https://pubsonline.informs.org/journal/mksc

MARKETING SCIENCE

Vol. 00, No. 0, Xxxxx 0000, pp. 000–000

Submitted to *Marketing Science*

ISSN 0732-2399, EISSN 1526-548X

A Fire Title

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Abstract. In humanitarian logistics, efficient resource allocation is paramount for ensuring timely and effective delivery of aid to populations in need. This paper presents a novel approach to optimize resource allocation in humanitarian logistics using stochastic programming. By integrating stochastic elements into the modeling framework, our approach accounts for uncertainty in demand, supply, and transportation constraints, providing decision-makers with robust and adaptable solutions. We develop a mixed-integer linear programming formulation to minimize the total cost of relief operations while meeting demand requirements under varying scenarios. Through computational experiments and a case study, we demonstrate the effectiveness of our approach in improving decision-making and resource utilization in humanitarian relief efforts. Our findings underscore the importance of incorporating stochastic programming techniques in addressing the complex challenges of humanitarian logistics.

Key words: Communication effectiveness, B2B sales, sales attribution

1. Introduction

Something about how communication is important in sales relationships, but we don't know which communication methods are the most important across the board or if it is strictly based on customer preference. We also don't know the limitations or opportunities on ChatGPT's ability to identify themes from customer reviews and correctly identify reviews that contain those themes.

Past model of attribution in this category?

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ATTENTION: The following displayed equation, in
its current form, exceeds the column width that
will be used in the published edition of your
article. Please break or rewrite this equation
to fit, including the equation number, within a
column width of 240 pt / 84.67 mm / 3.33 in (the
width of this red box).
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$$\text{Cost\_Red}_j = \rho_0 + \rho_1 N_{m_j} + \rho_2 N_{l_j} + \rho_3 I2_{m_j} + \rho_4 I2_{l_j} + \rho_5 OS_{m_j} + \phi \mathbf{X}_j + \mu_j \tag{1}$$

$$\begin{aligned}\text{Cost\_Red}_j = \rho_0 + \rho_1 N_{m_j} + \rho_2 N_{l_j} + \rho_3 I2_{m_j} \\ + \rho_4 I2_{l_j} + \rho_5 OS_{m_j} + \phi \mathbf{X}_j + \mu_j\end{aligned} \tag{2}$$

In this paper, we present a stochastic programming approach to optimize resource allocation in humanitarian logistics (**?**). Our approach aims to balance the trade-off between cost minimization and service quality while considering uncertainty in demand, supply, and transportation constraints. We develop a mixed-integer linear programming (MILP) formulation that captures the stochastic nature of humanitarian crises and provides decision support for relief agencies. The proposed model integrates both deterministic and stochastic components, allowing decision-makers to make informed decisions in uncertain environments.

2. Literature Review

In many business relationships, but especially B2B sales relationships, there is a critical component of creating and nurturing business relationships in order to maintain consistent customer transactions. This is particularly important in B2B sales as current and potential customers lists are usually much smaller than in typical B2C transactions. There is much literature on how relationships and their facets impact sales. The quality of the relationship between selling teams and their key accounts plays a critical role in determining profitability (Gupta, 2019). To create quality business relationships, salespeople need to shift from persuasion-based approaches to communication-centered strategies. Specifically, one should foster interactive communication processes in order to foster trust and commitment (Duncan, 1998). In conjunction with interactive communication, strategic collaboration communication that involves the customer in decision making positively influences key account performance through emphasized trust building, mutual understanding and shared goals (Schultz, 2002). Furthermore, co-producing the product or service with the customer increases performance. However, when the intensity, or stress, associated with co-producing the end result is high, it negatively affects customer satisfaction. But, implementing value-enhancing communication strategies can mitigate this effect (Haumann, 2015). Firms need to measure and manage the value they provide to customers, and the value customers provide to the firm through sales (Kumar, 2016). In order to effectively communicate value and maintain quality of relationships, firms need to understand the most effective type and frequency of communication with their customer. For differing levels of performance from the customer, the level of firm-initiated communication must differ (Ramos, 2024). There are also specific forms of communication that are situationally beneficial. For example, synchronous communication (i.e. face-to-face) is better for repairing a business relationship compared to asynchronous communication (i.e. email). The perceived salesperson competence and warmth mediate the effectiveness of communication formats as well (Mangus, 2024). Regarding modeling this relationship between communication and performance, there have been three key drivers identified: the volume of communication, the mix of communication channels, and the alignment with customers' preferences. Once the ideal level of communication is exceeded, customers begin to react negatively. That negative response can be exacerbated with the use of multichannel communication but mediated by aligning the channels with customer preferences (Godfrey, 2011).

