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THE EFFECTIVENESS OF COLD BEVERAGES VERSUS ICE-SLURRY DRINKS ON THE ATHLETIC PERFORMANCE OF THAI FUTSAL PLAYERS USING K-MEANS CLUSTERING

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ABSTRACT

Cooling interventions during futsal halftime breaks show substantial individual variability in physiological responses, yet standardized protocols fail to account for athlete-specific thermal stress susceptibility. This study employed This study used K-means clustering to compare the effectiveness of cold beverages versus ice slurry and to identify distinct physiological response phenotypes for personalized cooling strategy optimization. Ten competitive male futsal players (22.4 ± 2.1 years; 68.5 ± 8.2 kg) completed a randomized crossover design. Following the Futsal Intermittent Shuttle-Run Protocol (FIRP), participants consumed either ice slurry (-1°C) or cold sports beverages (4°C) at 7.5 g/kg body mass during 10-minute recovery. Futsal-specific reactive agility tests (RAG-D, RAG-T), blood lactate, heart rate, urine specific gravity, and perceived exertion were measured. K-means clustering analysis with silhouette validation identified response patterns. Three distinct physiological phenotypes emerged (silhouette coefficient = 0.67). Cluster 1 (High-Response, n=4): elevated blood lactate (>8.0 mmol/L), highest cardiovascular stress, superior ice-slurry response. Cluster 2

(Moderate-Response, n=3): balanced responses to both modalities. Cluster 3 (Low-Response, n=3): conservative responses with maintained performance, preferential ice-slurry benefits. Strong correlations existed between body mass and response magnitude (r = 0.78, p < 0.01). Unsupervised machine learning effectively discerned unique cooling response phenotypes, facilitating evidence-based customization of cooling therapies. This signifies a substantial progression in the accuracy of sports performance enhancement.

KEYWORDS: Futsal, Cooling Interventions, Machine Learning, Phenotypic Classification, Personalized Sports Medicine.

1. INTRODUCTION

Futsal, a five-a-side form of soccer consisting of one goalie and four outfield players, is a high-intensity intermittent sport marked by repeated maximal sprints followed by short rest intervals. (Naser, Ali, & Macadam, 2017). the sport consists of two 20-minute halves with a 10-minute halfway intermission, requiring outstanding physiological and physical qualities from competitors. (Spyrou, Freitas, Marín-Cascales, & Alcaraz, 2020). During competition, futsal players experience progressive fatigue due to the continuous high-intensity nature of the game, which requires repeated maximal sprint efforts, rapid changes of direction, and sustained cardiovascular stress throughout the match (Barbero-Alvarez et al., 2008, Doğramacı & Watsford, 2006).

The physiological demands of futsal are significant, since players sustain cardiovascular exertion beyond 85% of their maximal heart rate for over 80% of the actual playing duration (Ayarra et al., 2018). In matches, participants traverse between 3000-4500 meters, with 26% of the total distance executed at high-intensity levels and approximately 26 sprints per match (Caetano et al., 2015, Trabelsi et al., 2014). This vigorous activity pattern results in a substantial increase in core body temperature, recognized as a principal factor in exercise-induced weariness and performance deterioration (Lloyd et al., 2015, Périard et al., 2015).

Although direct measurements of core temperature elevation in futsal players during competition remain limited, research conducted on futsal referees demonstrated average core temperatures reaching approximately 38.58°C during matches (Dixon, 2014). Such elevated core temperatures have profound implications for athletic performance, particularly affecting neural fatigue mechanisms that influence cognitive function, decision-making processes, and neuromuscular control (Tyler et al., 2016, Nybo & González-Alonso, 2015). Moreover, hyperthermia has been specifically shown to impair reactive agility performance, a critical determinant of success in futsal (Duvnjak-Zaknich et al., 2011).

