *frequency* of use, and engagement with platforms like *Line* and *X*, as well as overall viewing behavior. Specifically, the analysis demonstrates that a one-unit increase in the *score* metric leads to a 1.397 rise in big data's influence on newsfeed personalization. Similarly, being female correlates with a 6.290 increase in this influence. In contrast, aging decreases the influence by 0.531 for each year, effectively lowering the initial value from 1 to 0.469. Further, educational advancement contributes a 5.836 increase, while higher *income* and occupational status lead to increases of 4.896 and 1.937, respectively. Additional expenditures correlate with a 1.759 rise, and increased usage *frequency* boosts the influence by 1.564. Remarkably, using the *Line* application substantially increases the influence by 23.722, while engaging with the *X* platform and viewing activities contribute increases of 8.849 and 33.543, respectively. These results highlight the complex interplay of demographic and technological factors in enhancing the efficacy of data-driven content personalization.

## 5. DISCUSSION

The study delves into the intricate ways big data facilitates the customization of newsfeeds, touching upon various factors that influence this personalization process. These factors are not just indicative of user preferences but also reflect broader socio-demographic and behavioral patterns, emphasizing the complexity and sophistication of modern content personalization algorithms. The study's findings revealed that the influence of big data enables the personalization of newsfeeds could be described by knowledge score, gender, age, education, income, occupation, expense, frequency, Line, X, and view. The increase in big data's influence might reflect algorithms' sensitivity to user engagement. Users with higher knowledge scores may engage more deeply with content, thereby making it easier for algorithms to discern their preferences and interests. This is in concordance with the findings of Fang and Jin (2022), who used a five-point scale to evaluate participants' understanding of algorithm technology and its application in online platforms. It was indicated that the users' self-reported knowledge level about algorithm technology was significantly noteworthy.

Gender appears to play a significant role in how big data influences newsfeed personalization. There seems to be a notable difference in the effectiveness or targeting of algorithm-driven content based on gender, with female users potentially experiencing a more pronounced impact. According to Haughey (2025), the influence of gender on CRM and online shopping is intertwined with the broader trend of personalized marketing and customer experience enhancement. CRM platforms in e-commerce are increasingly leveraging big data to offer personalized experiences, aiming to build stronger customer relationships and encourage brand loyalty. For instance, personalized marketing strategies are no longer just an option but a customer expectation, with 62% of consumers anticipating personalized offers based on their past purchases. Companies like Amazon attribute a significant portion of their revenue, about 35%, to personalized product recommendations. This level of personalization is achieved by collecting and utilizing detailed customer profiles, which include information like names, addresses, gender, email addresses, purchase history, favorite categories, and social interactions. This data facilitates targeted communications and personalized marketing, enabling brands to connect more effectively with their customers. In the opposite direction compared to gender, age also has a noteworthy effect. As age increases, the influence of big data tends to decrease. This could be due to a variety of reasons, including different media consumption habits among older users or their preferences for information sources. Boudet et al. (2019) demonstrated that modern personalization techniques, driven by machine learning and sophisticated algorithms, are getting better at interpreting data (including visual and auditory) and extrapolating emotions. Such technologies could potentially cater to specific moods, offering personalized promotions for media content. However, these advancements may resonate differently across age groups, with younger users potentially being more receptive to such tailored interactions.

Education level is another important factor. Individuals with higher levels of education might interact with digital platforms more extensively or have a wider range of interests, making them more susceptible to personalized content driven by big data. Yotrawat and Rungsawanpho (2022), indicated that the impact of educational background on online social media-based purchasing decisions differs among individuals based on their level of education. The study attributes this variation to the observation that people with different educational backgrounds exhibit unique behaviors in decision-making, lifestyle preferences, and expectations. Li and Jiang (2021) also underscore the growing importance and impact of big data in the educational context. Furthermore, occupational differences suggest varying degrees of susceptibility to big data personalization. This could be related to variations in digital literacy or the nature of online activities associated with different professions. In line with Kozyreva et al. (2021), people's attitudes towards personalization and privacy are not homogeneous and may vary based on the type of personalized services and the nature of personal data involved. This variation in attitudes could reflect differences in occupational backgrounds, where certain professions might be more aware of or sensitive to data privacy and personalization practices. For example, individuals in tech-savvy fields may be more accepting of personalization due to a better understanding of the technology, whereas those in professions less exposed to digital advancements might be more cautious. Boudet et al. (2019) demonstrated that industries increasingly adopt data-driven personalization strategies. This trend indicates a heightened emphasis on understanding and applying data-driven personalization, especially in sectors heavily integrated with digital technology and data analytics. Consequently, professionals in these areas are likely to be more engaged with and influenced by big data personalization, both in their occupational practices and personal online behaviors.

Income level also correlates with the influence of big data. People with higher incomes might have more digital engagement or diverse online behaviors, leading to more effective personalization by algorithms. In addition, online spending or expense habits are indicative of how big data personalization impacts individuals. Those who spend more online might be providing more data for algorithms to personalize content, enhancing the influence of big Data. In line with Saleem (2017), indicating that e-commerce personalization using big data relies on understanding customer behavior, including their purchasing habits. With higher-income individuals likely engaging more in online transactions, they provide richer data for personalization algorithms. This leads to more tailored recommendations and services, enhancing the personalization experience for these users. Rangaswamy et al. (2022) focused on consumer behaviors in the home furnishing sector and indicated a significant relationship between income levels and online shopping frequency. Contrary to expectations, it was found that those with lower incomes engage in online shopping more frequently than those with higher incomes. Furthermore, high-income groups demonstrated a higher intention to order furniture online, particularly when a physical view of the product was available. This suggests that income level influences not only the frequency of online shopping but also the preference for certain shopping methods, including the integration of online and offline experiences. As indicated by Guo et al. (2021), advanced methods are used to predict consumer behavior based on online activities and consumption habits. For example, the SeqLearn algorithm uses time series analysis to predict the next payment behaviors, which can be applied in product recommendation and advertising push. This shows that online spending habits, when analyzed with big data tools, can significantly influence the personalization of content and recommendations for consumers.