While there is much research on attribution in various business models, there is a lack of literature on attribution models in a B2B sales situation with emphasis on different communication methods or mix of communication methods. This study will empirically show the effectiveness of varying communication methods on sales performance, while also taking into account customer preferences.

Since the survey data that will be used will also feature qualitative data, a text analysis will be crucial to understanding the holistic picture of the customer's perspective. Two methods for making text analysis more effective were suggested by Allenby and Singh. Allenby found that incorporating sentence structure into the text analysis model helps with accuracy and added value, because many sentences are structured with a single underlying topic (Allenby, 2016). Singh tested differing sampling methods in developing a text-analysis model. He found that both a largest number of information units sampling method and a sequential random sampling method were more effective than traditional simple random sampling methods, as they only sampled for information rich data

(Singh, S.N., 2011). Singh emphasizes the limitation and place for further research in adding an additional analysis that draws common themes out of the customer reviews, which we will add to our text analysis model.

An effective model that combines different sectors of knowledge found in previous literature, both theoretical and empirical, will be able to provide empirical evidence that quality communication that aligns with customer preferences will increase sales performance. This would be a more applicable quantitative approach to many of the previously proven sales frameworks. A model showing the effectiveness of communication will provide salespeople with a starting point in their sales strategy as they will know which communication methods are most profitable.

3. The Data

4. BEGINNING OF DELIVERABLE 6

The data used for this research was collected from a Manufacturer Sales Representative Company in the Plumbing Industry. The data was collected using a survey that asked customers to rank their perceived value of various communication methods and how often they preferred those communication methods be used by their sales representative. They also were asked an open ended question about why that communication method was preferred and how that created value for their own companies. The customers were also asked about their preferred method of product trainings, with the same type of open-ended question asking to explain their preferences.

These survey responses were not collected anonymously, so they were then tied back to the sales data from each customer.

In order to make the model more innovative, we chose to implement machine learning text analysis on the open-ended questions from the survey. We input the open-ended text answers into ChatGPT with the prompt to deduce major themes from the answers given. Because the three open-ended questions were different in nature, we had ChatGPT run the answers to each question individually and deduce themes. The themes that selected by ChatGPT can be referred to in the table below.

5. BEGINNING OF DELIVERABLE 8

Question	Theme Number	Extracted Theme
Question 1	1	Preference for In-Person Communication
Question 1	2	Importance of Timely and Accurate Communication (Primarily via Email)
Question 1	3	Value of Strong Vendor Relationships and Support
Question 2	1	Preference for In-Person Interactions and Trainings
Question 2	2	Timely and Effective Communication
Question 2	3	Value of Knowledgeable and Accessible Representatives
Question 3	1	Importance of Knowledgeable, Responsive and Accessible Representatives
Question 3	2	Preference for In-Person Communication and Hands-On Training
Question 3	3	Need for Timely and Comprehensive Information and Support (including digital r

After identifying these themes with machine learning, we also prompted ChatGPT to dummy code whether or not each answer featured each theme or not, which will be taken into consideration with the model later. This was done by connecting to the ChatGPT API and prompting the model with the same prompt for each response.

The figures below indicate a numeric summaries of the preliminary findings of the data.

6. END OF DELIVERABLE 8

7. BEGINNING OF DELIVERABLE 7

Due to the low response rate of this survey, we simulated missing data using the mean quantitative response for each individual question. We did not simulate the open-ended responses, so the models that include the theme extraction binary variables will only be applied to the smaller sample size of question.

Furthermore, we also create variables that indicated whether the survey response was complete or incomplete, and also create a variable that displayed the percentage of questions that were complete within the incomplete survey. This allows us to weight the actual responses higher than the simulated responses. The sales data, however, was not simulated, as the first question allowed for the respondent to be identified. Therefore, only a portion of the survey responses were simulated in order to have a larger quantitative sample for the model to be trained on.