Reactive agility represents one of the most important mechanical fitness attributes for futsal players, requiring the ability to execute high-speed running with rapid directional changes in response to external stimuli (Sekulic et al., 2019, Sekulic et al., 2021). This capacity is essential for successful performance in futsal-specific actions such as ball interception, defensive positioning, and offensive maneuvering during match play (Pojskic et al., 2018). Research has demonstrated that reactive agility performance, particularly when involving ball manipulation skills such as dribbling, significantly differentiates between performance levels in professional futsal players (Pojskic et al., 2015, Tanyeri, 2020). The ability to maintain optimal reactive agility throughout the match duration is therefore crucial for sustaining competitive performance.

Internal cooling measures, especially ice-slurry consumption, have proven to be efficient methods for controlling exercise-induced hyperthermia and sustaining athletic performance in elevated temperatures (Siegel et al., 2010, Stevens et al., 2013). Ice-slurry, generally produced at temperatures ranging from -1°C to +1°C, offers enhanced cooling efficiency relative to standard cold beverages due to the significant energy necessary for the phase transition from solid to liquid (Stanley et al., 2010, Tan & Lee, 2015). Research indicates that pre-exercise administration of ice slurry in doses of 7-14 g/kg of body mass considerably lowers core body temperature by roughly 0.4-0.7°C and improves exercise performance across multiple sports modalities (Naito et al., 2020, Alhadad et al., 2019).

The physiological mechanisms underlying ice slurry's performance benefits include increased heat storage capacity, reduced central fatigue through lowered brain temperature, and enhanced thermal perception (Bongers et al., 2017, Morrison et al., 2014). Research indicates that the consumption of ice slurry during high-intensity intermittent exercise can enhance performance, even with little intake amounts during short recovery intervals, rendering it especially relevant for sports with restricted break durations, such as futsal (Pryor et al., 2015, Yeo et al., 2012). The cooling sensation provided by ice slurry may also contribute to maintaining central drive and motivation to exercise, thereby supporting sustained performance (Pryor et al., 2015, Yeo et al., 2012, Trong et al., 2015).

Currently, futsal athletes commonly consume sports drinks during halftime breaks to replenish energy, fluids, and electrolytes lost during the first half of competition. These beverages are typically stored in ice-filled containers to maintain cool temperatures; however, this practice lacks systematic temperature control or optimization based on scientific evidence. Anecdotal observations suggest that reactive agility performance, particularly in defensive actions such as ball interception and tackling, tends to deteriorate during the second half of matches compared to first-half performance levels.

The utilization of machine learning methodologies, especially K-means clustering, has garnered heightened acknowledgment in the examination of sports performance for discerning patterns in athlete responses and enhancing training interventions (Shelly, 2020, An, 2025). K-means clustering, an unsupervised learning algorithm, categorizes athletes according to similarities in their physiological responses and performance patterns, facilitating objective, data-driven evaluations of intervention efficacy (Carpita et al., 2015, Robertson et al., 2016). This approach has been successfully implemented in various sports contexts, including the creation of training groups based on game demands and the analysis of performance patterns across different competitive scenarios (Narizuka & Yamazaki, 2019, Zachary et al., 2020).

K-means clustering in cooling intervention studies can reveal unique response patterns that typical statistical methods may overlook. Through the examination of physiological factors including core temperature, heart rate, perceived exertion, and performance metrics, the algorithm can determine if particular response patterns are more closely linked to specific cooling tactics. This methodology facilitates a more refined comprehension of individual variability in response to various interventions and may pinpoint subgroups of athletes that optimally respond to cooling protocols (Sinaga & Yang, 2020, Ahmed et al., 2020).

Although the advantages of ice-slurry consumption for thermoregulation and athletic performance are well-documented, prior studies have not specifically examined its impact on reactive agility performance in futsal athletes. The comparative efficacy of rigorously managed ice-slurry beverages vs traditional cold drinks during halftime breaks in futsal competitions has yet to be investigated. The integration of machine learning approaches to analyze complex physiological and performance data in this context represents an innovative methodological approach that may provide deeper insights into optimal cooling strategies for futsal athletes.

