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## Interaction Effects of Somatic Cell Count and Milk Yield on Milk Composition in Lactating Dairy Cows: A Synergistic Analysis<sup>#</sup>

### ABSTRACT

**Objective:** This study aimed to investigate the interaction effect between somatic cell count and milk yield on the composition of milk components in dairy cows.

**Material and Methods:** The study involved 165 clinically healthy lactating Holstein cows with an average parity of 1.76 and an average of 221 days in milk. Cows were grouped using K-means clustering analysis based on somatic cell count and milk yield. Milk samples were collected daily during the 30-day experimental period and analyzed for composition. A 2x2 factorial design was employed to examine the main and interaction effects of somatic cell count and milk yield on milk components.

**Results:** The interaction affected various milk components. Specifically, a higher somatic cell count combined with increased milk yield was associated with higher levels of solids at  $12.70\% \pm 0.02$ , fat at  $3.76\% \pm 0.02$ , true protein at  $3.26\% \pm 0.01$ , casein at  $2.42\% \pm 0.01$ , and milk urea nitrogen at  $10.84 \text{ mg/dL} \pm 0.13$ . Lactose concentration significantly increased to  $5.06\% \pm 0.01$  ( $P=0.01$ ). Notably, this interaction effect resulted in a significant increase in lactose concentration ( $P=0.01$ ).

**Conclusion:** The study confirms an interaction effect between somatic cell count and milk yield on milk composition, emphasizing the need to consider both factors for optimizing milk quality. The observed increase in lactose concentration due to the interaction effect underscores the complexity of somatic cell count and milk yield dynamics, suggesting potential implications for udder health and dairy management practices.

**Keywords:** Somatic cell count, milk yield, milk composition, dairy cows, udder health, milk quality

## Laktasyon Dönemindeki Süt İneklerinde Somatik Hücre Sayısı ve Süt Verimi Etkileşiminin Süt Kompozisyonu Üzerindeki Etkileri: Sinerjik Bir Analiz

### ÖZ

**Amaç:** Bu çalışmanın amacı, somatik hücre sayısı ile süt verimi arasındaki etkileşimin süt ineklerinde süt bileşenleri üzerindeki etkisini araştırmak olmuştur.

**Materyal ve Metot:** Çalışma, ortalama 1,76 doğum sayısına ve ortalama 221 sağım gün sayısına sahip 165 adet klinik olarak sağlıklı laktasyon dönemindeki Holstein süt ineğini kapsamaktadır. İnekler, somatik hücre sayısı ve süt verimine göre K-means kümeleme analizi kullanılarak gruplandırılmıştır. Süt örnekleri, 30 günlük araştırma süresi boyunca günlük olarak toplanmış ve kompozisyonu analiz edilmiştir. Somatik hücre sayısı ve süt veriminin süt bileşenleri üzerindeki ana etki ve sinerjik etkisini incelemek için 2x2 faktöriyel tasarım methodu kullanılmıştır.

**Bulgular:** Etkileşim, süt bileşenlerini etkilemiştir. Özellikle, yüksek somatik hücre sayısı ile yüksek süt verimine sahip inek sütlerinin kuru maddesi  $12.70 \pm 0.02$ , süt yağı  $3.76 \pm 0.02$ , süt proteini  $3.26 \pm 0.01$ , süt kazeini  $2.42 \pm 0.01$  ve süt üre azotu  $10.84 \text{ mg/dL} \pm 0.13$  olduğu tespit edilmiştir. Süt laktoz konsantrasyonu anlamlı şekilde artarak  $5.06 \pm 0.01$  olduğu tespit edilmiştir ( $P=0.01$ ). Özellikle, etkileşimin laktoz konsantrasyonunda anlamlı bir artışa neden olduğu tespit edilmiştir ( $P=0.01$ ).

**Sonuç:** Çalışma, somatik hücre sayısı ile süt verimi arasındaki etkileşimin süt bileşenleri üzerine etkisini doğrulamakta ve süt kalitesini optimize etmek için her iki faktörün de dikkate alınması gerektiğini vurgulamaktadır. Etkileşim nedeniyle gözlenen laktoz miktarındaki artış, süt bileşenlerinin dinamiklerini öne çıkarmakta olup meme sağlığı ve yönetsel uygulamalar için potansiyel sonuçları göstermektedir.

**Anahtar Kelime:** Somatik hücre sayısı, süt verimi, süt içeriği, süt ineği, meme sağlığı, süt kalitesi



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## INTRODUCTION

Dairy farming plays a vital role in global agriculture (Bach et al., 2020; Brito et al., 2021; Odorcic et al., 2019; Tosun, 2021; Tricarico et al., 2020), providing essential nutrition and economic sustenance to populations worldwide (Ataallahi et al., 2023; Bach et al., 2020; Lim et al., 2020; Soufleri et al., 2021). Central to dairy production is the maintenance of udder health, milk production efficiency, and the quality of dairy products. Somatic cell count (SCC), an indicator of udder health, and milk yield (MY), a measure of production efficiency, are crucial parameters influencing milk composition and overall dairy farm dynamics (Gussmann et al., 2019; Santman-Berends et al., 2021; Waller et al., 2020). Understanding the interaction effect between SCC and MY on milk components is essential for early mastitis diagnosis, optimizing udder health, enhancing milk quality, and improving farm profitability (Neculai-Valeanu and Ariton, 2022; Sharun et al., 2021; Zigo et al., 2021). In recent years, researchers have increasingly recognized the complex relationship between SCC, MY, and milk composition. Although acceptable levels of somatic cells in milk can vary depending on various factors such as geographical region, regulatory standards, breed of cattle, and specific requirements of dairy processors (Alhussien and Dang, 2018), elevated SCC levels have been associated with alterations in milk components, impacting dairy product quality and consumer preferences. Conversely, variations in MY have been shown to influence milk composition, reflecting physiological changes in cows and affecting overall production efficiency. However, the interplay between SCC and MY remains a subject of ongoing investigation, with implications for dairy management practices and industry standards.