8. END OF DELIVERABLE 7

Numeric Summary of Communication Data

Communication Method	Mean on Scale of 1-5
Email	3.8
Phone Call	4.0
Virtual Meetings	3.0
In Person Meetings	4.1
Small Social Events	3.7
Large Social Events	3.1
Formal Business Meeting	3.3

Numeric Summary of Training Data

Training Method	Mean on Scale of 1-5
No Training	2.6
Hands-On Training	4.4
Distributor's Office Training	3.8
Contractor's Office Training	3.4
Large Group Training	3.5
Small Group Training	4.2
Virtual Training	2.9

9. END OF DELIVERABLE 6

Due to the

10. The Model

11. BEGINNING OF DELIVERABLE 9

In the preliminary stages of modeling, we began with a simple linear regression. Due to the small sample size and large number of variable, finding a variable with a p-value ¡0.05 was not expected.

The first regression run included all of the communication method ranking questions as explanatory variables. With all of these, the Small social gathering had a lower p-value of 0.07 and the Large social gathering had a p-value of 0.11. The small social gathering coefficient was -408,792, while the large social gathering coefficient was 358,269. This potentially shows us that high spending customers do not value small social gatherings with their sales reps, but much more highly value the large social gatherings.

The second regression model included all of the communication method ranking variables as well as the training methods ranking variables as well. With nore variables, it is expected that all of the p-values rise, however the small gathering and the large gathering variables still had relatively low p-values. However, in this model, the large training variable had a low p-value of 0.06 and a coefficient of 420,444 which shows another preference of high spending customers.

The third regression model included all of the dummy coded responses from the ChatGPT theme extraction. The lowest p-value from this regression was Question 2 Theme 1 with a p-value of 0.18.

The fourth regression model included all of the theme extraction responses and all of the ranking question variables as well. Interestingly, in this model, Question 2 Theme 1 had the lowest p-value of all variables at 0.13, while the previous low p-values of other variables increased significantly.

12. END OF DELIVERABLE 9

13. BEGINNING OF DELIVERABLE 10

Principal Component Analysis (PCA) transformation:

$$Z = XW \tag{3}$$

where:

- X is the centered data matrix ($n \times p$).
- W contains the principal component loadings ($p \times k$).
- Z contains the transformed principal components ($n \times k$).

PCA is computed via eigenvalue decomposition of the covariance matrix:

$$\Sigma = \frac{1}{n-1} X^T X \tag{4}$$

Alternatively, PCA can be derived using Singular Value Decomposition (SVD):

$$X = USV^T \tag{5}$$

14. Results and Discussion

Who the heck knows what this ”model” is going to find.

15. Managerial Implications

We apply our model to B2B data. This provides specific implications for business transactions that rely heavily on salesperson relationships with their customers. The results of this paper can help managers understand which communication methods are the most valuable to focus on in a salesperson’s limited time. In a relationship-based industry, the efficiency in which a salesperson can maintain multiple client relationships is directly linked to company profitability.

Variable	PC1	PC2	PC3	PC4
Email	-0.093214794	0.496446106	0.033853869	0.043592145
Phone	-0.133950571	0.195078564	0.628048781	0.393385813
Virtual Meeting	-0.153804265	0.617563168	-0.318525842	-0.011646173
In Person Meeting	-0.207339336	0.330048458	0.440957618	-0.207687462
Small Social Gathering	-0.320078259	-0.231833698	0.043211423	0.248045556
Large Social Gathering	-0.363178447	-0.199290485	-0.260501972	0.361347744
Formal Meeting	-0.444469118	-0.09575489	-0.004508041	0.233149568
No Training	-0.096885091	0.136969736	-0.183622293	0.17510007
Hands-on Training	-0.235522804	0.030385783	0.168364014	-0.034401917
Distributor Training	-0.286789593	-0.114096071	-0.001105666	-0.090902977
Contractor Training	-0.43140392	0.064761923	-0.219275759	-0.55157025
Large Training	-0.273901225	-0.201530254	0.165552479	-0.292169444
Small Training	-0.210035618	-0.144690974	0.11898529	-0.1750205
Virtual Training	-0.149897479	0.155212308	-0.295035073	0.305431373

Table 1 **15x5 Table for PCA Numeric Values**

Principal Component	Standard Deviation
PC1	2.185072953
PC2	1.642587598
PC3	1.416554362
PC4	1.345243993

Table 2 **Standard Deviations for Each Principal Component**

16. Conclusion

In this paper, we have presented a model approach for understanding effective communication techniques in B2B sales relationships. [1] The proposed model provides decision support for B2B companies to best allocate their human capital resources.