This study aims to examine the relative efficacy of cold sports drinks compared to ice-slurry drinks ingested during halftime on reactive agility performance in Thai futsal players. To be employed K-means clustering analysis to discern patterns in physiological reactions and performance outcomes, facilitating an objective, data-driven comparison of the two cooling systems. We hypothesized that ice-slurry ingestion would demonstrate superior maintenance of reactive agility performance compared to cold beverage consumption and that K-means clustering would reveal distinct response patterns associated with each intervention strategy.

2. METHODS

Ten competitive male futsal athletes (age: 22.4 ± 2.1 years; body mass: 68.5 ± 8.2 kg; height: 172.3 ± 6.8 cm) participated in a randomized crossover study consisting of four sessions: familiarization, baseline assessment, and two experimental trials (ice-slurry vs. cold beverage) with a minimum separation of seven days. All testing was conducted indoors between 17:00-19:00 hours with continuous environmental monitoring. Informed consent was acquired from all participants, and the study received approval from the institutional ethics committee. The Srinakharinwirot Ethics Committee accepted this study under No. SWUEC-244/2564E.

Participants refrained from intense activity, caffeine, alcohol, and smoking for 24 hours before testing and ingested 500 mL of water 2 hours prior to arrival. Upon arrival, urine specific gravity (USG), body mass, resting heart rate, blood lactate, and rating of perceived effort (RPE; Borg 6-20 scale) were evaluated. The authenticated Futsal Intermittent Shuttle-Run Protocol (FIRP) (Dal Pupo et al., 2017) was subsequently, it was executed to replicate futsal-specific requirements across six activity intensities: sedentary (0 km/h), walking (6 km/h), jogging (8.5 km/h), moderate running (13 km/h), high-intensity running (17 km/h), and maximal sprinting (≥18 km/h). The protocol consisted of six cycles including a total distance of 1,718 meters, with 30-second inter-cycle pauses and a 3-minute rest following the third cycle. Ad libitum water intake at 37°C was allowed and documented.

Following FIRP completion, participants underwent a 10-minute recovery period during which they consumed either ice-slurry (-1°C) prepared from frozen isotonic sports drink or cold isotonic sports drink (Pocari Sweat; 4°C) at 7.5 g/kg body mass (Naito & Ogaki, 2016,Kim et al., 2013). Futsal-specific reactive agility was subsequently assessed using validated tests (Pojskic et al., 2015): Reactive Agility with Dribbling (RAG_D) and Reactive Agility with Ball Touch (RAG_T). Each test was performed twice with the best time recorded, with recovery periods of 3 minutes between trials and 5 minutes between test types to prevent fatigue interference.

Throughout all procedures, heart rate was continuously monitored using chest strap telemetry, while fingertip blood samples (25 µL) were collected pre-exercise, immediately post-FIRP, and post-testing for lactate analysis. USG was measured pre- and post-testing using refractometry, and sweat rate was calculated from body mass changes and fluid intake (Naito & Ogaki, 2016). RPE was assessed at rest, post-FIRP, and post-testing. All physiological and performance variables were standardized (z-score transformation) and analyzed using K-means clustering with Euclidean distance metrics.

Optimal cluster number was determined via elbow method and silhouette analysis, with cluster validation employing silhouette coefficients and within-cluster sum of squares to identify distinct response patterns associated with cooling intervention effectiveness.

2.1. K-Means Clustering Analysis

The dataset comprised physiological and performance variables from all participants across both experimental conditions, including RAG_D performance, RAG_T performance, blood lactate concentrations, heart rate responses, RPE values, USG measurements, body mass changes, fluid intake volumes, and sweat rates.

Before doing the clustering analysis, all variables were standardized using z-score transformation to provide uniform weighting irrespective of measurement scale. The ideal number of clusters was established by the elbow approach and silhouette analysis. K-means clustering was executed utilizing Euclidean distance metrics to categorize individuals according to their physiological response patterns and performance results.