SCC levels signify the presence of somatic cells, primarily leukocytes, mobilized as part of the immune response to intramammary infections (Bronzo et al., 2020; Carvalho-Sombra et al., 2021). Monitoring SCC is integral for early disease detection and intervention, as persistent high counts can compromise milk quality, reduce yield, and impact animal welfare (Santman-Berends et al., 2021; Waller et al., 2020). On the other hand, MY, a fundamental measure of a cow's productivity is a key determinant of a dairy farm's economic success (Azooz et al., 2020; Sehested et al., 2019; Tosun and Ceyhan, 2015). While the individual impacts of breed, housing, feeding conditions, SCC and MY on milk quality have been extensively studied, the intricate interrelationship between these two factors remains a subject warranting deeper exploration (Costa et al., 2020; Pegolo et al., 2021).

This research aims to bridge this knowledge gap by investigating how variations in SCC and MY collectively influence the composition of milk components. Milk components are not only vital for product quality but also have economic implications for dairy farmers (Bozic and Wolf, 2022; Grace et al., 2020; Puerto et al., 2021). Understanding how SCC and MY synergistically shape these components can provide valuable insights for optimizing herd health, enhancing milk quality, and improving overall farm profitability. In summary, this study hypothesizes a significant interaction effect between SCC and MY, impacting the composition of milk components in dairy cows. Therefore, the main objective is to determine the quantitative impact of the interaction between SCC and MY on key milk components, including solid, fat, protein, lactose, casein, and milk urea nitrogen (MUN).

## MATERIAL and METHODS

This study was conducted at a commercial dairy farm in the Marmara region of Turkiye in September – October 2021, with a focus on examining the interaction effect between SCC and MY on milk components in dairy cows.

### Animals

A total of 165 clinically healthy lactating dairy cows of the Holstein breed, with an average parity of 1.76 and an average of 221 days in milk, were recruited for this study. The selection process aimed to ensure a diverse representation of characteristics, including age, parity, and lactation stage. Consequently, the significant differences observed in the age, parity, and days in milk among the animals in the study reflect the natural variation within the dairy herd population. The cows were housed in a well-ventilated and temperature-controlled barn with access to clean water and appropriate feed. All cows were fed a total mixed ration (TMR) three times a day at 0800, 1600, and 2200 h, aiming for a leftover of 5% to 10%. Feeding with formulated TMR began 30 days before the experimental period to allow for the adaptation of rumen microorganisms and to mitigate biases in milk yield and composition.



### Grouping of Cows

K-means clustering analysis was conducted to group cows with similar intra-group characteristics and inter-group differences, using SCC and MY as clustering variables. The K-means clustering method was assessed using the widely employed sum of square error (SSE) criterion outlined in the equation provided (Nainggolan et al., 2019; Tan et al., 2006).

$$SSE = \sum_{i=1}^K \sum_{x \in C_i} \text{dist}^2 (m_i, x)$$

Within the equation, "dist" represents the Standard Euclidean Distance, "x" denotes a member of cluster  $C_i$ , and "mi" stands for the centroid of cluster  $C_i$ . The Euclidean distance function operates as described below:

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^p (x_{ik} - x_{jk})^2}$$

In this function,  $x_i$  and  $x_j$  represent the coordinates of one point, while  $x_{ik}$  and  $x_{jk}$  represent the coordinates of another point. It calculates the Euclidean distance between two points in a  $p$ -dimensional space.

For evaluating the MY of cows, the 4% fat-corrected milk (4% FCM) is determined using the following formula (Hall, 2023):

$$4\%FCM = 0.4 \times \text{milk yield} + 15 \times \text{fat yield}$$

Following the clustering process, a 2x2 factorial design was employed to investigate the interaction effect between SCC and MY on milk components in dairy cows. The two independent variables were SCC and MY, each with two levels, resulting in four experimental groups structured as Factor A: Somatic cell count (SCC0 = low somatic cell count, and SCC1 = high somatic cell count), Factor B: Milk yield (MY0 = low milk yield, and MY1 = high milk yield). The combination of the levels of both factors results in the formation of four experimental groups: (1) SCC0+MY0, denoted as CON (control), (a) SCC1 representing high SCC, (b) MY1 representing high MY, and (ab) SCC1MY1 representing high SCC with high MY.