Future research directions include applying this model or a similar model to a larger dataset for better statistical validity. This also could be applied to B2B interactions with salesmen-reliant relationships as well to add to the generalizability of this model.

Variable	PC1	PC2	PC3	PC4
Question1 Theme1	0.260452493	-0.56208157	-0.597706212	-0.235135268
Question1 Theme2	0.153939689	0.452093702	-0.047070468	0.115867364
Question1 Theme3	0.337530562	0.073623854	-0.172974467	-0.432820334
Question2 Theme1	0.641353245	-0.409485458	0.475367009	0.358515497
Question2 Theme2	-0.157899623	-0.015950001	-0.146078454	0.004344504
Question2 Theme3	0.056584575	-0.106224828	-0.132984077	0.248354705
Question3 Theme1	0.472937052	0.375414491	0.200863318	-0.504147590
Question3 Theme2	-0.041573231	-0.105963304	-0.073792729	-0.257481135
Question3 Theme3	0.360103196	0.377987305	-0.547560569	0.482969042

Table 3 PCA Loadings for Questions and Themes

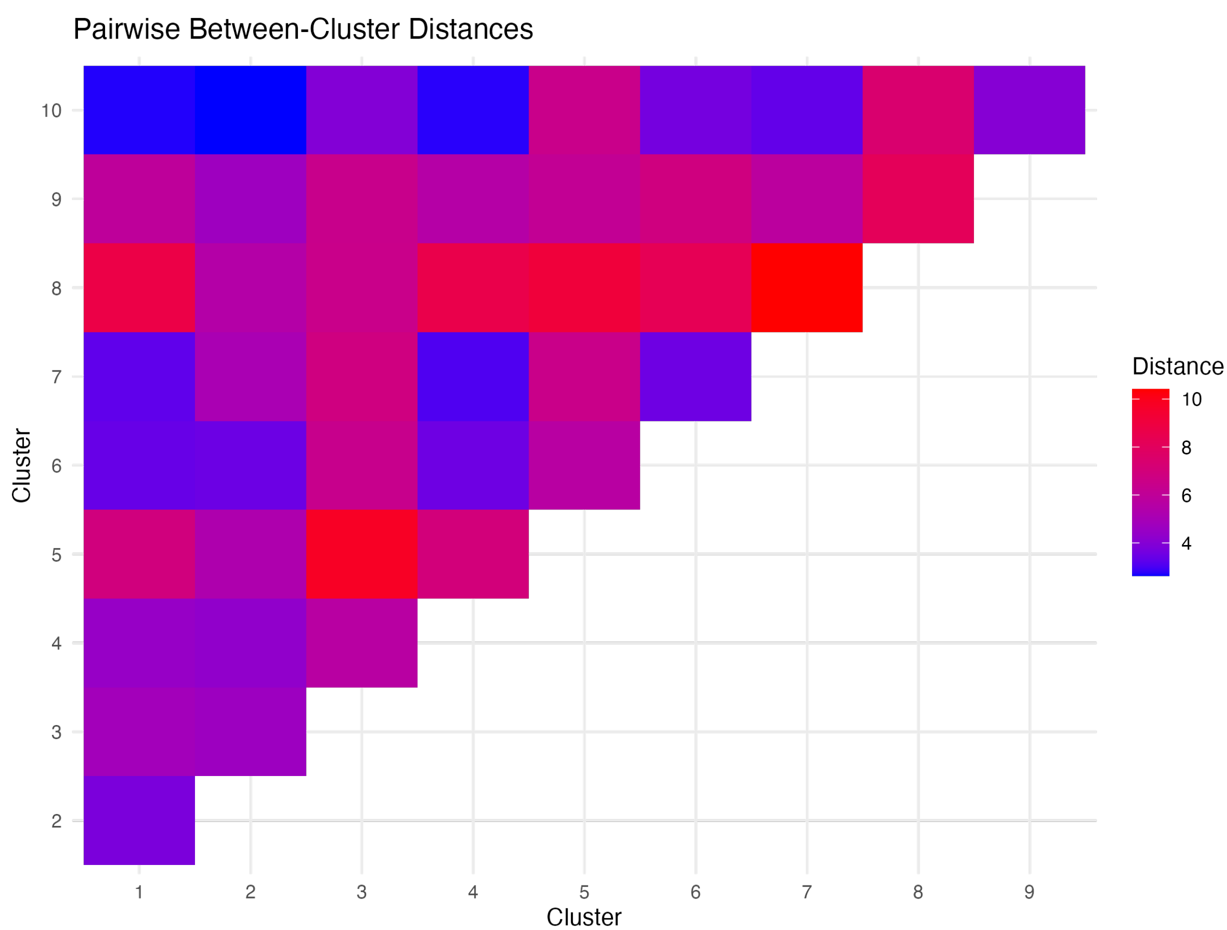

Figure 1 Clusters in PCA Space

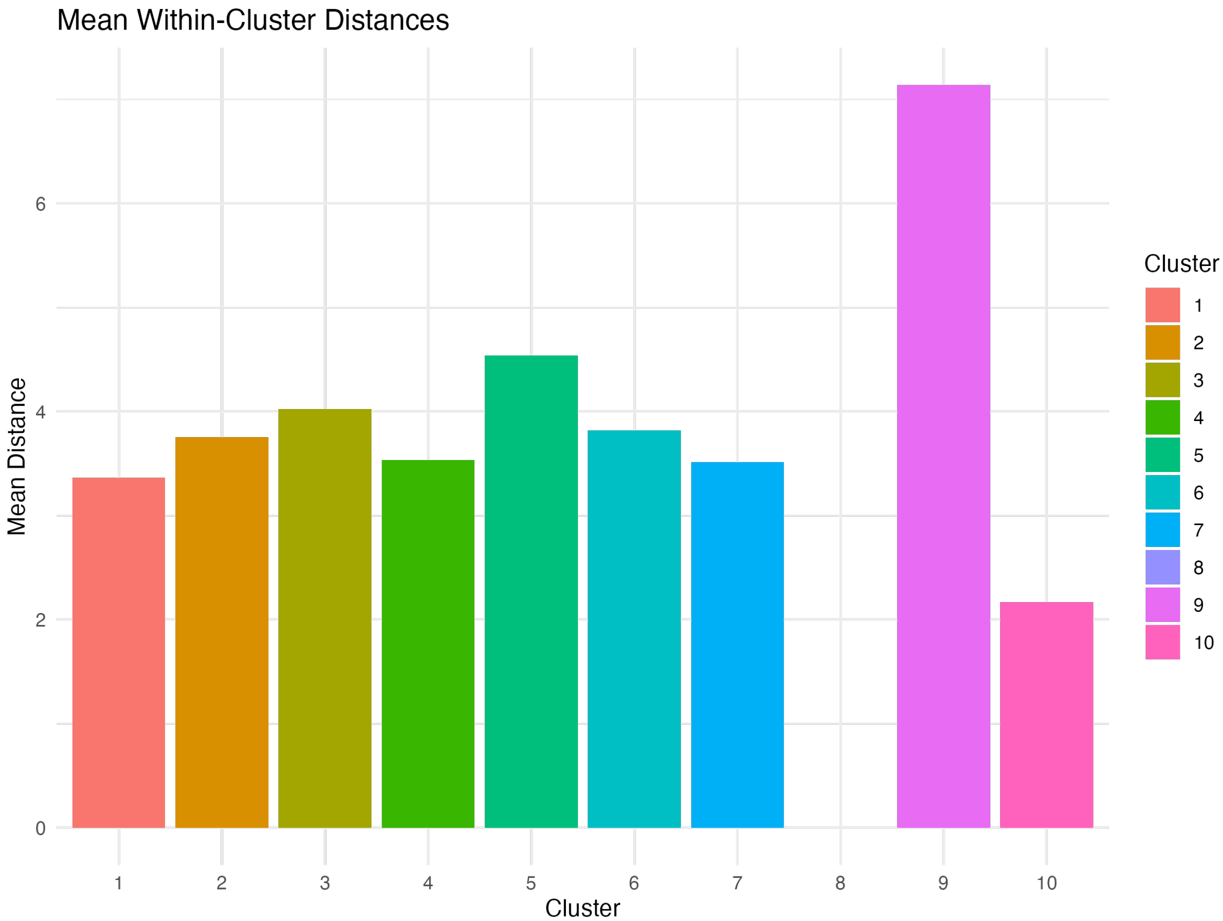

Figure 2 **Mean Distances Within Clusters**

Table 4 **Summary of Data for Case Study**

Parameter	Value
Number of Resources	5
Number of Facilities	10
Number of Scenarios	50
Demand Variability	High
Budget Constraint	$1,000,000
Transportation Cost	$10 per unit
Facility Setup Cost	$5,000 per facility

Table Notes.

Notes

[1]Sample endnote text.