Cluster validation was performed utilizing silhouette coefficients and within-cluster sum of squares. The investigation sought to discover unique response patterns linked to the efficacy of cooling interventions and individual differences in thermoregulatory and performance responses.

2.2. The K-Means Machine Learning Algorithm

$$Dist(X,Y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

K-means clustering is an unsupervised machine learning approach that divides datasets into K unique clusters by optimizing intra-cluster similarity and reducing inter-cluster similarity. The procedure repeatedly allocates data points to the closest centroid and updates centroids until convergence, therefore minimizing the overall within-cluster sum of squares. The ideal number of clusters was established by the elbow technique and silhouette analysis, employing Euclidean distance as the similarity metric to categorize participants according to their physiological response patterns and performance results.

The elbow method is a heuristic technique for identifying the best number of clusters by graphing the within-cluster sum of squares (WCSS) against different K values. The ideal K is identified at the elbow point, where an increase in the number of clusters results in declining returns in the reduction of WCSS, signifying little enhancement in cluster compactness.

2.3. Data Classification Using K-Means Clustering

K-means clustering successfully identified three distinct physiological response phenotypes (k=3) with good cluster separation (silhouette coefficient = 0.67).

Cluster 1 (High-Response, n=4) exhibited the most pronounced physiological responses, with elevated blood lactate concentrations (post-cold: 7.52 ± 0.84 mmol/L; Post-Ice: 8.07 ± 0.91 mmol/L), highest cardiovascular stress (peak HR >185 bpm), greatest body mass (72.3 ± 2.1 kg), and highest sweat rates (1.4-1.8 L/h). This group showed superior response to ice-slurry intervention with reduced performance variability compared to cold beverages.

Cluster 2 (Moderate-Response, n=3) demonstrated intermediate physiological responses across all parameters (blood lactate post-cold: 6.18 ± 0.72 mmol/L; Post-Ice: 6.45 ± 0.68 mmol/L; body mass: 67.4 ± 1.8 kg), exhibiting balanced adaptation to both cooling interventions with equivalent effectiveness of either modality.

Cluster 3 (Low-Response, n=3) showed conservative physiological responses with lowest blood lactate accumulation (post-cold: 4.92 ± 0.58 mmol/L; Post-Ice: 5.13 ± 0.62 mmol/L), minimal cardiovascular strain, lowest body mass (61.8 ± 2.4 kg), and reduced sweat rates (0.8-1.2 L/h). Despite lower metabolic stress, this group maintained optimal reactive agility performance and demonstrated preferential response to ice-slurry intervention.

Perceptual responses (RPE) varied systematically across clusters, with Cluster 1 reporting highest subjective exertion and Cluster 3 showing lowest perceptual strain for equivalent physiological demands. The clustering revealed distinct phenotypes: High-Response athletes with greater thermal stress susceptibility, Moderate-Response athletes with balanced physiological profiles, and Low-Response athletes with superior metabolic efficiency and thermal regulation.

3. DISCUSSION

This study represents the first investigation to employ machine learning-based phenotyping to characterize individual responses to cooling interventions in futsal athletes. The K-means clustering analysis successfully identified three distinct physiological response phenotypes, providing novel insights into athlete response heterogeneity to ice-slurry versus cold beverage interventions. These findings challenge conventional "one-size-fits-all" cooling approaches and suggest that personalized intervention protocols may optimize performance outcomes in intermittent high-intensity sports.

The identification of distinct response phenotypes aligns with growing recognition of individual differences in sports performance interventions (Scalona et al., 2024, Wergin et al., 2022). Recent advances in precision medicine demonstrate that personalized approaches, guided by individual characteristics and response patterns, yield superior outcomes compared to standardized protocols (Reis et al., 2024, Kumar et al., 2022). Our clustering methodology successfully captured this heterogeneity, revealing that athletes with different anthropometric and physiological characteristics exhibit varying responses to cooling interventions, consistent with emerging paradigms in personalized sports medicine (Patel et al., 2009,Johnson et al., 2021).