### Sampling and Data Collection

The data were collected for each cow, including initial SCC, MY, and milk component composition during the 30-d experimental period. Total mixed ration (TMR) and leftover samples were collected twice a week and frozen at  $-20^{\circ}\text{C}$  for subsequent analysis to calculate the dry matter intake (DMI) and net energy (NE) intake. NE intake was calculated using the equations provided by the National Academies of Sciences and Medicine (2021), and NE intake was determined by multiplying DMI by the net energy for lactation (NEL) in Mcal per kilogram of dry matter. Cows were milked three times a day at 0700, 1500, and 2100 h. Milk samples were collected daily during milking and refrigerated ( $4-6^{\circ}\text{C}$ ) until analysis of composition and SCC. Before analysis, each milk sample was homogenized using a magnetic stirrer. The homogenized samples were then transferred to falcon tubes, heated in a water bath to  $40^{\circ}\text{C}$ , and 20 mL was taken for analysis. The analysis of various milk components, including milk solids (%), fat (%), true protein (%), casein (%), lactose (%), and milk urea nitrogen (MUN) concentration (mg/dL), was performed using the MilkoScan (CombiFoss 78110; Foss Analytical A/S, Hillerød, Denmark).

### Data Analyses

The normality and homoscedasticity assumptions were evaluated using pertinent statistical tests, affirming that the dataset conformed to a normal distribution. Subsequently, a multivariate version of the general linear model analysis was conducted for the 2x2 factorial design utilizing the formula:

$$Y_{ij} = \mu + SCC_i + MY_j + (\alpha\beta)_{ij} + \epsilon_{ij}$$

where  $Y_{ijkl}$  is the dependent variable,  $\mu$  is the overall mean,  $SCC_i$  represents the main effect of the  $i$ th level of SCC,  $MY_j$  represents the main effect of the  $j$ th level of MY,  $(\alpha\beta)_{ij}$  represents the interaction effect between



the  $i$ th level of SCC and the  $j$ th level of MY,  $e_{ij}$  is the error term. For the 2x2 factorial design, a two-way analysis of variance (ANOVA) was conducted to assess the main effects of each independent variable (SCC and MY) and their interaction effect on the dependent variable (milk components). A post-hoc test (Tukey's HSD) was performed to explore specific differences between significant interaction groups. Statistical analyses were stratified based on relevant variables such as parity, lactation stage, and breed. Data analysis were conducted using IBM SPSS Advanced Statistics 20.0 (SPSS Inc., Chicago, IL, USA), and significance was set at a predetermined alpha level ( $p < 0.05$ ).

## RESULTS

The research findings have been given under two subheadings: (i) Characteristics of experimental groups, (ii) interaction effect on milk components. Descriptive statistics of the experimental cows are presented in Table 1.

**Table 1.** The descriptive statistics

**Table 1.** Tanımlayıcı istatistikleri

Cows <sup>1</sup>	Min	Max	Mean	SD
DMI, kg/d	19.27	23.63	22.59	1.42
Age, mo	21.30	54.90	43.25	5.44
Parity	1.00	3.00	1.76	0.47
DIM, d	2.00	859.00	221.05	222.73
Gestation, d	47.00	249.00	144.25	48.49
SCC, cells/mL	322.000	557.857	444.981	54.183
Milk yield, Lt/d	33.13	48.90	39.39	1.95
Solid, %	12.27	13.44	12.82	0.27
Fat, %	3.38	4.36	3.87	0.2
True protein, %	3.16	3.48	3.31	0.09
Casein, %	2.32	2.67	2.48	0.08
Lactose, %	4.75	5.21	4.97	0.10
MUN, mg/dL	8.56	15.97	11.59	1.62

<sup>1</sup>DMI: dry matter intake, DIM: days in milk, SCC: somatic cell count, MUN: milk urea nitrogen

### Characteristics of Experimental Groups

Table 2 displays the statistical characteristics of clusters categorized by SCC and MY. Notably, clusters with low SCC (SCC<sub>0</sub>) exhibited a mean of  $386.925 \pm 30.840$  cells/mL (95% CI: 379.160 to 394.690), contrasting with high SCC clusters (SCC<sub>1</sub>) with a mean of  $480.840 \pm 27.970$  cells/mL (95% CI: 475.350 to 486.335). Similarly, clusters representing low milk yield (MY<sub>0</sub>) showed a mean of  $37.92 \pm 1.14$  Liters/day (95% CI: 37.68 to 38.16), while those with high milk yield (MY<sub>1</sub>) had a mean of  $41.02 \pm 1.24$  Liters/day (95% CI: 40.74 to 41.30).

**Table 2.** The statistical characteristics of clustures for somatic cell count and milk yield

**Table 2.** Somatik hücre sayısı ve süt verimi bakımından kümelerin istatistiksel karakteristikleri

Items <sup>1</sup>	N	Min	Max	Mean $\pm$ SD	%95 CI	
					Lower	Upper
SCC <sub>0</sub> (cells /mL)	63	322.000	433.500	386.925 $\pm$ 30.840	379.160	394.690
SCC <sub>1</sub> (cells /mL)	102	435.000	557.850	480.840 $\pm$ 27.970	475.350	486.335
MY <sub>0</sub> (Liters /d)	87	33.13	39.43	37.92 $\pm$ 1.14	37.68	38.16
MY <sub>1</sub> (Liters /d)	78	39.56	48.90	41.02 $\pm$ 1.24	40.74	41.30