Acknowledgments

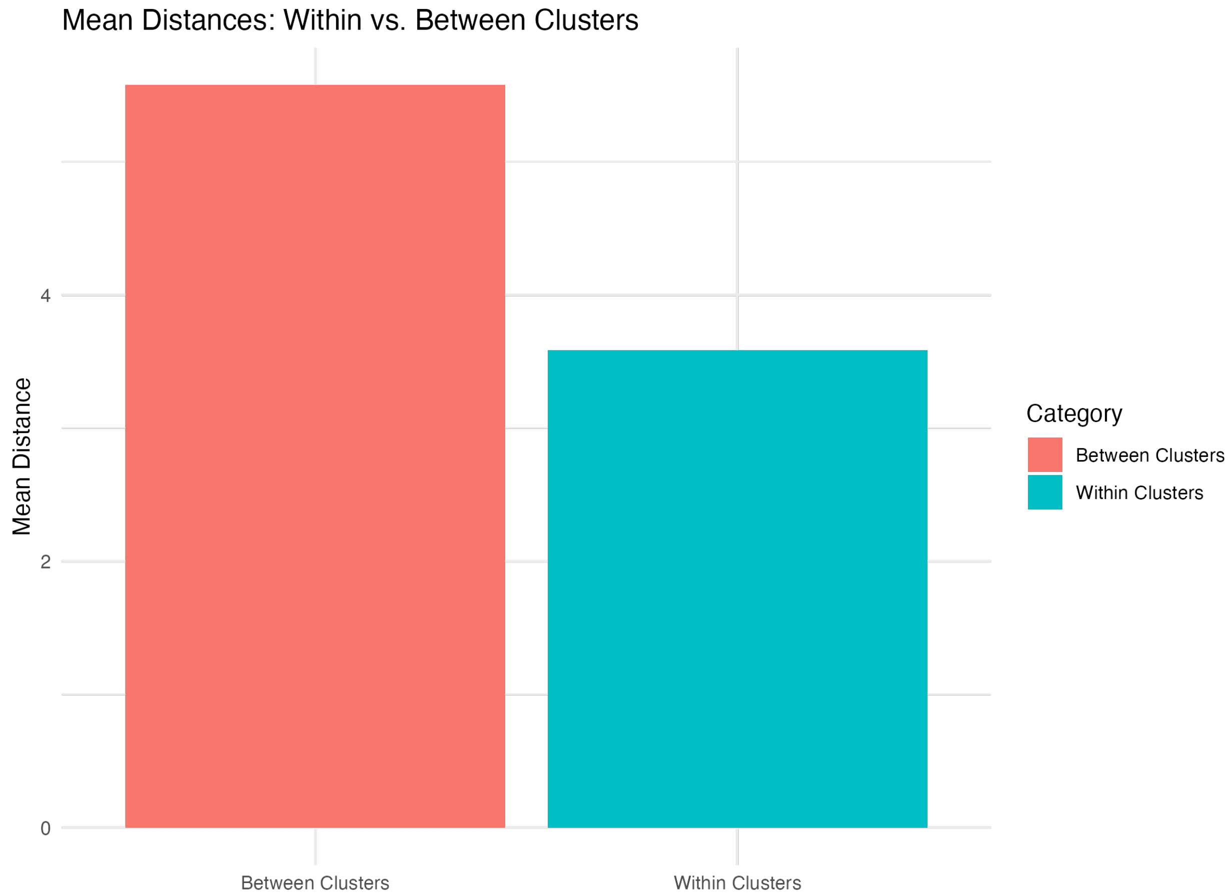

Figure 3 **Mean Distances With and Without Clusters Comparison**

We would like to express our sincere gratitude to Brigham Young University for their invaluable contributions to this research. We are also grateful to Mega Western Sales for their support and assistance throughout the course of this work.