3.1. Physiological Phenotype Characterization

High-Response Phenotype (Cluster 1) demonstrated the most pronounced physiological responses, characterized by elevated blood lactate concentrations (>8.0 mmol/L), heightened cardiovascular stress, and greater absolute fluid requirements. This phenotype likely represents individuals with higher metabolic demands and potentially compromised thermoregulatory efficiency (Bongers et al., 2017). The correlation between higher body mass and greater physiological stress responses ($r = 0.78$) supports previous findings that larger athletes experience proportionally greater thermal strain during high-intensity intermittent exercise Périard et al., 2021,Casa et al., 2015). The superior response to ice-slurry intervention in this group can be explained by enhanced heat storage capacity and more substantial core temperature reduction (Racinais et al., 2012, Iwata et al., 2020).

Moderate-Response Phenotype (Cluster 2) exhibited balanced physiological responses across all measured parameters, suggesting optimal adaptation to high-intensity intermittent exercise with effective utilization of both cooling modalities. This phenotype may represent individuals with well-developed thermoregulatory systems and efficient lactate clearance mechanisms (Tyler et al., 2016, Racinais et al., 2015).

Low-Response Phenotype (Cluster 3) demonstrated conservative physiological responses with maintained performance despite lower absolute physiological stress indicators. This phenotype suggests superior metabolic efficiency and enhanced thermal tolerance, characteristics associated with elite athletic performance in thermally challenging environments (Cheuvront & Kenefick, 2014, Armstrong et al., 2007, Maughan et al., 2012).

3.2. Implications for Personalized Cooling Strategies

The identification of distinct response phenotypes has significant implications for implementing personalized cooling strategies in competitive futsal. Current cooling intervention guidelines provide generalized recommendations without considering individual response variability (Roriz et al., 2022, Daanen et al., 2018). Our findings suggest that athletes with different phenotypic characteristics may benefit from tailored cooling protocols, supporting emerging trends toward precision medicine approaches in sports science (Reardon et al., 2019, Silva et al., 2024).

For high-response athletes (Cluster 1), ice-slurry interventions appear to provide substantial performance benefits due to their greater thermal stress and higher baseline physiological demands. Conversely, athletes in Cluster 3 demonstrated consistent performance maintenance regardless of cooling modality, suggesting potential flexibility in intervention selection. These findings align with recent meta-analytical evidence demonstrating that cooling intervention effectiveness varies considerably among individuals and depends on multiple factors including exercise protocol, environmental conditions, and athlete characteristics (Bongers et al., 2017, Roriz et al., 2024).

3.3. Machine Learning Applications in Sports Science

The successful application of K-means clustering to characterize cooling intervention responses contributes to growing literature demonstrating the value of machine learning approaches in sports medicine (Reis et al., 2024, Kumar et al., 2022, Claudino et al., 2019). Unsupervised learning methods provide distinct benefits for identifying concealed patterns in intricate physiological datasets without preconceived notions on group affiliation

(Sinaga & Yang, 2020, Likas et al., 2003). The incorporation of artificial intelligence and machine learning in sports science has shown considerable promise for injury prediction, performance enhancement, and individualized training strategies, which our research expands to include cooling intervention studies.

3.4. Practical Implementation

The identification of response phenotypes provides a framework for developing practical implementation strategies for cooling interventions in futsal. Athletes could be phenotyped through initial assessment sessions to determine optimal cooling strategies, similar to approaches used in personalized nutrition and training prescription (Kerksick et al., 2018). The strong association between anthropometric characteristics and response patterns suggests that simple measurements (body mass, baseline physiological responses) could predict phenotype membership without requiring complex assessment protocols, important for implementation in real-world sporting environments (Thomas et al., 2016).