<sup>1</sup>SCC<sub>0</sub>: low in somatic cell count, SCC<sub>1</sub>: high in somatic cell count, MY<sub>0</sub>: low in milk yield, MY<sub>1</sub>: high in milk



Table 3 provides a comprehensive summary of mean values for SCC and MY across various experimental groups. In the combined experimental groups, the mean SCC is 444.981 cells/mL, and the mean MY is 39.39 liters/day/cow. The control group exhibits a mean SCC of 388.453 cells/mL and a mean MY of 38.37 liters/day/cow. The experimental group SCC1 shows a mean SCC of 481.310 cells/mL and a mean MY of 37.65 liters/day/cow. For the high MY group MY1, the mean SCC is 385.241 cells/mL, and the mean MY is 41.29 liters/day/cow. Lastly, the experimental group SCC1MY1 displays a mean SCC of 480.311 cells/mL and a mean MY of 40.86 liters/day/cow.

**Table 3.** The mean values of somatic cell count and milk yield of the groups

**Table 3.** Gruplarının somatik hücre sayısı ve süt verimi ortalama değerleri

Factors <sup>1</sup>	N	SCC (cells/mL)		MY (Liters/d/cow)	
		Means	SD	Means	SD
(y)	165	444.981	54.183	39.39	1.95
(1)	33	388.453	30.435	38.37	0.80
(a)	54	481.310	30.279	37.65	1.23
(b)	30	385.241	31.705	41.29	1.77
(ab)	48	480.311	25.429	40.86	0.74

**1(y):** The combination of the experimental groups, **(1):** SCC0MY0 as control group (CON), **(a):** SCC1 as high somatic cell count, **(b):** MY1 as high milk yield, **(ab):** SCC1MY1 as high somatic cell count with high milk yield

#### Interaction Effect on Milk Components

Table 4 present the significant findings of the interaction effect analysis between SCC and MY regarding DMI and NE intake. For DMI, both SCC and MY significantly influence intake (p-values: 0.02 and 0.01, respectively), with SCCxMY showing non-significance (p = 0.431). Significant effect sizes ( $\eta^2$ ) indicate a medium effect for SCC ( $\eta^2=0.06$ ) and a high effect for MY ( $\eta^2=0.63$ ), while the effect size for the combined SCCxMY ( $\eta^2=0.01$ ) is not statistically significant, suggesting a small effect. Similarly, for NE intake, SCC and MY significantly influence intake (p-values: 0.02 and 0.01, respectively), while SCCxMY is not significant (p = 0.431). The SEM for NE intake is 11.19 Mcal/d. These findings highlight MY's substantial influence on intake measures compared to SCC, which has a large effect as known.

**Table 4.** The interaction effect of somatic cell count and milk yield on dry matter and net energy intake

**Table 4.** Somatik hücre sayısı ve süt verimi etkileşiminin kuru madde ve net enerji alımı üzerine etkisi

Items <sup>2</sup>	Factors					P-Values			Eta squared ( $\eta^2$ ) <sup>1</sup>		
	CON	SCC	MY	SCCxMY	SEM	SCC	MY	SCCxMY	SCC	MY	SCCxMY
DMI (kg/d)	18.53	18.18	19.94	19.73	19.02	0.02	0.01	0.431	0.06	0.63	0.01
NE intake(Mcal/d)	10.90	10.70	11.73	11.60	11.19	0.02	0.01	0.431	0.06	0.63	0.01

<sup>1</sup>Effect sizes, "large" when  $d \geq 0.08$ , "medium" when  $d \geq 0.05$ , and "small" when  $d \geq 0.02$  (Cohen, 1992), <sup>2</sup>DMI: dry Matter intake; NE: net energy

Table 5 presents significant findings on the intricate interplay between SCC and MY concerning various milk components, while Figure 1 illustrates the estimated marginal means of lactose levels resulting from their interaction. An increase in SCC is associated with elevated levels of solid content (12.91%), fat (3.93%), true protein (3.34%), casein (2.51%), and MUN (11.99 mg/dL), along with a reduction in lactose concentration (4.95%). Furthermore, an increase in MY significantly impacts solid content (12.83%) and casein levels (2.50%), while decreasing fat (3.87%) and lactose concentrations (4.94%), highlighting MY's role in shaping these milk components. Notably, the interaction effect of SCC and MY results in a significant increase in lactose



concentration (5.06%,  $p = 0.01$ ), indicating a dynamic synergy between SCC and MY. This interaction demonstrates a medium effect size ( $\eta^2 = 0.06$ ), underscoring their collective impact on lactose concentration.