References

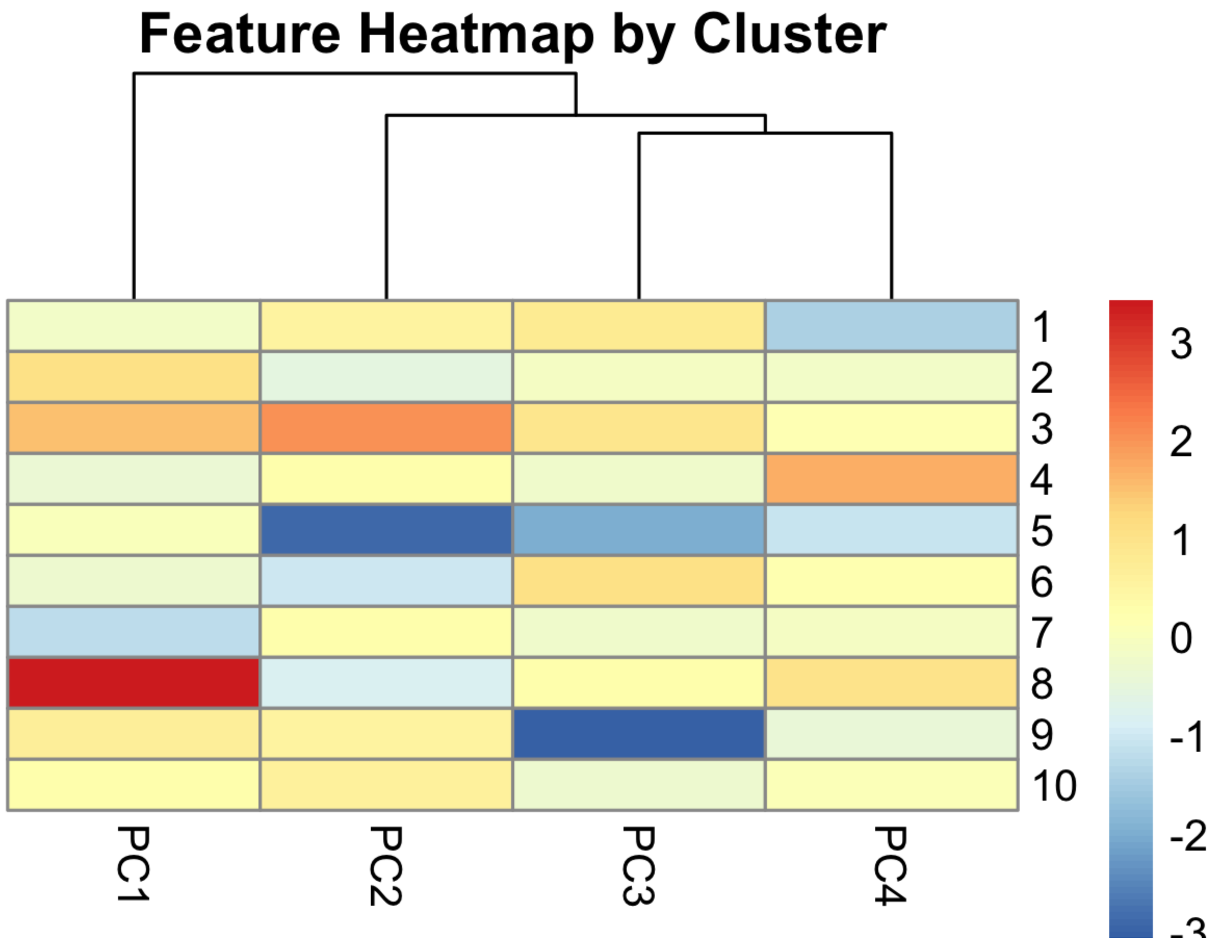

Figure 4 **Mean Distances With and Without