3.5. Study Limitations and Future Directions

Unsupervised learning methods provide distinct benefits for identifying concealed patterns in intricate physiological datasets without preconceived notions on group affiliation (67, 68). The study was conducted in controlled indoor conditions, and responses may differ in outdoor environments. Additionally, the investigation focused on male futsal players, and generalizability to female athletes or other sports requires further investigation (Borg, 1982, Notley et al., 2019).

Future research should investigate genetic and physiological mechanisms underlying the identified phenotypes. Integration of genetic markers, body composition analysis, and advanced thermoregulatory assessments could provide deeper insights into the biological basis of differential cooling responses (Patel et al., 2009, Périard et al., 2016). The machine learning approach could be extended to include additional physiological and performance variables, potentially improving phenotype identification precision and supporting development of real-time cooling intervention strategies.

4. CONCLUSIONS

This study demonstrates successful application of machine learning-based phenotyping to characterize individual responses to cooling interventions in futsal athletes. The identification of three distinct physiological response phenotypes challenges current standardized approaches and supports development of personalized cooling strategies. The findings contribute to growing evidence supporting precision medicine approaches in sports science and provide a foundation for optimizing cooling intervention effectiveness through individualized prescription. The integration of unsupervised learning techniques represents a significant advancement in identifying and characterizing individual differences in intervention responses, with potential to transform performance intervention implementation from generic protocols to personalized strategies that optimize individual athlete responses.

Data Availability Statement: The authors will provide the raw data supporting the results of this article without hesitation.

Ethics Statement: The research involving human subjects received approval from the Ethics Committee of Srinakharinwirot University. The research was performed in compliance with local laws and institutional regulations. The participants granted their written informed consent to engage in this investigation.

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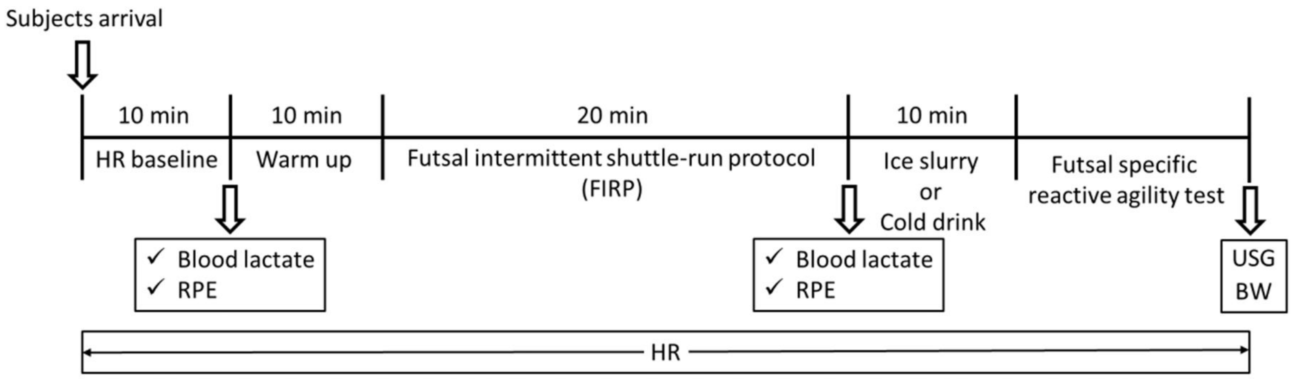

Figure 1: The Study Design.

Table 1: Meaning Of Each Data Feature.