**Table 5.** The interaction effect of somatic cell count and milk yield on milk components

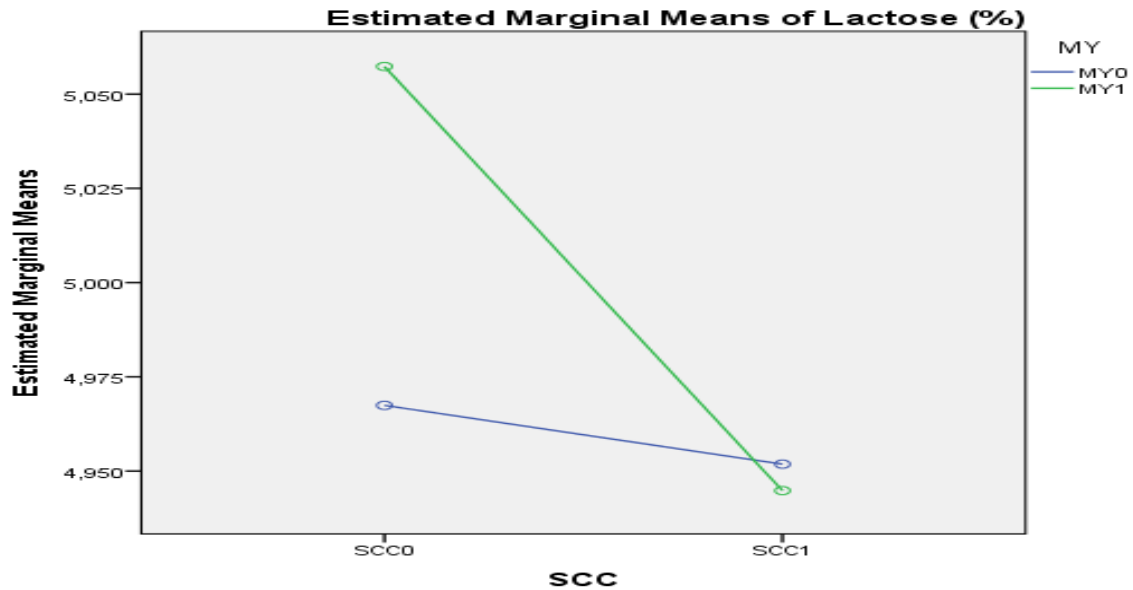
**Table 5.** Somatik hücre sayısı ve süt verimi etkileşiminin süt bileşenleri üzerine etkisi

Items	Factors				SEM	P-Values			Eta squared ( $\eta^2$ ) <sup>1</sup>		
	CON	SCC	MY	SCCxMY		SCC	MY	SCCxMY	SCC	MY	SCCxMY
Solid (%)	12.80	12.91	12.83	12.70	0.02	0.01	0.04	0.76	0.05	0.03	0.01
Fat (%)	3.88	3.93	3.87	3.76	0.02	0.01	0.01	0.29	0.04	0.05	0.01
Tru Prot. (%)	3.26	3.34	3.33	3.26	0.01	0.01	0.76	0.97	0.18	0.00	0.00
Casein (%)	2.46	2.51	2.50	2.42	0.01	0.01	0.05	0.13	0.16	0.02	0.02
Lactose (%)	4.97	4.95	4.94	5.06	0.01	0.01	0.01	0.01	0.10	0.04	0.06
MUN (mg/dL)	11.03	11.99	11.98	10.84	0.13	0.01	0.68	0.72	0.10	0.00	0.00

<sup>1</sup>Effect sizes, "large" when  $d \geq 0.08$ , "medium" when  $d \geq 0.05$ , and "small" when  $d \geq 0.02$  (Cohen, 1992)

**Figure 1.** Estimated marginal means of lactose concentration in response to the interaction between somatic cell count and milk yield

**Şekil 1.** Somatik hücre sayısı ve süt verimi arasındaki etkileşime bağlı olarak laktöz konsantrasyonunun tahmini marjinal ortalamaları



## DISCUSSION and CONCLUSION

Our study aimed to investigate the interaction effect of SCC and MY on various milk components to gain insights into milk quality dynamics. The results confirmed a notable interaction effect, highlighting the importance of jointly considering SCC and MY for understanding milk composition. Both SCC and MY significantly influenced DMI and NE intake, with MY showing a more pronounced effect, as expected. Effect sizes for SCC and MY in DMI and NE intake were moderate and high, respectively. The intricate interplay between SCC and MY significantly affected solid (%), fat (%), true protein (%), casein (%), MUN (mg/dL), and lactose (%) concentration. Specifically, the interaction effect led to an increased lactose concentration, indicating dynamic synergy between SCC and MY. These results align with our study's objectives and support the hypothesized interaction effect between SCC and MY on milk components. The greater impact of MY on DMI and NE intake is consistent with expectations, underscoring its significance in dairy farm economics. The observed influences on milk components highlight the importance of comprehensively understanding SCC and MY interactions.



Comparisons with existing literature highlight both consistencies and novel contributions. Consistent with prior studies (Stocco et al., 2020; Ndahetuye et al., 2020; Costa et al., 2020), our findings reaffirm the impact of SCC on milk quality. However, a significant novel contribution of our study lies in elucidating the substantial influence of MY on milk components, particularly the unexpected increase in lactose concentration when interacting with SCC (Goncalves et al., 2020; Leitner et al., 2004; Malek dos Reis et al., 2013; Pakrashi et al., 2023; Santman-Berends et al., 2021; Yalçın and Çakmak, 2022; Waller 2021; Waller et al., 2020). This unique finding challenges conventional perspectives and emphasizes the need for a more nuanced understanding of these interactions in the context of udder health. Previous research has consistently highlighted the potential of lactose concentration as an indicator for early detection of udder health issues (Pyorala, 2003; Ebrahimie et al., 2018; Antanaitis et al., 2021). Our study supports this notion while uncovering a contradiction concerning MY. Contrary to earlier findings, we observed a significant increase in lactose levels when interacting with SCC in cows with high MY. This suggests a complex relationship between lactose, MY, and SCC, underscoring the necessity for further investigation. Furthermore, our study emphasizes the intricate relationship between SCC and milk composition. Elevated SCC, indicative of potential udder health challenges, has been consistently associated with alterations in milk components (Rowe et al., 2024; Schwarz et al., 2020). Recognizing this link enhances our ability to implement targeted interventions for maintaining optimal udder health. Our findings also highlight the pivotal role of MY in modulating the impact of SCC on milk composition. Cows with higher milk yields exhibit distinct patterns in lactose concentration, further emphasizing the need for tailored approaches in managing udder health.