Clusters Comparison**

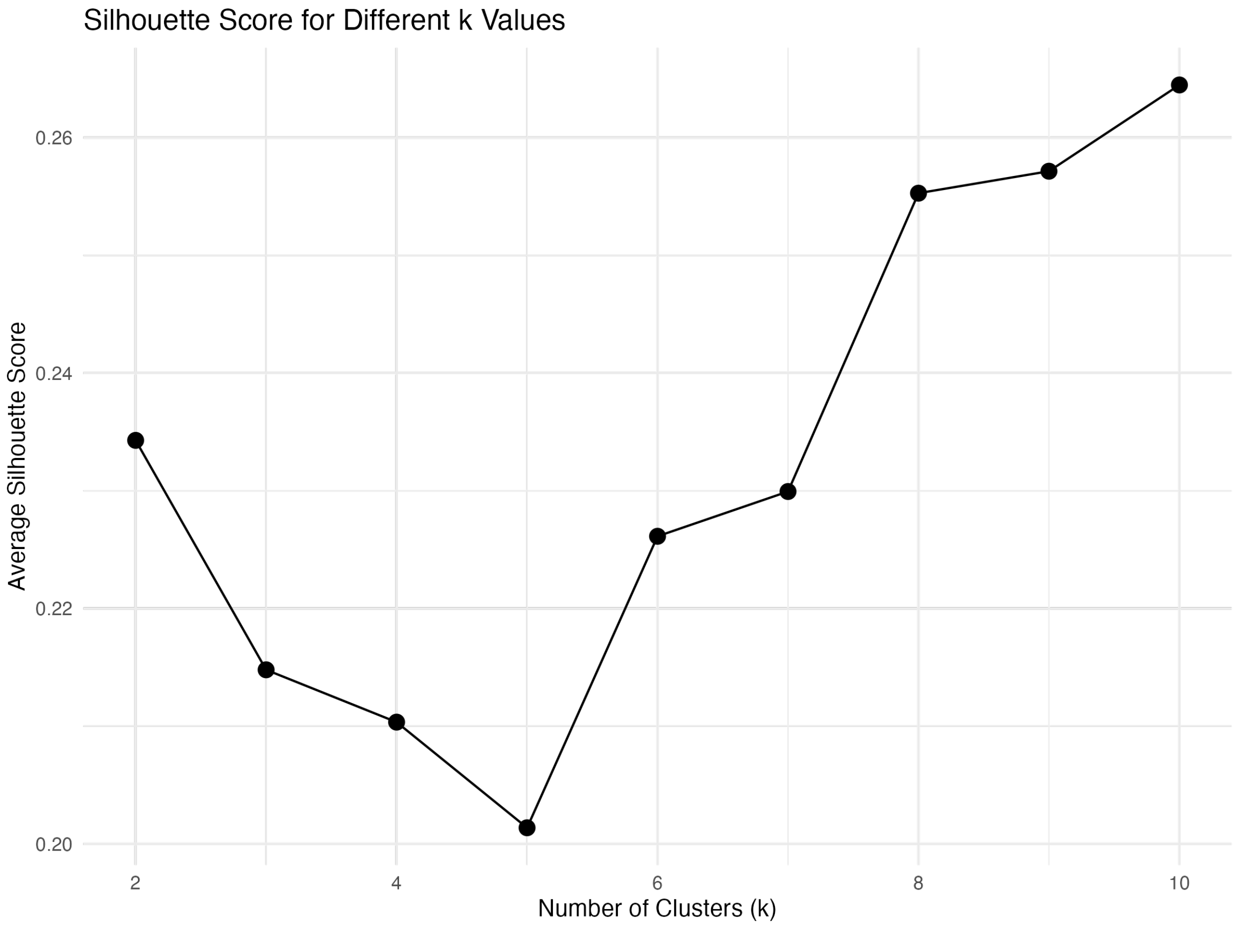

Figure 5 Silhouette Score