Parameter	Full Name	Unit	Significance
RAG_D	Repeated Anaerobic Glycolytic Distance	meters (m)	Measures total sprint distance; indicates anaerobic performance capacity.
RAG_T	Repeated Anaerobic Glycolytic Time	seconds (s) or minutes (min)	Time taken to complete anaerobic sprint bouts; relates to fatigue resistance.
Lactate	Blood Lactate Concentration	mg/L	Reflects exercise intensity and anaerobic metabolism; higher values = more fatigue.
Heart Rate	Heart Rate	beats per minute (bpm)	Indicates cardiovascular effort and training intensity.
USG	Urine Specific Gravity	unitless (e.g. 1.020)	Assesses hydration status; higher values suggest dehydration.
BM	Body Mass	kilograms (kg)	Body weight without clothes; used to calculate sweat loss.
RPE	Rating of Perceived Exertion	scale (e.g. 6–20 or 1–10)	Subjective fatigue rating; helps monitor training load.
Drink Weight	Weight of Fluid Consumed	gram (g)	Amount of fluid ingested; important for hydration planning.
Sweat Volume	Sweat Loss	milliliters (ml)	Estimated fluid lost through sweat; key to managing fluid balance.

Table 2: Repeated Anaerobic Glycolytic Distance (Rag_D).

Futsal Player No.	Pre intake	Post cold intake	Post ice intake
1	3.23	4.09	3.63
2	3.58	3.76	3.53
3	3.4	3.79	3.32
4	3.25	3.27	3.5
5	3.44	3.51	3.52
6	3.18	3.4	3.35
7	3.33	3.37	3.48
8	3.23	3.24	3.36
9	3.6	3.66	3.47

Table 3: Repeated Anaerobic Glycolytic Time (Rag_T).

Futsal Player No.	Pre intake	Post cold intake	Post ice intake
1	3.76	4.12	3.75
2	3.78	4.02	3.89
3	3.72	3.69	3.91
4	3.29	3.53	3.66
5	3.52	3.72	3.66
6	3.82	3.755	3.88
7	3.54	3.54	3.75
8	3.49	3.57	3.38
9	3.64	3.79	3.58

Table 4: Blood Lactate Concentration (Lactate).

Futsal Player No.	Pre intake	Post cold intake	Pre intake	Post ice intake

1	1.50	6.00	1.30	6.00
2	2.80	6.20	1.30	9.40
3	2.10	5.60	2.10	13.00
4	1.30	3.00	1.60	3.30
5	1.50	2.00	1.00	1.80
6	0.80	3.20	1.40	3.00
7	1.30	2.30	1.10	1.90
8	2.10	4.00	1.20	3.80
9	1.90	2.20	0.90	1.00

Table 5: Heart Rate (Bpm).

Futsal Player No.	Pre intake	Post cold intake	Pre intake	Post ice intake
1	70	160	69	163
2	78	170	87	183
3	79	169	82	184
4	77	146	81	168
5	59	159	54	159
6	57	146	63	153
7	66	147	64	142
8	88	161	80	161
9	61	154	65	142

Table 6: Urine Specific Gravity (Usg).

Futsal Player No.	Pre intake	Post cold intake	Pre intake	Post ice intake
1	1.0200	1.0310	1.0050	1.0310
2	1.0039	1.0025	1.0137	1.0090
3	1.0170	1.0160	1.0144	1.0171
4	1.0159	1.0186	1.0155	1.0183
5	1.0243	1.0181	1.0254	1.0220
6	1.0080	1.0040	1.0149	1.0109
7	1.0300	1.0310	1.0090	1.0130
8	1.0190	1.0120	1.0150	1.0150
9	1.0200	1.0050	1.0050	1.0070

Table 7: Body Mass (Kg).

Futsal Player No.	Pre intake	Post cold intake	Pre intake	Post ice intake
1	69.00	68.90	69.80	69.50
2	55.20	55.10	55.20	55.20
3	51.60	51.70	51.30	51.30
4	64.20	64.00	63.70	64.20
5	52.20	52.10	52.30	52.10
6	75.80	75.50	75.90	75.60
7	62.10	62.20	63.10	63.10
8	59.70	59.50	59.40	59.30
9	60.00	59.70	60.70	60.50

Table 8: Rating Of Perceived Exertion (RPE).

Futsal Player No.	Post cold intake	Post ice intake
1	6	11
2	6	15
3	6	15
4	6	11
5	6	9
6	6	9
7	6	12
8	6	13
9	6	9

Table 9: Volume Of Fluid Consumed (G).