Potential explanations for the findings include the immune response reflected in SCC, as indicated by previous studies (Stocco et al., 2020; Ndahetuye et al., 2020; Costa et al., 2020). The significant impact of MY on milk quality suggests physiological changes in cows that affect milk composition, as suggested by researches (Hennessy et al., 2020; Gorelik et al., 2021). Considering alternative explanations and potential confounding variables is essential, necessitating further investigation into the intricate mechanisms shaping milk quality. These findings have broader implications for dairy management practices, highlighting the interdependence of SCC and MY in shaping milk quality.

The dynamic interaction between SCC and MY underscores the necessity for holistic approaches in dairy management. While our study focused on elucidating the interplay between SCC and MY in shaping milk composition, it is crucial to recognize the growing interest in lactose-free milk driven by consumer concerns regarding lactose intolerance. However, a notable limitation of our study is the lack of specific assessment regarding the presence of genetic traits necessary for producing lactose-free milk in the studied animals. Future research endeavors could explore the feasibility and implications of integrating lactose-free gene editing techniques into dairy cow breeding programs, enabling a more comprehensive understanding of the impact of SCC and MY on lactose content. Acknowledging limitations, such as the specificity of the studied population and potential unaccounted variables, is essential for transparent interpretation of the results. Future studies should address these limitations to enhance the robustness of findings. Building upon this study, future research should delve into specific mechanisms governing the interaction between SCC and MY, exploring potential biomarkers and molecular pathways. Additionally, investigating the practical applications of these findings in on-farm management and diagnostics would significantly contribute to the field.

In conclusion, this study investigated the interaction between somatic cell count and milk yield on milk composition in lactating dairy cows. Our findings highlight a significant interaction effect, emphasizing the need to consider both factors to understand milk quality. The interplay between somatic cell count and milk yield affected milk components, including solids, fat, true protein, casein, milk urea nitrogen, and lactose, with a significant increase in lactose concentration. Our research underscores the importance of considering the interaction between somatic cell count and milk yield, rather than their individual effects, to better understand milk composition. We also found discrepancies in previous studies on lactose levels when accounting for MY, indicating the need for further investigation.

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## REFERENCES

- Alhussien MN, Dang AK. 2018. Milk somatic cells, factors influencing their release, future prospects, and practical utility in dairy animals: An overview. *Veterinary World*, 11(5), 562. [https://doi: 10.14202/vetworld.2018.562-577](https://doi.org/10.14202/vetworld.2018.562-577)
- Antanaitis R, Juozaitienė V, Jonike V, Baumgartner W, Paulauskas A. 2021. Milk lactose as a biomarker of subclinical mastitis in dairy cows. *Animals*, 11(6), 1736. <https://doi.org/10.3390/ani11061736>
- Ataallahi M, Cheon SN, Park GW, Nugrahaeningtyas E, Jeon JH, Park KH. 2023. Assessment of stress levels in lactating cattle: Analyzing cortisol residues in commercial milk products in relation to the temperature-humidity index. *Animals (Basel)*, 13(15). 2407. <https://doi.org/10.3390/ani13152407>
- Azooz MF, El-Wakeel SA, Yousef HM. 2020. Financial and economic analyses of the impact of cattle mastitis on the profitability of Egyptian dairy farms. *Veterinary World*, 13(9), 1750-1759. <https://doi.org/10.14202/vetworld.2020.1750-1759>
- Bach A, Terre M, Vidal M. 2020. Decomposing efficiency of milk production and maximizing profit. *Journal of Dairy Science*, 103(6), 5709-5725. <https://doi.org/10.3168/jds.2019-17304>
- Bozic M, Wolf CA. 2022. Negative producer price differentials in federal milk marketing orders: Explanations, implications, and policy options. *Journal of Dairy Science*, 105(1), 424-440. <https://doi.org/10.3168/jds.2021-20664>
- Brito LF, Bedere N, Douhard F, Oliveira HR, Arnal M, Penagaricano F, Schinckel AP, Baes CF, Miglior F. 2021. Genetic selection of high-yielding dairy cattle toward sustainable farming systems in a rapidly changing world. *Animal*, 15 Suppl 1, 100292. <https://doi.org/10.1016/j.animal.2021.100292>
- Bronzo V, Lopreiato V, Riva F, Amadori M, Curone G, Addis MF, Cremonesi P, Moroni P, Trevisi E, Castiglioni B. 2020. The role of innate immune response and microbiome in resilience of dairy cattle to disease: The mastitis model. *Animals*, 10(8), 1397. <https://doi.org/10.3390/ani10081397>
- Carvalho-Sombra TCF, Fernandes DD, Bezerra BMO, Nunes-Pinheiro DCS. 2021. Systemic inflammatory biomarkers and somatic cell count in dairy cows with subclinical mastitis. *Veterinary Animal Science*, 11, 100165. <https://doi.org/10.1016/j.vas.2021.100165>
- Cohen J. 1992. Statistical power analysis. *Current Directions in Psychological Science*, 1(3), 98-101. <https://doi.org/10.1111/1467-8721.ep10768>
- Costa A, Neglia G, Campanile G, De Marchi M. 2020. Milk somatic cell count and its relationship with milk yield and quality traits in Italian water buffaloes. *Journal of Dairy Science*, 103(6), 5485-5494. <https://doi.org/10.3168/jds.2019-18009>
- Ebrahimie E, Ebrahimi F, Ebrahimi M, Tomlinson S, Petrovski KR. 2018. A large-scale study of indicators of sub-clinical mastitis in dairy cattle by attribute weighting analysis of milk composition features: highlighting the predictive power of lactose and electrical conductivity. *Journal of Dairy Research*, 85(2), 193-200. <https://doi.org/10.1017/S0022029918000249>
- Goncalves JL, Kamphuis C, Vernooij H, Araujo JP, Grenfell RJ, Juliano L, Anderson KL, Hogeveen H, Dos Santos MV. 2020. Pathogen effects on milk yield and composition in chronic subclinical mastitis in dairy cows. *The Veterinary Journal*, 262, 105473. <https://doi.org/10.1016/j.tvjl.2020.105473>