The use of specific services or platforms (referred to as "Line" and "X") has a significant impact. The use of these platforms, possibly encompassing social media or messaging services, is closely linked with intensive data collection and personalized content delivery, making them key areas where big data exerts considerable influence. Limna et al. (2021) found that coffee shops increasingly rely on big data analytics and AI to gain a competitive edge. These technologies are integrated into various applications, including Line, offering valuable insights for business strategies and branding. Coffee shop owners recognize that effectively aligning data with business processes can notably enhance performance and decision-making quality. Albarrak et al. (2020) advocate for the utilization of Twitter (X) by companies as a means to enhance investor communication. This approach streamlines the process of obtaining firm-related news, diminishes information disparities, and boosts both investor awareness and the visibility of the firm. Moreover, the frequency of platform usage is another factor. Regular users of digital platforms provide more data, allowing algorithms to refine their personalization strategies, thereby increasing the influence of big data. The findings are consistent with a study by Blackburn et al. (2020), which describes a tripartite approach to handling social media data, encompassing collection, analysis, and visualization. Initially, it is essential to accumulate relevant data from various social media platforms, with a focus on identifying data that is critical for further analysis. Businesses and marketers can then utilize key indicators such as frequency of visits, conversion rates, and other measures of user engagement to assess the effectiveness of their social media strategies. Finally, viewing behavior, particularly online content viewing, is a major predictor of the influence of big data. This underscores the powerful role of visual media and how it is consumed in shaping personalized newsfeeds driven by algorithmic data analysis. Tariq et al. (2021) demonstrated how big data, collected from various sources like social media, can be processed to predict market trends, consumer behavior, and other phenomena. This includes applications in areas like stock market predictions and trend analysis in e-commerce, highlighting the significant role of online content viewing in shaping big data insights. Zhang and Tan (2020) outlined the AISAS model (attention, interest, search, action, share), emphasizing the importance of search and share in consumer behavior. Big data analysis helps businesses understand consumer demand, create targeted marketing strategies, and guide consumers in decision-making, thereby continuously affecting their behavior choices.

These aspects highlight the complex interplay of various factors in the realm of digital content personalization. Understanding these dynamics is crucial for not only users who seek to comprehend how their online experience is shaped, but also for creators of these algorithms who aim to design ethical and effective personalization strategies.

## 6. CONCLUSION

The study highlights the crucial role of big data in customizing newsfeeds for individual users. This personalization transcends mere user choices, representing a complex integration of diverse socio-demographic and behavioral factors. The "knowledge score" may reflect the user's awareness or understanding of a topic, which subsequently influences the content displayed to them. Traditional demographic variables such as gender, age, education, income, and occupation significantly impact content personalization, each playing a role in shaping a user's interests and preferences. Behavioral and usage patterns, encompassing aspects like spending, frequency of platform use, and specific content preferences (potentially indicated by terms like "Line", "X", and "View"), further dictate personalization. These patterns could involve the amount of time and money users invest in news platforms, their usage frequency, and favored content types or topics. The study also underscores the sophistication of the algorithms used for content personalization. These algorithms proactively incorporate a wide array of factors, going beyond mere reactive measures like user clicks or views, to deliver a highly tailored experience. The manner in which newsfeeds are personalized, based on these factors, suggests an intricate melding of individual preferences with broader socio-economic and behavioral trends. This indicates that personalization algorithms are intricately woven into the societal fabric, reflecting broader structures and norms.

This study's exploration of big data's role in CRM and newsfeed personalization offers valuable contributions to both policy and practice. The government, policymakers, and other stakeholders can use these insights to strike a balance between consumer privacy and data-driven innovation, guiding the development of regulations that protect user data while fostering technological advancement. For businesses, the findings are instrumental in refining CRM strategies, allowing for more targeted marketing approaches by understanding the impact of demographic factors on content personalization. Additionally, this research empowers consumers with greater awareness of how their online behaviors and characteristics shape their digital experience. It also provides crucial guidance for algorithm developers, emphasizing the need for ethical and effective personalization strategies. Academically, the study lays a foundation for further research, particularly in the ethical considerations and consumer privacy aspects of big data analytics. Overall, the research underscores the importance of a nuanced understanding of big data's application in the digital landscape, highlighting its significant implications across various domains.

While this study provides valuable insights, there are certain limitations and ample scope for future research to build upon these findings. Its reliance on convenience sampling and a focus on Thai respondents may affect the generalizability of the results. The quantitative approach, although robust, might have missed nuanced qualitative aspects of user experiences. Moreover, the study did not explore some potentially influential factors like cultural background or psychological aspects. Future research should aim for a more diverse and global sample, incorporate qualitative research methods, and consider conducting longitudinal studies to track changes over time. It is also important to investigate additional variables, including cultural and psychological factors, and stay abreast of technological advancements in big data. A greater focus on the ethical and privacy aspects of big data in CRM is suggested to align with evolving data protection norms and user privacy concerns. These approaches will enhance the comprehensiveness and applicability of future research in this field.

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