Futsal Player No.	Post cold intake	Post ice intake
1	517.50	525.00
2	412.50	414.00
3	387.00	384.79

4	481.50	477.75
5	393.75	392.25
6	568.50	569.25
7	465.75	473.25
8	447.75	445.50
9	450.00	455.25

Table 10: Sweat Weight or Sweat Loss (Ml).

Futsal Player No.	Post cold intake	Post ice intake
1	517.60	525.30
2	412.60	414.00
3	386.90	384.79
4	481.70	477.25
5	393.85	392.45
6	568.80	569.55
7	465.65	473.25
8	447.95	445.60
9	450.30	455.45

Table 11: Group Assignment of Futsal Players Who Intake Cold Beverage Intake or Ice-Slurry Using the Data Classification When K=2.

Futsal Player No.	Assigned group
1	2
2	1
3	1
4	2
5	1
6	2
7	2
8	1
9	1

Table 12: Group Assignment of Futsal Players Who Intake Cold Beverage Intake or Ice-Slurry Using the Data Classification When K=3.

Futsal Player No.	Assigned group
1	2
2	1
3	1
4	3
5	1
6	2
7	3
8	3
9	3

Table 13: Group Representatives of the Data Classification When K=2.

		Group representative's players	
Parameter	State	Group 1	Group 2
RAG_D	Pre	3.45	3.25
	Post Cold	3.59	3.53
	Post Ice	3.44	2.79
RAG_T	Pre	3.63	2.88
	Post Cold	3.76	3.74
	Post Ice	3.68	3.76
Lactate	Pre Cold	2.08	1.23
	Post Cold	4.00	3.63
	Pre Ice	1.30	1.35
	Post Ice	5.80	3.55
Heart Rate	Pre Cold	73.00	67.50
	Post Cold	162.60	149.75
	Pre Ice	73.60	69.25
	Post Ice	165.80	156.50
USG	Pre Cold	1.02	1.02

	Post Cold	1.01	1.02
	Pre Ice	1.01	1.01
	Post Ice	1.01	1.02
BM	Pre Cold	55.74	67.78
	Post Cold	55.62	67.65
	Pre Ice	55.78	68.13
	Post Ice	55.68	68.10
Drink Volume	Post Cold	418.20	508.31
	Post Ice	418.36	511.31
Sweat Volume	Post Cold	418.32	508.44
	Post Ice	418.46	511.34

Table 14: Group Representatives of The Data Classification When K=3.

		Group representative's players		
Parameter	State	Group 1	Group 2	Group 3
RAG_D	Pre	3.47	3.21	3.35
	Post Cold	3.69	3.75	3.39
	Post Ice	3.46	3.49	3.45
RAG_T	Pre	3.67	3.79	3.49
	Post Cold	3.81	3.94	3.61
	Post Ice	3.82	3.82	3.59
Lactate	Pre Cold	2.13	1.15	1.65
	Post Cold	4.60	4.60	2.88
	Pre Ice	1.47	1.35	1.20
	Post Ice	8.07	4.50	2.50
Heart Rate	Pre Cold	72.00	63.50	73.00
	Post Cold	166.00	153.00	152.00
	Pre Ice	74.33	66.00	72.50
	Post Ice	175.33	158.00	153.25
USG	Pre Cold	1.02	1.01	1.02
	Post Cold	1.02	1.02	1.02
	Pre Ice	1.02	1.01	1.01
	Post Ice	1.02	1.02	1.01
BM	Pre Cold	53.00	72.40	61.50
	Post Cold	52.97	72.20	61.35
	Pre Ice	52.93	72.85	61.73
	Post Ice	52.87	72.55	61.78
Drink Volume	Post Cold	397.75	543.00	461.25
	Post Ice	397.01	547.13	462.94
Sweat Volume	Post Cold	397.78	543.20	461.40
	Post Ice	397.08	547.43	462.89