- Grace D, Wu F, Havelaar AH. 2020. Foodborne diseases from milk and milk products in developing countries- Review of causes and health and economic implications. *Journal of Dairy Science*, 103(11), 9715-9729. <https://doi.org/10.3168/jds.2020-18323>
- Gorelik OV, Galushina PS, Knysh IV, Bobkova EY, Grigoryants IA. 2021. Relationship between cow milk yield and milk quality indicators. *Earth and Environmental Science*, Vol. 677, No. 3, p. 032013. <https://doi.org/10.1088/1755-1315/677/3/032013>
- Gussmann M, Denwood M, Kirkeby C, Farre M, Halasa T. 2019. Associations between udder health and culling in dairy cows. *Preventive Veterinary Medicine*, 171, 104751. <https://doi.org/10.1016/j.prevetmed.2019.104751>
- Hall MB. 2023. Corrected milk: Reconsideration of common equations and milk energy estimates. *Journal of Dairy Science*, 106(4): p. 2230-2246.
- Hennessy D, Delaby L, Van den Pol-Van Dasselaar A, Shalloo L. 2020. Increasing grazing in dairy cow milk production systems in Europe. *Sustainability*, 12(6), 2443. <https://doi.org/10.3390/su12062443>
- Leitner G, Merin U, Silanikove N. 2004. Changes in milk composition as affected by subclinical mastitis in goats. *Journal of Dairy Science*, 87(6), 1719-1726. [https://doi.org/10.3168/jds.S0022-0302\(04\)73325-1](https://doi.org/10.3168/jds.S0022-0302(04)73325-1)
- Lim DH, Mayakrishnan V, Lee HJ, Ki KS, Kim TI, Kim Y. 2020. A comparative study on milk composition of Jersey and Holstein dairy cows during the early lactation. *Journal of Animal Science Technology*, 62(4), 565-576. <https://doi.org/10.5187/jast.2020.62.4.565>
- Malek dos Reis CB, Barreiro JR, Mestieri L, Porcionato MA, Dos Santos MV. 2013. Effect of somatic cell count and mastitis pathogens on milk composition in Gyr cows. *BMC Veterinary Research*, 9, 67. <https://doi.org/10.1186/1746-6148-9-67>
- Nainggolan R, Perangin-Angin R, Simarmata E, Tarigan AF. 2019. Improved the performance of the K-means cluster using the sum of squared error (SSE) optimized by using the Elbow method. *Journal of Physics: Conference Series*.
- National Academies of Sciences Engineering and Medicine. 2021. Nutrient requirements of dairy cattle: Eighth revised edition. The National Academies Press. <https://doi.org/doi:10.17226/25806>
- Neculai-Valeanu AS, Ariton AM. 2022. Udder health monitoring for prevention of bovine mastitis and improvement of milk quality. *Bioengineering (Basel)*, 9(11), 608. <https://doi.org/10.3390/bioengineering9110608>
- Ndahetuye JB, Artursson K, Bage R, Ingabire A, Karege C, Djangwani J, Persson Y. 2020. Microbiological quality and safety of milk from farm to milk collection centers in Rwanda. *Journal of Dairy Science*, 103(11), 9730-9739. <https://doi.org/10.3168/jds.2020-18302>
- Odorcic M, Rasmussen MD, Paulrud CO, Bruckmaier RM. 2019. Milking machine settings, teat condition and milking efficiency in dairy cows. *Animal*, 13(S1), s94-s99. <https://doi.org/10.1017/S1751731119000417>
- Pakrashi A, Ryan C, Gueret C, Berry DP, Corcoran MT, Keane MT, Mac Namee B. 2023. Early detection of subclinical mastitis in lactating dairy cows using cow-level features. *Journal of Dairy Science*, 106(7), 4978-4990. <https://doi.org/10.3168/jds.2022-22803>
- Pegolo S, Giannuzzi D, Bisutti V, Tessari R, Gelain M, Gallo L, Schiavon S, Tagliapietra F, Trevisi E, Marsan PA. 2021. Associations between differential somatic cell count and milk yield, quality, and technological characteristics in Holstein cows. *Journal of Dairy Science*, 104(4), 4822-4836. <https://doi.org/10.3168/jds.2020-19084>
- Puerto MA, Shepley E, Cue RI, Warner D, Dubuc J, Vasseur E. 2021. The hidden cost of disease: Impact of the first incidence of mastitis on production and economic indicators of primiparous dairy cows. *Journal of Dairy Science*, 104(7), 7932-7943. <https://doi.org/10.3168/jds.2020-19584>
- Pyorala S. 2003. Indicators of inflammation in the diagnosis of mastitis. *The Veterinary Research*, 34(5), 565-578. <https://doi.org/10.1051/vetres:2003026>



- Rowe S, House JK, Zadoks RN. 2024. Milk as diagnostic fluid for udder health management. *Australian Veterinary Journal*, 102(1-2), 5-10. <https://doi.org/10.1111/avj.13290>
- Santman-Berends I, Van den Heuvel KWH, Lam T, Scherpenzeel CGM, Van Schaik G. 2021. Monitoring udder health on routinely collected census data: Evaluating the short- to mid-term consequences of implementing selective dry cow treatment. *Journal of Dairy Science*, 104(2), 2280-2289. <https://doi.org/10.3168/jds.2020-18973>
- Schwarz D, Santschi DE, Durocher J, Lefebvre DM. 2020. Evaluation of the new differential somatic cell count parameter as a rapid and inexpensive supplementary tool for udder health management through regular milk recording. *Preventive Veterinary Medicine*, 181, 105079. <https://doi.org/10.1016/j.prevetmed.2020.105079>
- Sehested J, Gaillard C, Lehmann JO, Maciel GM, Vestergaard M, Weisbjerg MR, Mogensen L, Larsen LB, Poulsen NA, Kristensen T. 2019. Extended lactation in dairy cattle. *Animal*, 13(S1), s65-s74. <https://doi.org/10.1017/S1751731119000806>
- Sharun K, Dhama K, Tiwari R, Gugjoo MB, Iqbal Yatoo M, Patel SK, Pathak M, Karthik K, Khurana SK, Singh R, Puvvala B, Amarpal Singh R, Singh KP, Chaicumpa W. 2021. Advances in therapeutic and managerial approaches of bovine mastitis: A comprehensive review. *Veterinary Quarterly*, 41(1), 107-136. <https://doi.org/10.1080/01652176.2021.1882713>
- Singla A, Karambir M. 2012. Comparative analysis & evaluation of euclidean distance function and manhattan distance function using k-means algorithm. *International Journal of Advanced Research in Computer Science and Software Engineering (IJARSSE)*, 2(7), 298-300.
- Stocco G, Summer A, Cipolat-Gotet C, Zanini L, Vairani D, Dadousis C, Zecconi A. 2020. Differential somatic cell count as a novel indicator of milk quality in dairy cows. *Animals*, 10(5), 753. <https://doi.org/10.3390/ani10050753>
- Soufleri A, Banos G, Panousis N, Fletouris D, Arsenos G, Kougioumtzis A, Valergakis GE. 2021. Evaluation of factors affecting colostrum quality and quantity in Holstein dairy cattle. *Animals (Basel)*, 11(7), 2005. <https://doi.org/10.3390/ani11072005>
- SPSS Inc. 2011. *IBM SPSS Statistics Base 20*. Chicago, IL: SPSS Inc.
- Yalçın H, Çakmak T. 2022. İnek Sütlerinde Somatik Hücre Sayısı ve Bazı Parametrelerin Araştırılması. *MJAVL Sciences*. 11 (2) 81-88. <https://doi.org/10.53518/mjavl.1092994>
- Tan PN, Steinbach M, Kumar V. 2006. *Data mining introduction*. People's Posts and Telecommunications Publishing House, Beijing.
- Tosun HI. 2021. TRCI bölgesinde süt sağırıcılığı işletmelerinin karlılık ve etkinlik analizi Ondokuz Mayıs Üniversitesi. PhD Thesis
- Tosun HI, Ceyhan V. 2015. Current situation in dairy industry and feed efficiency of professional dairy farms of Turkey. *Sustainable Agriculture and Environment Proceeding Book*, 175.
- Tricarico JM, Kebreab E, Wattiaux MA. 2020. Sustainability of dairy production and consumption in low-income countries with emphasis on productivity and environmental impact. *Journal of Dairy Science*, 103(11), 9791-9802. <https://doi.org/10.3168/jds.2020-18269>
- Waller KP, Lundberg A, Nyman AK. 2020. Udder health of early-lactation primiparous dairy cows based on somatic cell count categories. *Journal of Dairy Science*, 103(10), 9430-9445. <https://doi.org/10.3168/jds.2020-18346>
- Zigo F, Vasil M, Ondrasovicova S, Vyrostkova J, Bujok J, Pecka-Kielb E. 2021. Maintaining optimal mammary gland health and prevention of mastitis. *Frontier Veterinary Science*, 8, 607311. <https://doi.org/10.3389/fvets.2021.607311>